Understanding the relationship of lumber yield and cutting bill requirements: a statistical approach

by

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Wood Science and Forest Products

(ABSTRACT)

Secondary hardwood products manufacturers have been placing heavy emphasis on lumber yield improvements in recent years. More attention has been on lumber grade and cutting technology rather than cutting bill design. However, understanding the underlying physical phenomena of *cutting bill requirements* and yield is essential to improve lumber yield in rough mills. This understanding could also be helpful in constructing a novel lumber yield estimation model.

The purpose of this study was to advance the understanding of the phenomena relating cutting bill requirements and yield. The scientific knowledge gained was used to describe and quantify the effect of part length, width, and quantity on yield. Based on this knowledge, a statistics based approach to the lumber yield estimation problem was undertaken. Rip-first rough mill simulation techniques and statistical methods were used to attain the study's goals.

To facilitate the statistical analysis of the relationship of cutting bill requirements and lumber yield, a theoretical concept, called *cutting bill part groups*, was developed. Part groups are a standardized way to describe cutting bill requirements. All parts required by a cutting bill are clustered within 20 individual groups according to their size. Each group's midpoint is the representative part size for all parts falling within an individual group. These groups are made such that the error from clustering is minimized. This concept allowed a decrease in the number of possible factors to account for in the analysis of the cutting bill requirements - lumber yield relationship. Validation of the concept revealed that the average error due to clustering parts is 1.82 percent absolute yield.

An orthogonal, 2^{20-11} fractional factorial design of resolution V was then used to

determine the contribution of different part sizes to lumber yield. All 20 part sizes and 113 of a total of 190 unique secondary interactions were found to be significant ($\alpha = 0.05$) in explaining the variability in yield observed. Parameter estimates of the part sizes and the secondary interactions were then used to specify the average yield contribution of each variable. Parts with size 17.50 inches in length and 2.50 inches in width were found to contribute the most to higher yield. The positive effect on yield due to parts smaller than 17.50 by 2.50 inches is less pronounced because their quantity is relatively small in an average cutting bill. Parts with size 72.50 by 4.25 inches, on the other hand, had the most negative influence on high yield. However, as further analysis showed, not only the individual parts required by a cutting bill, but also their interaction determines yield. By adding a sufficiently large number of smaller parts to a cutting bill that requires large parts to be cut, high levels of yield can be achieved.

A novel yield estimation model using linear least squares techniques was derived based on the data from the fractional factorial design. This model estimates expected yield based on part quantities required by a standardized cutting bill. The final model contained all 20 part groups and their 190 unique secondary interactions. The adjusted R^2 for this model was found to be 0.94. The model estimated 450 of the 512 standardized cutting bills used for its derivation to within one percent absolute yield. Standardized cutting bills, whose yield level differs by more than two percent can thus be classified correctly in 88 percent of the cases. Standardized cutting bills whose part quantities were tested beyond the established framework, i.e. the settings used for the data derivation, were estimated with an average error of 2.19 percent absolute yield. Despite the error observed, the model ranked the cutting bills as to their yield level quite accurately. However, cutting bills from actual rough mill operations, which were well beyond the framework of the model, were found to have an average estimation error of 7.62 percent. Nonetheless, the model classified four out of five cutting bills correctly as to their ranking of the yield level achieved. The least squares estimation model thus is a helpful tool in ranking cutting bills for their expected yield level. Overall, the model performs well for standardized cutting bills, but more work is needed to make the model generally applicable for cutting bills whose requirements are beyond the framework established in this study.

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CHAPTER 1

1. INTRODUCTION

1.1 PERSPECTIVE

Solid wood dimension parts[1] are produced from better quality, kiln dried lumber. Dimension parts are slightly oversized rectangular pieces[2]. The parts are cut in the rough mill of furniture, cabinet and of dimension parts plants. Rough mills consist of a series of machines and allied equipment intended to convert kiln dried lumber into dimension stock. A list of needed pieces, called a cutting bill, describes the parts to be produced during a given rough mill production run. The objective of a rough mill is to produce these parts at the lowest overall cost in the quality and quantity required by the cutting bill. Lumber yield is the most commonly used measure of efficiency in a rough mill. Yield is defined as the ratio of aggregate part surface area output to aggregate lumber surface area input (Gatchell 1985). The cost of lumber accounts for approximately 70 percent of total costs incurred in a rough mill (Wengert and Lamb 1994b). Total costs consist of the material and processing costs incurred to produce parts in a rough mill. The furniture, cabinet, and dimension industries typically use intermediate quality and priced lumber (Wiedenbeck 1997, Luppold and Baumgras 1996). Due to the large amount of lumber used in a typical rough mill and high lumber prices (Cubbage et al. 1995, Luppold and Baumgras 1995, Muench 1993), product yield becomes crucial to the profitability of the overall operation (Anderson et al. 1992).

Producing dimension stock from lumber is a unique manufacturing step unknown in other industries (Anonymous 1979). Lumber boards must be cut in such a way as to obtain all the parts listed in a cutting bill while maximizing yield. The process is complicated because lumber is a heterogeneous raw

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1 Dimension parts, in this case, refer to all solid wood parts that are used in the furniture, cabinet and dimension part industries. The terms dimension part, dimension part industries or dimension producers applies for all three industries listed.

2 Dimension parts are also called blanks, cutting stock, component parts, or dimensions parts

material with varying sizes and unusable areas (defects) spread throughout the boards (Brunner et al. 1990). Extensive work has been done and is currently underway to improve yield in the furniture, cabinet, and dimension parts rough mills. However, the industries' rough mills lag behind other manufacturing sectors in state-of-the-art technology adoption. Presently, the cutting decisions as to how to cut a board are made by human operators with little technical help. Kline et al. (1997) compared the yield obtained in a state-of-the-art rip-first rough mill and the maximum yield achievable for the same lumber using computer simulation. The authors found that yield in the state-of-the-art rip-first rough mill was 3.5 percent below the level achieved by the computer simulation. As computerized vision systems become available (Conners et al. 1997), near optimal cutting decisions will become a reality. Optimal cutting decisions occur when a board is cut such that no material is lost except for defective areas. However, engineered scrap[3] due to poorly composed cutting bills will continue to exist.

Cutting bill requirements are a major determinant of the yield achieved (BCWood Specialties Group 1996, Wengert and Lamb 1994b). Cutting bill requirements refer to geometric and quantitative parameters of the parts contained in cutting bills. More specifically, cutting bill requirements refer to the size of individual parts in a cutting bill, the distribution of this sizes, and the individual quantities of parts required. Other expressions for cutting bill requirements include cutting bill geometry, cutting bill characteristics or cutting bill parameters. Appendix A elaborates on the concept of cutting bill requirements.

Existing yield prediction models, such as the widely used yield nomograms FPL 118 by Englerth and Schumann (1969) consider cutting bill requirements in their algorithms. The expected yield for each part in respect to all other parts contained in a cutting bill is calculated. FPL 118 and rules-of-thumb used in industry assume that the smallest part sizes determine yield (Wengert and Lamb 1994b, Englerth and Schumann 1996). Total predicted yield is then the sum of individual yields for the different part sizes in a cutting bill. However, some authors doubt the accuracy of predictions derived with the FPL

[3] Engineered scrap is defined as wasted material incurred because of poor planning or design (Ittner and Kaplan 1988).

118 nomograms (Thomas et al. 1996, Wiedenbeck and Scheerer 1996, Manalan et al. 1980).

Despite the high influence of cutting bill requirements on yield, little fundamental knowledge about this relationship exists. Advancing the understanding of the cutting bill parameters that influence yield is therefore a critical task. This study attempts to advance this understanding.

1.2 PROBLEM STATEMENT AND JUSTIFICATION

The forest products industries have contributed significantly to the wealth of the United States for the last 350 years. In 1992, primary wood products contributed $77 billion to the U.S. economy, making it the largest single U.S. agricultural crop (Hoff et al. 1997). Semi-finished parts from the rough mills of the furniture, cabinet, and dimension part producers[4], were worth $16 billion in 1992 (U.S. Department of Commerce - Bureau of the Census 1994). The secondary hardwood products manufacturers employed more than 383,000 people in 11,754 companies in 1992 (U.S. Department of Commerce - Bureau of the Census 1994).

The wooden furniture, cabinet, and dimension part industries are highly competitive (Smith and West 1990, Forbes 1995) and face considerable pressure from imports (Hoff et al. 1997, West 1996, Idrus 1994). These industries have historically been characterized by low productivity[5], small investments in new equipment, low employee training and low returns (Geiger et al. 1990). The prospect of continuing low returns in the industry led to divestment in secondary hardwood processing industries in the 1990s by renowned investment firms like Armstrong World Industries and Masco Corporation (Ross 1996, Manoogian 1995). To make the industry attractive for new capital and to survive in the global economy, the U.S. secondary hardwood industry needs to improve existing processing technologies to boost

4 Following industries were included for aggregate values: hardwood dimension and flooring mills (SIC 2426), wood kitchen cabinet (SIC 2434), wood household furniture (SIC 2511), upholstered household furniture (SIC 2512), wood office furniture (SIC 2521), public building and related furniture (SIC 2531), wood partitions and fixtures (SIC 2541).

5 Rough mill productivity is typically measured as: (1) parts-volume/hour; (2) Value or Volume/Employee; (3) Value or Volume/$ of equipment; or (4) $ value of parts produced/$ spent on material. Yield is used as a productivity measure, but yield is not a profitability measure.

efficiency and to lower production cost (Lin 1993).

Mainly the higher value, better quality lumber is used for appearance applications in the dimension industries (Sinclair 1992). According to Luppold (1993), in 1991 the dimension industries used about 36.4 percent (equal to 4.5 billion board feet) of the total industrial hardwood lumber produced. With a 33 percent market share, red oak was by far the most important species consumed (Hansen et al. 1995, Meyer et. al. 1992)[6]. Increasing demand for high quality species (Luppold 1991, Bush et al. 1990) and limited availability of the more highly valued hardwood logs (Luppold 1994, Bechtold and Sheffield 1991, Tansey 1988) led to increases in real prices for red oak lumber (Luppold and Baumgras 1995, Muench 1993) and to a decrease in the availability of higher graded lumber. Since species substitution is unlikely to occur for several reasons and no other alternative lumber sources are available (Lamb 1994a), price increases are expected to continue in the future (Cubbage et al. 1995). Thus, hardwood-based product manufacturers are under increasing pressure to optimally use their raw material.

West and Hansen (1996) estimate that total material costs for U.S. furniture producers are about 50 percent of the total product costs. Wood material costs are between a quarter and half of the total material costs for solid wood furniture (Lamb 1997, Anonymous 1984, Weidhaas 1969). Accordingly, Wengert and Lamb (1994b, p. 19) state, "*Efforts to reduce operating costs by saving labor, saving energy, or reducing drying time are usually quite unrewarding.*" This is true, because raw material costs are by far the most significant costs in rough mills. Saving one percent of raw material (i.e. increasing yield by one percent) potentially saves two percent of total production costs (Kline et al. 1998, Wengert and Lamb 1994a). Higher yield not only saves raw material, but at the same time increases production capacity of the operation because fewer boards have to be processed for the same output.

Increasing lumber yield in the rough mills of the wood processing industries is not only important on a micro scale, but also on a macro scale for the economy and ecology. Sutton (1993) predicts

6 The use of species is based on observations of the furniture industry (SIC 2511, 2512, 2521, and 2531), which contributed 66 percent of the value added by the dimension part industries, who are supplying the furniture industry. Therefore, species mix in the dimension industry is not assumed to deviate from this observation to a great extend.

serious timber shortages in the near future. Global industrial wood demand is expected to increase every year by 18.3 billion board feet to 1.1 trillion board feet in 2010. This global demand implies that every year one and a half times the total industrial hardwood consumption of the U.S. in 1991 has to be added to satisfy the additional need for industrial wood worldwide. As a consequence, the pressure on the American hardwood resources will further increase.

There is a vast potential for improving the utilization of wood for dimension part producers. On average, only about one-sixteenth (6.25 percent) of the original tree is converted into solid wood parts (Khan and Mukherjee 1991). Also, fewer than 25 percent of a log is utilized for parts, assuming 50 percent conversion rates in rough mills and in the sawmill, respectively (Wiedenbeck and Buehlmann 1995). The rest is either processed to other secondary wood products or wasted. To produce the correct number of parts in the most economical way, the secondary wood products industry has developed and adopted different technologies and systems. Gang-rip first rough mills, computer-based optimization of cuttings, changes in product specifications, and better use of lower quality lumber are some examples of these innovations (Wiedenbeck and Thomas 1995b). Today, research is done on improved computer based yield maximization algorithms (Thomas 1997a and 1996a), vision systems (Conners et al. 1997), laser cutting techniques that reduce sawkerf width (Khan and Mukherjee 1991), and other innovative ideas.

Despite the large impact of cutting bill requirements on yield, little research has addressed this phenomena yet. Except for some simple, empirically based studies, scientific research of yield obtained from hardwood lumber in rough mills did not start before the simulation of the lumber cut-up process on computers became available. The most widely used yield nomograms were constructed by Englerth and Schumann (1969) for 4/4 hard maple. These yield nomograms estimate the expected yield for a specific cutting bill. Today, several experts consider these nomograms as inaccurate and unpractical (Thomas et al. 1996, Wiedenbeck and Scheerer 1996, Yaussy 1986, Manalan et al. 1980).

Cutting bill requirements have a major influence on yield when cutting dimension parts from lumber (Buehlmann et al. 1998a and 1998b, BC Wood Specialties Group 1996, Wengert and Lamb 1994b). Buehlmann et al. (1998a) found that different cutting bill requirements can lead to yield

differences greater than 5 percent in a rip-first rough mill among different cutting bills. Figure 1.1 shows the yield obtained for seven different cutting bills when processing No. 1 Common lumber. The bars depict the average yield from five replicates, the error bars show maximum and minimum values observed, respectively.

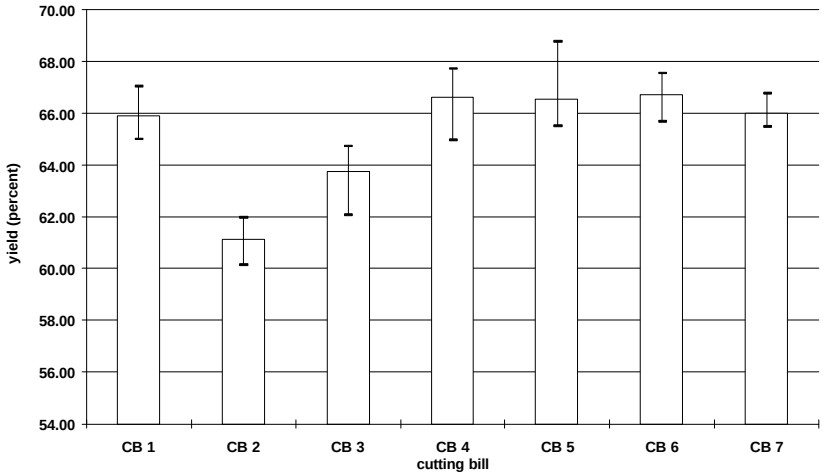


Figure 1.1: Influence of cutting bill requirements on yield when using No. 1 Common lumber in a gang-rip-first processing sequence (Buehlmann et al. 1998a)

The influence of cutting bill requirements on yield was found to be substantial. Analysis of variance revealed that there are significant ($\alpha = 0.05$) yield differences among cutting bills. The maximum yield difference observed between cutting bill two and cutting bill six was 5.6 percentage. While the geometry of these two cutting bills, as Table 1.1 shows, was different, similar cutting bills like CB three and CB five, still had a yield difference of 2.8 percent. This experiment proves that differences in cutting bill requirements influence the yield obtained. However, the importance of the different factors governing this physical phenomena and how they interact is unknown.

Figure 1.1 opens several questions that cannot be answered with today's available knowledge. As stated earlier, it is commonly believed that the smallest part sizes determine yield (Wengert and Lamb 1994b). However, cutting bill two asks for the shortest part of all cutting bills (5.8 inches), but cutting bill

Table 1.1: Cutting bill requirements of the seven cutting bills studied (Buehlmann et al. 1998a).

Name	Part Distribution		Geometry								
			Length			Width			Area		
Cutting bill	# of sizes in cutting bill	Total # of parts in cutting bill	Min. in.	Max. in.	Average in.	Min. in.	Max. in.	Average in.	Min. sq. in.	Max. sq. in.	Average sq in.
CB 1	77	1086	8.5	78.8	34.6	1.0	5.8	3.2	18.5	334.7	106.2
CB 2	13	1200	5.8	77.3	26.5	1.0	6.0	3.1	15.8	240.0	80.1
CB 3	45	1515	12.0	63.0	26.6	1.0	6.8	3.4	17.5	330.8	98.4
CB 4	36	1362	18.5	81.3	29.7	1.5	3.3	2.2	31.5	203.1	75.4
CB 5	42	1220	12.3	68.8	23.1	1.3	6.8	3.0	16.9	364.5	74.4
CB 6	47	1648	17.8	73.0	31.0	1.5	3.3	2.2	30.4	164.3	68.6
CB 7	12	2000	14.5	75.5	27.2	2.0	3.5	2.7	36.0	188.8	73.5

two achieves the lowest yield level. Levels of yield cannot be explained by average cutting lengths, either. Cutting bill six has the second longest average length but achieves the highest yield of all cutting bills in this study. Cutting bill six, however, does have the smallest average part area and average part width. These two facts may explain some of the superior yield level that cutting bill six achieves. The total number of parts required by a cutting bill may also influence the level of yield achieved. Comparing cutting bill two and cutting bill seven support the notion that the number of parts to be cut matters. Clearly, the facts presented here indicate that the determination of the level of yield a cutting bill achieves is determined by more than one factor that have a direct and an indirect (correlation) effect on yield a cutting bill achieves.

Because of the dependence of yield on cutting bill requirements, yield prediction becomes a difficult endeavor. A general yield prediction model would have to take into account cutting bill requirements, lumber grades, part qualities, and rough mill specific process settings to make accurate forecasts. Even for the case where only cutting bill requirements is variable, prediction is complex.

Figure 1.2 and Figure 1.3 compare the yield for two hypothetical situations as calculated by the FPL 118 Nomograms (Englerth and Schumann 1969). The situations depicted are:

(a) Figure 1.2 shows predicted yield when only one part is cut. The size (i.e. length and width) of this part is variable.

(b) Figure 1.3 shows predicted yield when two parts are cut simultaneously. One part's

size changes as in (a). The second part's length does not change and is fixed to 10 inches, its width is variable.

The two figures show the impact of different cutting bill requirements on yield. In situation (a), yield is dependent on the size of the one part to be cut. In situation (b), however, the small part determines yield, the larger part is only cut when feasible. Thus a high baseline yield is achieved independent of the

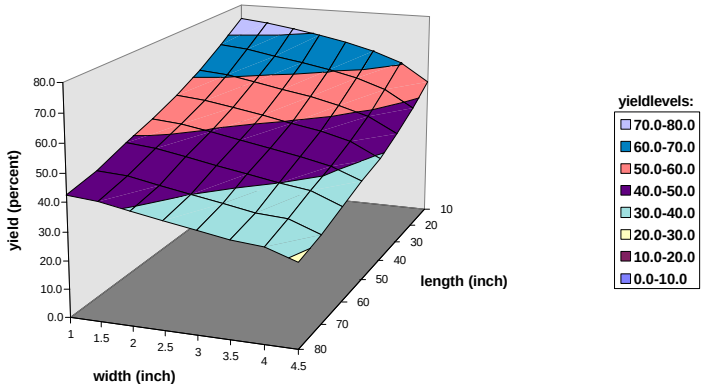


Figure 1.2: Situation (a), yield surface for one part (calculated from Englerth and Schumann 1969).

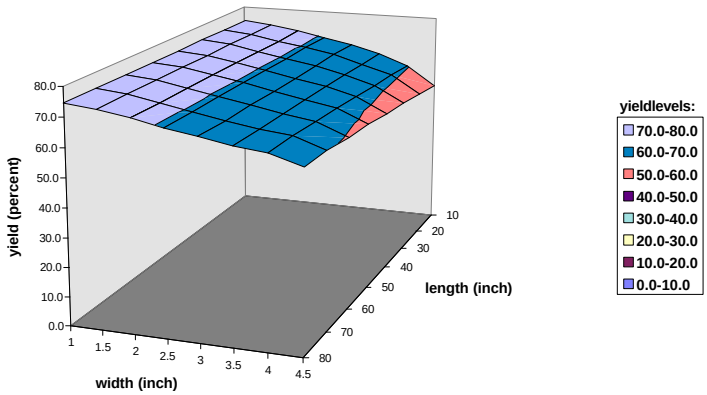


Figure 1.3: Situation (b), yield surface for two parts (calculated from Englerth and Schumann 1969).

size of the larger part. However, these two cases are not realistic. Rough mills do not cut only one part at a time, and part quantities will be restricted. In more realistic cases, there will be many parts of different sizes and quantities. In such cases, yield determination is very complex. Thomas (1997a, p. 3) correctly stated "T*he problem of yield optimization is greatly complicated by the processing demands of cutting bills. Rather than optimizing for the best fit of parts to each board, cutting bill optimization must consider specific quantities attached to each part. Specific quantities of different sized parts must be obtained, without producing additional or excess parts*". What Thomas stated for the optimization of yield is equally applicable to the yield prediction problem.

As demonstrated, cutting bills affect yield. Yield prediction for different cutting bills is needed by manufacturers to enable them to better cost customer orders. At the same time, an understanding of how cutting bill parameters affect yield could be used to assemble cutting bills that optimally utilize the available lumber resource. However, there is insufficient knowledge as to how cutting bill requirements affect yield. Existing models to describe this interaction are inaccurate and unpractical to apply (Thomas et al. 1996, Wiedenbeck and Scheerer 1996, Yaussy 1986, Manalan 1980). The goal of this study is to gain a fundamental understanding of the physical phenomena relating cutting bill requirements and lumber yield. This understanding will ultimately lead to models that make the rough mill operation more predictable and methods to make rough mill yield more controllable. The study will utilize a statistical approach to gain a better understanding of the complex interactions between cutting bill requirements and lumber yield. Today, no detailed knowledge exists about the individual interactions between parts and yields. Questions such as "Are there ways to increase lumber yield by combining specific parts into the same cutting bill?" or "Should a producer reject certain parts that will decrease his/her mill's yield?" are asked but cannot be answered with the existing knowledge. A fundamental understanding of the yield and cutting bill requirements interaction is needed to answer these questions. The results of this study were expected to provide an understanding of the relationship between cutting bill requirements and yield.

1.3 HYPOTHESIS AND OBJECTIVES

1.3.1 Hypothesis

In a gang-rip-first rough mill, when cutting lumber to obtain parts specified in a cutting bill, complex interactions between cutting bill requirements and yield exist. This research investigated the relationship between yield and cutting bill requirements for a gang-rip-first system. It was hypothesized that by understanding the exact relationships and interactions of cutting bill factors, yield can be more accurately characterized and predicted. Also, it was proposed that the fundamental understanding of the cutting bill factors and yield will allow the design of cutting bills such that higher yield is achieved.

1.3.2 Objectives

The purpose of this study was to advance the understanding of the physical phenomena relating cutting bill requirements and yield in a rip-first rough mill. This knowledge was used to describe and quantify the effect of part length, width, and quantity on yield. In addition, interactions among different part lengths, widths, and quantities were described and quantified. This in-depth understanding resulted in a novel approach for a yield estimation model to estimate the expected yield based on cutting bill requirements. Questions as to how to increase yield by specifically designing cutting bills for maximum yield were addressed. The specific objectives of this research were:

1. Create cutting bill part groups such that parts within each part group have a similar influence on yield. Part-groups are groups made up of parts with similar geometric sizes.
2. Determine the importance and contribution of the different cutting bill part-groups derived in Objective 1 on lumber yield in a gang-rip-first rough mill.
3. Develop, test, and validate a lumber yield model using a statistical approach that can estimate the yield for a cutting bills processed in gang-rip-first rough mills.

CHAPTER 2

2. LITERATURE REVIEW

This chapter provides first an overview of rough mill processes and rough mill yield. Thereafter, simulation models that mimic the complex processes occurring in rough mills are described, followed by explanations about cutting bills and their quantity requirements. In the next section, the existing knowledge about the relationship between cutting bill requirements and yield is presented. Subsequently, the lumber used for dimension parts is described and analyzed. At the end of this chapter, analytical tools that are used by the wood products industry are explained. More specifically, this section presents the ideas and the use of fractional factorial designs and multiple linear regression analysis.

2.1 DIMENSION PART ROUGH MILL OPERATIONS

2.1.1 Rough mill processes

The production process for dimension parts starts with the cut-up of lumber in the rough mill. Other processes like drying, grading, sorting, or skip planing may precede this process. Cutting lumber into parts is essentially a discrete event batch process. Two types of cutting systems are employed: crosscut-first and rip-first. The distinction between these two systems is the sequence in which the boards are cut to smaller pieces. Rip-first systems cut the incoming boards to long, narrow strips and then crosscut the strips to length in the second stage. Crosscut-first systems cut the parts to length first and thereafter to width. Both systems contain process loops that allow to repeat the cutting sequence to salvage parts with defects. This is done to increase overall yield (Anderson et al. 1992).

Which of the two systems results in higher yield is object to much controversy. Several studies (Harding 1991, Pepke 1980, Hall et al. 1980, Araman 1978, Lucas and Araman 1975) researched yield differences between the two systems. However, no conclusive answer was reached. In the most recent

study, Buehlmann et al. (1998b), found significant yield differences between these two systems. However, one system did not consistently outperform the other. Yield levels for the individual system are dependent on lumber grade, cutting bill requirements, and other system specific parameters. Also, dimension producers normally are more concerned about total production cost rather than yield. However, Hall et al. (1980) did not find a significant cost difference between the two systems.

In the past, crosscut-first systems were dominantly used to cut-up lumber. Recently, rip-first systems are getting more attention (Mullin 1990, BC Wood Specialties Group 1996). Reasons include that rip-first systems produce higher yields of longer parts from lower grades of lumber (Gatchell 1987), require fewer and simpler operational decisions (Mullin 1990), and make it easier for operators to recognize and locate defects. Mullin (1990) expects 90 percent of the newly installed rough mill systems in the future to be of the rip-first type.

The dimension part industry strives for greater automation of their lumber processing operations. Reduction of labor cost (Huber et al. 1989), consistent defect removal (Huber et al. 1990) and increased yield from improved cut-up decisions (Lamb and Wengert 1981) are expected to be achieved through automated systems. Automated rough mills will require automatic lumber feature recognition (Kline et al. 1993) to create digital data of the board, so that further processing strategies can be calculated and implemented by computers.

McMillin et al. (1984) suggested a completely automated lumber processing system called Automated Lumber Processing System (ALPS). ALPS would integrate log sawing, lumber drying and dimension part cut-up. Laser based breakdown of the boards would reduce sawkerf losses and allow to punch-cut the boards. Yield increases of up to 23 percentage points could be expected (Wengert and Lamb 1994a, Yun 1989). However, ALPS is still in its prototype stage (Klinkhachorn 1993) and is not very likely to be commercialized in the near future (Lamb 1997). One setback of the system is that the edges of parts when cut are charred and thus are hard to glue up and may represent an aesthetical problem. Another problem is the production capacity of the system, which is low due to the slow moving laser-cutting head(s).

2.1.2 Rough mill yield

Rough mill yield, i. e. the "*ratio of the surface area of output to the surface area of input of common thickness expressed as a percent*" (Gatchell 1985, p. 146), is traditionally used as a measure of rough mill performance. Yun (1989) pointed out that yield can be considered in terms of value instead of the more usual volume or surface measure. In her study, she defined value as the cost of the material expended to produce a cutting. Value can also be defined according to some other specifications like urgency to obtain a part or by the price that a part achieves when sold. Still other definitions of value are possible and used for part prioritization strategies (Thomas 1996b and 1995b). In this study, yield always refers to surface area output to surface area input, unless otherwise mentioned.

Several authors (Wengert and Lamb 1994b, Gatchell 1985, Anonymous 1985) list the individual factors affecting rough mill yield. Table 2.1 presents an overview of the factors mentioned in these literature sources.

Table 2.1: Factors affecting rough mill yield according to three authors.

Factor	Wengert and Lamb (1994)	Gatchell (1985)	Anonymous (1985)
Grade of lumber	Yes	Yes	Yes
Drying quality	Yes	-	Yes
Cutting bill	Yes	Yes	Yes
Operator's skill	Yes	Yes	Yes
Part quality	Yes	-	Yes
Rough mill layout	Yes	-	Yes
Kerf	Yes	-	-
Edging practices	Yes	-	-
Lumber size	Yes	Yes	Yes
Lumber grading (consistency)	Yes	Yes	Yes

Missing identification of factors does not necessarily suggest disagreement among the authors, but is more likely due to varying assumptions. Wengert and Lamb (1994b, p. 11) ranked the factors in "*approximate order of importance*". The ranks of the factors in Table 2.1 represent this order, starting on top with the extremely important to the ones of smaller importance at the bottom of the table according to Wengert and Lamb (1994b).

All the points listed in Table 2.1 are sources of yield variability. Researching the lumber cut-up – lumber yield relationship is therefore understandably a very difficult area. Besides the many different factors that affect yield, all of them are heavily interrelated with each other. There is little understanding in the scientific community or in the industrial operations as to how this system of interrelated factors really works. The complexity of the entire system can be better appreciated when one realizes how difficult it is to study each of these factors in isolation.

2.1.3 Rough mill yield simulation models

Before the advent of electronic computing techniques, dimension part producers relied on empirically derived post hoc heuristics to estimate the expected yield from a particular order (Suter and Calloway 1994. Mathematical solutions, which would provide optimum results and faster computing, exist only for simplified cases of the lumber cut-up problem (Carnieri et al. 1993). Gilmore and Gomory (1961, 1965, and 1966) developed a general two-phase procedure using uni-dimensional knapsack algorithms to build an optimal cutting model that can be applied for any material in two dimensions. However, this model does not account for directional requirements (grain orientation) or for defects within the rectangular area of a board. Gilmore and Gomory's model does not allow to account for part quantity requirements, either. It was Wang (1983), who introduced a way to account for part quantity requirements. Carnieri et al. (1991a and 1991b) were the first who employed the work by Gilmore and Gomory and by Wang to solve the lumber cut-up problem. However, these authors did not address the problem of random defects in the board area. Foronda and Carino (1991) were then the first to solve the problem of having defects in lumber boards, although only for the general case. Their solution does not consider the geometrical location of the defects, but makes the simplistic assumption that, on average of all boards processed, a certain amount of different areas of clear lumber are available. Even though this approach allows to obtain information about the optimal amount of parts (or, equivalently, yield) that can be obtained from a given lumber stack, it does not provide the actual cutting solutions. Carnieri et al., in 1993, presented the first mathematical solution for the lumber cut-up problem that is able to find an

optimal cut-up solution. However, their procedure is not a real optimum method, but rather a heuristic process that determines the optimal cutting pattern for boards with differing sizes (length and width). Unfortunately, their model only works for boards that contain not more than one defect, which severely limits its applicability.

Due to this lack of general applicable mathematical models to solve the lumber cut-up problem, computer simulation techniques are widely used for the simulation of rough mill processing and lumber yield (Wiedenbeck and Kline 1994, Lin 1993). Computers allow the use of either exhaustive search methods or heuristic approaches (Brunner et al. 1990). It was Thomas (1962) who pioneered the use of computer-based simulation to estimate yield. He mapped the board geometry and the defects of approximately 35,000 board feet of oak, yellow poplar, and hard maple on punch cards. A computer based heuristic algorithm that simulated "*as closely as possible the performance of a cross-cut saw operator*" then processed the boards. Thomas' program included two simplifying assumptions: 1) kerf losses were not considered, and 2) cuts were not extended over the full board length and width. Therefore, some of the cuts were in fact infeasible. Both these assumptions inflated yield. Assumption two implies that the program did not crosscut-first or rip-first, but employed a punch-cut approach. After performing various combinatorial experiments (Thomas 1965c), Thomas published yield prediction tables based on his research (Thomas 1966a and 1966b).

Wodzinski and Hahn (1966) addressed the kerf loss and infeasible cutting problem of Thomas' program. Their algorithm, called YIELD, found the clear areas in a board, then extracted the largest parts first consecutively to the smallest parts from the available clear areas. The program also checked for violations of kerflines from other parts. The decision to crosscut- or to rip-first was based on the smaller number of kerflines.

Using YIELD, Schumann and Englerth (1967a and 1967b) developed yield tables for random and fixed width cuttings from six different grades of 4/4 hard maple. They republished these results in a more generalized form using nomograms in the widely employed Forest Service Research Paper FPL 118 (Englerth and Schumann, 1969). The yield prediction tables were found to produce reasonable yield

estimates for other species graded under the same National Hardwood Lumber Association (NHLA) rules as well. To make the information contained in FPL 118 more widely applicable for different thicknesses, Dunmire (1971) developed "*yield reduction adjustment factors*" for three thickness (5/4, 6/4, and 8/4) for four different lumber grades. Schumann (1971, 1972) later investigated yield for black walnut and alder lumber because both species are graded using special NHLA-grading rules (NHLA 1986).

MULRIP (Stern 1978) was the predecessor of RIPYLD (Stern and MacDonald 1978). Both programs performed multiple-rip operations at one time instead of only one as in YIELD. RIPYLD, ripped the board first into strips from the board edges using the best combination of width for yield. Defects were only considered in the second stage when the strips were crosscut. This is the way current rough mills operate. Also, the program allowed reripping for salvage parts. OPTYLD (Giese and McDonald 1982), the ancestor of RIPYLD, employed more sophisticated procedures. Also OPTYLD was the first program that allowed to optimize either for maximum area yield or for maximum value yield. Both, RIPYLD and OPTYLD used the enumerate method of maximization, meaning that all possible outcomes were calculated and the best then selected.

CORY, developed by Brunner (1984) was the first program that performed either rip-first or crosscut-first sawing sequences according to user specifications. Brunner also found that only the kerf lines from the largest two weighted areas need to be investigated to improve yield. Compared to YIELD, CORY produced 2.7 to 4.2 percent more yield and executed an average 63 times faster. Another significant improvement was that CORY allowed prioritization of parts. For example, CORY preferred longer parts over shorter ones. The original formula employed was:

$$Priority = Length^2 \; x \; Width \tag{2.1}$$

Later, Maristany et al. (1990) wanted to be able to more specifically manipulate the prioritization of parts and introduced an exponential weighting factor of the form

$$Priority = Length^{wf} \; x \; Width \tag{2.2}$$

where wf is the weighting factor, a value specified by the user.

In 1991, Hoff et al. (1991) enhanced program MULRIP by adding a movable outer blade and

three different saw arbor options. The arbor options were fixed saw arbor, variable saw arbor, and equally spaced arbor. This program was called GR-1ST. It's major shortcoming was that it used an inferior algorithm (both, in terms of mathematical sophistication and in computing speed). AGARIS, the successor of GR-1ST, was based on the same algorithm, but possessed a better user interface and salvage algorithm (Thomas et al. 1994).

In 1995, Thomas (1995a and 1995b) developed ROMI RIP (ROugh MIll RIP-first simulator), a rough mill simulator with greatly enhanced capabilities. ROMI RIP is the first rough mill simulation tool that can closely reflect a real rough mill. Unique features include random width and random length counter, salvage operations according to primary parts or specified parts, six different arbor set-ups, and six different prioritization strategies. Also, ROMI RIP featured enhanced user interfaces and data output capabilities. More significantly, ROMI RIP allows the user to choose from a set of prioritization strategies that influence yield (Thomas 1996b). Thomas showed that dynamic prioritization methods, that take into account the length, width, and quantity of parts to determine which parts to cut, achieve superior yield compared to more simple prioritization strategies. Widoyoko (1996) describes a simple experiment where he tested all the six prioritization strategies available for ROMI RIP. The results of these tests are shown in Table 2.2.

Table 2.2: Yield obtained dependent on prioritization strategy used

Test	Prioritization Strategy	Yield obtained
1	Complex Dynamic Exponent	70.30%
2	Simple Dynamic Exponent	69.80%
3	L^2*W*NEED	68.80%
4	L^2*W	68.30%
5	Dynamic Value	67.30%
6	Value	67.30%

However, as Thomas (1996b) pointed out, there are cutting bills that perform better with strategies other than complex dynamic exponent. As it appears, the best prioritization strategy is dependent on lumber grade and cutting bill requirements. More details on the features of ROMI RIP can be found in Thomas (1996a, 1995a and 1995b). Thomas (1996a) also pointed out that the speed of ROMI

RIP may allow direct integration with a scanning system in a rough mill, which may be useful when automated rough mills become a reality.

Following ROMI RIP, Thomas (1997b) developed ROMI-CROSS (ROugh MIll CROSScut-first simulator). This program is the counterpart of ROMI RIP for crosscut-first mills and features similar capabilities.

2.1.4 Cutting bills

Manalan et al. (1980, p. 40) defined cutting bills as "*a schedule of dimension parts where any one of these parts can be cut out from this schedule during a given rough mill setup*." Cutting bills are thus an aggregated list of parts to be cut in a rough mill. Compared to other issues relating to rough mill operations, cutting bills are a largely overlooked issue. The only comprehensive work describing cutting bill requirements for different dimension part producers dates back to 1982 (Araman et al. 1982, Araman 1982). Araman et al. (1982) proposed a new system to produce dimension parts called "*Standard-size Hardwood Blanks*". The authors suggested to produce glued blanks out of massive hardwood strips. The blanks then would be used to cut the necessary parts instead of cutting the parts from individual lumber boards. In order to find the size for the suggested hardwood blanks, the author surveyed the industry. They collected part sizes, quantities and qualities used in the industry and published the results (Araman et al. 1982). The authors listed detailed cutting bill part size distributions for 5 different subgroups of dimension part producers. The subgroups, in particular, were: (1) solid furniture, (2) veneered furniture, (3) upholstered furniture, (4) recliners, and (5) kitchen cabinets. The authors sampled the cutting requirements of 32 producers. They then analyzed and grouped the thousands of individual parts according to length, width, thickness, and quality for each subgroup separately. Quality was defined by the definitions of the Hardwood Dimension Manufacturers Association (1961)[7]. For each subgroup the authors then showed the rough part requirements and the nominal length/width distribution. Table 2.3

7 The Hardwood Dimension Manufacturers Association (HDMA) later changed its name to National Dimension Manufacturers Association (NDMA) and recently to Wood Component Manufacturers Association (WCMA).

displays the rough part requirements for solid wood furniture.

Table 2.3: Overview of rough part quality requirements for solid wood furniture (Araman et al. 1982)

Nominal Thickness (inches)	***Part Quality***	***Used for percent of total surface area produced***
5/8	Clear (C1F and C2F)	5.5
4/4	Clear (C1F and C2F)	44.5
4/4	Sound interior	14.9
5/4	Clear (C1F and C2F)	16.0
6/4	Clear (C1F and C2F)	6.7
8/4	Clear (C1F and C2F)	6.7
All other		5.7
	Total	100

Solid wood furniture producers required 44 percent of their parts to be 4/4 inches thick and clear of defects. Kitchen cabinet producers used 70 percent parts of this type. For producers of more specialized products like upholstered furniture or recliners, the distribution of part thickness and quality was different. The distribution of part sizes within the size ranges covered by the study was found to be producer dependent. The average length/width distribution of parts for the solid wood furniture industry as found by Araman et al. (1982) is displayed in Table 2.4.

Table 2.4: Length/Width distribution of 4/4 nominal thickness, clear quality rough parts for solid wood furniture (adapted from Araman et al. 1982)

Length groupings (inches)	**Width groupings (inches)**								
	0-1.5	1.51-2.0	2.01-2.5	2.51-3.0	3.01-3.5	3.51-4.0	4.01-5.0	>5.0	Percent of total
0-15	0.2	0.7	0.7	0.3	0.2	0.2	0.3	3.7	6.3
15.01-18	0.3	1.1	1.0	0.4	0.4	0.2	0.5	5.9	9.8
18.01-21	0.4	0.5	0.5	0.4	0.2	0.1	0.3	7.5	9.9
21.01-25	0.2	0.4	0.9	0.4	0.3	0.1	0.2	7.4	9.9
25.01-29	0.3	0.3	0.2	0.3	0.0	0.1	0.1	8.3	9.6
29.01-33	0.1	0.6	0.2	0.2	0.1	0.3	0.3	8.7	10.5
33.01-38	0.1	0.4	0.2	0.2	0.2	0.2	0.3	8.2	9.8
38.01-45	0.1	0.4	0.2	0.4	0.1	0.1	0.1	11.7	13.1
45.01-50	0.1	0.1	0.2	0.0	0.0	0.1	0.1	2.2	2.8
50.01-60	0.0	0.4	0.1	0.4	0.1	0.0	0.0	6.1	7.1
60.01-75	0.1	0.4	0.3	0.2	0.2	0.1	0.2	5.1	6.6
75.01-100	0.1	0.1	0.1	0.0	0.1	0.2	0.0	4.0	4.6
% of total	2.0	5.4	4.6	3.2	1.9	1.7	2.4	78.8	100.0

Four quarter inch clear solid wood furniture parts were found to be more evenly distributed in length and width than, for example, 4/4 inch clear kitchen cabinet parts. More than 50 percent of the parts in the kitchen cabinet production were equal or shorter than 25 inches. Conversely, in furniture parts, only 36 percent of the solid wood parts were shorter than 25 inches.

The data used in the study described above (Araman et al. 1982) were also used for a second publication by Araman (1982) entitled "*Rough-part sizes needed from lumber for manufacturing furniture and kitchen cabinets.*" The author analyzed the part distribution using different length and width groups compared to the first study. The smallest length group for solid wood furniture was now 0-1 inch instead of 0-1.5 inch as used in the preceding paper.

2.1.5 Cutting bills and yield

The relationship of cutting bill and lumber yield is complex. Thomas (1997a) correctly states that yield optimization is complicated by the presence of a cutting bill. If the cutting bill forces a rough mill operation or the simulation program to cut specific amounts of each part, yield declines. However, depending on the cutting bill requirements, the yield decline can be more or less severe.

Cutting bills are a determinant of the yield achieved (BC Wood Specialties Group 1996, Wengert and Lamb 1994b). To estimate yield, rules of thumb such as "the normal 2 Common yield range is 50 to 67 percent" are used frequently. However, their precision is limited. More accurate prediction models were therefore developed by several researchers. Thomas (1966a and 1966b), Englerth and Schumann (1969), Dunmire (1971) and others published extensive tables for estimating yield given a specific cutting bill and lumber species. The most widely used yield nomograms are the ones published in the Forest Service Research Paper FPL 118 (Englerth and Schumann 1969). These nomograms are still in use today (Hoff 1997, Wengert and Lamb 1994b). Figure 2.1displays the nomogram for 1 Common lumber. Even though these nomograms were derived for crosscut-first operations, they are also widely used in rip-first rough

mills today. This is mainly due to a lack of alternatives. However, some authors doubt as to how accurate the FPL 118 nomograms are (Thomas et al. 1996, Wiedenbeck and Scheerer 1996, Manalan et al. 1980). There is some justified reasoning that technological innovations in the rough mills, changes in the lumber characteristics, and shortcomings in the estimation procedures used to derive the nomograms, question the accuracy of yield predictions based on these charts (Thomas et al. 1996, Wiedenbeck and Scheerer 1996, Yaussy 1986, Manalan et al. 1980). Also, there are difficulties involved in incorporating such tables into computer software (Yaussy 1986).

Manalan et al. (1980), in the most thorough study about the accuracy of the Forest Service's FPL 118 yield nomograms, found yield differences between the actual yield obtained in a rough mill and the yield predicted by the FPL 118 nomograms to be as high as 19 percent absolute yield. From observing 22 sample cutting bills obtained from dimension producers, the authors contended that variables other than the ones used by FPL 118 (length and width of parts), such as maximum length, range of lengths (the minimum length subtracted from the maximum length), percentage of clear areas in the boards processed, or the number of different part sizes, could be missing in the FPL 118 nomograms to make the prediction more accurate. Whereas none of these additional variables was significantly correlated with the prediction error (the authors used the term yield deviation, i.e. predicted yield - actual yield), the ratio of the maximum part length to the range of lengths (i.e. $[L_{max}]/[L_{max} - L_{min}]$, where L_{max} is the maximum length of any part in the cutting bill and L_{min} is the minimum length of any part in the cutting bill) was found to be negatively correlated with the prediction error (significant at $\alpha = 0.01$). They named this ratio "batching index (BI)". Using regression analysis, the authors obtained a third degree polynomial regression equation of the form

$$Y = 14.56 - 1.08(BI)^3 \qquad (2.3)$$

where Y is the yield deviation and BI is the batching index. The R^2 of this model was 0.47. Figure 2.2 shows the regression line for equation (2.3).

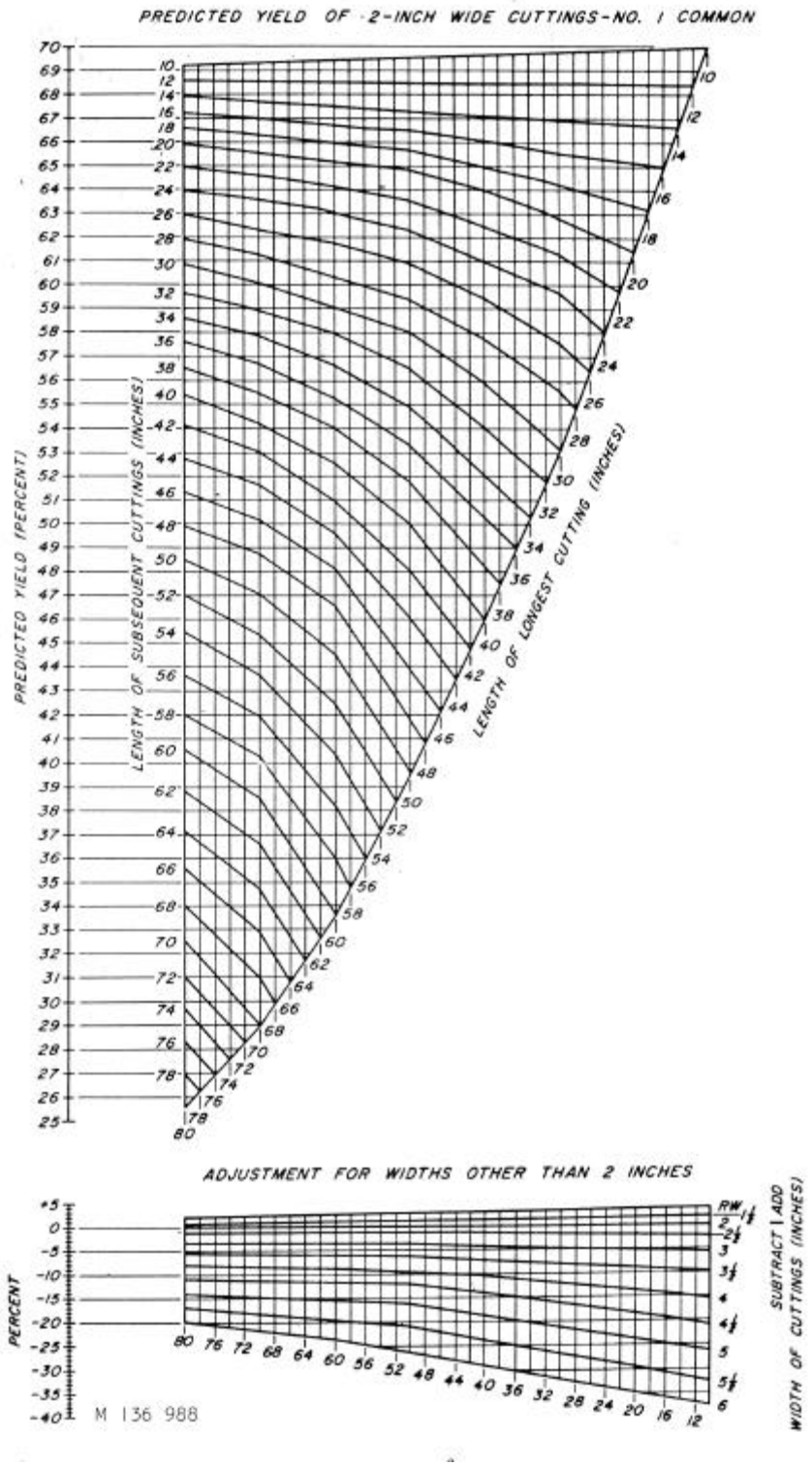


Figure 2.1: Yield nomogram for No. 1 Common lumber (Englerth and Schumann 1969)

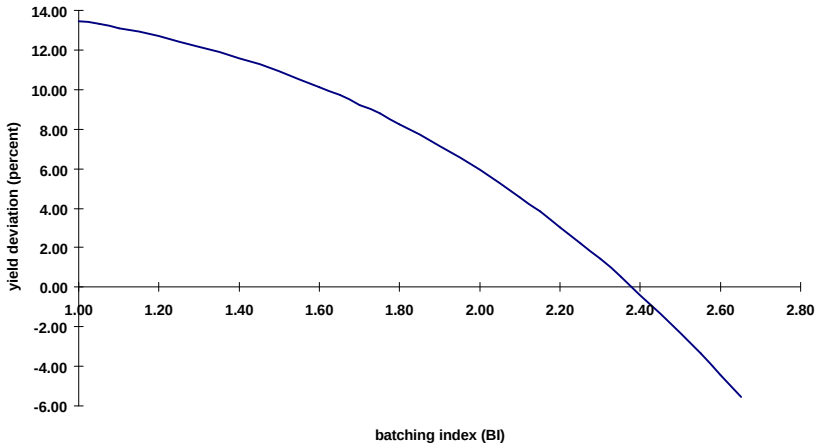


Figure 2.2: Graphical representation of equation (2.3) for predicting the yield deviations observed using FPL 118

Figure 2.2 implies, that when the batching index becomes larger (i.e. L_{max} large and L_{min} large), the yield deviation observed becomes smaller and thus needs less correction. This means that FPL 118 does predict yield better when the difference between the longest and the shortest length in a cutting is small. However, the batching index only accounts for 47 percent of the prediction error observed. Unfortunately, the authors never validated their yield-prediction correction procedure, so nothing can be said about the improvement in accuracy gained. Correcting the prediction error of the FPL 118 yield nomograms may in fact be as hard as deriving a new estimation model.

Wiedenbeck and Thomas (1995a and 1995b) therefore developed new yield matrixes for rip-first and crosscut-first rough mills. The two authors divided twenty four cutting bills obtained from members of the Wood Component Manufacturers Association (WCMA) into four groups: (1) Short Narrow, (2) Short Wide, (3) Long Narrow, and (4) Long Wide. The cutting bills were processed using either rip-first (ROMI RIP) or crosscut-first (CORY) simulation software. The tests were performed for

three different grades: FAS, 1 Common and 2A Common (National Hardwood Lumber Association NHLA 1994). The results are shown in Table 2.5.

Table 2.5: Yield matrixes as established by Wiedenbeck and Thomas (1995a and 1995b)

Type of cutting bill	***YIELD (%)***					
	RIP-FIRST			**CROSSCUT-FIRST**		
	Lumber Grade			Lumber Grade		
	FAS	1 C.	2A C.	FAS	1 C.	2A C.
Short-Narrow	72-82 [76]	59-71 [65]	35-64 [51]	[80]	[70]	[63]
Short-Wide	-	-	-	[81]	[69]	[61]
Long-Narrow	63-82 [72]	43-71 [60]	32-55 [50]	[73]	[62]	[54]
Long-Wide	51-72 [62]	45-61 [53]	29-33 [31]	[70]	[49]	[39]

The small number of cutting bills ($0 \le n \le 6$) used in this study limits the usefulness of these estimates. More importantly, the results for all individual groups are widely dispersed. Some overlapped significantly. Significant yield differences may therefore be hard to detect. Interestingly, even as the cutting bills were clustered according to their respective geometry, large yield differences persist within the same group. Wide yield variances due to dissimilar cutting bill requirements were also found by Buehlmann et al. (1998a and 1998b).

A systematic study on the interdependence between part sizes and lumber quality was done by Thomas (1965c). He pointed out that lower lumber grades react more sensitively on increasing part lengths in cutting bills. Thomas also showed the influence of adding longer parts to a cutting bill. However, as long as an unlimited amount of shorter lengths were allowed to be cut, as it was the case in Thomas' study and whose results are shown in Figure 2.3, the total yield achieved did not change.

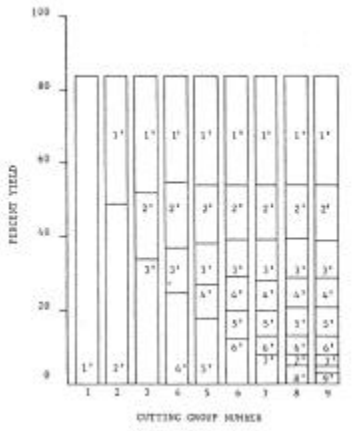


Figure 2.3: Yield for target lengths for 9 different lengths under a maximum yield strategy for No. 1 Common lumber (Thomas 1965c).

When a longest length cutting strategy was employed to force the cut-up of the longest possible length in a clear area, yield was reduced considerably. Thomas also researched the impact of width on yield. He found that width alone has not necessarily a big impact on yield. However, when a wide width is combined with a long length, then yield decreases significantly. These relationships are displayed in Figure 2.4. The uppermost line in Figure 2.4 shows the yield curve when the pieces to be cut are 2 feet in length, the next curve shows yield for 4 feet long pieces and the last one for 8 feet pieces. Figure 2.4 thus illustrates the interdependence of width and length.

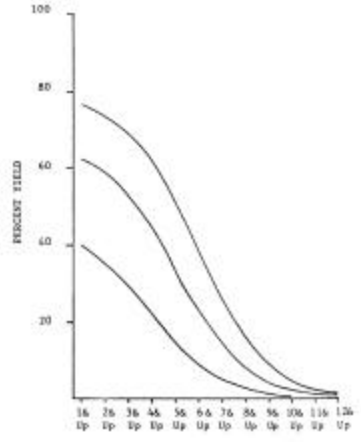


Figure 2.4: Interdependence of width to length for No. 1 Common lumber (Thomas 1965c)

Thomas' results, however, are not necessarily applicable today. His simulation tool, YIELD (Thomas 1962) had several shortcomings as discussed previously. Moreover, the author did not cut for specific numbers of parts as defined in a cutting bill. He allowed the program to cut the pieces according to its prioritization strategy (longest length or maximum yield). Yield would have been lower if a cutting bill were employed. Also, Thomas made no indications about the lumber he used. Lumber graded 1 Common

in the 1960s is not necessarily the same as lumber graded 1 Common today. There are indications that the lumber quality is declining. More specifically average sizes of boards in the same quality class are getting smaller. However, there is no body of literature that would support this claim.

2.1.6 Lumber used for dimension parts

Hardwood lumber is abundant in the Eastern United States (Sheffield and Bechtold, 1990). Hardwood growing stock is estimated at 1.8 billion m^3, that is 40 percent of total U.S. wood stock (Bechtold and Sheffield, 1991). Luppold and Dempsey (1996) contend that the eastern hardwood sawtimber inventory increased significantly over the last 22 years. Increasing hardwood inventories seem to contradict the long standing concern of the hardwood industry for timber supply (Luppold 1994).

The secondary hardwood industry is a major user of hardwoods (Hansen et al. 1995, Luppold 1993). Total hardwood consumption in 1991 was estimated to be 12.3 billion board feet for the entire secondary hardwood industry (Luppold 1993). The furniture, kitchen cabinet, and dimension industry's share was about 36.5 percent (Luppold 1993). red oak (32.8%), yellow poplar (15.8%), and white oak (10.9%) were the three most important species used (Hansen et al. 1995). Also, as stated earlier, high quality lumber of selected species are experiencing price increases (Luppold and Baumgras 1995; Muench 1993). This trend is likely to continue in the future since the demand for wood continues to increase (Cubbage et al. 1995, Sutton 1993)

Lumber quality is of significance for two reasons: yield and productivity. Several authors found that lumber grade has a significant impact on yield (Buehlmann et al. 1998a and 1998b, Gatchell

and Thomas 1997, Wengert and Lamb 1994b, Gatchell 1985). Lumber grades are used to describe the quality of boards according to well defined rules. Since high yield means that less boards have to be processed to obtain a given amount of parts, productivity of rough mills is dependent on lumber quality, too (Perera 1994, Pepke 1980).

Quality classes (i.e. lumber grades) are established by the National Hardwood Lumber Association NHLA (NHLA 1994). The most important feature of hardwood lumber boards is the clear area contained in a board proportional to the overall surface area of that board. The five most important grades traded are FAS (Firsts and Seconds), Selects, No. 1 Common, No 2 Common and No. 3 Common. A No. 1 Common board, for example, needs to have 66.67 percent of its surface as clear area. Moreover, the rule limits, among other characteristics, the numbers of cuts necessary to extract these clear areas, and the minimum length/width dimensions of the board. To make matters worse, several subclasses of grades exists, such as No. 2A Common. Also, numerous other special grading rules, some only used locally, exists. An example for this grade would be WHND (Worm-Holes-No-Defects) which excludes wormholes as defects. This complicated network of rules is necessary to capture the natural variability of wood and to form groups with limited within group variability.

Despite the grading rules, within grade quality differences exist (Gatchell and Thomas 1997, Wiedenbeck et al. 1995). Gatchell and Thomas (1997, p. 90) found that in 1 and 2A Common lumber graded according to NHLA rules, "*... half or so of each grade having a maximum grading surface area that falls into the next higher grade*." Other authors came to similar conclusions (Wiedenbeck et al. 1995). Also, board quality does vary within a grade (Gatchell et al. 1995). Gatchell et al. concluded that wood defects in hardwood lumber are not randomly distributed. Theoretically, this would allow to cut boards prior to processing and then feeding each part of the board to operations that would result in highest yield or highest value. Better quality ends, for example, would be used to cut hard to find lengths or widths (Gatchell et al. 1995).

2.2 ANALYTICAL TOOLS

Wood is, due to its heterogeneity, a rather difficult material to be used for the production of goods. This also applies to analytical tasks. The cutting bill requirement - yield relationship, for example, is not only difficult because a cutting bill requires many different parts to be cut. What makes the problem much more complicated is the inherent variability contained in wood. To cope with the variability stemming from the cutting bill requirements and the natural variability of boards, statistical tools are widely used by researchers.

2.2.1 Fractional factorial designs

Fractional factorial experiments are suggested when experiments involving many factors are performed. A complete factorial design in k factors would involve n_1 levels of factor 1, n_2 levels of factor 2, n_k levels of factor k, and then selecting the $n = n_1 n_2 ... n_k$ possible combinations (Box and Draper 1987). Even though n can assume any positive integer value, 2 levels are most commonly used (Mays 1995) resulting in a 2^k factorial design. Fractional factorial designs, which consist of a subset of the 2^k complete factorial design, consequently are designated as 2^{k-p} fractional designs, where k-p is the fraction of the total design space k that is researched. Orthogonal fractional factorial designs allow the selection of a suitable subset of all possible factor combinations so that the part-worth of the main effects still can be estimated (SPSS Inc. 1990). Higher order interactions, which are confounded with same order interactions, however, cannot be estimated. However, main effects and lower order interactions can be reliably estimated due to the sparsity of effects principle (Montgomery 1984, Box et al. 1978). Only when a complete factorial set of data is obtained, all the interactions be estimated. There is wide agreement as to the efficiency and the statistical merits of factorial designs among authors (Mize et al. 1994, Oles 1992, Willingham and Graham 1988, Montgomery 1984, Box et al. 1978). However, few forest products researchers have applied them (Mize et al. 1994, Reddy 1994).

Mize et al. (1994) show the application of a one-eight replicate of an 2^8 factor fractional factorial experiment used to research white oak plywood bond quality. The results of the treatments were

analyzed as a randomized complete block design. Glue-mix extender content turned out to have the most significant effect on bond quality. The authors of this study also give an extensive overview of fractional factorial designs.

The ability of fractional factorial designs to detect significant main effects when many factors are involved is unquestioned (Mize et al. 1994, Oles 1992, Willingham and Graham 1988). Several authors maintain that the higher order interactions are most often small if not negligible (Mize et al. 1994, Montgomery 1984, Box et al. 1978). Oles (1992) points out that for cases where significant higher order interactions are suspected, a higher resolution for the design has to be chosen.

2.2.2 Multiple linear regression models

"*In any system in which variable quantities change, it is of interest to examine the effects that some variables exert (or appear to exert) on others"* (Draper and Smith 1981, p. 1). Multiple linear regression is one of the methods that allow to extract information from data obtained by a system. Multiple Linear Regression can be used in a wide variety of applications with largely differing degrees of sophistication.

Multiple linear regression involves multiple independent variables. The model is still linear with respect to all the parameters (b_i). A statistical multiple linear regression model can be expressed as

$$Y_i = b_0 + b_1 X_{1i} + b_2 X_{2i} + \ldots + b_p X_{pi} + e_i \qquad (2.4)$$

where the Y_i s are observed responses; $b_0, b_1 \ldots b_p$ are unknown constants, $x_{1i}, x_{2i}, \ldots x_{pi}$ are fixed, observed variables and e_i are random errors that are independently, identically normally distributed with mean 0 and common variance s^2 (Ott 1993).

Several methods exist to select the best regression equation for a given set of data (Mays 1995, Ott 1993). Backward elimination starts with the model that contains all candidate independent variables. After a minimum level of significance is specified, it then drops the most insignificant variable from the model if its significance level is below the specified limit. Thereafter, the significance of all the remaining

variables is recalculated and the procedure starts anew. Forward selection works in a similar fashion. However, it starts with the simplest model that only includes the intercept and the error term. The most highly significant variable is then entered into the model and the level of significance recalculated. This cycle is repeated until no remaining variable is below the specified level of significance. Both these procedures do not allow to drop variables from the model once they are entered. Stepwise regression, which is similar to the forward procedure, allows to drop variables from the model when they become insignificant due to the addition of other variables. Often, all three procedures are employed and the model achieving the highest adjusted R^2 is then chosen as the solution (Mays 1995).

Linear regression models are widely used in the forest products and related industries. The different applications of the models can be grouped according to the purpose of the model. The five groups found were: (1) Business related (MacKay and Baughman 1996, Hammett et al. 1992), (2) Process related (Lavery et al 1995, Somerville et al. 1984), (3) Mechanical properties (Gupta et al. 1996, Yadama et al. 1991), (4) Physical and Chemical properties (Mantanis et al. 1995, Hachmi and Moslemi 1989), and (5) Yield related (Lynch and Clutter 1998, Yaussy 1986, Howard and Yaussy 1986, Howard and Gasson 1989, Steele et al. 1989, Wiedenbeck 1992, El-Radi et al 1994). The following discussion will concentrate on yield related applications of regression models.

Lynch and Clutter (1998), in recent study published, used nonlinear 3-stage estimation univariate regression analysis to estimate expected veneer yields from logs. Their complex system of equations encompasses 15 parameters that influence the amount of veneer obtained from logs. Multivariate regression equations were employed to predict lumber yield from logs of different species. Yaussy (1986) used a weighted regression model developed by Bruce (1970) as basis to predict expected lumber yield from logs for three oak species. Bruce's model predicts lumber yield as a function of scaling diameter of the log, log length, and a factor P that describes the proportion of a log that is considered defective. Yaussy expanded the model to include factory log grades as an additional independent predictor. A set of seven multivariate regression models was developed, so that the yield for each lumber grade can be predicted. A continuation of this work for yellow birch yield prediction can be found in

Howard and Yaussy (1986). When analyzing their model's residuals, Howard and Yaussy found heteroscedasticity in their data. However, transformation allowed the authors to obtain a valid model nonetheless. In a related study, Howard and Gasson's (1989) created a model that predicts lumber yield from lodgepole pine sawlogs for different quality classes. Their model also accounts for the possibility that a tree has been dead for a longer time span before harvest. Usually, grade recovery from dead trees is lower than from freshly logged trees. All three papers report acceptable predictive accuracy of their models ($0.64<=R^2<=0.85$). These successful models for predicting lumber yield from logs open the question how well such an approach would perform when applied for part yield from lumber.

However, there are unsuccessful applications of regression models, too. A more recent one is reported by Steele et al. (1989). The authors hypothesized that a centered, symmetric sawing pattern for logs is inferior to an asymmetric one. They simulated the sawing of logs using symmetric and asymmetric patterns. Then, a linear regression equation was fitted to the data. The regression model predicted the amount of asymmetry a sawing pattern should have to obtain maximum yield given log specific characteristics. Unfortunately, even though the amount of asymmetry found in the regression model was statistically significant ($\alpha = 0.05$) and the model explained almost all of the variability in yield ($R^2=0.99$), yield did not improve when the model was employed. The authors attributed this to the fact that the model occasionally lead to patterns with far inferior solutions. This case illustrates a regression model with significant regression coefficients and high R^2 , but with no or negative influence on the outcome.

Wiedenbeck (1992) used simple linear regression as an analytical tool to analyze the relationship of lumber length on yield. Her model

$$Yield = b_0 + b_1(Length) + e \tag{2.5}$$

tested the contribution of the $b_1(Length)$ term to the prediction of yield. She found that total yield was dependent on lumber length in some cases. For a crosscut-first system, length was found to be positively correlated to yield, when the length term was significant. When the length term was significant for a rip-first system, yield was negatively correlated to length because of the adverse effect of crooked boards. In

general, her model had little explanatory power (low R^2), meaning that the error term was big.

Multiple linear regression is widely used in analytical or predictive projects. However, authors agree that special attention has to be paid so as not to violate the assumptions underlying the least square models (Lynch and Clutter 1998, Howard and Yaussy 1986, Howard and Gasson 1989).

2.3 SUMMARY

Rough mill yield, the surface area of output to the surface area of input expressed as a percentage (Gatchell 1985), is dependent on many factors. The lumber grade used, the drying quality of the lumber, and the cutting bill requirements are three of the most important factors (Wengert and Lamb 1994, Gatchell 1985, Anonymous 1985). Computer simulation techniques, the most advanced being ROMI CROSS and ROMI RIP (Thomas 1997a, 1997b, 1995a, and 1995b), simulate the cut-up of lumber as it would occur in actual rough mills. They thus allow to observe the influence of the different factors on yield in a near realistic setting.

Cutting bills, the schedule of dimension parts to be cut (Manalan 1980), influence yield significantly (Buehlmann 1998a and 1998c, Thomas 1996b). However, the influence of cutting bills on yield, which is a complex problem, is not well researched. The relationship of cutting bill requirements and lumber yield is made more complex due to the presence of fixed part quantities to be produced (Thomas 1997a).Araman et al. (1982) published a report that showed the average part quantities required for different sizes of parts. These authors found that 36 percent of all parts required by furniture rough mills are shorter than 25 inches. Prediction of yield based on cutting bill requirements is a difficult endeavor. Existing prediction models, like the yield nomograms contained in the USDA Forest Service Report FPL 118 (Englerth and Schumann 1996), the most prevalent prediction model used today, do not result in consistent and accurate yield predictions (Thomas et al. 1996, Wiedenbeck and Scheerer 1996, Manalan et al. 1980).

Several studies published in recent years used regression analysis to predict expected yield from logs (Howard and Gasson 1989, Yaussy 1986, Howard and Yaussy 1986, Bruce 1970). However, no

such approach exists for the yield prediction for dimension parts. Cutting bills can require any possible combination of part sizes and quantities to be cut. One way this complexity can be decreased is the use of fractional factorial designs (Box and Draper 1987). Orthogonal fractional factorial designs allow to decrease the number of factors by confounding higher order interactions with lower order terms (SPSS Inc. 1990). Despite being confounded with higher order interactions, lower order terms can still be reliably estimated according to the sparsity of effects principle (Montgomery 1984, Box et al. 1978). The sparsity of effects principle, a principle based on empirical observations and not a theorem that can be proven, states that higher term effects tend to be smaller than lower term effects.

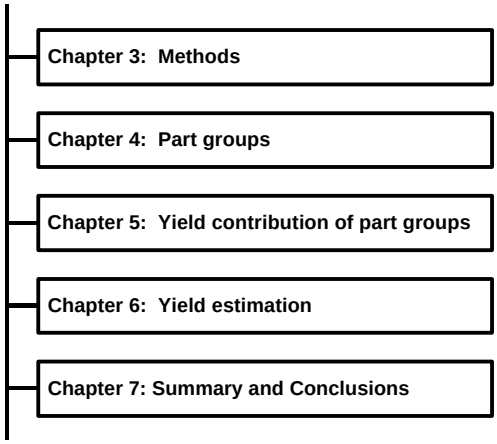
CHAPTER 3

3. METHODS

3.1 INTRODUCTION

As was shown in Chapter 2, yield[8] in rip-first rough mills is dependent on many parameters (Wengert and Lamb 1994b, Gatchell 1985, Anonymous 1985). Chapter 3 details the methods used to assure that the observations concerning the relationship of cutting bill requirements and yield are valid. The methods used to conduct the major individual tests of the study - the derivation of part groups, the establishment of the marginal contributions of individual part groups to yield, and the construction of the least squares yield estimation model - will be explained in separate chapters. Table 3.1 gives an overview of the partitioning of the parts of this study and their allocation to the individual chapters.

Table 3.1: Chapter overview of study report



Chapter 3, METHODS, describes basic settings and conventions that apply for all the tests of this study. For example, the rough mill settings of the simulation software (Thomas 1995a and 1995b), the

[8] Yield, in Section 2.1.2, was defined as the "*ratio of the surface area of output to the surface area of input of common thickness expressed as a percent* (Gatchell 1985, p. 146)."

lumber boards used (Gatchell et al. 1998), and other basic information is provided here. Chapter 4, PART GROUPS, explains the methods used and the results found from the derivation of the part groups. Chapter 5, YIELD CONTRIBUTION OF PART GROUPS, discusses the methods and results found from the fractional factorial design. Moreover, it outlines the importance of individual part groups on yield. Thereafter, chapter 6, YIELD ESTIMATION, is intended to give a thorough review of the methods and the results from the creation of the yield estimation model. Chapter 7, SUMMARY AND CONCLUSIONS, sums up the observations made and presents the conclusions.

3.2 EXPERIMENTAL PROCEDURES

As was pointed out in Section 2.1.2, many sources for the variability of yield in rough mill operations exist. There is very little understanding of the whole system that governs this yield variability. This is not surprising since the relationships are so complex, that their complete understanding is not even remotely achieved today. For this study, to contribute to this overall goal, it was necessary to isolate the experiments from sources of variability other than the ones being researched. For this purpose, parameters such as lumber grades, drying quality, operator skills and all the other parameters listed in Table 2.1, were fixed. This way, the observation of the relationship between cutting bill requirements and lumber yield became attainable.

This research consisted of a series of sequential steps. After the general methodologies and procedures had been worked out, the part groups that were used to observe the behavior of “real” cutting bills, were derived. “Real” cutting bills are cutting bills that were obtained from actual operations, as opposed to theoretical cutting bills that were constructed specifically to research certain phenomena. Then a fractional factorial design was used to observe the contribution of individual part groups to yield. The data derived based on the fractional factorial design were then used to develop a least squares yield estimation model to estimate expected yield depending on cutting bill requirements. The construction of this model was then followed by a validation procedure. The following list summarizes the individual steps in this study:

(1) Define the rip-first rough mill simulation

(2) Determine the minimum lumber sample size

(3) Determine the influence of the lumber-board-size distribution on yield

(4) Create preliminary part groups

(5) Find average part quantities that approximate part quantities used in real operations

(6) Derive cutting-bill part groups such that the influence of different within part group part sizes on yield is relatively of the same magnitude for all part groups

(7) Verify the validity of the assumption that yield is an approximately linear function of part quantity within a part group

(8) Based on the part groups established, contrive a resolution V fractional factorial design that allows to establish the importance of individual groups

(9) Use the data derived in step (8) to create a least squares yield estimation model

(10) Validate the model obtained from step (9)

Steps one to three are explained in this Chapter, steps four to six in Chapter 4, steps seven to eight are to be found in Chapter 5, whereas the last two steps are treated in Chapter 6.

3.3 METHODS

Empirical methods and statistical analysis were employed to help understand the physical phenomena involved in the cut-up of cutting stock. Computer based simulation techniques helped with the derivation of the necessary data.

3.3.1 Experimental set-up

Simulation is "*the easiest and most cost-effective method*" (Anderson et al. 1992, p. 74) for the observation and testing of rough mills. ROMI RIP 1.0, the most advanced rough-mill yield simulation tool currently available, was employed for this study (Thomas 1996a, 1995a, 1995b). ROMI RIP allows the user to "*examine the interactions and impacts of various rough mill operations*" (Thomas 1996a, p.

57). More importantly, ROMI RIP allows for user-specified systems settings. However, one has to be aware that ROMI RIP has never been validated for real rough mill applications. Thomas (1998) estimates that ROMI RIP achieves yield levels that are three to five percent above current rough mill operations' typical yield levels. Nonetheless, the general observations obtained by using ROMI RIP should be comparable to actual rough mills. The influence of different rough mill settings such as arbor types, prioritization strategies, feedback, and others will always make yields between rough mills hard to compare. ROMI RIP allows to mimic these settings in great detail, which should make observations obtained in an actual rough mill using somewhat similar settings and the observations from the simulation software comparable, except that ROMI RIP's yield will generally be higher.

3.3.1.1 Rough mill settings

The rough mill's set-up used for this study as they were entered in the ROMI RIP simulation software (Thomas 1995a and 1995b) are listed below. These settings were consistently employed to perform all the necessary simulations.

- all-blades-movable type arbor
- dynamic exponential cutting bill part prioritization (Thomas 1996b)
- smart salvage operation (Thomas 1996a), no excess salvage, unlimited salvage operations (Anderson et al. 1992)
- no random width and no random length parts
- continuos update of part counts
- 1/4 inch end trim on both sides
- 1/4 inch side trim on both sides

These settings were chosen to reflect as closely as possible the state-of-the-art rough mill of the future. The assumption that no random parts were cut is a violation of most rough mill strategies employed today. However, this limitation prevents random parts from masking the effects of interest to this study. Thomas (1997c) found that random parts do not change a trend, but make differences observed less pronounced. Therefore, random parts are not included in this study. The same is true for layback parts

(excess primary parts) which are also avoided. Additionally, this study only considered Clear-2-Face (C2F) parts.

Cutting bills were cut to cutting bill specification, i.e. no excess primary parts were counted as usable parts. Also, since no random width or random length parts were taken into account as usable yield, exact compliance of the parts obtained and the parts specified was assured. By cutting parts to cutting-bill specification, no value consideration were necessary. Since the simulation program had to cut an exact number of parts, all parts required by a cutting bill had to be produced during that particular production run.

3.3.2 Materials

The materials needed for this study are a cutting bill that represents the average part quantity distributions as they are found in actual rough mills and red oak lumber in a digital representation to be processed by the ROMI RIP simulation program.

3.3.2.1 Cutting bill

Cutting bills, as they are used in different industrial operations, display a wide variety of requirements as to part sizes and part quantities. For this study, the diversity observed between different cutting bills had to be reduced and controlled in order to perform the analyses needed. For this purpose, the concept of part groups was introduced. Section 4.2.1 elaborates this concept. In addition, part quantities, i.e. the quantity of individual parts that are required by a cutting bill, had to be established such that the part quantities used for this study would reflect average quantities used in actual operations. A study done by Araman et al. (1982) provided this average part quantity distribution by size used in the furniture industry. Araman et al.'s study was used to develop the part quantities for the cutting bills employed in this research. Section 4.2.3 in Chapter 4 explains the methods used to derive the part quantities.

3.3.2.2 Lumber

This research used 4/4 inch thick No. 1 Common red oak lumber from the 1998 Data Bank for Kiln-Dried Red Oak Lumber (Gatchell et al. 1998) as study material. Lumber from this data bank is considered to represent the typical quality of red oak lumber available in the Appalachian region. (Gatchell and Thomas 1997). Red oak is the most widely used lumber in the secondary hardwood industry (Hansen et al. 1995, Luppold 1993). Lumber graded 1 Common is the preferred grade with more than 50 percent of the market share (Hansen et al. 1995, Sinclair et al. 1989). Four-quarter inch board thickness is mostly used for dimension parts . Forty-four and a half percent of the lumber used for solid wood furniture is 4/4 inch thick, for the cabinet industry the percentage is about 70 percent (Araman et al. 1982).

The quality of lumber within the same grade varies widely (Gatchell and Thomas 1997, Wiedenbeck et al. 1994). However, the most significant impact on yield is due to crook of boards (Gatchell et al. 1998). When lumber is gang ripped first, crook causes a decrease in yield (Gatchell 1990). However, the 1998 Data Bank for Kiln-Dried Red Oak Lumber does not contain boards with more than 1/4 inch crook or side bend.

The boards from the 1998 Data Bank for Kiln-Dried Red Oak Lumber (Gatchell et al. 1998) are compatible with the ROMI RIP rip-first rough mill simulator (Thomas 1995a and 1995b) and are therefore ready to be used. However, research done by Wiedenbeck et al. (1996) indicated a different distribution of board sizes than the one contained in the 1998 Data Bank for Kiln-Dried Red Oak Lumber. Gatchell et al.'s digital data bank contains 4/4 inch red oak boards from two earlier data banks, which were developed for specific research purposes. These boards influence the board-size distribution of the databank. To find the appropriate lumber board size distribution, yield differences between these two distributions were compared. Section 3.3.4 elaborates on this research. Before being able to establish the

influence of board size distributions, however, the minimum lumber sample size had to be established.

3.3.3 Minimum lumber sample size

Lumber sample size refers to the amount of lumber (i.e. area of boards or, as used here, number of boards) needed to cut all the pieces required in a cutting bill. The necessary lumber sample size is dependent on cutting order size. Preliminary work showed yield differences of 5 percent and more can be due to different lumber sample sizes used (Buehlmann et al. 1998a). Buehlmann et al's study also showed that a lumber sample of 150 boards eliminates significant influence on yield. Thus, if approximately 150 boards are processed to satisfy the cutting bill requirements, the resulting yield is not biased by the number of boards used. However, the findings of Buehlmann et al. are based on a lumber sample consisting of five different grades. In particular, the lumber sample used was composed of approximately equal numbers of First and Seconds, Selects, 1 Common, 2A Common, and 3A Common boards. Furthermore, a cutting bill that was randomly selected from a pool of cutting bills obtained from several manufacturers was used. The randomly selected cutting bill does not reflect the cutting bill that was employed for this study. Therefore, the minimum lumber sample size had to be verified, and, if necessary, readjusted.

3.3.3.1 Methods

The cut-up of 1 Common lumber was simulated on the ROMI RIP rough mill simulator (Thomas 1995a and 1995b) using the 1 Common lumber board data available in the 1998 Data Bank for Kiln-Dried Red Oak Lumber (Gatchell et al. 1998). A preliminary cutting bill, which is shown in Table 3.2, was used. This cutting bill is based on findings by Araman et al. (1982) and does reflect the average part-size distribution found in rough mills. The part quantities shown for each part are the percentage of the total part quantity for a specific cutting bill that are required for each part size.

Table 3.2: Cutting bill with part quantities in percent used for the determination of the minimum lumber sample size

Width (inch)	Length (inch)			
	15	**35**	**55**	**75**
1.50	24.2	12.2	5.0	5.6
2.75	18.8	8.6	4.4	6.0
4.00	7.1	5.9	0.8	0.8

The minimum quantity for this cutting bill is for part $L_{75}W_{4.00}$ (i.e. the part with size 75 inches in length and 4.00 inches in width), where less than 0.8 percent of all parts in the cutting bill are required. This part was used to create cutting bills with increasing part quantity requirements for all parts. Thus, the part quantity distribution was maintained, the number of parts was changed proportionally. The first cutting bill required only one piece of part $L_{75}W_{4.00}$, with all the other part quantities adjusted proportionally. Table 3.3 shows the resulting cutting bill that asked for a total of 131 parts.

Table 3.3: Part quantities (pieces) when part $L_{75}W_{4.00}$ asks for 1 part only

Width (inch)	Length (inch)			
	15	**35**	**55**	**75**
1.50	32	16	8	8
2.75	25	11	5	8
4.00	9	8	1	1

Starting from this minimum quantity cutting bill (i.e. the minimum quantity for part $L_{75}W_{4.00}$ is one piece), the quantity was increased incrementally. The maximum quantity researched was when part $L_{75}W_{4.00}$ required 300 parts. The total part quantity required for this cutting bill was 39,720 parts. Table 3.4 shows the design of the 20 tests performed for the minimum lumber sample size determination.

Table 3.4: Design of experiments for researching the influence of lumber sample size used on yield

test #	increase quantity by (%)	minimum quantity (L_{75} $W_{4.00}$)	total part quantities required
1	- -	1	131
2	400	5	662
3	100	10	1324
4	50	15	1986
5	33	20	2648
6	25	25	3310
7	52	38	5031
8	32	50	6620
9	26	63	8341
10	19	75	9930

test # (cont)	increase quantity by (%)	minimum quantity (L_{75} $W_{4.00}$)	total part quantities required
11	11	83	10989
12	14	100	13240
13	25	125	16550
14	20	150	19860
15	17	175	23170
16	14	200	26480
17	13	225	29790
18	11	250	33100
19	10	275	36410
20	9	300	39720

The rationale for this design of experiment was, that the more parts were required to be cut to fill a cutting order, the more boards were needed to cut these parts. According to preliminary calculations, requiring 10 parts for part $L_{75}W_{4.00}$ would require a lumber sample size of more than 150 boards. This amount of boards was found to be nonsignificant ($\alpha = 0.05$) by Buehlmann et al. (1998a) in influencing yield. However, in order to ascertain that no significant ($\alpha = 0.05$) yield change occurs above this sample size, the research was extended significantly. When part $L_{75}W_{4.00}$ required 300 parts, the total required quantity of boards should be more than 5,000.

By always employing the same part sizes with proportionally increased part quantities from test to test, the influence of processing increasing amounts of boards on yield could be observed. The incremental part quantities were chosen such that the incremental part quantity increased more for large part quantities. For the first six tests, from one part $L_{75}W_{4.00}$ to 25 parts, part quantity was increased by five for each test. Thereafter, from 25 parts to 100 parts, the part quantity increase for part $L_{75}W_{4.00}$ was 13 and 12, respectively, such that two tests resulted in a total increase of 25 parts. Above 100 parts for part $L_{75}W_{4.00}$, the incremental increase was 25 parts. By using this staggered incremental part quantity increase, it was assumed to be able to capture the sample size - yield relationship in detail over a wide range of boards processed.

3.3.3.2 Statistics used for the minimum lumber sample size problem

For the decision of what is the minimum lumber sample size that does not influence yield, the power of the tests was important. For this study, the level for a type I-error (i.e. the probability of detecting a difference given none exists) was set at 0.05. The power for a type II-error (i.e. not detecting a difference given a difference exist) was set at 0.80 (i.e. $b = 0.2$). Given these settings, the formula presented by Hinkelmann and Kempthorne (1994, p. 176) for establishing the number of replicates is:

$$\Delta^* = \frac{t_{\max} - t_{\min}}{s_e} \tag{3.1}$$

where Δ^* is the standardized minimum difference between two treatment effects; t_{max} is the maximum yield observation; t_{min} is the minimum yield observation; and s_e is the standard deviation

Two preliminary runs were obtained. Based on these two results, t_{max} was found to be 68.63 percent, t_{min} 66.99 percent and the standard deviation s_e 0.72. According to equation (3.1), Δ^* became 2.26. The number of replications found in Table 6.6 (Hinkelmann and Kempthorne 1994, p. 181) for t=20, where t is the number of different treatments, was 9. The results from these tests were then analyzed using Duncan's multiple range test to detect significant ($\alpha = 0.05$) yield differences between treatment levels.

3.3.3.3 Results

The minimum yield found for these tests was 63.49 percent for the case when the minimum total quantity of parts (i.e. a total of 131 parts, see Table 3.4) was required by the cutting bill. The maximum yield was found to be 68.05 percent, when the third largest quantity of parts, i.e. 33,100 parts of the 20 tests were required by the cutting bill. Yield showed significant increases up to a certain level of part quantities required and the standard deviation decreased. Table 3.5 shows the results of the statistical analysis.

The findings presented in Table 3.5 show that, when at least 177 1 Common red oak lumber boards are processed to fill the requirements of a cutting bill, then the resulting yield is no longer significantly different ($\alpha = 0.05$) from any other cutting bill that requires more boards to be cut. Therefore, for all future tests, the minimum lumber board requirement for any test was set at a minimum of 177 boards. However, in a very few cases for the tests given by the fractional factorial design, a minimum of 144 boards used was observed. Such a small amount of boards was used when the fractional factorial design only required parts from four part groups. However, only one such case occurred. The error from this occurrence, though, should be small.

Table 3.5: Yield, standard deviation, and Duncan's groupings for the results of the minimum lumber sample test

test #	minimum part quantity	total part quantities required	average number of boards used	yield	difference between tests	std.dev.	Duncan Grouping (a = 0.05)		
1	1	132	19	63.49		2.68	**A**		
2	5	662	86	67.10	3.61	0.59		**B**	
3	10	1324	177	67.47	0.38	0.49		**B**	**C**
4	15	1986	256	67.97	0.49	0.54			**C**
5	20	2648	335	67.72	-0.25	0.31		**B**	**C**
6	25	3310	418	67.76	0.04	0.53		**B**	**C**
7	38	5031	645	67.72	-0.04	0.39		**B**	**C**
8	50	6620	845	67.61	-0.11	0.46		**B**	**C**
9	63	8341	1062	67.74	0.13	0.30		**B**	**C**
10	75	9930	1270	67.82	0.08	0.31		**B**	**C**
11	83	10989	1398	67.87	0.05	0.38		**B**	**C**
12	100	13240	1687	67.93	0.06	0.26			**C**
13	125	16550	2103	68.01	0.07	0.30			**C**
14	150	19860	2522	67.94	-0.07	0.38			**C**
15	175	23170	2945	67.95	0.01	0.35			**C**
16	200	26480	3362	68.04	0.09	0.32			**C**
17	225	29790	3781	68.00	-0.03	0.31			**C**
18	250	33100	4200	68.05	0.05	0.30			**C**
19	275	36410	4621	68.04	-0.01	0.31			**C**
20	300	39720	5045	68.03	-0.02	0.29			**C**

3.3.4 Lumber board size distribution

No knowledge exists today as to the influence of different board-size distributions on yield when cutting parts out of 1 Common red oak kiln dried lumber. On one hand, smaller boards offer a smaller total area for the cut-up of parts. On the other hand, the clear area of smaller boards has to be larger and to be obtainable with fewer cuttings (NHLA 1990) that the board still classifies for the better grade category. Therefore, no certainty exists if processing smaller boards leads to lower yield. This part of the study researched this question for 1 Common red oak kiln dried lumber and the cutting bill displayed in Table 3.2.

3.3.4.1 Methods

The lumber board size (length and width) distribution found in the 1998 Data Bank for Kiln-Dried Red Oak Lumber (Gatchell et al. 1998) does not exactly represent the lumber board size found on the market today as established by Wiedenbeck et al. (1996). Wiedenbeck et al. surveyed the incoming

lumber in 14 secondary wood products plants to find the size distribution of the 1 Common red oak lumber boards processed by the companies surveyed. Gatchell et al's data bank, however, contains boards that were created for special purposes, such as the short lumber used in Wiedenbeck's (1992) study. These shorter boards influence the board-size distribution of the databank from Gatchell et al. The board size distribution for 1 Common 4/4 inch red oak lumber found in the 1998 Data Bank for Kiln-Dried Red Oak Lumber and the one found by Wiedenbeck et al. are displayed in Table 3.6.

Table 3.6: Frequency distribution of 1 Common red oak lumber board sizes as used by Gatchell et al. and as found by Wiedenbeck et al.

standard length	width (inches)										
(feet)	< 4	4	5	6	7	8	9	10	11	=> 12	**Total**
	Survey of 14 rough mills by Wiedenbeck et al. (1996) (%)										**%**
4-8	1.4	3.2	8.7	4.8	3.9	2.1	1.4	0.7	0.5	0.7	*27.2*
9-10	1.9	2.8	7.8	3.5	3.0	1.8	1.9	1.3	0.8	1.0	*25.6*
11-12	0.9	2.1	7.8	3.0	3.6	1.6	1.4	1.5	0.9	1.1	*23.7*
13-14	0.7	1.3	4.7	2.2	2.9	1.4	1.3	0.9	0.7	0.9	*16.9*
15-16	0.1	0.4	1.5	1.6	0.5	1.0	0.8	0.3	0.2	0.5	*6.7*
Total	*4.8*	*9.8*	*30.4*	*15.1*	*13.8*	*7.9*	*6.6*	*4.6*	*3.0*	*4.0*	*100*
	Wiedenbeck et al. (1996) based on Gatchell (1998)										**Total**
4-8	1.4	3.3	8.7	4.8	3.9	2.1	1.4	0.6	0.4	0.6	*27.3*
9-10	1.9	2.7	7.9	3.5	2.9	1.9	1.9	1.2	0.8	0.8	*25.4*
11-12	1.2	2.3	7.9	3.7	4.1	2.1	1.4	1.4	0.8	1.2	*26.2*
13-14	0.0	0.4	5.6	1.2	2.1	0.6	1.2	0.6	0.6	0.8	*13.2*
15-16	0.0	0.2	1.4	2.1	0.8	1.4	0.8	0.4	0.2	0.4	*7.9*

Gatchell et al.'s (1998) sample contains 1038 1 Common boards whereas Wiedenbeck et al.'s (1996) observations are based on a sample size of 1987 boards. When looking at Table 3.6, it is evident that Gatchell et al.'s databank contains more short boards than Wiedenbeck et al. found. For example, 46.9 percent of the boards contained in Gatchell et al.'s databank are between 4 and 8 feet in length, whereas Wiedenbeck et al. found only 27.2 percent of the boards having this length. A new digital board sample was created using the boards contained in the 1998 Data Bank for Kiln-Dried Red Oak. This new board sample was created such that its distribution of board sizes is as closely as possible to the one found by Wiedenbeck et al. A complete match of the board-size distribution found by Wiedenbeck et al. by the boards contained in Gatchell et al. was not possible, since some of the board sizes observed by Wiedenbeck et al. are not contained, or are not available in sufficient numbers, in the 1998 Data Bank for

Kiln-Dried Red Oak Lumber. The boards used were selected randomly from Gatchell et al.'s databank from their respective size group and put in that sequence into the new board file. Appendix B lists the board numbers of the new board file in the sequence they were selected.

If a yield difference between these two size distributions exists, then the board file that is an approximation of the distribution found by Wiedenbeck et al. (1996) were employed. Otherwise, if no difference exists, the boards contained in the 1998 Data Bank for Kiln-Dried Red Oak Lumber (Gatchell et al. 1998) were employed.

3.3.4.2 Statistics used for the lumber sample size distribution problem

The sample size necessary to detect differences in yield due to the two lumber board size distributions discussed above, was calculated using equation (3.1) [Hinkelmann and Kempthorne 1994]. Two preliminary tests brought forth the maximum yield, t_{max}, to be 69.03 percent, t_{min} 67.72 percent, and the standard deviation s_e 0.04 percent. According to equation (3.1), Δ^* became 29.29. The number of replications found in Table 6.6 (Hinkelmann and Kempthorne 1994, p. 177) for t = 2, was 2, meaning that no additional tests were necessary. Simple two-sided t-tests ($\alpha = 0.05$) were then used to detect significant yield differences due to different lumber board size distributions.

3.3.4.3 Results

As shown above, two preliminary runs were enough to perform the statistical test with the probability of a type I error set at 0.05 and the type II error set at 0.8 according to Hinkelmann and Kempthorne (1994). The fact that the two preliminary runs sufficed, already indicated that there must be a rather large difference in yield. Performing a double sided t-test assuming unequal variances then indeed revealed a significant yield difference between the two lumber-board sizes tested. The unequal variance assumption was used since the variances of the two board-size distributions varied by a magnitude of approximately 20. Table 3.7 shows the results from the analysis.

Table 3.7: Results from the statistical analysis of the yield difference between the two board-size distributions under consideration

	Wiedenbeck et al. (1996)	*Gatchell et al. (1998)*
Mean	69.02	67.77
Variance	0.0002	0.0040
Observations	2	2
Hypothesized Mean Difference	0	
df	1	
t Stat	27.225	
P(T<=t) one-tail	0.012	
t Critical one-tail	6.314	
P(T<=t) two-tail	0.023	
t Critical two-tail	12.706	

Given the large yield difference between the two board-size distributions, which was found to be, on average, 1.25 percent, and the rather low standard deviation, there can be no doubt that differences in yield levels ($\alpha = 0.05$) exist. Therefore, for all the following tests the distribution found by Wiedenbeck et al. (1996) was used for the creation of board files utilized by the computer simulation.

3.3.5 Statistics

Throughout this study, the Statistical Analysis System SAS Institute (1996) software was used for the analysis of the data gathered. To ensure proper statistical analysis, following issues were considered: 1) number of replicates needed, 2) normality of data, 3) repeated measure, 4) equal variance assumption, and 5) independent results

3.3.5.1 Replicates

To establish the number of replicates for the tests to be performed, the standard deviation obtained from preliminary runs for 1 Common lumber was used. The equation used was:

$$n = \frac{\left(z_{a/2}\right)^2 s^2}{E^2} \tag{3.2}$$

where: n is the sample size, $z_{a/2}$ the confidence level, s the estimated standard deviation and E is the estimated acceptable error for estimating the sample size for a $100(1-a)\%$ confidence interval for m (Ott

1993, p. 208). Using 1.96 for $z_{\alpha/2}$, 0.85 for s, and 1.00 for E, it was found that the necessary number of replicates is 3. The study used three replicates for the tests based on the fractional factorial design and for the within part-group linearity assumption. However, for the test to derive the part-group sizes, only two replicates were performed. This was done to minimize the amount of computing time necessary to find the sizes of the part-group. Also, since the influence of the part groups was tested in 2.5 inch increments in length and 0.25 inch increments in width, the sensitivity of the part group tests was limited anyway. However, this resolution is thought to be accurate enough for the purpose of creating the part groups.

3.3.5.2 Normality

If normality is assumed, observations within each group should be roughly unimodal and symmetric. Normality in this study was not a problem (Noble and Hughes 1997), because there were no severe outliers observed in previous work involving cutting bills and ROMI RIP (Thomas 1995a and 1995b). Techniques exist that would allow to handle serious nonnormality otherwise.

3.3.5.3 Repeated Measure

Repeated measure occurs when more than one observation per treated sample is obtained (Ott 1993). The boards used for the simulation of the cut-up are repeatedly used for different runs. Thus, several observations will be obtained using the same sample specimen. However, repeated measure would only occur when the boards were always at the same place in the lumber stack and the cutting priorities were the same for these boards every time (Neff and Ligozio 1996). Due to the random composition of the board stacks with the ROMI RIP lumber composition module (Thomas 1995a), the probability that a board will be cut up with the same cutting priorities is infinitesimally small. Therefore, repeated measure is of no concern in this study.

3.3.5.4 Equality of Variance

The equal variance assumption is not of crucial importance if the number of samples for all

tests are the same (Ott 1993). Given equal sample size (i.e. number of tests), the population variance can differ by a factor up to 3, and still be reasonable (Ott 1993). If heteroscedasticity is observed transformation of the data may be possible.

3.3.5.5 Independence of samples

Independence of samples is the most critical assumption (Ott 1993) for the comparison of means and variances procedures as well as for least squares estimation. Compliance with this assumption was accomplished by the design of the experiments (orthogonal designs).

3.4 SUMMARY

This chapter presented the general methodologies, the materials, and the system settings used for this study. It was found that, when at least 177 boards are processed, then yield is no longer significantly different ($\alpha = 0.05$) from any other cutting bill that requires more boards to be processed. Therefore, for all tests undertaken in this study, the cutting bills were always set up such that at least 177 boards were processed. Differences in the lumber board size distributions, as they exist between boards contained in the 1998 Data Bank for Kiln-Dried Red Oak Lumber (Gatchell et al. 1998) and boards observed on the market today (Wiedenbeck et al. 1996), have a significant ($\alpha = 0.05$) impact on the level of yield achieved. Since the distribution found by Wiedenbeck et al. (1996) was thought to more accurately represent the average lumber board size distribution for 1 Common red oak lumber used in rough mills today, this distribution was used for all tests conducted throughout the study. This chapter ended with some remarks as to the statistical framework employed for the experiments conducted.

CHAPTER 4

4. PART GROUPS

4.1 INTRODUCTION

Part groups are a theoretical concept that tries to create a framework to describe “real” cutting bills in a standardized format. Deriving part groups that reflect “real” cutting bills is a difficult endeavor because these cutting bills can have an almost unlimited variety of requirements with respect to part quantities, part sizes, and distribution of part sizes. Therefore, it was necessary to create an average cutting bill that could serve in representing “real” cutting bills. The goal was to make a standardized cutting bill that can represent “real” cutting bills as closely as possible in terms of yield. To create this standardized cutting bill, minimum and maximum part sizes had to be established. Also, part quantities for individual part sizes had to be found such that they would reflect average values as observed in industrial operations. Using a preliminary cutting bill and statistical tests, the final part-group matrix, that represents the standardized cutting bills, could be established and evaluated for its utility.

4.2 METHODS

The following sections will explain the methodology used to derive the preliminary part group matrix, the part group quantities, and the tests used to determine the final part group matrix.

4.2.1 Preliminary part groups

Part sizes and part quantities are specified in cutting bills. Such cutting bills, as they are used in industry, can contain many different part sizes (some cutting bills have 70 or more parts). More than 95 percent of solid wood parts required by “real” cutting bills are between 5 and 85 inches in length and 1.00 and 4.75 inches in width, as was found from the analysis of 40 cutting bills obtained from industry and the literature. Within these size ranges, any different combination of part sizes can be found. Since large

quantities of different part sizes cannot be handled and modeled easily for analytical purposes, the concept of part groups was used.

Part groups are a subdivision of the total length and width range of all the part sizes found in a typical cutting bill. The length range of parts (i.e. 5 to 85 inches) was divided in five segments of equal length (i.e. each segment's range in length is 16 inches, [85 - 5]/5). The width range was divided into four segments, three of them being 1.00 inches and one being 0.75 inches in width. This way, 20 groups of equal sizes were created. Figure 4.1 shows a graphical representation of the partitioning of the part-size space into 20 part groups. The part group midpoint of each group is shown as a solid circle. In the lower right corner, the designation of each part group is given.

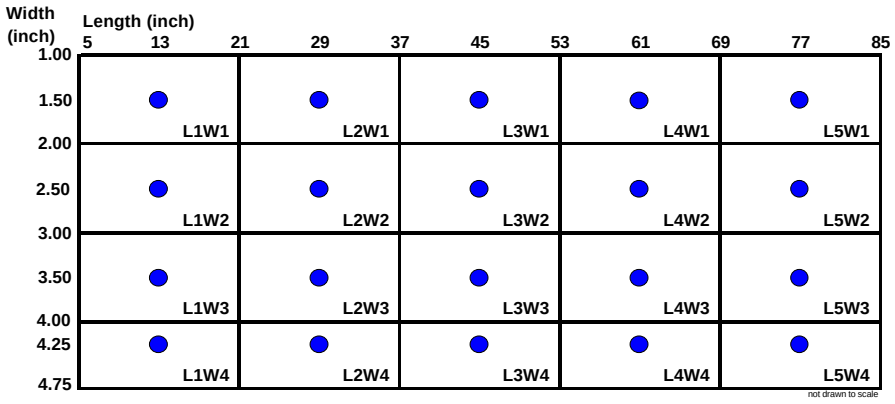


Figure 4.1: Graphical display of the length (x-axis) and width (y-axis) dimension of the part-size range of cutting bills and its partitioning into 20 part groups.

As one can see in Figure 4.1, the part group midpoints are in the middle (median) of their respective part group in terms of both length and width, except for the groups with widths ranging from 4.00 to 4.75 inches (i.e. groups $_{LxW4}$. This is because for this width group the mathematical midpoint would be 4.38 inches. However, since most rough mills and the simulation software used (Thomas 1995a and 1995b) work only in quarter-inch increments for the ripping, such a measure cannot be used. Therefore, the midpoints in width, that are not at a quarter inch increment, are set to the next lower quarter-inch increment available, i.e. to 4.25 inches for group L_xW_4 in the example explained above.

The partitioning of the length and width ranges as shown in Figure 4.1, can alternatively be shown as a five by four matrix of part-groups, as is shown in Table 4.1. This figure is intended to familiarize the reader with the notation for part groups that was used throughout the study. The numbers in the headings of Table 4.1 indicate each part group's range (or, respectively, each part group's boundaries). The value in rectangular brackets is the median of the range for each part group (i.e. the mean of part-group L_1W_1 is 13 inches in length and 1.50 inches in width). This median value of each part group is designated the part-group midpoint. Each group is identified by the subscript i for length and j for width (i.e. L_iW_j , where i = 1, 2, 3, 4, 5 and j = 1, 2, 3, 4).

Table 4.1: Partition of length and width range into 20 groups.

Width (inch)	Length (inch)				
	5=<L<=21 [13.0]	21<L<=37 [29]	37<L<=53 [45]	53<L<=69 [61]	69<L<=85 [77]
1.00=<W<2.00 [1.50]	L_1W_1	L_2W_1	L_3W_1	L_4W_1	L_5W_1
2.00=<W<3.00 [3.50]	L_1W_2	L_2W_2	L_3W_2	L_4W_2	L_5W_2
3.00=<W<4.00 [3.50]	L_1W_3	L_2W_3	L_3W_3	L_4W_3	L_5W_3
3.75=<W<=4.75 [4.25]	L_1W_4	L_2W_4	L_3W_4	L_4W_4	L_5W_4

Part groups allow for the clustering of all parts that fall within a specified part-group range. Each part group contains all the parts that are within this part group's range and are represented by the part-group midpoint of this part group. Thus, a particular part group's midpoint is thought to represent all parts having sizes that fall within this part group's size range. This way, the amount of different part sizes to be handled for analytical purposes can be reduced significantly. For example, if a part group's size range is 5 to 21 inches in length and 1.00 to 2.00 inches in width (i.e. part group L_1W_1), then all the parts that have a length between 5 and 21 inches and a width between 1.00 and 2.00 inches belong to this group. The midpoint of this part group (i.e. 13 inches in length and 1.5 inches in width) represents all these parts that fall within this particular part group. Thus, the parts called X_1, X_2, and X_3, in Figure 4.2, would belong to part group L_1W_1, whereas the parts called X_4 and X_5 would not belong to part group L_1W_1 (X_4 would belong to part group L_1W_2, whereas X_5 would belong to L_2W_1).

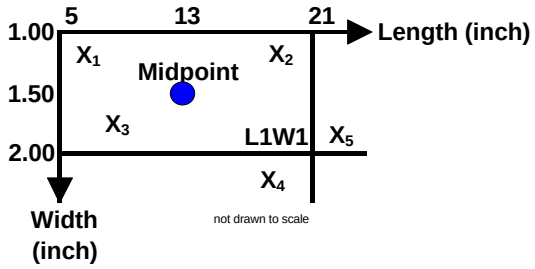


Figure 4.2: Schematic presentation of the idea of part groups.

For the situation shown in Figure 4.2, the midpoint of part group L_1W_1 is then the representative for the three parts, i.e. X_1, X_2, and X_3, that fall within part group L_1W_1. The sum of the part quantities specified in the cutting bill for X_1, X_2, and X_3 is the part quantity assigned to the part group midpoint of part group L_1W_1.

One has to be aware, though, that the clustering of parts within part groups can change the yield obtained. This happens for two reasons: First, the size of parts changes because the original part size (as required by the "real" cutting bill) is reset to its respective part-group midpoint, Second, the number of different part sizes to be cut decreases when two or more part sizes within one part group are represented by their common part-group midpoint. This error can be minimized by having part groups that are small, such that the change between the real part size and the size of the part when clustered is not very large and not too many part sizes are represented by one part-group midpoint. However, there is a trade-off to make here. On one hand, fewer part groups will make the analytical work easier. On the other hand, the error in yield due to the clustering of the parts will increase when there are fewer, but larger, part groups. This tradeoff necessitates the investigation of the influence of part groups on yield in order to make an appropriate choice concerning the size and number of individual part groups.

In general, by assuming that parts are distributed over the entire part-size range of a cutting bill, the error from resetting the part sizes to their respective midpoints should cancel out to a certain degree. This is because the parts should be distributed on all sides of the midpoints. However, there exists no evidence that the influence on yield from changing part sizes is proportional. Or, in other words, there is no evidence that yield is equally affected by an increase in a part's size and a decrease of equal amount

in another part's size. Moreover, for individual cutting bills, parts may not be evenly distributed around midpoints. Also, the influence on yield is not only determined by the part size, but also by the quantity requirements of individual parts (Buehlmann et al. 1998c). Therefore, part groups preferably have to be made rather small as to minimize the distortion occurring from the resetting of the original part size to the part group midpoint. Section 4.2.4 presents the steps for a scientific, methodological way of deriving the part-group sizes that takes account of the problems described here.

4.2.2 The importance of part quantity on yield

Buehlmann et al. (1998c) showed that yield is not only dependent on the part sizes and part size distribution but also on part quantity. These authors used the cutting bill space partitioning shown in Figure 4.1 and sequentially moved the part group midpoints of selected part groups to different locations within each respective part group. For example, Figure 4.3 shows the positions of the part-group midpoints for length group L_3 (ranging from 37 to 53 inches). The first test was performed with the part-group midpoints for all part groups of the same length set at position one. Then the second test was performed with the part-group midpoint at position two and so on until the part group midpoint was at position three. Thus, nine tests were performed for each length group, for a total of 45 tests for all five length groups. For each test, only the part group midpoint of the part group under consideration was changed, the position of the four remaining length groups stayed unaltered.

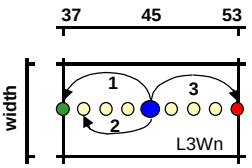


Figure 4.3: Schematic representation of the positions for the part-group midpoint when testing the influence of part quantity on yield

To observe the influence of quantity as a function of part-size changes within a particular length group, three experiments, each requiring different part quantities were performed. First, the ROMI RIP rough mill simulator (Thomas 1995a and 1995b) was allowed to cut as many parts of any of the 20

different parts as could be obtained. Second, part quantities were restricted according to the part quantity distribution found by Araman et al. (1982). Third, the part quantities were set even for all 20 part sizes. Given these part quantities and the different positions of the part group midpoints for the length group under consideration, two observations could be made. First, for any part-quantity requirement, the influence of the change in part-group midpoint position on yield could be observed. Second, the difference in yield due to different part quantity requirements could be detected.

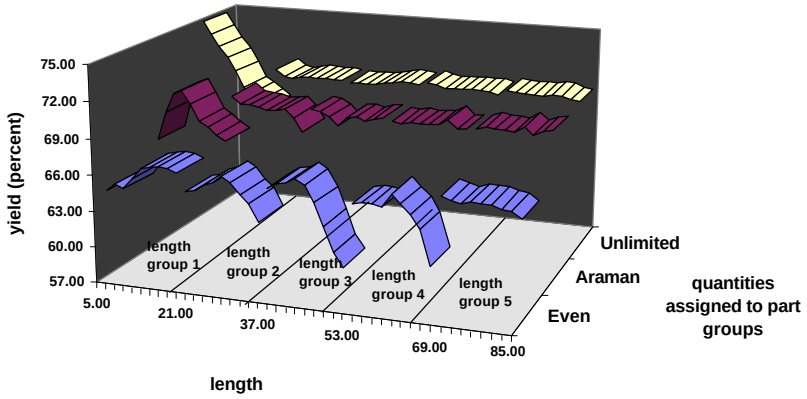


Figure 4.4: Yield dependent on quantity requirements and part size

As Figure 4.4 shows, when an unlimited quantity of any part can be produced, then the shortest length determines yield. In fact, the shorter the shortest part, the higher yield can be achieved. However, when the part quantities are limited, the maximum yield achievable is no longer when the shortest length is cut, but when lengths longer than minimum are cut. However, for the case of unlimited quantities and when quantities according to the distribution of Araman et al. (1982) are required, longer parts than 21 inches have a relatively small influence on maximum yield. Given sufficient quantities of short parts are required, the longer parts can be obtained from the larger clear areas in a board, with the remaining areas being used for the shorter parts. However, since the shorter lengths are limited in quantity when using the distribution shown by Araman, no longer the very shortest part is best for achieving high yield. Instead, when the shortest part in the cutting bill is 11 inches long, instead of five inches when part

quantity is not restricted, highest yield is achieved. This is because when the shortest part length is only five inches, there are no longer enough of these short parts to effectively use all the remaining clear areas after having obtained the longer parts. When even quantities of all parts are required, highest yield is achieved when the shortest part is 21 inches in length. Also, changing the length of medium long parts now has a distinct influence on yield. The longer these parts become, the more yield suffers.

Similar observations, even though less pronounced, were made with width. Again, it was found, when no part quantity restrictions exist, yield is highest. When the smallest part is of minimum width (i.e. 1 inch wide), then maximum yield is achieved given that no part quantity restrictions exist. However, as was found for length, when part quantity is restricted, wider parts rather than minimum width achieved maximum yield.

4.2.3 Part quantity derivation

As was shown in Section 4.2.2, part quantities influence yield significantly (Buehlmann et al. 1998c). When an unlimited quantity of the smallest part in a cutting bill can be cut, this part determines yield. When the quantity of the smallest part is limited, however, other parts in a cutting bill have a larger influence in the determination of yield (Buehlmann et al. 1998c, Thomas 1965c). Since part quantities are always restricted in the typical cutting bill, the part quantities used for this study are of high importance and will significantly affect the results obtained.

To establish the average part quantity required in cutting bills employed in rough mills, a study conducted by Araman et al. (1982) was used. Araman et al.'s study was thought to be the most appropriate representation of average part quantities for a given size used by furniture producers. As discussed in Chapter 2, Araman et al. collected data from 32 secondary wood product producers. Twenty of them produced furniture. The data from these 20 furniture producers was used to find average part quantities required in cutting bills. These authors' findings for the "*Length/Width distribution (in percent) of 4/4 nominal thickness, clear (C1F and C2F) quality rough parts for solid wood furniture* (Araman et al. 1982, Table 3, p. 6)" was used for the determination of part quantities. The numbers published by Araman

et al. are the average part sizes and part quantities required by the 20 furniture makers surveyed. Araman et al.'s findings are reproduced in Table 2.4.

Araman et al.'s (1982) information, to be useful, had to be adapted to the framework of the study at hand. The range of lengths listed by Araman et al. was from 0 inch to 100 inches, the width from 0 inches to "*bigger than 5*" inches. The study's range here, is limited from 5 to 85 inches in length and from 1.00 to 4.75 inches in width. Assuming a uniform distribution of quantities within each size group presented in Araman et al., these quantities were recalculated to fit the limitations imposed for the part groups used in this study. Table 4.2 displays the resulting part quantity distribution for parts limited to 5 to 85 inches in length and 1.00 to 4.75 inches in width based on the data by Araman et al. For example, the width group from 4.01 to 5.00 inches as given by Araman et al. was converted to a width group of 4.01 to 4.75 inches to fit the boundaries of the study. Mathematically, the part quantity in the width group ranging from 4.01 to 5.00 by Araman et al. was multiplied by 0.75 to approximate the part quantity that should be found in the part range form 4.01 to 4.75 inches. This conversion rests on the assumption that the quantities in Araman et al. were uniformly distributed.

Table 4.2: Length/Width distribution of 4/4 nominal thickness, clear quality rough parts for solid wood furniture fitted to the boundaries of this study

Length groupings (inches)	**Width groupings (inches)**								
	0-1.5	1.51-2.0	2.01-2.5	2.51-3.0	3.01-3.5	3.51-4.0	4.01-5.0	>5.0	Percent of total
0-15	0.2	0.7	0.7	0.3	0.2	0.2	0.3	3.7	6.3
15.01-18	0.3	1.1	1.0	0.4	0.4	0.2	0.5	5.9	9.8
18.01-21	0.4	0.5	0.5	0.4	0.2	0.1	0.3	7.5	9.9
21.01-25	0.2	0.4	0.9	0.4	0.3	0.1	0.2	7.4	9.9
25.01-29	0.3	0.3	0.2	0.3	0.0	0.1	0.1	8.3	9.6
29.01-33	0.1	0.6	0.2	0.2	0.1	0.3	0.3	8.7	10.5
33.01-38	0.1	0.4	0.2	0.2	0.2	0.2	0.3	8.2	9.8
38.01-45	0.1	0.4	0.2	0.4	0.1	0.1	0.1	11.7	13.1
45.01-50	0.1	0.1	0.2	0.0	0.0	0.1	0.1	2.2	2.8
50.01-60	0.0	0.4	0.1	0.4	0.1	0.0	0.0	6.1	7.1
60.01-75	0.1	0.4	0.3	0.2	0.2	0.1	0.2	5.1	6.6
75.01-100	0.1	0.1	0.1	0.0	0.1	0.2	0.0	4.0	4.6
% of total	2.0	5.4	4.6	3.2	1.9	1.7	2.4	78.8	100.0

Few cutting bills contain parts with lengths shorter than 5 inches (an analysis of 40 cutting

bills, found no parts shorter than 5.75 inches) and widths smaller than 1 inch (the same analysis found only one part smaller than 1.00 inch). Therefore, the part groups expressed as 0 - 15 inches in length and 0.00 - 1.50 inch in width in the study by Araman et al. were taken as representative quantities for the smallest sizes, which is 5 inch in length and 1 inch in width in this study. Thus, for this size range, no proportional redistribution of quantities was undertaken. One can argue that this is not consistent with the way the other, larger part groups were treated, where the part-group quantities were changed proportionally to the part group sizes. However, since the likelihood of finding parts smaller than 5 inches in length and 1.00 inch in width is very small, this assumption has a very small impact on the part quantity distribution.

The part-size quantities shown in Table 4.2 were then employed to find the part-quantity distribution for any part-group disposition (i.e. sizes of individual part groups) used throughout the study. That is, the part quantity required by each part group was calculated according to their sizes based on the part-quantity distribution published by Araman et al. (1982). Whenever the size of a part group had to be changed, the part quantity had to be recalculated. Appendix C shows the part quantity matrix that was used for this purpose.

The part quantities given by Araman et al. (1982) that lie within each of the part groups defined in Figure 4.1, expressed as a percentage, are shown in Table 4.3. Since each part-group midpoint is a representative for all parts lying within a particular part group, a cutting bill with 20 parts whose quantities were derived from Araman et al. could now be created. Table 4.3 shows the part groups and the associated quantities (in percent of the total) derived for the 20 parts of the preliminary cutting bill.

Table 4.3: Preliminary part groups with part quantity distribution in percent

Width (inch)	Length (inch)				
	5=<L<=21 [13.0]	21<L<=37 [29.0]	37<L<=53 [45.0]	53<L<=69 [61.0]	69<L<=85 [77.0]
1.00=<W<2.00 [1.50]	14.3	12.4	4.8	2.9	1.5
2.00=<W<3.00 [3.50]	14.8	13.5	5.2	3.3	1.4
3.00=<W<4.00 [3.50]	5.9	6.1	2.4	1.2	1.3
3.75=<W<=4.75 [4.25]	3.7	3.3	1.2	0.4	0.3

As stated earlier, every time the part group sizes changed, the distribution of part quantities changed, too. For example, when part group L_1W_1 would become smaller, thus encompassing a smaller part of the cutting bill size range, the associated part quantity would decrease, too.

4.2.3.1 Verification of cutting bill assumptions

To assure the appropriateness of the part size restrictions imposed and the part quantities found by Araman et al. (1982), 40 cutting bills, obtained from manufacturer's rough mills, researchers, and from literature sources, were analyzed and compared to the work of Araman et al. To make these 40 cutting bills comparable among each other, the part quantities were normalized, i.e. the quantity for the minimum part quantity required in a cutting bill was set at 1 part of this size. For example, assuming that a cutting bill originally asked for two parts, X_1 and X_2, where X_1 would require 100 units and X_2 500 units, this cutting bill would be normalized such that it would ask for 1 part of X_1 and 5 parts of X_2. Of these 40 cutting bills, one asked for only two different part sizes to be cut, another one listed 76 different parts. Unfortunately, no information as to the processing capabilities of the different rough mills where these cutting bills were employed, was available. Most likely, a rough mill does not cut 76 different part sizes at once due to system constraints, but splits the cutting order into several cutting bills.

The maximum part length observed in any individual cutting bill ranged from 31 inches to 144.5 inches. Maximum widths were found ranging from 1.25 to 6.75 inches. However, most often, the widths above 4.75 inches are made up of glued strips, since cutting a width so wide would lead to low yield, assuming 1 Common or lower grade lumber is used. Table 4.4 shows a summary of the analytical work done with the 40 cutting bills.

As can be seen in Table 4.4, only a very small percentage of all parts required in those 40 cutting bills exceeds the part-size limits (5 to 85 inches in length, 1.00 to 4.75 inches in width) set forth in this study. As few as 3.11 percent of all part lengths and 6.49 percent of all part widths were found to be beyond these boundaries. This indicates that the part-size boundaries set for this study are reasonable.

Table 4.4: Summary of 40 cutting bills analyze, part quantities normalized

	Maximum in any cb	Minimum in any cb	Total of all 40 cbs	Average of all cbs	Std. Dev. of all cbs
# of different part sizes [units]	76	2	771	19.28	14.89
total quantity of parts [units]	1497	5	9042	226.05	324.49
average length in all cbs [inches]				37.15	12.31
max. length in any cb [inches]	144.5	31		74.13	30.05
min length in any cb [inches]	50	5.75		16.26	8.89
# of part sizes beyond length limits found in any cb [units]	4	0	24	0.6	1.26
percentage of total # of part sizes beyond length limits [percent]			3.11		
average width in all cbs [inches]				2.52	0.72
max. width in any cb [inches]	6.75	1.25		3.809	1.35
min. width in any cb [inches]	4	0.35		1.63	0.62
# of part sizes beyond width limits found in any cb [units]	19	1	50	1.23	3.38
percentage of total # of part sizes beyond width limits [percent]			6.49		

notation: cb = cutting bill
cbs = cutting bills
empty cells = not applicable

Also, when looking at the part-quantity distribution, similar trends as published in the study of Araman et al. (1982) can be found. Most of the parts required are grouped in the length range from 5 to 45 inches, and in the width range from 1.00 to 3.00 inches. The graphical representation of the part size - quantity relationship for the 40 cutting bills combined, as displayed in Figure 4.5, confirms the importance of the shorter and smaller part sizes.

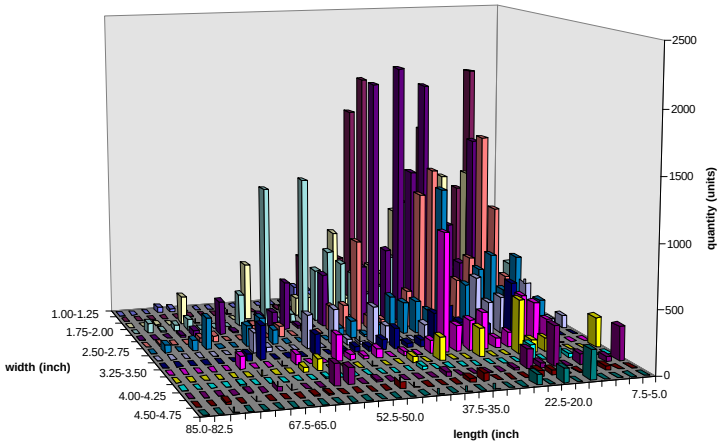


Figure 4.5: Part size - quantity distribution as found in 40 cutting bills, part quantities not normalized

Clearly, the most parts required in these 40 cutting bills are relatively short and small, few are long and/or wide. This is confirmed by the average length found for all 40 cutting bills which is, according to Table 4.4, 37.15 inches. One has to be aware, though, that this is not the weighted average length, but the average of all different part sizes that exist in these 40 cutting bills. A weighted average length for these cutting bills would be lower, since a higher quantity of short parts are required. The part quantity distribution displayed in Figure 4.5 resembles the one found by Araman et al. (1982). Both, the 40 cutting bills analyzed and the distribution found by Araman et al. have more than 60 percent of the parts required in the length range of 5 to 45 inches and in the width range of 1.00 to 3.50 inches. However, since the 40 cutting bills are not based on a methodological selection, the study will use, as stated earlier, the distribution given by Araman et al.

4.2.4 Derivation of part-group sizes

The objective of the study to better understand the influence of cutting-bill requirements on lumber yield required the ability to statistically analyze these relationships. Parts-groups, as described previously, were used to limit the number of factors involved and thus to make the statistical analysis attainable. As was explained in Section 4.2.1, the part-group midpoint of each part group is assumed to represent all the parts in a cutting bill that fall within a particular part-group range. To minimize the influence on yield due to the clustering of parts, part groups have to be made as small as possible. However, part groups cannot be too small, because having too many part groups would make the statistical analysis more complicated.

This section outlines the procedure to research and describe the influence of resetting parts to the part-group midpoint. A rational, methodological way to find (1) the number of part groups needed and (2) to control the influence on yield due to the resetting of part sizes, will be presented. First, in Section 4.2.4.1, the general method to research the influence on yield of resetting part sizes is described. For this purpose, the part-group midpoint will change position within its part-group limits. Indeed, when the midpoint is moved away from the center of a part group, it is no longer the midpoint. In this study,

however, the midpoint is always considered the point that represents all the parts that fall within a particular part group, no matter it's location within its respective part-group range. Second, in Section 4.2.4.2, the systematic method to measure the influence on yield of different part-group midpoint locations is presented. Third, the decision tree that was used to adjust individual part-group's sizes according to the yield influence measured is revealed in Section 4.2.4.3. And fourth, the sequence in which the tests were performed is explained in Section 4.2.4.4. Finally, to confirm the size of the part groups found by employing the methodology developed so far, a last set of tests on all part groups was performed. The methods for these final tests is shown in Section 4.2.4.5.

4.2.4.1 Influence of location of the midpoint

Changing the part-group midpoint from the place in the center of the part group (position 0,0 in Figure 4.6) to an extreme corner (positions +/-1,+/-1 in Figure 4.6) of this part group will influence the yield obtained. The center position is designated as 0,0, because it is the original, unaltered position of the part-group midpoint (shown as a solid circle in Figure 4.6). The four extreme positions in the corners of the part group, where the midpoint could be set at, are then designated as +/- one in length and +/- one in width. These points are shown as circles in the corners of the part group. The number one is just a representation of the possible position and does not confer any information as to the real geometric position of the midpoint. Figure 4.6 shows the idea explained graphically.

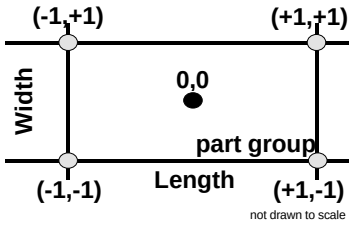


Figure 4.6: Midpoint (0,0) and extreme points (corners of the part group) that will be used to test for the maximum possible influence of a part group on yield.

For example, according to the schematic shown in Figure 4.6, the five positions that the part-

group midpoint for part group L_1W_1 will assume, when the part-group size displayed in Table 4.1 is used, are:

Position 0,0: $L_1 = 13$, $W_1 = 1.50$ (this is the original midpoint position)
Position -1, -1: $L_1 = 5$, $W_1 = 2.00$
Position +1, -1: $L_1 = 21$, $W_1 = 2.00$
Position +1,+1: $L_1 = 21$, $W_1 = 1.00$
Position -1,+1: $L_1 = 5$ $W_1 = 1.00$

All the other part groups' midpoints will stay unaltered, except for the ones that lie in the same row or same column as the part group under consideration. The midpoints of part groups in the same row or same column will assume the same value in the dimension that the midpoint of the part group under consideration has. The rationale for this set-up scheme is that it increased the change in yield measured due to changes in one part-group's midpoint position when the cut up of lumber is simulated. The effect on yield of the change of the part-group midpoint location is thus amplified. This was intended to make sure that, ultimately, no part group has a too big influence on yield due to the change in the position of its midpoint. Also, since changing the size of one part-group's size, required a change in size of the other part groups, this set-up was considered a more reliable indication of the real influence on yield of the part group under consideration. Figure 4.7 illustrates this concept. The solid circles represent the part size of each part as it was entered into the cutting bill used for the simulation, when the part group midpoint of part group L_1W_1 takes position +1,+1.

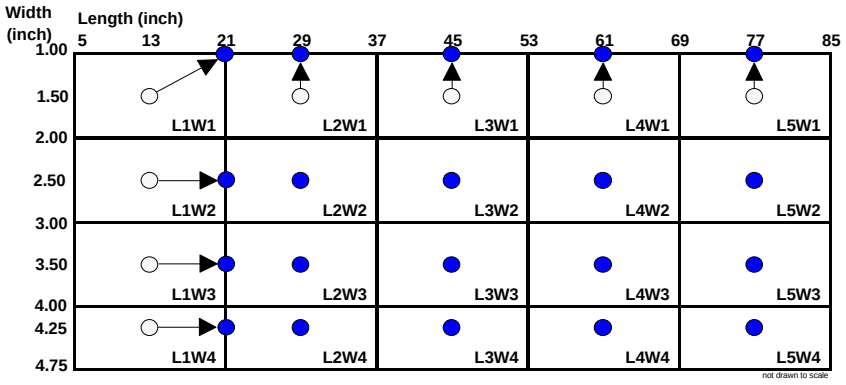


Figure 4.7: Configuration of part-group midpoints when part group L1W1 takes position +1,+1

When the midpoint of part group L_1W_1 is set at position +1,+1 (i.e. at 21 inches in length and 1.00 inch in width), as shown in Figure 4.7, then the midpoints of the part groups L_2W_1, L_3W_1, L_4W_1, and L_5W_1 would stay at their respective position in length (i.e. 29, 45, 61, and 77 inches in length), but would be reset from 1.50 inches to 1.00 inches in width. Similarly, the midpoints of part groups L_1W_2, L_1W_3, and L_1W_4 would stay at their respective position in width (i.e. at 2.50, 3.50 and 4.25, respectively), but their position in length would change from 13 inches to 21 inches.

4.2.4.2 Measuring the influence of part groups on yield

The method described above allowed to create cutting bills that test the influence of extreme within part group part sizes that a part group could require to be cut. To make the yield differences between individual observations for the same part group independent of the absolute yield-level, the within part-group yield changes due to different locations of the midpoint were measured using statistical analysis. The five observations (Figure 4.6) obtained for a part group were fitted to the following general linear model:

$$Y_{ij} = L_i + W_j + (LW)_{ij} + Curvature \tag{4.1}$$

where Y_{ij} is the average yield (two replicates) from simulating the cut-up of the n^{th} cutting bill testing part group ij with the part-group midpoint at one of the five possible positions. L_1 is the average yield on the low length level, L_2 is the average yield at the long length level, W_1 is the average yield at the small width level, and W_2 is the average yield at the wide length level. L_i checks for significant changes in yield due to changes in length. W_j does the same thing for width, whereas the third term (L_iW_j) looks for a significant interaction between length and width. The curvature term assures that the yield surface in a part group is flat over the entire surface. The level of significance for these tests was set at $\alpha = 0.01$.

4.2.4.3 Adjusting the size of part groups

Once a measure of the influence that a particular part group has on yield was established, rules as to how to adjust a part group that did not conform to the minimum level of significance ($\alpha \geq$

0.01), had to be developed. The decision tree to adjust length based on the tests for length was as follows:

Step 1:

Is curvature significant?
if yes, shorten length, rerun simulation, and start step 1 again
if no, go to step 2

Step 2:

Is L_iW_j significant?
if yes, shorten length, rerun simulation, and start with step 1 again
if no, go to step 3

Step 3:

Is L_i significant?
if yes, shorten length, rerun simulation, and start with step 1 again
if no, check W_j

Is W_j significant?
if yes, shorten length, rerun simulation, and start with step 1 again
if no, part-group length is determined or can be enlarged

In the case that the size of the part group under consideration had to be made smaller or larger, the sizes of all other 19 part groups had to be adapted, too. This was done to always cover the entire range of the part-size range, i.e. 5 to 85 inches in length and 1.00 to 4.75 inches in width. For example, should the shortest length group L_1 be changed to 5 to 15 inches in length, the remaining four part groups' length would increase to 17.5 inches from 16 inches to cover the remaining length range between 15 and 85 inches. The length of part groups L_1W_2 and L_1W_3 would become 5 to 15 inches. This way, all part groups in the same row or column remained of the same size. Moreover, the part quantities belonging to each part group was recalculated based on the distribution of Araman et al. (1982) every time a change in the part-groups' sizes occurred.

The increments to change the part-groups size were set at 2.5 inches in length and 0.25 inches in width. However, the incremental change in length was implemented as a 2 inch change followed by a 3 inch change, such that the length of the part group was an integer and two subsequent changes always equaled 5 inches.

4.2.4.4 Sequence of testing part groups

Since only one part group at one time was tested for significant yield differences, a sequence

of tests had to be developed. Since the shorter part groups were thought to experience more pronounced yield changes due to differences of the within part group part sizes, testing started with part group L_1W_1. Also, to be able to focus on one part-size dimension (length or width), the sequence of testing was first for significant influences ($\alpha \geq 0.01$) on yield due to part-group length. Once the lengths of all part groups did conform to the level of significance set forth, testing on width was performed. Figure 4.8 shows the sequence of tests undertaken. Tests one to five tested the length of the part groups, whereas tests six to nine tested the influence of width.

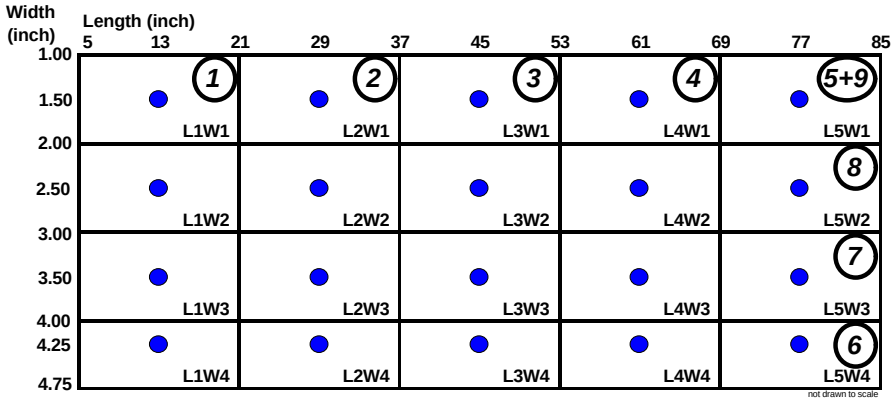


Figure 4.8: Sequence of tests, first testing length (tests 1 to 5), thereafter testing widths (tests 6 to 9)

Testing for part-group length was done using the smallest width-group, i.e. W_1, since this way, width is not as influential on yield as when parts are wider. Testing part-group width, on the other hand, was done using the longest length group, i.e. L_5, since the influence of width on yield is more pronounced when parts are long.

4.2.4.5 Assuring that all part groups comply with the allowable level of influence

Since these tests were performed to check all 20 part groups to assure compliance with the rules for all part groups, only the midpoint of the particular part group researched was manipulated. The midpoints of all 19 other part groups were held constant at the center of the respective part group. Figure 4.9 gives a schematic view of the positions of each part-group midpoint when testing the influence on

yield of part group L_1W_1.

As Figure 4.9 shows, only the part group midpoint in the part group under consideration changed its position for these tests, whereas the midpoints of all 19 other part groups stayed at the center (i.e. at position 0,0). Two replicates of each test were obtained.

These tests were also used to observe the maximum yield difference between any of the five average yield observations obtained from testing an individual part group. The term “yield span”, introduced here and henceforth used throughout the study, connotes the maximum absolute yield deviation

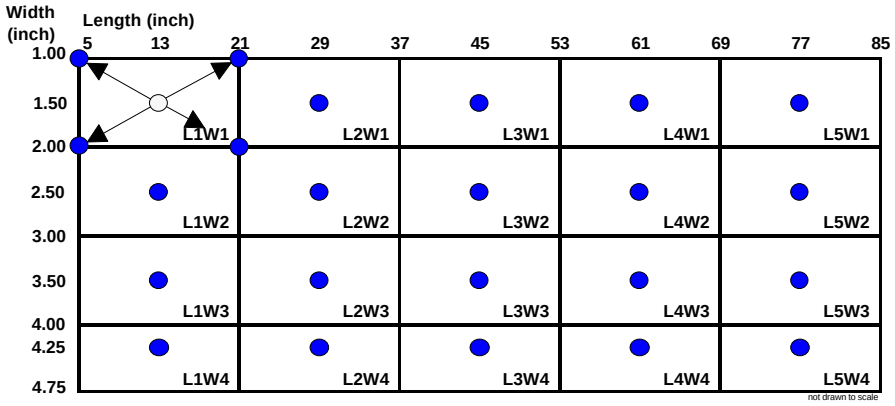


Figure 4.9: Procedure to test part group L_1W_1 for its influence on yield

between any two of the five tests done for a particular part group (i.e. the difference between the maximum and minimum yield level). The yield span gave insight as to the level of absolute yield changes that occurred within a specific part group due to changes in the position of the midpoint.

4.2.4.6 Limitations

The section about deriving the part groups used in the study, described a rational, methodological way to establish the size of the part groups. However, one has always to be aware that the concept of part groups is an artificial construct that can mimic “real” cutting bills only to a certain degree. Cutting bills whose part-size distribution are concentrated over a narrow range of sizes, or cutting bills whose part quantity for one part is totally dominant, will always defy the concept of part groups. Still, the

concept of part groups allows to gain a better understanding of and the ability to estimate the relationship of cutting bill requirements and lumber yield. Also, by controlling the maximum influence of resetting part sizes on yield, the distortion occurring due to the clustering of actual parts in a cutting bill to the respective part-group midpoints was minimized.

4.3 RESULTS

Obtaining the final part group matrix required an extensive set of iterative testing. However, a part group matrix that complied with the requirement set forth in section 4.2 could be found.

4.3.1 Part group derivation

Testing for the part group's size was started with part group L_1W_1, as shown in Figure 4.8. The preliminary part group matrix shown in Figure 4.1 with its associated part quantities shown in Table 4.3 were used for the first test. Employing the tests described in Section 4.2, the final part group matrix was established. This section elaborates the results obtained and gives an example as to how the size of one part group was found in detail. Since group L_2 was the most revealing group size to be established, this group's tests will be presented. However, before being able to establish the size for group L_2, the size of group L_1 had to be established. L_1's length range was found to be from 5 to 15 inches in length, according to the tests described in Section 4.2. Having this size, the change in the midpoint location of part group L_1W_1 did not result in significant ($\alpha = 0.01$) yield changes, and thus conformed to the rules established.

Since group L_1's final length was found to be 5 to 15 inches (instead the original 5 to 21 inches), the four remaining length group's sizes had to be readjusted. Instead of covering the length range from 21 to 85 inches, these four length groups had now to cover the length range from 15 to 85 inches. Each individual's length range thus increased from 16 inches to 17.5 inches. Two length groups (L_2 and L_3) were made 18 inches and two length groups (L_4 and L_5) 17 inches, as to have only length groups without decimals. The new part group matrix before resuming testing for group L_2 with its associated part

quantities in percent was thus as shown in Table 4.5.

Table 4.5: Part groups and part quantities before resuming testing for group L_2

Width (inch)	Length (inch)				
	5=<L<=15 [10.0]	15<L<=33 [24.0]	33<L<=51 [42.0]	51<L<=68 [59.5]	68<L<=85 [76.5]
1.00=<W<2.00 [1.50]	4.0	20.3	6.8	3.1	1.7
2.00=<W<3.00 [3.50]	4.5	22.2	6.4	3.6	1.5
3.00=<W<4.00 [3.50]	1.8	8.6	4.0	1.2	1.4
3.75=<W<=4.75 [4.25]	1.0	5.0	2.1	0.3	0.4

Using the part groups as shown in Table 4.5, testing was resumed on group L_2. This group required six tests to achieve that its level of significance was $\alpha \geq 0.01$. The individual results for each of the six tests are shown in Table 4.6.

Table 4.6: Summary of testing length group L_2, levels of significance and yield span

Test for	length group 15 - 33 in.	length group 15 - 30 in.	length group 15 - 28 in.	length group 15 - 25 in.	length group 15 - 23 in.	length group 15 - 20 in.
Length	0.0001	0.0001	0.0001	0.0001	0.0002	0.1542
Width	0.2886	0.1465	0.0146	0.7005	0.1161	0.2314
Interaction	0.1251	0.0139	0.2611	0.3424	0.4749	0.1027
Curve	0.0224	0.0392	0.0103	0.0009	0.0126	0.0474
Yield-span	10.91%	9.36%	8.41%	5.51%	5.84%	2.27%

Group L_2's length range decreased from 15 to 33 inches to 15 to 20 inches before all four parameters [equation (4.1)] were no longer statistically different ($\alpha \geq 0.01$) from each of the five tests conducted. The yield span decreased considerably over these six tests. For the first test, when group L_2's length range was 15 to 33 inches, the yield span was almost 11 percent, but was only 2.27 percent when L_2's length range was 15 to 20 inches. All the tests for the remaining length groups (i.e. L_3, L_4, and L_5) were conducted equally to the one shown for group L_2. As expected, the lengths of these remaining three length groups were found to be longer again. These length groups' range were found to be 20 to 35, 35 to 60 and 60 to 85 inches, for length groups L_3, L_4. and L_5, respectively.

The range of the part groups in width, as it was detected through performing the tests for width, was more evenly distributed than the one found for length. The four width groups' width range was

found to be 1.00 to 2.00, 2.00 to 3.00, 3.00 to 3.75, and 3.75 to 4.75 inches, for width groups W_1, W_2, W_3, and W_4, respectively. Given these width-group sizes, no width groups' level of significance was below the threshold of 0.01. Unlike it was expected, the widest width group (W_4) did not become the smallest one, but it was width group W_3 that was 0.25 inches smaller than the other three. Despite being the narrowest width group already, its level of significance was 0.0115, barely above the threshold value of 0.01. As was found with length, there seems to be a width range that is more influential on yield than others. However, this hypothesis was not tested.

After these tests, the final part group matrix was a five by four matrix with 20 part groups. The length groups differed in its range from 5 inches in length (L_2) to 25 inches in length (L_4 and L_5). One width group assumed a width range of 0.75 inch (W_3) and all the other three assumed width ranges of 1.00 inch (W_1, W_2, and W_3). Given these findings, the final part group distribution with its associated part quantities based on the study of Araman et al. (1982) became as shown in Table 4.7.

Table 4.7: Final part groups with its associated part quantities in percent

Width (inch)	Length (inch)				
	5=<L<15 [10.0]	15=<L<20 [17.5]	20=<L<35 [27.5]	35=<L<60 [47.5]	60=<L<=85 [72.5]
1.00=<W<2.00 [1.50]	4.0	8.8	12.9	7.2	3.1
2.00=<W<3.00 [2.50]	4.5	8.9	14.2	7.8	2.9
3.00=<W<3.75 [3.50]	1.4	3.0	4.3	2.6	1.7
3.75=<W<=4.75 [4.25]	1.5	3.0	4.7	2.5	1.2

After having obtained the final part group matrix, it was necessary to assure that all part groups conformed to the requirements set forth in Section 4.2.4.5. The following section presents the results obtained from these tests.

4.3.2 Assuring that all part groups comply with the allowable level of influence

Since for these tests only the midpoint of the part group under consideration was changed, the change in yield was expected to be lower. It was hypothesized that the significance of these tests, because the part groups were derived under more stringent settings before, would be above the level of significance

($\alpha = 0.01$) set as a threshold. This hypothesis was found to be true. None of the part groups violated the significance level ($\alpha = 0.01$) requirement. Table 4.8 shows the individual levels of significance for each test and the yield span observed for each part group.

The minimum level of significance observed for length was found to be 0.02 for part group L_4W_2, the average for all 20 observations was 0.56. For width, the minimum observation of significance was observed for part group L_3W_4, which was slightly higher than 0.01. The average significance for width was 0.39. The levels of all observations for the interaction term and the curvature terms were found to be considerably higher than 0.01. Therefore, the part group configuration shown in Table 4.7 was accepted as the one to be used for all further tests.

Table 4.8: Summary of results when testing all part groups for compliance with the requirement

Part Group	Length	Width	Test for Interaction	Test for Curve	Yield-span
L1W1	0.8810	0.9007	0.9900	0.9777	0.11%
L2W1	0.8093	0.5068	0.1461	0.0836	1.01%
L3W1	0.3239	0.0435	0.8069	0.2590	1.65%
L4W1	0.2635	0.0635	0.3490	0.6822	0.93%
L5W1	0.2255	0.1869	0.9261	0.8737	0.89%
L1W2	0.9494	0.4962	0.3516	0.3865	0.66%
L2W2	0.7002	0.1310	0.3824	0.0510	0.88%
L3W2	0.4924	0.2874	0.3621	0.6840	1.17%
L4W2	0.0198	0.0832	0.6966	0.1963	1.05%
L5W2	0.1697	0.1167	0.2546	0.3344	1.99%
L1W3	0.8679	0.8431	0.5295	0.2523	0.27%
L2W3	0.7978	0.9152	0.5198	0.5867	0.37%
L3W3	0.6886	0.3885	0.5380	0.2367	0.51%
L4W3	0.9081	0.7305	0.8409	0.8890	0.43%
L5W3	0.1056	0.2409	0.2661	0.6299	1.26%
L1W4	0.5694	0.6180	0.3248	0.2502	0.44%
L2W4	0.9873	0.1354	0.2085	0.4505	0.96%
L3W4	0.4469	0.0125	0.2823	0.8995	1.52%
L4W4	0.4038	0.7330	0.4922	0.6047	0.48%
L5W4	0.5590	0.4069	0.7718	0.5630	0.57%

The average maximum yield span for the 20 observations was measured to be 0.86 percent (absolute percentage), whereas the maximum average yield span for a single observation was 1.99 percent. This observation occurred in part group L_5W_2, as can be seen in Table 4.8. Seven out of the 20 part groups had a yield span larger than one percent. As one can see, changing the location of the part group midpoint can have a substantial impact on yield. However, these tests are conducted under the most severe assumptions (i.e. part-group midpoints set at the extreme corners of each part group). Under more realistic

settings, such extreme situations should rarely occur.

4.4 DISCUSSION

The 5 by 4 part group matrix shown in Table 4.7 is the smallest matrix that is able to satisfy all requirements set forth in Section 4.2. A smaller matrix, for example of the size 4 by 3, results in yield differences that are too large to satisfy the requirements. From an analytical standpoint, a smaller part-group matrix would have facilitated the statistical analysis of the problem. However, the error from having too large part groups would have made the results not being representative of the real cutting bill requirement - yield relationship. Therefore, the 5 by 4 part group matrix is the smallest solution to the part group formation problem.

The part-group sizes obtained by the part-group derivation procedure resulted in part groups that are of different sizes (Table 4.7). Note that there is considerable variability in length ranges. The length of group L_2 is five inches, whereas the length of groups L_4 and L_5 is 25 inches. However, all three groups conform to the maximum level of influence on yield as required by the procedure. Two reasons contribute to these differences in part group size, 1) the part geometry, and 2) the part quantities that are required for a particular size. This is consistent with findings of Buehlmann et al. (1998c) that yield from a specific cutting bill is not only dependent on the size of the parts (i.e. the part geometry) and the distribution of the parts over the cutting bill size range, but on the part quantities as well. The length range that group L_2 encompasses, 15 to 20 inches, is the one where the highest quantities of parts per unit length are required. This length range requires, on average, 4.72 percent per one inch length increment of the total part quantity in a cutting bill with quantities distributed according to Araman et al. (1982). On average of the entire length range from 5 to 85 inches, each one inch length increment requires only 1.25 percent of the total part quantity (100 percent quantity / 80 inches)

Figure 4.10, which shows the results from the derivation of the size of length group L_2 shows how part quantity and length range decreased when the level of significance (i.e. the influence on yield of a particular part group) approached the required value of $\alpha \geq 0.01$. The lower boundary for length group

L_2 was 15 inches, whereas the upper boundary varied between 33 and 20 inches according to the tests performed. Figure 4.10 displays the length range of length group L_2 (x-axis), the part quantity required (right y-axis) and the level of significance (left y-axis) for the seven tests performed to obtain the final size of length group L_2.

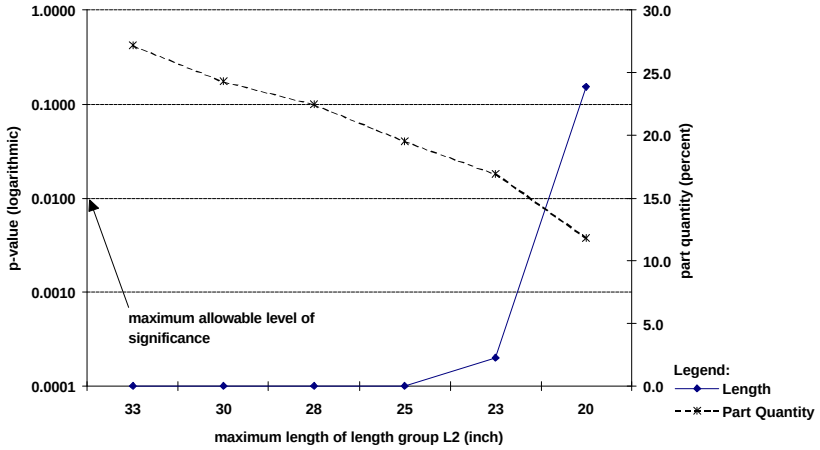


Figure 4.10: Length range, part quantity and level of significance for length group L_2

As Figure 4.10 shows, as the length range and the part quantity for length group L_2 declines, the level of significance for the test of length decreased. Simultaneously with the level of significance, the magnitude of the yield span decreased with declining length range and part quantity, too. When the length range for group L_2 was from 15 to 35 inches, the yield span observed was 12.79 percent. When the length range was 15 to 20 inches, the yield span was 2.67 percent. Would only the length range decrease in size, but part quantity stay the same, the trend of these observations would still be the same, but the decrease of significance for length and the decrease of the yield span would be slower. How much of the decreasing influence on yield is attributable to the decreasing part group size and how much to the decreasing part quantity requirements was not established.

However, one has to be aware that not only the yield differences observed, but also the standard deviations within replicates influenced the level of significance. For example, the level of significance achieved for curvature when testing to find the length of group L_2, shows the influence of the

standard deviation on the level of significance. As Figure 4.11 shows, the level of significance for curvature between tests with different length ranges for group L_2, did not continuously increase with decreasing group length. For example, the yield for individual tests observed for test four and test five were similar. However, the level of significance for curvature for tests four ($p = 0.010$) and five ($p = 0.009$) were different. Figure 4.11 shows the level of significance for curvature for all tests performed for length range of group L_2.

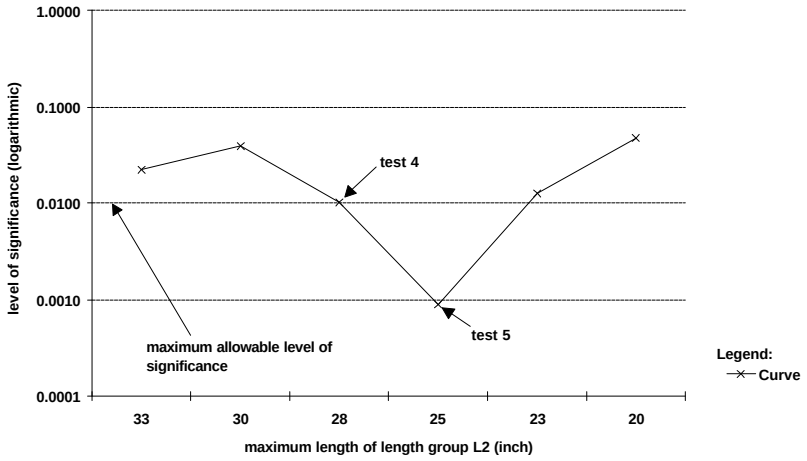


Figure 4.11: Level of significance observed for curvature when establishing length group L_2

The difference in levels of significance between test four and test five can be explained by the differences in variability within replicates for each test. For test four, the average standard deviation within replicates was found to be 1.00 percent, whereas for test five the average standard deviation was 0.47 percent. A low standard deviation between replicates makes the same yield difference between tests more highly significant than when the standard deviation between replicates is low. The highly significant term for curvature for test five, as shown in Figure 4.11, can therefore partially be attributed to the lower standard deviation between replicates. The point is, that the level of significance a particular test achieves is not only a function of the yield difference observed within a test, but is also dependent on the variability between the replicates, since the observed variance is a random variable.

Therefore, the measure used to establish the part-group sizes in this study was somewhat

relative. However, since the tests to establish the part-group sizes did not only change the midpoint position of the part-group under consideration, but also the part-group midpoints in the same row and column, the yield differences obtained for different positions of the part-group midpoint were quite large. Therefore, the sizes established can be assumed to reflect the true influence on yield of individual part groups well. Also, as the tests for assuring that all 20 part groups comply with the allowable level of influence, showed, no part group violated the allowable level of significance of 0.01.

Unfortunately, the influence on yield due to the change in position of the midpoint within a part group is still large for some part groups. On average, the maximum yield difference between extreme points within part groups was found to be 0.86 percent. The maximum yield difference found was for part group L_5W_2, where a yield difference of 1.99 percent between the two extreme yield values was observed. This large yield difference occurred when the length of the parts to be cut for part group L_5W_2 was increased from 60 inches to 85 inches. The only way to decrease this high variability would be to make the part groups smaller. Still, since most parts in "real" cutting bills are likely to be closer to the part group midpoint of 72.5 inches, the impact on yield observed should be smaller. The ultimate test for the concept of part groups, of course, is when the yield from processing a "real" cutting bill is compared to the yield of the same cutting bill, but where the parts were clustered. This question will be answered in Chapter 6.

4.5 SUMMARY

This chapter explained the concept of part groups and showed the methods used to obtain a part-group matrix that has part groups with similar influence on yield for parts of different sizes within a part group. Thereafter, the actual part group matrix that was obtained through iterative testing was presented. A large variability in length of individual part groups was found. The shortest part-group length range was 5 inches, whereas the longest part-group range was 25 inches. Two reasons are thought to be responsible for this observation. First, lengths in the range around 20 inches are important determinants of yield since they use the available clear areas in boards effectively (Buehlmann et al. 1998c). Second, a large percentage of parts require lengths around 20 inches. Since part quantity, as

Buehlmann et al. showed, is a major determinant of the effect on yield of a given part size, lengths around 20 inches influence yield substantially.

Tests to assure that no parts within part groups developed did influence yield more significantly than 0.01, were conducted. None of the 20 part groups did violate the threshold, therefore the existing part-group matrix was accepted as the one to be used for all subsequent tests. However, despite that the influence of different part sizes within individual part groups on yield was made as similar as possible for all part groups, the yield differences observed in these tests were found to be quite large. The maximum yield influence of any part group was found to be 1.99 percent yield, the minimum was 0.02 percent. On average of all 20 part groups, the yield influence observed was 0.86 percent. However, to decrease the yield influence of individual part groups further, more part groups would have been needed. Since this would further complicate the statistical analyses planned, the existing part-group matrix (shown in Table 4.7) was accepted as the solution to the part-group formation problem.

CHAPTER 5

5. YIELD CONTRIBUTION OF PART GROUPS

5.1 INTRODUCTION

Chapter 4 derived 20 part groups such that part sizes within each group have a similar influence on yield. By knowing the part sizes and quantities of the 20 part groups, the relative importance of individual part groups on yield could be researched. As was stated in Chapter 1, the goal was to gain a better understanding of the importance and influence of part groups on yield. This knowledge could help, it was hypothesized, in designing cutting bills that achieve higher yield. Furthermore, the data gathered from these tests then could be used to derive a statistics-based yield estimation model, as explained in Chapter 6.

5.2 METHODS

To be able to derive the design of the fractional factorial design (Section 2.2.1) to be used in this study, the relationship between part quantity and yield had to be established. A linear part quantity - yield relationship would allow to use a two-factor factorial design. Should this relationship be nonlinear, however, the fractional factorial design would have to be based on more than two factors. Therefore, before the fractional factorial design could be derived, the within part group linearity assumption had to be tested.

5.2.1 Validation of the within part group linearity assumption

The within part group linearity assumption describes the relationship between part quantity required by a part group and yield. When part quantity of one part group changes, yield changes, in most cases, too. However, it is unknown if the change in yield is a linear function of the change in quantity. Figure 5.1 displays two hypothetical part quantity - yield relationships. The dashed line represents a

linear, whereas the full line represents a nonlinear relationship.

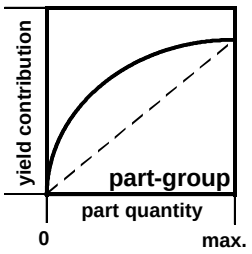


Figure 5.1: Example of a nonlinear and a linear part quantity - yield relationship

If the part quantity - yield relationship would be found to be approximately linear, a two factor factorial design would suffice to capture the effect of a part quantity change on yield over the entire part quantity range, i.e. from zero part quantity to maximum part quantity. If this relationship would be found to be nonlinear, more than two factors would be needed, since information about the curvature between zero and maximum part quantity would have to be obtained. Increasing the numbers of factors, however, would require an increased number of tests to be performed for the fractional factorial. For example, for a resolution V two factor fractional factorial design with 20 part groups, the number of tests would be 512 (without 3 replicates), for a three factor fractional factorial design of resolution V, the number of tests would increase to 6561 (without replicates). Therefore, if possible, a two factor factorial fractional design would be much more preferred due to its smaller number of tests required.

Nonetheless, as shown, nonlinearity of the within part group quantity - yield relationship would not cause the statistical approach to the yield estimation problem to fail, but would require additional research to be performed. Also, one has to be aware that the linearity assumption only applies for the within-part group quantity - yield relationship, but is not required between part groups.

To test for the assumed within part group linearity, each of the part groups was tested as follows:

(1) Set all part groups at maximum quantity

(2) Run ROMI RIP simulation (3 replicates)

(3) For i = 1, j = 1, set part quantity in part group (LiWj) at 75 percent of maximum, all other part groups remain at maximum quantity

(4) Repeat step 2

(5) Repeat steps 3 and 4 but set part quantity for the part group under investigation at 50 percent, then at 25 and, subsequently, to 0 percent

(6) Repeat steps 2 to 5 for all i (i = 1 to 5), and all j (j = 1 to 4)

Five tests each with three replicates for each part group were thus necessary. The design of experiments for part group L_1W_1 is displayed in Table 5.1.

Table 5.1: Experiments to research whether or not the within part group linearity assumption holds for part group L_1W_1

Part Group	**Length**	**Width**	**Test 1** quantity 100%	**Test 2** quantity 75%	**Test 3** quantity 50%	**Test 4** quantity 25%	**Test 5** quantity 0%
L1W1	10.00	1.50	**341**	**256**	**171**	**85**	**0**
L2W1	17.50	1.50	742	742	742	742	742
L3W1	27.50	1.50	1083	1083	1083	1083	1083
*	*	*	*	*	*	*	*
*	*	*	*	*	*	*	*
L3W4	27.50	4.25	395	395	395	395	395
L4W4	47.50	4.25	213	213	213	213	213
L5W4	72.50	4.25	100	100	100	100	100

When testing the within part group linearity assumption for part group L_1W_1, for the first test maximum part quantity was required, then 75, 50, 25, and 0 percent of the maximum quantity for this part group, respectively, as shown in the second row of Table 5.1. When testing part group L_1W_1, all the other 19 part groups required maximum quantity throughout all five tests. Similar to the experiment for part group L_1W_1, tests for all the other part groups were performed. The statistics employed to determine if there is a linear relationship between part quantity and yield within an individual part group are explained in the following section.

5.2.1.1 Statistical procedures employed to test the within part group - yield relationship

Linearity is defined as the yield results that lie on the straight line between yield obtained for

maximum quantity and yield obtained for zero quantity for a particular part group. Nonlinearity is measured as the distance between the linear line and the actual yield-point obtained (see Figure 5.1). Z-tests (Schulman 1995) were employed to detect if there is a significant deviation ($\alpha = 0.05$) from linearity. The standard deviation of all the tests conducted for the determination of linearity was used as the population standard deviation. Even though the true population standard deviation is unknown, the standard deviation derived from the 243 tests conducted becomes a close estimate of the true value (Noble 1998).

Since there may be some part groups that behave nonlinearly under the tests described above, but the error they introduce may be rather small, the following thresholds to conclude nonlinearity were defined: (1) no more than 1/5 of all points tested are allowed to be nonlinear at the 95 percent level of significance, and (2) no single part groups' nonlinear deviation shall exceed one percent absolute yield. These thresholds were set such that the possible error due to nonlinearity cannot become too large. If the results obtained lie within these thresholds, the study will be conducted using a linear model.

5.2.2 Fractional factorial design

In the past, few studies have been conducted to better understand the influence of cutting bill requirements on yield. Several researchers used cutting bills with different geometry to research the cutting bill requirements - yield relationship (Buehlmann et al. 1998a and 1998b, Thomas 1996b, Wiedenbeck and Thomas 1995a). However, due to the large amount of factors and their complex interactions, no detailed analyses of individual parameters or of interactions were conducted. To allow for such analyses, a fractional factorial design was applied in this study.

Fractional factorial designs allow to select a suitable fraction of factors of all possible combinations for analytical purposes (SPSS Inc. 1990). The efficiency of fractional factorial designs is enhanced when independent factors can be used (Box et al. 1978). These orthogonal arrays can be analyzed by standard statistical methods (Oles 1992). A qualified fractional factorial design confounds lower term effects with higher term interactions. It is assumed that higher term effects tend to be smaller

than lower term effects, as stated in the sparsity of effects principle (Montgomery 1984, Box et al. 1978). This is supported by Mize et al. (1994, p. 242) who stated that "*Experience has shown that high order interactions generally are negligible.*" Therefore, confounded effects can be reliable estimates of the lower term effects.

The design explained in this section is based on the assumption that the assumed within part group linearity assumption, as discussed in Section 5.2.1, is found to hold. Given these assumption the study's fractional factorial design was a 1/2048 replicate of a 20 level 2 factor fractional factorial design with resolution V, i.e. a 2^{20-11} fractional factorial design (Box et al. 1978). The complete factorial design for this study would consist of 2^{20} = 1,048,576 experiments. For a resolution V design, 512 tests (each with 3 replicates) were necessary. Each replicate did use a different set of red oak lumber boards (Gatchell et al. 1998) using the distribution established by Wiedenbeck et al. (1996) [Section 3.3.4]. In a resolution V fractional factorial design, main effects are free of secondary and third degree interactions and secondary interactions are free of other secondary interactions. Hence, according to the sparsity of effects principle (Montgomery 1984, Box et al. 1978), both, the main effects and the secondary interactions, can be reliably estimated. Appendix D shows the fractional factorial design used.

Should the within part group linearity assumption be violated, a three factor fractional factorial design would become necessary. This design, again of resolution V, would require 6561 tests (each with 3 replicates) to be performed. The complete factorial design when 3 factors were introduced, would have more than three billion different combinations, the 6561 tests needed would thus be a small fraction of all possible combinations.

Analysis of variance ($\alpha = 0.05$) of the data obtained from the resolution V fractional factorial design was performed to establish the importance of individual part groups on yield. Since both, main effects and secondary interactions are free of same order effects, the importance of all the 20 main effects and the 190 unique secondary interactions could be established. Unique secondary interactions encompass the interaction between two part groups, where no relevance is attached to the sequence of which part

group is named first. For example, the interaction between part group L_1W_1 and L_5W_4 is the same as the interaction between part groups L_5W_4 and L_1W_1.

5.3 RESULTS

As stated above, before the resolution V fractional factorial design could be executed, the within part group linearity assumption had to be tested. Only after knowing if a two factor fractional factorial design could possibly capture the part-group quantity - yield relationship, the numbers of factors could be set. Whereas for the derivation of the importance of individual part groups on yield this knowledge is not absolutely necessary, the least squares model presented in Chapter 6 could only be built appropriately when the number of factors tested would reflect the relationship between part-group quantity and yield. Therefore, first the results from testing the within part group linearity assumptions are presented, followed by the tests based on the fractional factorial design.

5.3.1 Validation of the within part group linearity assumption

Eighty-one tests, each with three replicates, were conducted to obtain the data necessary to test the within part group linearity assumption. Table 5.2 shows the results obtained. Test one (column 4) and test five (column 8) were used to set the starting and ending point of the linear yield-line for each part group. This line was then compared with the deviation of the yield data obtained for tests number two, three, and four. Using Z-tests, this deviation was tested as to if there is a significant difference ($\alpha = 0.05$) of the actual yield point obtained and the linear line calculated earlier.

As can be seen in Table 5.2, the largest nonlinearity observed was found to be 0.62 percent for part group L_2W_2 when asking for 50 percent of the maximum quantity. In fact, part group L_2W_2 was the only part group that resulted in significant nonlinearity ($\alpha = 0.05$) for all three points tested (i.e. part quantities at 75, 50, and 25 percent). Part group L_2W_4 had two observations that were significant ($\alpha = 0.05$), however, its maximum deviation from linearity was about half of the one found for part group L_2W_2, namely 0.34 percent. Overall, however, only ten observations out of 60 were found to be significant

Table 5.2: Results of the experiments testing the within part-group linearity assumption

Part Group	Length	Width	Yield Test 1 100%	Yield difference in percent (absolute) Test 2 75%	Test 3 50%	Test 4 25%	Yield Test 5 0%
L1W1	10.00	1.50	70.19	0.19 *	0.06	0.01	69.55
L2W1	17.50	1.50	70.19	0.15	0.11	0.06	68.89
L3W1	27.50	1.50	70.19	0.12	0.20	0.35 **	69.48
L4W1	47.50	1.50	70.19	0.02	0.13	0.08	70.28
L5W1	72.50	1.50	70.19	0.12	0.18	0.08	70.39
L1W2	10.00	2.50	70.19	0.00	0.01	0.02	69.25
L2W2	17.50	2.50	70.19	0.33 **	0.62 **	0.38 **	68.55
L3W2	27.50	2.50	70.19	0.04	0.01	0.11	70.36
L4W2	47.50	2.50	70.19	0.02	0.04	0.04	70.25
L5W2	72.50	2.50	70.19	0.09	0.21 *	0.19	70.33
L1W3	10.00	3.50	70.19	0.03	0.05	0.06	69.85
L2W3	17.50	3.50	70.19	0.13	0.05	0.16	69.52
L3W3	27.50	3.50	70.19	0.11	0.11	0.04	70.05
L4W3	47.50	3.50	70.19	0.11	0.18 *	0.05	70.22
L5W3	72.50	3.50	70.19	0.09	0.06	0.17	70.12
L1W4	10.00	4.25	70.19	0.05	0.12	0.03	69.68
L2W4	17.50	4.25	70.19	0.25 *	0.34 **	0.01	69.14
L3W4	27.50	4.25	70.19	0.08	0.03	0.18 *	70.32
L4W4	47.50	4.25	70.19	0.13	0.09	0.04	70.33
L5W4	72.50	4.25	70.19	0.09	0.10	0.06	70.23

notation: * = significant at 95 percent level
** = significant at 99 percent level

($\alpha = 0.05$). Since less than one fifth of the observations were found to be significant and no deviation from linearity was larger than one percent absolute yield, it was concluded that a linear model may appropriately reflect the cutting bill - yield relationship.

However, the nonlinearity observed in ten of the 60 observations indicates, that nonlinearity exists. Once more than one part group's quantity changes, the nonlinearity may become more severe. This could be a possible source of errors of the yield estimation model to be developed later (Chapter 6). However, only by developing and testing a linear model, its merits could be determined.

5.3.2 Fractional factorial design

The two factor resolution V fractional factorial design required to perform 512 tests (each with 3 replicates). Appendix D lists the yield results for each of the three replicates for all the tests conducted based on the fractional factorial design. Table 5.4 displays the results of the Analysis of Variance for the 20 main effects and Appendix E shows the results of the Analysis of Variance for the 190 unique secondary interactions. Table 5.3 presents a summary of the results obtained.

Table 5.3: Summary statistics of the 512 tests performed

	Results	Std. Dev.
average yield of 512 tests	65.09%	3.59%
maximum average yield	70.81%	0.28%
minimum average yield	48.63%	0.48%
single maximum yield	71.09%	
single minimum yield	47.87%	
average # of part groups	10.00	2.24
maximum # of part groups	20.00	
minimum # of part groups	4.00	

The maximum yield response difference between minimum and maximum yield observed from these 512 tests was 23.22 percent yield. This percentage, like all yield percentages shown in this report (unless otherwise stated), are absolute percentages. The average yield found for these tests was 65.09 percent yield, with a standard deviation of 3.59 percent. Hence, 95 percent of all observations lie within 58 and 72 percent yield (Ott 1993). The median was observed to be 65.88 percent, confirming that the frequency distribution of yield-responses is skewed to the right. Figure 5.2 shows this observation visually.

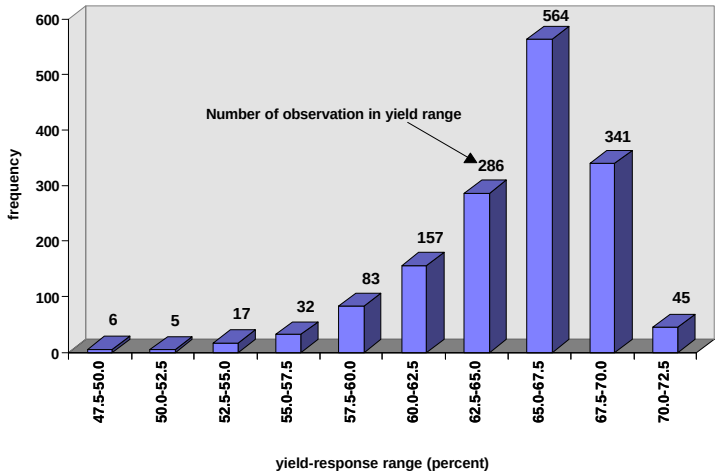


Figure 5.2: Distribution of yield responses for the 512 tests (including the 3 replicates)

The results shown in Figure 5.6, reflect only 0.05 percent of all possible cutting bill combinations, For a full 2^{20} factorial design the variability of the yield observed for all possible cutting bills would definitely be larger. The standard deviation remained quite steady over the entire range of

observations. The overall average standard deviation for each of the 512 tests between the three replications was found to be 0.29 percent. The standard deviation between replicates for the cuttings that resulted in low yield was higher than the one observed for the cuttings that resulted in high yield. The standard deviation between replicates for the ten lowest yielding cutting bills was found to be, on average, 0.48 percent compared to an average standard deviation for the ten cutting bills resulting in highest yield of 0.29 percent. However, this heteroscedasticity observed was still below levels that would require transformation (Ott 1993) given that an equal sample size was maintained for all tests.

Analysis of Variance performed on the 20 main effects and 190 secondary interactions returned a F-Value of 123.5 ($p > 0.0001$), showing that at least one of the effects is different from the others. Actually, all 20 main effects were found to be significantly ($\alpha = 0.05$) different from each other. One-hundred and thirteen of the 190 secondary interactions were also found to be significant ($\alpha = 0.05$). Table 5.4 shows the results obtained for the 20 main effects and Appendix E displays the results for the 190 unique two-way interactions.

Table 5.4: Statistical significance of the 20 main effects

Part Group	Length	Width	F-Value	Probability (p)
L1W1	10.00	1.50	475.90	0.0001
L2W1	17.50	1.50	3267.30	0.0001
L3W1	27.50	1.50	3015.82	0.0001
L4W1	47.50	1.50	700.39	0.0001
L5W1	72.50	1.50	43.21	0.0001
L1W2	10.00	2.50	1461.52	0.0001
L2W2	17.50	2.50	5405.53	0.0001
L3W2	27.50	2.50	1913.96	0.0001
L4W2	47.50	2.50	89.68	0.0001
L5W2	72.50	2.50	52.09	0.0001
L1W3	10.00	3.50	189.01	0.0001
L2W3	17.50	3.50	1271.26	0.0001
L3W3	27.50	3.50	859.93	0.0001
L4W3	47.50	3.50	122.91	0.0001
L5W3	72.50	3.50	4.10	0.0430
L1W4	10.00	4.25	437.70	0.0001
L2W4	17.50	4.25	1656.56	0.0001
L3W4	27.50	4.25	219.69	0.0001
L4W4	47.50	4.25	7.45	0.0064
L5W4	72.50	4.25	214.70	0.0001

Nineteen of the 20 main effects were found to be highly significant ($p < 0.01$) and one, part

group L_5W_3, was found to be significant ($p < 0.05$). For the two-way interactions, 97 were found to be highly significant ($\alpha = 0.01$) and 16 were found to be significant ($\alpha = 0.05$). The coefficient of determination, R^2 (Ott 1993), i.e. the proportion of the variability in the dependent variable (yield) that is accounted for by the independent variables (part groups) was found to be 0.95.

5.4 DISCUSSION

Obtaining the highest possible yield from a given set of lumber is the central challenge for every rough mill operation (Buehlmann et al. 1998a, Wiedenbeck and Thomas 1995, Wengert and Lamb 1994). Planning is important, because "L*umber yield is largely foreordained in the planning process and only secondarily influenced by operations on the cutting room floor* (Moser 1996, p.22)." Knowing that a one to two percent yield increase can save from $ 150,000 to $ 300,000 annually in a medium sized rough mill (Kline et al. 1998), the importance of understanding what parameters contribute to high yield is of great importance. Several authors contend that total rough mill cost is dependent on the cutting bill compositions a company uses (Fortney 1994, Anderson et al. 1992, Brunner 1984). Wengert and Lamb (1994, p. 17) used the following words to emphasize the importance of yield to the profitability of a rough mill operation: "*A concentration* [in the rough mill] *on yield is justified because of the close connection between yield and profit.*" These two authors estimated that a one percent increase in yield in a furniture rough mill can save up to two percent of the manufacturing costs (Wengert and Lamb 1994). Other authors (Buehlmann et al. 1998a, Wiedenbeck and Thomas 1995b, Manalan et al. 1980) too, emphasize the considerable importance of achieving high yield in a rough mill. Today, techniques like gluing up random width parts (Thomas 1997c) or fingerjointing random length parts (Snider 1985, Effner 1985) are used to increase yield. However, normally, primary parts are the ones that have the highest value and are hardest to obtain, therefore a focus on these parts is warranted.

Little knowledge about the interaction between cutting bill requirements and yield exist. One reason may be the complexity of this interaction, another reason is the focus of rough mill operations on the production schedule which mandates the cutting of dimension parts according to due dates. The

question of what determines yield is discussed in the following sections. At the core of this discussion is to find out what distinguishes cutting bills that achieve high yields from cutting bills that achieve lower yields.

5.4.1 Importance and yield contribution of part groups

The question as to what parameters in a cutting bill lead to high yield can be looked at in three different ways. The first question to ask would be “What part sizes are going to improve the yield of cutting bills?”. This question looks at a cutting bill under the perspective of adding additional parts of different sizes than the ones already contained in the cutting bill, such that high yield is achieved. Of course, this course of action is constrained by the fact that the amount of different part sizes that can be processed at one time is limited. When researching cutting bills as they are, i.e. without adding or removing parts, the second question to ask becomes “Which parts in a cutting bill are positive contributors to high yield?”. Researching this question means to look at existing cutting bills (i.e. no parts are added or removed) and to learn which parts are the ones that are most positively correlated to high yield. A third way of exploring the yield of cutting bills is to ask “Does yield improve when more different part sizes are cut concurrently?”. This question looks at the influence of having different number of part sizes required in a cutting bill. All three questions will be discussed in the following sections.

5.4.1.1 Parts that contribute the most to high yield when added to a cutting bill

As the ANOVA tests shown in Table 5.4 reveal, all 20 part groups, which are represented by the 20 main effects tested, are significant ($\alpha = 0.05$) explanatory variables of the variability in yield observed for the 512 cutting bills tested. Also, as shown in Appendix E, 113 out of the 190 unique secondary interactions were found to be significant ($\alpha = 0.05$). The secondary interactions describe the interference between two part groups that are contained in a cutting bill. In this discussion, the focus will first be on the main effects, since they have a more pronounced impact on yield than the secondary interactions do.

A measure of the contribution of each part group (i.e. main effect) to yield are the parameter estimates that will be used for the least squares model developed in Chapter 6 (Table 6.2), These estimates are an indicator of the average yield contribution of a specific part group to yield, on average of the 512 tests performed. However, to better understand their contribution to yield, some words as to how they were derived are necessary. When the least squares estimation procedure (Proc GLM in SAS [1996]) was run, the amount reflecting zero part quantity in a given part group was encoded as -1. Maximum part quantity was encoded +1. Hence, 50 percent part quantity was encoded as 0. The yield contribution of a part group as measured by the parameter estimate thus is multiplied by a negative value (between 0 and -1) when no or less than 50 percent of the maximum part quantity are required, zero when 50 percent quantity is required, and positive (between 0 and +1) when more than 50 percent of the maximum part quantity is required. Figure 5.3 displays the yield slopes of two part groups, namely part groups L_2W_2 and L_5W_4 to illustrate the concept explained above.

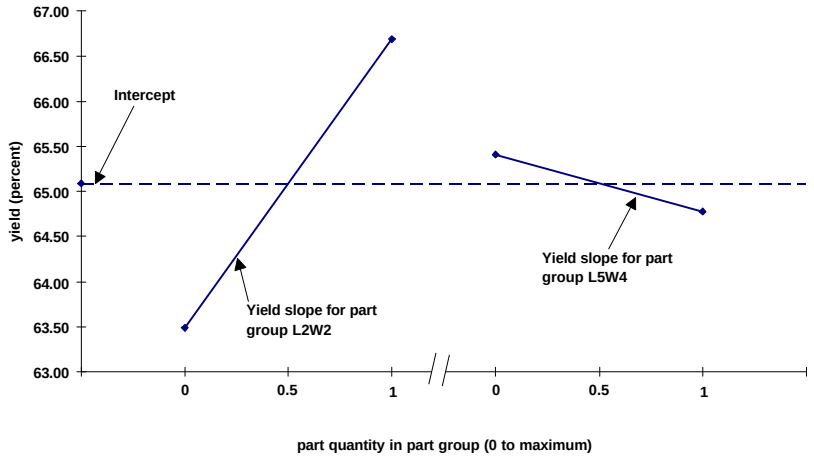


Figure 5.3: Intercept and yield slopes of part groups L_2W_2 and L_5W_4 to yield

The intercept (i.e. the average yield of all 512 cutting bills tested) was found to be 65.09 percent, the parameter estimates (i.e. the slopes) of part groups L_2W_2 and L_5W_4 were found to be 1.60 and -0.32, respectively. Thus, when part group L_2W_2 requires no parts to be cut, i.e. part quantity is zero, then yield will decrease by 1.60 percent. If L_2W_2 requires 50 percent of the maximum part quantity to be cut,

this part group will have zero impact on the average yield represented by the intercept. When L_2W_2 asks for maximum part quantity, however, this part group will increase yield by 1.60 percent. The same principle applies for part group L_5W_4. However, since this part group has a negative impact on yield when required by a cutting bill, its slope is negative (-0.32). Hence, yield will be higher when zero parts from part group L_5W_4 are required to be cut and lower when maximum part quantity is required.

As shown in Figure 5.3, the total possible contribution to yield of a particular part group between zero and maximum part quantity required is twice the value of the parameter estimate (since the coding for zero to maximum quantity stretches from -1 to +1). Hence, on average of the 512 tests performed, part group's L_2W_2 overall contribution to yield is 3.20 percent (2 x 1.60 percent) when observed in isolation. For the same situation, part group's L_5W_4 contribution to yield is -0.64 percent (2 x -0.32 percent). However, this observations hold only when all the other 19 part groups ask for 50 percent of maximum quantity. Only then all secondary interactions are zero and thus do not influence the yield from the part group observed. If not all the 19 other part groups ask for 50 percent quantity, the secondary interaction terms alter the influence of part groups L_2W_2 and L_5W_4 on yield (positively or negatively).

For the following discussion, to eliminate the effect of the secondary interactions, we will assume that all part groups ask for 50 percent of their respective maximum quantity. Of course, then the main effects of all the 20 part groups would be zero, too. However, the slope of their parameter estimate in this case is a true representation of their average contribution to yield. Only under this assumption, the yield slopes presented in Figure 5.4 show the varying influence on yield of the 20 part groups. For part quantities other than 50 percent, the secondary interactions would change the influence of each part group on yield.

As Figure 5.4 shows, part group L_2W_2 has the most positive impact on yield, followed by part group L_2W_1 and L_3W_1. All these three part groups have a yield slope that is steeper than one. Part group L_5W_4 has the most negative impact on yield followed by part groups L_5W_2, L_4W_4 and L_5W_3. All these four part groups contribute negatively to yield.

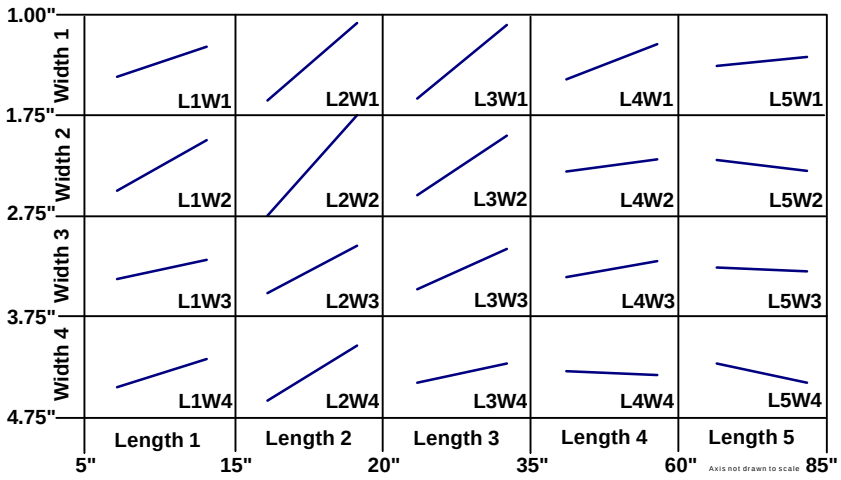


Figure 5.4: Yield slopes for the 20 part groups reflecting their average influence on yield

The numbers used to create Figure 5.4 can also give information about the average influence of a specific length or width group on yield. This information is gained by taking the average slope (i.e. parameter estimate) of each length or width group. Table 5.5 presents this information along with the parameter estimates for each individual part group.

Table 5.5: Parameter estimates and average parameter estimate of each length or width group

Width/Length	L1	L2	L3	L4	L5	average
W1	0.475	1.245	1.196	0.576	0.143	0.727
W2	0.833	1.601	0.953	0.206	-0.157	0.687
W3	0.299	0.777	0.639	0.241	-0.044	0.382
W4	0.456	0.886	0.323	-0.059	-0.319	0.257
average	0.516	1.127	0.778	0.241	-0.094	

Table 5.5 shows that length is more influential to yield than is width. This can be concluded from the observation that the parameter estimates vary more over length (i.e. rows) than over width (i.e. columns). This is consistent with the way prioritization programs deal with these two dimensions (i.e. length and width). These advanced prioritization programs (Brunner 1984, Maristany et al. 1990, Thomas 1995a and 1995b) set length to the power of some value, as can be seen, for example, from equations (2.1) and (2.2), whereas width is not leveraged. This makes good sense, since when a part is short and wide, it can be obtained relatively easily. However, if a part is long and wide, this part is much harder to obtain and thus needs to have a high prioritization such that it is cut whenever possible.

Width group W_1, ranging from 1.00 to 2.00 inches, is the one that contributes most positively to yield of any width group, followed by width group two, three, and four. This is consistent with general accepted knowledge. The wider parts required to be cut become, the more difficult it is to find a clear area within the board that allow to cut these parts. Also, when a board is cut into wider strips, the probability of having defects in these strips that will necessitate to cut out segments of the strips increases and thus reduce yield. However, as Table 5.5 shows, the difference in positive contribution to yield between width group one and width group two is only 0.04. Therefore, it is appropriate to say that the difference of adding parts to a cutting bill with either widths between one and two inches (group W_1) or two and three inches (group W_2) has almost the same effect on yield, on average of the 512 cutting bills researched. Adding parts wider than three inches, however, has a less favorable impact on yield.

As to length groups, Table 5.5 shows that group L_2, ranging from 15 to 20 inches has the most positive effect on yield. Thus, not the shortest length is most favorable, but the longer parts belonging to group L_2. This is consistent with findings by Buehlmann et al. (1998c) that, given part quantities are restricted, the shorter parts do not contribute the most to yield. This is because very short parts are produced at a high rate out of the remaining area of a board after the larger parts are cut. Given the high production rate of the short parts from group L_1, the required quantities are obtained after few boards are processed. This thus does not leave short parts (from group L_1) that could be cut from the remaining boards later in the production cycle. Yield therefore declines. Somewhat longer parts, i.e. parts from group L_2, are harder to obtain and require larger areas when cut. In extreme cases, where two of the shortest parts (i.e. from group L_1) could be produced, only one may be produced from group L_2. However, even though obtaining only one part from this area of size L_2 lowers the yield obtained from this particular board, overall the yield increases since parts of length L_2 will be available for more boards. In addition to that, as Table 4.7 shows, more parts are required for group L_2 according to the research of Araman et al. (1982). Therefore, given restricted part quantities, group L_2 is more favorable for achieving high yield than group L_1. Group L_5, on the other hand, is a negative contributor to yield on average of the 512

cutting bills tested. This contradicts the often heard rule of thumb that long lengths do not influence yield heavily. Even though the average parameter estimate for group L_5 is not much below zero, it is by far the most negative contributor to yield compared to all other length groups. The negative influence of long length (i.e. L_5) is further amplified when the part required is also wide. Therefore, part group L_5W_4 was found to be the one group that did influence yield most negatively. Not only is it hard to find such large clear areas in boards, but when shorter parts have to be cut and no shorter parts of this wide width are required, the salvage operation will make the part smaller, which thus lowers overall yield achieved.

However, inferences about the contribution of part groups to yield cannot be made in isolation from their respective interactions, except for the special case when all part groups require 50 percent part quantity, as explained earlier. The secondary interactions, i.e. the mutual influence of two part groups together on yield can reduce the positive contribution of individual part groups observed in isolation to a smaller yield-contribution when combined. Assessing the effects of secondary interactions is not only complicated by the fact that there are 190 secondary interactions which have to be taken into account, but also because their effect on yield changes depending on the part quantities associated with the two main effects (i.e. part groups) involved. Interaction-slopes are not unidimensional lines as the main effects are, but they are in fact twisted planes, except when the parameter estimate of the interaction is zero (Noble 1998). Figure 5.5 shows the yield response surface for part groups L_3W_1 and L_4W_1 for zero to maximum part quantity. For the situation depicted in Figure 5.5, all the other part quantities were set at 50 percent of their respective maximum quantity.

The interpretation of the secondary interactions for part groups and their influence on yield, as shown in Figure 5.5, is therefore more complicated as it is for main effects. Also, as was to be expected according to the sparsity of effects principle (Montgomery 1984, Box et al. 1978), the magnitude of the secondary interaction parameters was found to be lower than the one for the main effects. The absolute average parameter estimate for all the 190 secondary interactions was 0.08 compared with a value of 0.57 for the main effects. Nonetheless, the most pronounced secondary interactions deserve some attention.

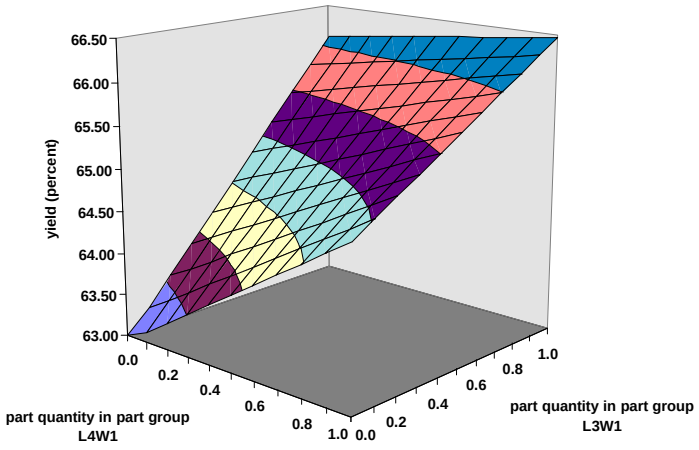


Figure 5.5: Yield response surface for an average cutting bill containing part groups L_3W_1 and L_4W_1

With a parameter estimate of -0.39, the interaction between part groups L_3W_1 and L_4W_1 (significant at $\alpha = 0.01$) had the most negative impact on yield of all secondary interactions. The influence of this secondary interaction is best explained for the case when the two part groups, L_3W_1 and L_4W_1, require maximum part quantity and all the other part groups require 50 percent part quantity. The parameter estimates of the main effects of part groups L_3W_1 and L_4W_1 are +1.20 and +0.58, respectively. Their secondary interaction parameter estimate is -0.39, as stated above. For this scenario, the yield contribution above the intercept of the two main effects of part groups L_3W_1 and L_4W_1 is 1.78 percent yield (1.20 + 0.58). However, since their secondary interaction parameter is -0.39, their effective contribution to yield above the intercept is only 1.39 percent. Theoretically, this loss in yield could be avoided when part groups L_3W_1 and L_4W_1 would not be included in the same cutting bill, but be separated in two cutting bills. Again, this calculation holds only when all the other 18 part groups ask for 50 percent quantity.

As the rather theoretical observations above show, secondary interactions complicate the cutting bill requirement - yield relationship. However, there can be no doubt, that cutting bills that achieve a high yield level, not only require parts from part groups which have a pronounced positive parameter

estimate, but do not have interactions that are severely negative. Only two other secondary interactions had parameter estimates of -0.30 or lower (significant at $\alpha = 0.01$). Another nine secondary interaction's parameter estimate was found to be between -0.20 and -0.30 (significant at $\alpha = 0.01$). Of the 190 secondary interactions, 120 were found to have negative parameter estimates (not all significant at $\alpha = 0.05$). This shows the importance of selecting parts to be included in a cutting bill carefully, such that the negative effect of the secondary interactions does not lower yield too severely. Table 5.6 shows the 12 secondary interactions with parameter estimates smaller than -0.20.

Table 5.6: Secondary interactions with parameter estimates smaller than -0.20

Interaction between Part Group	Part Group	Parameter Estimate	t for H0	Probability (p)
L3W1	L4W1	-0.39	-17.98	0.0001
L3W1	L3W2	-0.35	-16.02	0.0001
L2W2	L3W1	-0.32	-14.59	0.0001
L3W2	L4W2	-0.27	-12.49	0.0001
L3W2	L3W3	-0.27	-12.43	0.0001
L3W2	L4W1	-0.26	-11.82	0.0001
L2W2	L3W2	-0.25	-11.58	0.0001
L2W1	L3W1	-0.25	-11.33	0.0001
L2W2	L4W1	-0.25	-11.28	0.0001
L2W4	L3W2	-0.23	-10.63	0.0001
L3W2	L3W4	-0.23	-10.60	0.0001
L3W1	L3W3	-0.23	-10.54	0.0001

It is interesting to note that all the part group combinations whose parameter estimates are below –0.20, are part groups that are adjacent, or near each other. Their part sizes are thus similar and do not offer a large probability of fitting the clear area in a board where one part size does not fit to be used by the other part. As this and the following observation shows, secondary interactions are generally negative for similar part sizes, and positive for dissimilar part sizes. Dissimilar part sizes allow to use the clear areas in boards more efficiently, since one of the two sizes has a greater probability to fit this area quite well.

If the secondary interaction between two part groups is positive, as it was found, for example, between part groups L_2W_4 and L_5W_4, then yield increases due to the presence of these two part sizes in the

same cutting bill. The secondary interaction parameter estimate between part groups L_2W_4 and L_5W_4 was found to be +0.28 (significant at $\alpha = 0.01$). Thus, the yield of a cutting bill that requires maximum part quantity from both part groups L_2W_4 and L_5W_4 will be higher, as compared to one where these two part groups are not required together. That this secondary interaction is the highest positive one makes perfect sense. Given that parts from the largest part group L_5W_4 must be cut, strips of width W_4 must be produced. If there are no parts from part group L_2W_4 required, the clear areas in the strips that do not accommodate lengths as long as L_5, cannot be used efficiently. Of course, parts of length L_1 could be cut, but there are not enough parts of this length required to use all the remaining areas that do not accommodate length L_5. The most efficient use of the remaining areas in a strip of width W_4, after parts from L_5W_4 are cut, is thus to cut parts from L_2W_4. Therefore, the secondary interaction between part groups L_5W_4 and L_2W_4 is the highest observed. The secondary interaction between L_5W_4 and L_2W_4 was the only secondary interaction that had a parameter estimate above 0.20. Ten more secondary interactions, were found to have parameter estimates between 0.10 and 0.20 (significant at $\alpha = 0.01$). Table 5.7 shows the 11 secondary interactions with a parameter estimate larger than -0.10.

Table 5.7: Secondary interactions with parameter estimates larger than +0.10

Interaction between Part Group	Part Group	Parameter Estimate	t for H0	Probability (p)
L2W4	L5W4	0.27	12.53	0.0001
L2W3	L5W3	0.19	8.92	0.0001
L4W4	L5W2	0.17	7.97	0.0001
L2W2	L5W2	0.16	7.51	0.0001
L2W4	L4W4	0.15	7.08	0.0001
L3W4	L5W4	0.15	6.87	0.0001
L2W2	L4W2	0.13	5.85	0.0001
L1W1	L1W3	0.12	5.42	0.0001
L1W3	L5W3	0.11	5.22	0.0001
L3W2	L5W4	0.11	5.05	0.0001
L2W3	L4W3	0.11	4.99	0.0001

Only 113 of the secondary interactions were found to be significantly different from zero according to the ANOVA tests performed (Appendix E). All the secondary interactions whose parameter estimate was close to zero were found to be nonsignificant. The one closest to zero, the interaction

between part groups L_2W_1 and L_2W_4 with a value of 0.00 implies that it does not matter whether a cutting bill requires parts from these part groups to be cut simultaneously or not. However, such a statement is dangerous, since it means that these interactions would be observed in isolation. Since this cannot be done, one would have to look at all the other interactions that occur for a given cutting bill due to the presence of parts from these two part groups. Taking the interactions of all parts in a cutting bill into account, one could find that, in fact, requiring parts from part groups L_2W_1 and L_2W_4 in the cutting bill may have a positive or negative effect on yield. This relationship is entirely dependent on all the other parts that are required by a cutting bill. This observation shows that not only main effects and secondary interactions are of importance for the determination of yield, but that higher order interactions play a role in this complex relationship, too. Unfortunately, this study did not allow to quantify interactions higher than the second degree.

In summary, adding parts to a cutting bill that belong to part group L_2W_2 has the most positive effect on yield of all part groups based on the slope of the main effect. On the other hand, adding parts to a cutting bill that belong to part group L_5W_4 has the most detrimental effect on yield. In general, adding shorter parts to a cutting bill will help improve yield, whereas adding parts longer than 60 inches to a cutting bill has a negative effect on yield. Secondary interactions, even though present, but most of small magnitude, have a far less pronounced impact on yield than do the main effects.

In the next section, the viewpoint of the contribution of different part groups to yield will be changed slightly. The impact of requiring parts belonging to a particular part group will be researched under the assumption of having cutting bills where no parts are added or removed. Or in other words, based on the 512 different cutting bills researched, which parts (or, equivalently, part groups) have been most positively correlated with high yield?

5.4.1.2 Parts that are closely correlated with high yield

The coefficient of linear correlation (r) is a measure of strength of the relationship between two variables (Ott 1993). The formula for the correlation coefficient, r, as given by Ott (1993, p. 461) is:

$$r = \frac{\sum_{i=j=1}^{i=j=n} x_i y_j - \frac{\left(\sum_{i=1}^{i=n} x_i\right)\left(\sum_{j=1}^{j=n} y_j\right)}{n}}{\sqrt{\left(\sum_{i=1}^{i=n} x_i^2 - \frac{\left(\sum_{i=1}^{i=n} x_i\right)^2}{n}\right)\left(\sum_{j=1}^{j=n} y_j^2 - \frac{\left(\sum_{j=1}^{j=n} y_j\right)^2}{n}\right)}} \qquad (5.1)$$

where ρ is the coefficient of linear correlation, X_i is the i^{th} setting of variable X, Y_j is the j^{th} result of variable Y (average of 3 replicates), and n is the number of tests (i.e. 512).

Employing the correlation coefficient to measure the linear relationship between one independent variable (for example a particular part group, or a length group, etc.) and the corresponding dependent variable (yield), a measure of the positive or negative correlation of that independent variable to the dependent variable can be established. The correlation coefficient is indeed closely related to the parameter estimates (slopes) derived above. However, instead of establishing a directional measure of an independent variable, it establishes the strength of a relationship between an independent and a dependent variable. The correlation coefficient, thus, measures the correlation of the independent variable based on all the 512 cutting bills tested to the dependent variable. The least squares estimation parameter, on the other hand, allows to estimate the expected change in the dependent variable, when a particular independent variable is added or removed from other independent variables.

An approximate $100(1-\alpha)$ % confidence interval for correlation, ρ, (Draper and Smith 1981) is found by solving

$$\frac{1}{2}\ln\left(\frac{1+r}{1-r}\right) \pm z\left\{\frac{1}{n-3}\right\}^{1/2} = \frac{1}{2}\ln\left(\frac{1+r}{1-r}\right) \qquad (5.2)$$

for ρ where r is the sample correlation and z is the critical value for the normal distribution for the level of confidence chosen (i.e. 1.96 for 95% confidence). Using the confidence interval, one can establish if the correlation coefficient found is significantly different from zero at the level of significance chosen.

The correlation coefficients found for the four width groups' main effects and secondary interactions to yield are displayed in Table 5.8. The main effects are displayed in the cells with identical headings (i.e. the main effect for group W_1 is found in the cell with the row heading W_1 and the column heading W_1, which does not indicate the correlation coefficient with itself, but the correlation coefficient between W_1 and yield, which is 0.14). The secondary interactions are displayed in the cells with the appropriate row and column headings (i.e. the secondary interaction between W_1 and W_2 with yield is 0.35).

Table 5.8: Correlation coefficients for width groups, main effects and secondary interactions

	Yield			
	W_1	**W_2**	**W_3**	**W_4**
W_1	0.14 **	0.35 **	0.03	-0.01
W_2		0.12 **	0.01	-0.03
W_3			-0.23 **	-0.35 **
W_4				-0.30 **

notation: * = significant at 95 percent level
** = significant at 99 percent level

The interpretation of the correlation coefficients, especially of the interaction terms, is much easier than it was for the least squares estimates. The closer the correlation coefficient is to positive one, the more closely this term is associated with high yield. The closer the correlation coefficient is to negative one, the more closely this term is associated with low yield. As Table 5.8 shows, the interaction between groups W_1 and W_2 has the highest positive correlation coefficient. Thus, having parts from these two width groups in a cutting bill will lead to high yield. Only having, say, parts from width group W_1, will lead to a lower yield, on average, than having parts from both groups, W_1 and W_2. This is because the correlation for group W_1 with high yield is lower than the one found for groups W_1 and W_2 combined. Also note that there are always pairs of values with opposite signs. For example, the interaction of the two groups W_1 and W_2 has a correlation coefficient of 0.35. The interaction of the two remaining groups, W_3 and W_4, has a correlation coefficient of -0.35. This makes sense, since establishing the correlation coefficient for all four width groups would yield no detectable correlation (i.e. correlation is zero).

For width, a high yielding cutting bill would be composed of parts from groups W_1 and W_2. If

parts from groups W_3 and W_4 have to be cut, one should avoid pairing parts from these two width groups with only one of the two smaller width groups (i.e. W_1 or W_2). The more of the narrow parts can be cut simultaneously, the less yield should decrease from the wide parts that are required, too. Unfortunately, since third degree interactions are confounded with the secondary interactions, this observation cannot be proved explicitly.

For length, the results obtained show that parts required in group L_5 have the most negative correlation with high yield with a value of -0.49. This value is highly significantly ($\alpha = 0.01$) different from zero. On the other hand, group L_2 with a value of 0.28 has the highest positive correlation with high yield. This value, too, was found to be highly significantly different from zero ($\alpha = 0.01$). Group L_1 was found to be negatively correlated with high yield. Its value, which is significantly different from zero ($\alpha = 0.01$), was -0.17. This is, as stated earlier, another confirmation proving the rule of thumb that the shortest parts determine yield is wrong when part quantities to be cut are limited (Buehlmann et al. 1998c). However, could an unlimited amount of parts from the shortest length group be cut, this group would have the highest positive correlation with high yield. Unfortunately, this is very rare in real operations. Table 5.9 shows the correlation coefficients found for all the five length groups and its ten secondary interactions.

Table 5.9: Correlation coefficients for length groups, main effects and secondary interactions

	Yield				
	L_1	L_2	L_3	L_4	L_5
L1	-0.17 **	0.17 **	0.13 **	-0.30 **	-0.42 **
L2		0.28 **	0.47 **	0.06 *	0.05
L3			0.20 **	0.04	0.03
L4				-0.24 **	-0.44 **
L5					-0.49 **

notation: * = significant at 95 percent level
** = significant at 99 percent level

For length, the best selection of parts to achieve high yield is to have parts from length groups L_2 and L_3 in a cutting bill. If long length parts (i.e. parts from groups L_4 and L_5) have to be cut, it is best to combine one (preferably not both at the same time) of these two length groups (L_4 and L_5) with parts from length groups L_2 and L_3 simultaneously. Therefore, mixing long parts (i.e. groups L_4 and L_5) with a

sufficient amount of medium length parts (i.e. groups L_2 and L_3) is the appropriate course of action. Of course, when a large enough amount of the shortest length parts (i.e. group L_1) would be required, high yield could be achieved, too. Unfortunately, though, not that many short length parts are required by the average production order.

So far, the influence of width and length on yield was considered. However, parts to be cut combine these two dimensions. Therefore, the most revealing information is found in the correlation between part sizes (length and width) and yield. The part groups, or the part groups midpoints derived for this study to be more exact, are thought of as representatives of this part sizes. The most positive influential part group was part group L_2W_2. This part group's correlation coefficient with yield was found to be 0.26 (significant at $\alpha = 0.01$). This observation is consistent with the findings from the parameter estimates, explained earlier. However, unlike it was found for the parameter estimates, where the influence of adding a specific part to a cutting bill was established and the smallest part groups contributed positively to yield, here, the smallest part group L_1W_1 is negatively correlated to high yield with a value of -0.14 (significant at $\alpha = 0.01$). Here, the different viewpoint, i.e. of either looking at the influence on yield of a part when added to a cutting bill versus the influence of a part when being required by a given cutting bill, becomes evident. When adding parts, the small parts can still help increase the yield achieved. When being part of a cutting bill, yield suffers because it would be better to have parts from medium size part groups (i.e. L_2W_1, L_2W_2, L_3W_1, L_3W_2) in the cutting bill instead of the ones from the smallest part group (L_1W_1). Table 5.10 displays the correlation coefficients found for the 20 part groups.

Table 5.10: Correlation coefficients for the 20 part groups

	Yield				
width/length	**L_1**	**L_2**	**L_3**	**L_4**	**L_5**
W_1	0.14 **	0.14 **	0.19 **	-0.03	-0.20 **
W_2	-0.01	0.26 **	0.13 **	-0.14 **	-0.31 **
W_3	-0.19 **	-0.03	-0.04	-0.17 **	-0.28 **
W_4	-0.13 **	-0.02	-0.13 **	-0.27 **	-0.35 **

notation: * = significant at 95 percent level
** = significant at 99 percent level

Actually, only four part groups (L_2W_1, L_2W_2, L_3W_1, and L_3W_2) were found to be positively correlated with high yield (all significant at $\alpha = 0.01$) . Five part groups' (L_1W_2, L_2W_3, L_2W_4, L_3W_3, and L_4W_1) correlation coefficient were found not to be significantly different from zero ($\alpha = 0.05$). Thus, whether a cutting bill requires parts from this part groups or not is irrelevant. However, this statement only holds based on the average of the 512 cutting bills researched, for individual cutting bills, this may be different. Also, this statement does not take into account secondary interactions. Eleven part groups had negative correlation coefficients that were all highly significantly different from zero ($\alpha = 0.01$). In order to obtain high yield on average of the 512 cutting bills, parts from the four positively correlated part groups need to be required by the cutting bill.

The statement above is supported by an analysis of some of the 512 individual cutting bills tested under the fractional factorial design. Six out of the ten cutting bills that achieved lowest yield did not require any parts from the four part groups with positive correlation to yield (i.e. L_2W_1, L_2W_2, L_3W_1, L_3W_2), the remaining four did require parts from only one of the four part groups. Conversely, five out of the ten cutting bills that achieved highest yield required parts from all four of the positively correlated part groups with yield, three required parts from three of these part groups and two from two of these part groups. The conclusion from these observations has to be, that parts in the approximate range of 15 to 35 inches in length and 1.00 to 3.00 inches in width are absolutely crucial to achieve high yield. Figure 5.6 gives a graphical impression of these findings by presenting the yield response surface of the correlation of part sizes to high yield. This surface was extrapolated from the 20 data points derived for Table 5.10.

Figure 5.6 shows that only a small amount of the par sizes in a cutting bill are beneficial to achieving high yield. Luckily, these parts, ranging from 15 to 35 inches in length and 1.00 to 3.00 inches in width, combine approximately 45 percent of the total part quantity required by the average cutting bill according to Araman et al. (1982). Therefore, it should be possible to balance cutting bills such that a high yield can always be achieved. However, cutting bills used by industry are often dominated by parts of a limited size range, leading to cutting orders that obtain very variable yield. By better spreading the

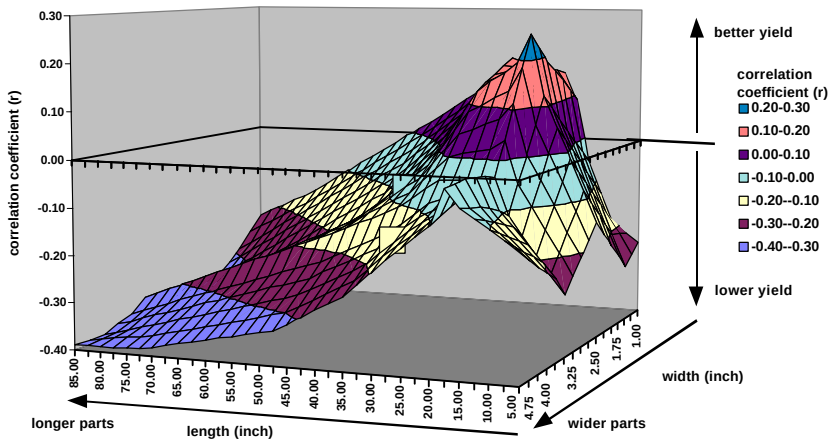


Figure 5.6: Yield response surface of the correlation of part sizes to high yield

different part sizes, especially the ones with a positive correlation to high yield, over all cutting bills to be processed, a higher average yield should be obtainable. This statement leads to the question of the impact of the distribution of part sizes and the number of different part sizes required by a cutting bill and its influence on yield. The next section will try to shed some light on this question.

5.4.1.3 The importance of the number of different part sizes in the same cutting bill

The number of different part sizes required in a cutting bill is positively correlated with yield, as was observed for the 512 yield-results obtained (average yield of 3 replicates). The correlation coefficient found between the number of different part sizes and high yield was 0.64. This value is highly significantly different from zero ($\alpha = 0.01$) . Thus, there must be a positive influence on yield from having more different part sizes in a cutting bill. Selected observations from the 512 average yield results obtained confirm this claim. The lower ten percent quartile of the 512 yield-results obtained required an average of 7.10 parts per cutting bill and achieved an average yield of 57.28 percent. The upper ten percent quartile required an average of 12.00 parts per cutting bill and yielded, on average, 69.71 percent yield. Analysis of variance (ANOVA) indicated that there must be a highly significant difference ($\alpha = 0.01$) in level of yields achieved depending on the number of parts required by the cutting bill. Duncan's multiple range test ($\alpha = 0.05$) resulted in the following six groups that produced different levels of yield,

depending on the number of different part sizes to be cut simultaneously. These results are shown in Table 5.11.

Table 5.11: Statistically significant differences in yield-levels due to number of parts in a cutting bill.

test #	# of parts in cutting bill	# of obser-vations	yield	difference between tests	std.dev.	Duncan Grouping (a = 0.05)		
1	5	6	54.56%		3.94%	**A**		
2	6	25	60.95%	6.39%	4.39%		**B**	
3	7	44	60.95%	0.00%	3.53%		**B**	
4	8	65	63.38%	2.43%	3.60%	**C**		
5	9	72	64.57%	1.18%	2.43%	**C**	**D**	
6	10	70	65.57%	1.00%	2.24%		**D**	**E**
7	11	84	66.74%	1.17%	1.78%	**F**		**E**
8	12	76	66.80%	0.06%	2.22%	**F**		**E**
9	13	50	67.85%	1.05%	1.73%	**F**		
10	14	17	67.93%	0.08%	1.29%	**F**		

Even though the increase in yield observed between different numbers of part sizes required by a cutting bill is unsteady, the general trend is that yield increases when more and more part sizes have to be cut simultaneously. However, for more than 11 different part sizes to be cut simultaneously, there was no significant ($\alpha = 0.05$) yield increase observed, as the Duncan's multiple range test ($\alpha = 0.05$) displayed in Table 5.11 reveals. There seems to be a diminishing return in increasing the number of parts of different size in a cutting bill. Increasing the number of different part sizes required by a cutting bill from five to six, increased yield by an average of 6.39 percent. Increasing parts in a cutting bill from 13 to 14, increased yield by an average of 0.08 percent. However, as Table 5.11 shows, the results are somewhat erratic. Also, some tests are based on as little as six observations. If requiring more than 14 different part sizes simultaneously would further increase yield, could not be established with the data obtained for this study.

The question as to how many different part sizes need to be cut simultaneously in order to achieve highest yield is not only of great importance for minimizing raw material cost, but moreover is also important for the investment decisions to be made. When planning a rough mill, the question as to how many sorting stations are needed is crucial, because more sorting stations increases investment costs and adds to the complexity of the system. Even though this study found no significant yield increase when

more than 11 different part sizes are cut simultaneously, it would be wrong to limit the capacity of the sorting stations to 11. More than 11 sorting stations may still pay off handsomely for several reasons: First, as was pointed out above, significant yield increases when more than 14 different part sizes are cut simultaneously may be achieved. Second, when different part qualities are cut simultaneously, more than 11 sorting stations are an absolute necessity to allow the grouping of parts according to size and quality. Third, special orders that may have to be processed immediately require additional sorting capacity.

Even though increasing the number of parts required by a cutting bill does result in different levels of yield and is positively correlated with achieving higher yield, the distribution of part sizes in a cutting bill is of importance, too. Little benefit is gained from adding one more part size to a cutting bill when this part has a size that is very similar to one or several already contained in the cutting bill. The most benefit is gained from adding part sizes that are diverse from the ones already required. This can be shown by looking at the differences in yield levels for cutting bills requiring the same number of parts to be cut simultaneously. For example, the range of yield from cutting bills that required 11 parts to be cut (84 observations), was found to be between 62.34 (cutting bill 266) and 69.80 percent yield (cutting bill 191). Figure 5.7 shows the distribution of parts required by these two cutting bills. The black cells indicate part groups requiring maximum part quantity for this particular cell.

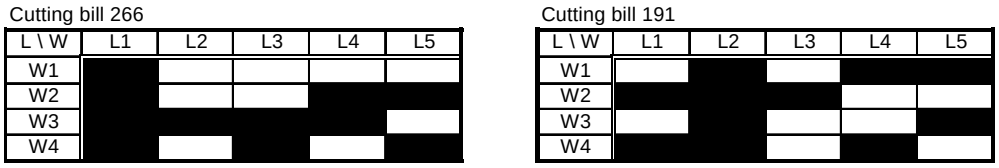


Figure 5.7: Distribution of parts for the two cutting bills requiring 11 parts and achieving lowest and highest yield

The parts required by cutting bill 266 (the one achieving 62.34 percent yield) are less evenly dispersed over the entire range of part groups than the parts required by cutting bill 191 (which achieved, on average of the three replicates, 69.80 percent yield). However, one has also to take into account that not both cutting bills require parts from part groups that are as favorable to yield as others. For example, cutting bill 191 asks for parts from part group L_2W_2, which, as was shown previously, is the most

positively correlated part group to yield. Cutting bill 266, on the other hand, does not require parts from this part group. Therefore, the difference in yield observed between these two cutting bills cannot uniquely be attributed to the differences in the distribution of the part sizes. However, undoubtedly, trying to make cutting bills that require parts from different part groups that are well distributed over the entire range of part groups helps to achieve higher yield. For example, assuming that parts from all the 20 part groups have to be produced according to the production plan, but only ten can be cut at one time, making two cutting bills were the parts included in each cutting bill are selected evenly over all part groups, will lead to higher average yield, than when each of the two cutting bills ask for parts from one half of the part group range.

5.5 SUMMARY

This chapter first tested the assumption that within part group linearity could be a true approximation of how part quantity and yield are related to each other. Even though the tests conducted stayed within the thresholds set forth, significant deviations ($\alpha = 0.05$) from linearity could be observed. Once the within part group linearity assumption was tested and confirmed under the rules set forth in this study, a resolution V fractional factorial design could be derived. This design required 512 tests, each with three replicates, to be performed. Analysis of variance performed on the data obtained, showed that all 20 main effects and 113 of the 190 secondary interactions were significant ($\alpha = 0.05$). The coefficient of determination, R^2, which shows as to how much of the variability of the data can be explained by the variables tested, was found to be 0.95.

Thereafter, the question of what cutting bill characteristics are responsible for high yield was discussed. This question was researched under two different aspects. First, the benefit of adding a new part group (i.e. part size) to an existing cutting bill was discussed. This assumes, that more part groups can be added to the ones already in the cutting bill. Second, the question of what part groups are most closely correlated to high yield was researched. This question looked at existing cutting bills and tested the correlation of part groups and yield. Due to the different frameworks and methodologies used for this two

questions, slightly different results were obtained.

The highest positive impact on yield from adding a part group to a cutting bill was observed when adding parts from part group L_2W_2 to a cutting bill. The parameter estimate, or slope, of part group L_2W_2 was the steepest positive one observed for all part groups. On the other hand, part group's L_5W_4 parameter estimate was the one with the most negative value, indicating that this part group size decreases yield the most when added to a cutting bill. However, when taking secondary interactions into account, such statements become much more difficult to make. Secondary interactions change the effect of the main effects (i.e. the part groups) on yield. Also, secondary interactions are not unilateral lines (as, for example, the main effects), but twisted planes. Their influence on yield is dependent on the part quantities that are required for each of the two part groups under consideration. However, there are secondary interactions that have a positive and such that have a negative impact on yield. By carefully selecting which part groups are added to a cutting bill, taking into account both, the influence of the main effect as well as the influence of the secondary interactions, yield can be increased.

When observing the correlation between part groups required by a cutting bill and yield, some part groups that were found to have a positive parameter estimate were now found to be negatively correlated to yield. This was observed for parts from group L_1, i.e. the shortest length group, that were negatively correlated with yield. Thus, having parts from this length group in a cutting bill decreased yield, compared to the case when these parts would be from group L_2 or L_3. Also, parts longer than group L_3 were found to be negatively correlated with high yield, thus, having such part sizes in a cutting bill decrease the yield obtained. The important role of parts from part group L_2W_2, that had the most positive parameter estimate, was confirmed by the correlation coefficients again. This part group is the single most important factor for achieving high yield.

By observing the correlation of secondary interactions with high yield, it could be shown that there are combinations of part sizes that do allow to achieve high yield even when long (i.e. parts from groups L_4 and L_5) are required. When long parts have to be cut, one should make sure that a sufficient amount of parts from groups L_2 and L_3 have to be cut simultaneously. By requiring sufficient amounts of

medium length (i.e. from groups L_2 and L_3) parts in a cutting bill that requires long parts (i.e. groups L_4 and L_5) to be cut, yield will not decrease or not decrease significantly.

The last question addressed in this chapter was concerned with the question if the number of different part sizes to be cut simultaneously has an impact on the level of yield achieved. Duncan's multiple range test ($\alpha = 0.05$) revealed that there is increased yield by having more different part sizes in a cutting bill. However, once 11 different part sizes were required by a cutting bill, yield did no longer significantly ($\alpha = 0.05$) increase for more part sizes. There seems to be a diminishing return from adding additional part sizes to a cutting bill. However, the upper limit of number of part sizes tested in this study was 14, so, possibly, yield could further increase above this number.

Chapter 6

6. YIELD ESTIMATION

6.1 INTRODUCTION

Existing yield estimation models do not provide the accuracy and consistency required by industry to be used in planning for yield or for cost calculations (Thomas et al. 1996, Wiedenbeck and Scheerer 1996, Yaussy 1986, Manalan et al. 1980). Therefore, a new approach to the yield estimation problem was developed in this study. By using the data obtained from the tests of the fractional factorial design, a least squares yield estimation model was derived. The parameter estimates used in Chapter 5 to quantify the contribution of individual part groups to yield, were indeed part of the model that was built. This chapter outlines the methods employed for the creation of the least squares model and shows its performance in estimating yield for different cutting bills.

6.2 METHODS

As mentioned earlier, multiple linear regression is a widely used analysis and predictive tool. For example, multiple linear regression is employed by the forest products industry to predict expected yield from the cut-up of logs in the sawmill (Yaussy 1986, Howard and Yaussy 1986, Howard and Gasson 1989). However, no comparable approach exists for the estimation of yield when producing dimension parts.

6.2.1 Least squares estimation

Assumptions for ordinary least squares models include that factor levels are known constants, the observed responses are random variables, and the random error terms are independently, identically, normally distributed with mean 0 and common variance s^2 (Mays 1995). Researchers in forest products often assume that this assumptions are met in their experiments. The data derived by the fractional

factorial design was used to estimate the parameter estimates for a linear least squares model. Therefore, no additional experiments were necessary for the construction of the least squares model. However, some discussion as to the form and functioning of the model is appropriate here.

Graphically, the ordinary least squares model does describe 20 yield slopes that account for the influence of each part group on yield. In fact, the 20 slopes represent the contribution (positive or negative) of each of the main effects (i.e. the part groups) to the dependent variable (yield), as was discussed in Chapter 5. Their contribution to yield is altered by the 190 secondary interactions that were also derived from the data. Starting from the intercept (i.e. the average yield for all cases), each main effect contributes to the final yield estimate, unless its parameter estimate would be zero. For quantities between zero and maximum part quantity, the yield-contribution of a part group is supposed to change proportionally to the quantity (here, as stated previously, the linearity assumption becomes relevant). As Draper and Smith (1981 p. 103) state, linear hypotheses preferably arise "*From the knowledge of the experimenter and his/her conjectures about possible models"*. Based on the experience gained in former work with lumber yield, there is some reason to believe that the linearity assumption holds to a certain degree. However, as tested previously, there are part groups whose part group - quantity relationship is not linear.

The parameter estimates were attained using the method of least square with help of the "General Linear Model" function contained in the Statistical Analysis System Institute software package (SAS 1996). The data used was screened to find outliers. If outliers existed, the settings (i.e. cutting bills) associated with these observations could be eliminated from the set of data and the range over which the model would be able to estimate yield could be restricted. This would make the range of settings for which the model would be applicable smaller, but the model would gain estimation accuracy because it would not be influenced by outliers. However, experience shows that ROMI RIP simulations tend to produce fairly consistent data. Residual plots of the fitted model were used to reveal if there were any problems with the model data that went undetected before. If heteroscedasticity of the error would be found, transformation may be able to solve the problem. Due to the orthogonal experimental design, multicollinearity was

nonexistent.

The simplest model that was fitted to the data from the experiment was of the form:

$$Y_m = b_0 + \sum_{i=1}^{5}\sum_{j=1}^{4} b_{ij}\left(L_i W_j\right) + e_m \tag{6.1}$$

where Y_m is the yield for the m^{th} observation, b_0 is the intercept, b_{ij} are the parameter estimates for part group ij, L_iW_j is part group ij, and e_m are random errors that are independently, identically normally distributed with mean 0 and common variance s^2 (Ott 1993).

However, since the importance of secondary interactions for the determination of yield is not clear yet, a more extensive model could be of the form:

$$Y_m = b_0 + \sum_{i=1}^{5}\sum_{j=1}^{4} b_{ij}\left(L_i W_j\right) + \sum_{i=1}^{5}\sum_{j=1}^{4}\left\{\sum_{k\neq i}\sum_{l\neq j} b_{ijkl}\left(L_i W_j\right)\left(L_k W_l\right) + \sum_{k\neq i} b_{ijkj}\left(L_i W_j\right)\left(L_k W_j\right) + \sum_{l\neq j} b_{ijil}\left(L_i W_j\right)\left(L_i W_l\right)\right\} + e_m \tag{6.2}$$

where the explanation of the variables is identical with the ones for equation (6.1).

The possibility that not all main effects (LiWj) are significant contributors to the explanation of yield exists. The significance level for the terms to be included into the model is set at $\alpha = 0.05$. Should one or several main effects turn out to be not significant, then the model would not contain all 20 main effects, but only a subset of them.

The selection of the final model was first done using common statistical procedures, such as backward, forward, or stepwise model building (see Section 2.2.2). The adjusted R^2 was used as the decision criterion for the selection of the model. This would be the way statistical knowledge guides us in building a least squares model. However, it may turn out that including all main effects (and, maybe, even all secondary interactions) is necessary to improve the accuracy of the estimation model, because there are situations where the model has to predict yield for cutting bills where some part groups contain no parts (i.e. quantity for this part group is zero). Thus, the estimated yield would only come from the part groups that contain parts. But if these part groups that contain parts (or some of them) are the part groups that were found to be not significant for the explanation of the changes in yield on average of the 512 cutting

bills tested, they would not be in the model now. However, due to having other part groups that ask for zero quantity, these formerly nonsignificant part groups gain in importance and thus should be in the model. At the same time, secondary interactions most likely will be important explanators of the variability in yield observed, too. This is because the influence on yield of one particular part group changes depending on the quantities asked for in other part groups. Only the analysis of the data derived from this study allowed to gain a better understanding and thus to make a final judgment.

6.2.2 Validation of the least squares model

Once the final model was established, validation of the model was important since this study introduced a novel approach to the yield estimation problem. The validity of the least square model was tested by comparing the estimated yield from the model with results obtained from simulation runs using the ROMI RIP simulation software (Thomas 1995a and 1995b). In particular, three steps were employed for the validation of the least squares yield estimation model. First, the model was compared with the data on which it was built (i.e. the results form the 512 cutting bills tested from the fractional factorial design). Second, the model was tested using the same geometrical part sizes that are given by the part-group midpoints, however, the quantities of the part groups were determined as a uniform randomly distributed number. This step therefore tested as to how accurately the model works when only part quantities are changed. Third, cutting bills as found in the literature and as used in real rough mills were used to test the practical usefulness of the least squares model. By analyzing these results, the possible error could be quantified and suggestions as to how to improve the model could be made. The following sections describes the three validation procedures in more detail.

6.2.2.1 Validation based on data from the fractional factorial design

This first step of the validation procedure for the model did provide information as to how well the least squares model derived is able to estimate the yield of the cutting bills that were used to derive the underlying data. This information was used to confirm or reject the claim, that a statistics-based

model is able to deal with the variability observed when producing dimension parts in rough mills. If the accuracy would be found to be acceptable, then the assumption that a least squares model could estimate lumber yield dependent on cutting bills that conform to the framework on which it was derived, could be answered affirmative. The term acceptable is hard to quantify before the first results were obtained. Given the complexity of the problem, an acceptable level of accuracy could mean an error smaller than five percent.

However, this first test will not answer the question if the model is able to capture configurations that were not part of the settings used to derive the data. Should the later tests, i.e. tests that use settings different from those used to derive the data, result in less satisfactory estimation accuracy, it will be because the new settings violate the framework established to derive data to construct the model. An analogy would be when a least squares model has to extrapolate data. The confidence interval for such predictions becomes large. Lynch and Clutter (1998, p. 88) stated the danger of extrapolating precisely by writing: "*As usual for predictive models in which parameters have been estimated using a least squares methodology, caution should be used in applying this system of equations to conditions not represented in the sample data*."

6.2.2.2 Validation with part quantities determined randomly

This second step in the validation procedure will focus on detecting the ability of the model to cope with part quantities that are no longer either maximum or zero quantity for each individual part group. These two settings, maximum or zero part quantity, were used to derive the data points. Changing the quantity levels used for the derivation of the data, this test will provide information as to how well the least squares estimation model estimates yield between the quantitative settings (zero or maximum quantity) used to derive the model.

For these tests, the part quantities used for the 20 part groups were obtained as random uniform numbers between zero and maximum part quantity for each part groups. Table 6.1 displays one of the cutting bills that was used as an example. Shown in Table 6.1 are the actual part quantities required by

the cutting bill used for the tests, and, in brackets, the maximum part quantity for each part group based on the findings of Araman et al. (1982), as it was shown in Table 4.7. For all part groups, minimum quantity is zero parts. Because there was uncertainty concerning the amount of parts that would be required by the cutting bills, the part quantity for part group L_5W_4 was set at 100 parts as the maximum quantity for this part group. This way, certainty was achieved that all cutting bills with random uniform part quantities would require at least 177 boards to be processed.

Table 6.1: Uniform random quantities for the 20 part groups as they were used to test the model

Width (inch)	Length (inch)				
	5=<L<15 [10.0]	15=<L<20 [17.5]	20=<L<35 [27.5]	35=<L<60 [47.5]	60=<L<=85 [72.5]
1.00=<W<2.00 [1.50]	44 [341]	600 [742]	726 [1083]	437 [608]	92 [258]
2.00=<W<3.00 [3.50]	69 [379]	395 [746]	1013 [1200]	88 [654]	206 [246]
3.00=<W<3.75 [3.75]	18 [114]	10 [254]	76 [365]	151 [221]	81 [142]
3.75=<W<=4.75 [4.25]	115 [123]	110 [248]	365 [395]	43 [213]	70 [100]

Five such cutting bills, one of them shown in Table 6.1, were created. Appendix F shows all five cutting bills used. Three replicates of each cutting bill were produced with different lumber board samples based on the distribution found by Wiedenbeck at al. (1996).

This test series was considered the most appropriate one for this study, since it follows the framework for the model closely, yet allows for different part quantities. The error expected from this model should be rather low. Again, quantifying low is problematic, but an accuracy with an error below two percent absolute error could be considered low. However, for the model to have the promise of being applied one day, the tests validating the model based on “real” cutting bills are of more importance. These tests are described next.

6.2.2.3 Validation based on “real” cutting bills

Five cutting bills from industrial operations were employed for the validation of the model for this tests. These cutting bills were all published in scientific studies and they cover a wide range of different combinations of parts. They thus allow to observe the performance of the estimation model under

a wide range of settings reflecting industry distributions of part sizes and part quantities (Wiedenbeck 1998). Appendix G lists each of the five cutting bills, cutting bills A, B, C, D, and E as they are named.

One has to be aware though, that these tests are a significant extension of the underlying framework of the model. From the conception of the model, the limits within which the model should perform rather well, are that either zero or maximum part quantity for all 20 part groups are required. These "real" cutting bills, however, may only require parts from very few part groups and part quantities that are above the maximum quantity used in this study. That may lead to quantity requirements that are much different from the ones assumed for the derivation of the model. Since these "real" cutting bills' part quantities may be completely different from the ones used in this study, scaling became necessary. Scaling decreases or increases the actual part quantities of a cutting bill such, that the new, scaled part quantities conform to the framework established for this study (i.e. all cutting bill part quantities will be between zero and maximum part quantity for all part groups). However, the effect of scaling may not be neutral. This may result in estimated yield that is different from the yield obtained by the simulation. However, this is the reason why the tests employing the "real" cutting bills are undertaken, namely to quantify the error due to extending the model's framework.

These five cutting bills were used to measure three sources of the estimation error that may occur. First, the yield as achieved by processing the cutting bills using the ROMI RIP rip-first simulator (Thomas 1995a and 1995b) compared to the estimated yield by the yield estimation model was established. This allowed to quantify the total error of the yield estimation model. In a second step, the overall error could then be broken down into three different sources of error, namely: 1) the error due to the clustering of parts within part groups, 2) the error due to the necessary scaling of the part quantities obtained from the cutting bill to fit the yield estimation model's framework, and 3) the error due to the model not being perfect. The total error, thus, could be partitioned into the following parts:

$$Error_{Total} = Error_{Clustering} + Error_{Scaling} + Error_{Model} \tag{6.3}$$

The error due to the clustering of the parts within its respective part group could be

established by obtaining the yield-results from the ROMI RIP simulator (Thomas 1995a and 1995b) of the five cutting bills where the parts were clustered within its respective part groups. The midpoint of each part group and the sum of all parts required within each part group was then the new cutting bill used for these test runs. Appendix H lists cutting bills A, B, C, D, and E when their parts are clustered with its respective part quantities. Thus, the comparison between the yield-results of the "real" cutting bills shown in Appendix G and the cutting bills with parts clustered as shown in Appendix H revealed the magnitude of the error due to clustering of the parts.

Scaling, the second error whose magnitude was established, refers to the necessary adaptation of the part quantities for each part group as obtained by the clustering procedure to the part quantity framework established to derive the model. The scaled part quantities for the five cutting bills used are shown in Appendix H. The procedure of scaling is best explained by an example: Assuming that three part groups, L_2W_1, L_3W_1, and L_4W_1 from an actual cutting bill under investigation required the following part quantities: 900, 1800, and 1170, respectively. The maximum part quantities for these three part groups established for this study were, 742, 1083, and 608. respectively. To be able to use the estimation model, the part quantities obtained from the cutting bill need to be scaled such that their range is within the quantities used for the derivation of the model. Thus, since the quantity for part group L_4W_1 exceeds the original quantity in its respective part group the most, this quantity is used to establish the scaling factor, which is 1.92 [1170 parts / 608 parts]. Now, all part quantities of the cutting bill have to be scaled by the scaling factor, i.e. 1.92. The part quantities used for the calculations by the yield estimation model thus would be 386, 563, and 608 for part groups L_2W_1, L_3W_1, and L_4W_1, respectively. However, even though the scaling of part quantities occurs in a proportional fashion, as was shown above, its impact on yield may not be completely zero. Therefore, by comparing the yield obtained by ROMI RIP (Thomas 1995a and 1995b) from the unscaled, clustered cutting bill to the yield from the scaled, clustered cutting bill the error from scaling could be quantified.

The remainder of the error observed can be attributed to the least squares model's inability to perfectly mimic the true cutting bill - yield relationship. It was hoped that the error due to the model would be small, confirming the viability of the statistical yield estimation approach.

6.3 RESULTS

First, the parameter estimates for the 20 main effects (i.e. part groups) and for the 190 unique secondary interactions were established. This parameter estimates were already used for the discussion of the importance of individual part groups on yield in Chapter 5. Once the model was established, its performance was researched as described in the previous sections.

6.3.1 Least squares estimation model

Ordinary least squares estimates were obtained using the Statistical Analysis Software Package (SAS 1996). First, the data was screened for outliers. However, no outliers were found on the yield results. The ten percent trimmed mean (Ott 1993), i.e. when the ten highest and the ten lowest yield results observed are dropped and the mean of the remaining 80 percent of all observations is taken, was 65.48 percent yield, close to the overall mean of 65.09 percent, indicating that no severe outliers at the minima and maxima of the spectrum exist. The variability between replicates was of interest, too. If this variability is high, the error term from the noise in the system will be large. The maximum yield difference between the three replicates observed was 2.47 percent yield for cutting bill 461 (the cutting bills used for the fractional factorial tests are numbered from 1 to 512, see Appendix D). This yield difference between replicates is attributable to the different lumber board compositions used as input for the three replicates. However, few replicates attained such a large yield difference (only ten observations had a yield difference between two replicates larger than 2.00 percent). The average yield difference between replicates observed was 0.35 percent. Given these observations, the parameter estimates were obtained from all the data available. Table 6.2 displays the values found for the 20 main effects and Appendix E shows the values for the 190 secondary interactions.

Table 6.2: Parameter estimates and significance for the 20 main effects

Part Group	Length	Width	Parameter Estimate	t for H_0	Probability (p)
Intercept			65.09	2988.79	0.0001
L1W1	10.00	1.50	0.48	21.82	0.0001
L2W1	17.50	1.50	1.24	57.16	0.0001
L3W1	27.50	1.50	1.20	54.92	0.0001
L4W1	47.50	1.50	0.58	26.47	0.0001
L5W1	72.50	1.50	0.14	6.57	0.0001
L1W2	10.00	2.50	0.83	38.23	0.0001
L2W2	17.50	2.50	1.60	73.52	0.0001
L3W2	27.50	2.50	0.95	43.75	0.0001
L4W2	47.50	2.50	0.21	9.47	0.0001
L5W2	72.50	2.50	-0.16	-7.22	0.0001
L1W3	10.00	3.50	0.30	13.75	0.0001
L2W3	17.50	3.50	0.78	35.66	0.0001
L3W3	27.50	3.50	0.64	29.33	0.0001
L4W3	47.50	3.50	0.24	11.09	0.0001
L5W3	72.50	3.50	-0.04	-2.03	0.0430
L1W4	10.00	4.25	0.46	20.92	0.0001
L2W4	17.50	4.25	0.89	40.70	0.0001
L3W4	27.50	4.25	0.32	14.82	0.0001
L4W4	47.50	4.25	-0.06	-2.73	0.0064
L5W4	72.50	4.25	-0.32	-14.65	0.0001

The least squares parameters shown in Table 6.2 for the main effects reflect the individual importance of the 20 part groups on yield. As stated earlier, the estimated slopes of the parameters is the average marginal contribution (positive or negative) of each part group on yield. Main effects are free of second and third degree interactions and should thus, according to the sparsity of effects principle (Mize et al. 1994, Montgomery 1984, Box et al. 1978), be good estimates of the true values. Secondary interactions, which are confounded with third degree interactions but free of the same degree interactions, obtained lower parameter estimates, which is in accordance with the sparsity of effects principle. All main effects (i.e. part groups) were found to be significant ($\alpha = 0.05$), thus all contribute to the explanation of the variability observed in the dependent variable (yield). Sixteen of the main effects were found to have a positive effect on yield (positive slope), whereas four had a negative effect (negative slope), on average of the 512 cutting bills tested.

As was discussed in Section 5.4.1.1, SAS (1996) derives all parameter estimates such, that the range of quantities from zero (i.e. zero percent) to maximum quantity (i.e. 100 percent) ranges from minus one to plus one. This coding scheme, however, does not change the actual slope of the line, but sets

50 percent quantity at the intercept. The total possible influence of a part group becomes twice the value of the slope. For example, the contribution of part group L_3W_1, which has a parameter estimate of +1.20 ranges from -1.20 to +1.20 percent yield, i.e. the total influence of part group L_3W_1, on average of all 512 cutting bills tested, becomes 2.40 percent.

It was found that secondary interactions help explain the variability observed. The 20 main effects alone were found to be able to explain 78 percent of the variability observed (i.e. R^2=0.78). R^2 for the model containing all main effects and all interactions was found to be 0.95. However, since the coefficient of determination, R^2, can always be increased by adding additional regressor variables (Mays 1995), adjusted R^2, is considered a better representative of the ability of the model to account for the variability observed. Adjusted R^2 for the model containing all 210 terms (20 main effects and 190 secondary interactions) was found to be 0.94. Forward selection at the 95 percent level of significance created a model containing all 20 main effects and 113 secondary interactions. The adjusted R^2, however, was found to be about the same as for the full model with a value of 0.95. Similar values for R^2 were obtained for the backward, the forward, and the stepwise procedure. Given that the additional terms in the full model, with all main effects and all secondary interactions included, did not decrease the adjusted R^2 markedly, the full model was chosen as the appropriate one. The model used, thus, was the one presented in equation (6.2). Using this model, the validation procedure described earlier was used to observe the performance of the model.

6.4 Validation of the least squares estimation model

As pointed out in Section 6.2.2, three different types of validation procedures were employed. First, the model was compared with the data on which it was built. Then, the performance of the model was tested against situations where the part quantities in each part group were no longer either maximum or zero, but were uniform random numbers between zero and maximum part quantity. Finally, the model's performance was compared to five cutting bills that reflect industry distributions of part sizes and part quantities (Wiedenbeck 1998).

6.4.1 Validation based on data from the fractional factorial design

Accurate yield estimation is made difficult by the variability between replicates. As was shown in the previous section, this variability can be as large as 2.47 percent (as found between replicates 2 and 3 for cutting bill 461). This variability is because of the different lumber samples used for each replication of the same test. However, on average, this variability is much lower. The average standard deviation between replicates for the same cutting bill was found to be 0.29 percent. Nonetheless, since the yield estimation model estimates the yield of the average response, the error between an individual yield-response from the simulated cut-up and the estimated value can become quite large. Since this error cannot be attributed to the model, but is inherent in the variability existing from using different lumber boards and sequences of lumber boards, the validation procedure used the average yield response obtained from the three replicates for assessing the merits of the yield estimation model.

On average of the 512 tests, the error between the model's estimated yield response and the data obtained from the fractional factorial tests, was found to be 0.00 percent, as expected from the least squares procedures. Three hundred and three yield estimations had an error no larger than 0.50 percent as compared to the average yield obtained from the ROMI RIP software (Thomas 1995a and 1995b). The maximum estimation error observed was 4.27 percent. Table 6.3 shows the number of observations where the estimated yield was within the range of error given in the first column.

Table 6.3: Number of observations that fall within the specified range of error

	# of observations
# of errors <=0.5%	303
# of errors 0.5%>E<=1.0%	147
# of errors 1.0%>E<=2.0%	54
# of errors >2.0%	8

As Table 6.3 shows, the estimated yield of 303 cutting bills was within 0.50 percent of the observed yield from the simulation runs (Thomas 1995a and 1995b). Only eight observations had an error larger than two percent. For the data used, the model thus estimates yield quite accurately.

Table 6.4 presents the summary statistics for the comparison of the yield obtained from the

simulation software and as estimated by the yield estimation model. The table shows, in column two, the average yield over all 512 cutting bills tested, as well as the maximum and the minimum observation from these tests. The average yield and maximum and minimum yield estimation from the least squares model are shown in column four. The maximum and minimum observation from the simulation runs and from the yield estimation are not from the same cutting bill. The absolute error, shown in column six, therefore is not the difference between the yield results shown in Table 6.4, but was observed from other cutting bills not specifically presented.

Table 6.4: Summary statistics comparing the actual yield response to the estimated yield response

	ROMI RIP		Model		absolute
	Yield	Std. Dev.	Yield	Std. Dev.	Error
average	65.09%	3.59%	65.09%	3.51%	0.00%
maximum	70.81%	0.16%	71.71%		4.27%
minimum	48.63%	0.48%	52.48%		0.00%

The range of yield-results observed (i.e. the minimum and maximum yield on average of the three replicates) was from 48.63 percent yield to 70.81 percent. The maximum estimation error was found for cutting bill 257 where the error between the actual average yield obtained from the simulation tests and the estimated yield from the model differed by 4.27 percent. Cutting bill 257 was also the one that resulted in the lowest yield response of all 512 cutting bills. The largest errors were observed at the lower end of the yield-results obtained. Two cutting bills (i.e. cutting bills 257 and 265) obtained yields below 50 percent. The magnitude of the estimation errors for both cutting bills were large. For the model, it seems to be difficult to estimate such extreme values.

On the other hand, for five cutting bills, the model estimated yield almost perfectly and the error observed was close to zero. Overall, 247 of the estimated yields were within the 95 percent confidence interval (Ott 1993) and 265 were outside. The model estimated the yield of a given cutting bill within 1 percent absolute yield accuracy in 88 percent of the cases. However, these comparisons were all based on the data used to derive the model. Therefore, the next set of tests, the tests using the part group framework but assigning random quantities to each part group, revealed more information about the true

merits of the model.

6.4.2 Validation with part quantities determined randomly

As explained previously, this step in the validation procedure consisted of establishing the accuracy of the yield estimation model when the part quantities were no longer either zero or maximum quantity for a given part group. Five cutting bills based on the part group framework (i.e. part sizes equal to the midpoints of each part group) were created assigning uniformly distributed random quantities to each part size. Appendix F shows the five cutting bills and the part quantities associated with each part. For each of these five cutting bills, the estimated yield was compared to the average yield obtained from three replicates using the ROMI RIP simulation software (Thomas 1995a and 1995b). Table 6.4 shows the results obtained.

Table 6.5: Individual results and summary statistics for the five tests with random quantities

	Test 1	Test 2	Test 3	Test 4	Test 5	Average
Simulation	68.73%	68.45%	69.48%	70.11%	70.08%	69.37%
LS-Model	65.95%	66.56%	66.59%	68.35%	68.46%	67.18%
Difference	2.78%	1.89%	2.89%	1.76%	1.62%	2.19%
Significant Diff.	yes	yes	yes	yes	yes	yes

The significance of the difference between yield obtained by the simulation and yield from the model was determined using a two sided t-test (Schulman 1995). The average estimation error of these five cutting bills was found to be 2.19 percent, with the maximum error being 2.78 percent and the minimum error 1.62 percent. All the estimated yields were significantly different ($\alpha = 0.05$) from the simulated yield. It is interesting to note that all the yield estimates are below the actual yield-level as achieved by the ROMI RIP simulation (Thomas 1995a and 1995b). A reason could be that the assumed within part group linearity does poorly represent the true cutting bill - yield relationship when several or all part group's quantity are between minimum (i.e. zero parts) and maximum part quantity. The trends in yield estimated by the model are consistent with the yield achieved by the simulation program. Both cutting bills that achieved yield results above 70 percent when simulated, were also the ones that achieved

highest yield when using the yield estimation model. The model can thus be used to assess the potential of individual cutting bills by ranking them.

6.4.3 Validation based on "real" cutting bills

As was stated in Section 6.2, these tests allowed to quantify the sources of the estimation errors observed. In particular, the error due to clustering, the error due to the scaling, and the error due to limitations of the model. However, one has to be aware that these tests stretch the assumptions made for the development of the model. First, as will be shown, the cutting bills do not contain parts in all the part groups, in fact, often a high percentage of the parts is clustered in a few part groups. Second, the error attributable to the clustering of the parts within part groups can become large, especially when a cutting bill's parts are not distributed well within a part group. Third, for cutting bills where one part size's quantity is dominant, the remaining part sizes become very small due to the scaling necessary.

The five cutting bills used, in their original form, clustered, and clustered and scaled, are shown in Appendix G and Appendix H, as stated previously. Yield was first obtained for the "real", unaltered cutting bills using the ROMI RIP rough mill simulator (Thomas 1995a and 1995b). This yield-results were then compared to the estimated yield. This way, the total error of the model could be established. Then, the parts in the cutting bills were clustered within their respective part groups. The yields from this configuration obtained by the ROMI RIP rough mill simulation software were then also compared with the estimated yields from the least squares model (this yield estimate did not change since the model does always clusters and scale the parts). Last, the clustered cutting bills were then scaled identical to the way the estimation model scales part quantities. Then, these cutting bills' yields were again obtained from the ROMI RIP simulation software. Comparing these results with the results from the clustered cutting bill allowed to estimate the error occurring due to the scaling of the quantities in the cutting bills. The breakdown of the errors observed could thus be done as shown previously in equation (6.3).

Table 6.6 shows the average results obtained from testing the five cutting bills. Also shown

are the maximum and minimum values observed. These maximum and minimum values do not necessarily belong to one particular cutting bill, but are the extreme values observed from any of the five cutting bills. All the individual results for each of the five cutting bills can be found in Appendix I.

Table 6.6: Average results and maximum and minimum values obtained when testing the five "real" cutting bills

Line #	Observation	Average	Std. Dev.	Max.	Min.
1	Simulation	67.61	3.11	72.39	64.40
2	Clustered simulation	65.79	3.14	70.16	62.64
3	Clustered and scaled simulation	64.94	2.69	68.13	62.09
4	LS Model	57.31	3.17	60.20	52.71
5	Simulation-clustered simulation [1-2]	1.82	3.12	4.48	2.28
6	Simulation - clustered and scaled simulation [1-3]	2.68	3.31	5.58	2.99
7	Clustered simulation - clustered and scaled simulation [2-3]	0.85	0.77	2.04	0.00
8	Simulation-LS Model [1-4]	10.30	1.69	12.19	8.01
9	Clustered simulation - LS Model [2-4]	8.48	4.32	15.26	4.85
10	Clustered and scaled simulation - LS Model [3-4]	7.62	4.24	14.68	3.92
11	# of parts in cutting bill	20	15	36	7
12	# of part groups used	9	4	16	6

The average yield obtained from the original cutting bills tested, as shown in Table 6.6 (line 1), was 67.61 percent. When the original cutting bill parts were clustered within their respective part groups and their size set equal to the respective part group midpoints, the average yield decreased by 1.82 percent, on average of the five cutting bills tested (line 5). This result is obtained when subtracting the average yield from the clustered simulation (line 2) from the average yield of the simulation (line 1) in Table 6.6. This was expected, since the average number of parts in the cutting bill decreased from 20 (line 11) for the full cutting bill to nine (line 12) when the parts were clustered. As explained previously, yield from a cutting bill generally increases when the number of parts to be cut increases. This observation is consistent with observations of Buehlmann et al. (1998d).

The scaling of the part quantities influenced yield, on average, by 0.85 percent (line 7). This result is obtained by subtracting the average yield of the clustered and scaled cutting bills (line 3) from the average yield of the clustered cutting bills (line 2). This result was thought of having a minor influence on yield since the proportions of the part quantity remain the same in the full cutting bill compared to the scaled one. However, as this observation reveals, yield does not change in a completely proportional fashion when the part quantities for a cutting bill are changed proportionally (i.e. scaled).

The error term due to the least squares estimation model, however, was by far the largest of all error terms observed. On average of the five cutting bills used, the model's estimation error was 7.62 percent (line 10). This result is obtained when the average yield from the least squares estimation model (line 4) is subtracted from the average yield of the clustered and scaled simulation tests (line 3).

In summary, the overall error, on average of the five cutting bills tested, can be distributed as shown below:

$$10.30\% = 1.82\% + 0.85\% + 7.62\% \tag{6.4}$$

The term on the left side of the equation is the total error observed, the first term on the right side of the equation is the error due to the clustering of the parts, followed by the error due to the scaling of the part quantities. The last term on the right side, and the largest, is the error term due to the limitations of the least squares estimation model. Thus, of the total error of 10.30 percent, 18 percent of the error is due to the clustering of parts, another 8 percent can be attributed to the scaling of the part quantities and the remainder, 74 percent, is due to the least squares yield estimation model, on average of the five cutting bills tested.

Individual cutting bills, however, can obtain very different results. The minimum overall error found for these five cutting bills was for cutting bill B whose overall error was 8.01 percent. For this cutting bill, the error attributable to the least squares yield estimation model was 4.85 percent. On the other hand, the maximum overall error, found for cutting bill E, was 12.19 percent. This cutting bill's error attributable to the yield estimation model was 7.93 percent. As already indicated by the average values shown in Table 6.6, the two other sources of errors, clustering and scaling, respectively, were always found to be lower in magnitude than the error due to the model. The error due to the clustering of the parts was found to be between 2.23 percent (cutting bill E) and 4.48 percent (cutting bill C), whereas the error due to scaling ranged from 0.00 percent (cutting bill B) to 2.04 percent (cutting bill E) [see Appendix I].

Since the errors observed for these tests were rather large, attempts to improve the accuracy of

the least squares model were undertaken. First, the cutting bills were analyzed as to their particular configuration concerning their part size and part quantity distribution. As it was found, there are patterns that lead to better or worse estimation result. The analyses and efforts to increase the accuracy of the model are presented in Section 6.5.3.3.

6.5 DISCUSSION

In 1966, C. D. Dosker (p. 67) contended, that "*Wood is missing out as a raw material in thousands of usages simply because the industry has no information on which a designer, or a user, can determine in advance what the refining costs of wood as a raw material will be*." Despite more recent acknowledgments about the missing ability of the industry to obtain "*accurate and consistent* (Wiedenbeck and Scheerer 1996, p. 121)" yield information to estimate costs and to improve yield (Wiedenbeck and Thomas 1995b), no tool that would allow to easily and reliably obtain this information exists. The yield matrixes and tables established for different species by several authors (Wiedenbeck and Thomas 1995b, Schumann 1973, 1972 and 1971, Dunmire 1971, Englerth and Schumann 1969, Schumann and Englerth 1967a and 1967b, and Thomas 1965a and 1965b) do not result in accurate yield estimates (Thomas et al. 1996, Wiedenbeck and Scheerer 1996, Yaussy 1986, Manalan et al. 1980). Manalan et al. (1980) found yield differences between yield predicted using the USDA Forest Service's FPL 118 yield tables and actual yields obtained in rough mills as high as 19 percent. The only reliable way for estimating expected yield, today, is to employ rough mill simulation tools (Thomas 1997a, 1997b, 1995a, and 1995b). However, besides being a time consuming and labor intensive undertaking, the validity of the results obtained by the simulation software has never been established.

Three sources contribute to the complexity of the problem of estimating yield. These are, (1) cut-up system related, (2) lumber related and (3) cutting bill induced. Lumber yield obtained for a given cutting bill changes depending on the cut-up system (rip-first vs. crosscut-first) used (Buehlmann et al. 1998b, Harding 1991, Hall 1978). Even within the same system, different modes of operation lead to differences in yield achieved. The lumber used, too, influences yield. Differences occur between different

species, grades, and board sequences (Buehlmann et al. 1998a and 1998b, Hoff 1997, Fortney 1994). No less influence have the different cutting bill requirements encountered (Buehlmann et al. 1998a and 1998c). The influence of each of this factors on yield is interrelated with all the others, thus making it hard to develop a generally applicable model.

This section will discuss the performance of the statistical approach to the yield estimation problem undertaken in this study. Sources for the errors observed and ways to improve the model will be elaborated. However, first, attention will be given to the influence of different levels of confounded main effects and secondary interactions from the fractional factorial design.

6.5.1 Resolution of fractional factorial design

Originally, this study used a resolution IV, 2^{20-14} fractional factorial design to establish the importance of individual part groups and to derive the least squares model. This design, shown in Appendix J among with the yield-results, required 64 tests (each with 3 replicates) to be performed. However, due to problems in establishing an accurate least squares model, a resolution V design was then employed. A resolution IV fractional factorial design is the smallest design where the main effects are free of same order and secondary order interactions (Montgomery 1984, Box et al. 1978). The secondary interactions, however, are confounded with each other and can not be estimated separately.

The major problem with the resolution IV fractional factorial design, was that, even though the main effects are free of same order and secondary interactions, each main effect is confounded with 16,384 three and higher order interactions. Furthermore, secondary interactions, thought to be relevant, too, are confounded with each other in some cases. Because this design tested only 1/16,384 of all possible combinations, five of the 20 part groups (L_5W_4, L_4W_2, L_5W_1, L_5W_3, and L_4W_4) were found to be nonsignificant ($\alpha = 0.05$) according to the ANOVA test performed. The results for these tests along with the parameter estimates found are displayed in Appendix K.

The five part groups that were not found to be significant at the 95 percent level when tested based on the resolution IV fractional factorial design, turned out to be significant explanatory parameters

($\alpha = 0.05$) when using the data from the resolution V fractional factorial design (512 tests). This observation can be explained by the varying importance of individual part groups depending on which other part groups require parts to be cut. For example, when a cutting bill requires many parts from the shorter part groups to be cut simultaneously with parts from the longer part groups, then the shorter part groups are the major determinants of yield (Buehlmann et al. 1998c). Due to the low number of tests performed under the resolution IV fractional factorial design, only few tests required to cut long parts without requiring short parts at the same time. Thus, the testing for significance for the longer part groups (L_5W_4, L_4W_2, L_5W_1, L_5W_3, and L_4W_4) turned out to be insignificant ($\alpha = 0.05$) based on the resolution IV design.

However, the results of the least squares estimation model derived from the resolution IV design were encouraging, except for the case when the estimation model had to estimate the expected yield for the five "real" cutting bills. Lack of fit tests (Neter et al. 1996) comparing the estimated values to the values obtained by the 64 tests did not indicate a significant error ($\alpha = 0.05$) due to lack of fit. The model, based on the parameter estimates displayed in Appendix K, worked well when compared to the 64 data points obtained by the resolution IV fractional factorial design. The maximum estimation error for this comparison was 0.17 percent absolute yield. Also, the results for the random part quantity tests, indicated that the least squares model works reasonably well. The maximum estimation error for these five tests was found to be 2.75 percent, with an average error of 2.02 percent. However, the tests on the "real" cutting bills showed a large estimation error. The maximum error was 12.27 percent, whereas the average estimation error for the five "real" cutting bills was found to be 10.27 percent.

Given the absence of lack of fit (Neter et al. 1996) and the reasonable performance on two of the three validation tests for the model based on the resolution IV fractional factorial design, it was hypothesized that a model based on less confounded parameters (i.e. based on a resolution V fractional factorial design) would significantly improve the estimation accuracy. Using the results of a resolution V fractional factorial design would, it was reasoned, improve the least squares estimation model in two

aspects: First, by testing more combinations of part groups containing maximum or zero quantity, the model would be able to better approximate the situations encountered with the "real" cutting bills since it would have more reference points. Second, a resolution V design would allow to obtain secondary interactions that are free of the same order effects, thus allowing to estimate all secondary interactions separately.

However, as the analysis of the results from the estimation model based on the resolution V fractional factorial design in Section 6.4 showed, the estimation accuracy improvements anticipated by enlarging the fraction factorial design did not materialize. In fact, the average error when comparing the estimated yield to the one obtained by the simulated tests from the resolution V fractional factorial design increased considerably. This observation can be explained by the fact, that the results obtained under the resolution V fractional factorial are so diverse, that the least squares model is no longer able to find a reasonable fit for all datapoints obtained. Testing the new model for lack of fit, then, showed that there is significant ($\alpha = 0.05$) lack of fit for the new model. However, the average error between the estimated yield for the five "real" cutting bills and the results obtained from the rough mill simulation (Thomas 1995a and 1995b) declined from 10.27 percent when the model was derived from the resolution IV data, to 8.63 percent when the model was derived from the resolution V data. Table 6.7 presents a comparison of the performance of the yield estimation model based on a resolution IV and on a resolution V fractional factorial design.

Table 6.7: Comparison of the performance of the yield estimation model based on a resolution IV and V fractional factorial design

Validation Test	based on res. IV design				based on res. V design			
	Average Error	Standard Deviation of Error	Maximum Error	Minimum Error	Average Error	Standard Deviation of Error	Maximum Error	Minimum Error
Orig. Data Points	0.00	0.04	0.17	0.00	0.00	0.74	4.27	0.00
Random Quantities	2.02	1.02	2.75	0.12	2.19	0.01	2.89	1.62
Real Cutting Bills	10.27	1.90	12.27	8.19	8.63	4.19	13.34	3.71

As Table 6.7 shows, the estimation error of the model based on the data from the resolution V design increased for the case where the data points from the fractional factorial design were compared to

the estimated yield from the model. The maximum error using the model based on the resolution V data was 4.27 percent, whereas the error of the model based on the resolution IV data was only 0.17 percent. The error for the five cutting bills with random quantities for each part group was only slightly different between the two versions of the model. The benefit of the resolution V design is only evident when the increased accuracy of the least squares model for "real" cutting bills is considered. The average estimation error for "real" cutting bills decreased by 1.64 percent. Nonetheless, the total estimation error remained high. However, the additional information gained from enlarging the design to a resolution V, allowed to obtain the importance of all unique secondary interactions. A better understanding of the relationship between cutting bill requirements and yield could thus be gained.

6.5.2 Within part-group linearity assumptions revisited

As was contended earlier, the within part-group linearity assumption is of crucial importance for the yield estimation model to be accurate. As shown in Table 5.2, ten out of 60 observations (16.67 percent) did not conform to the linearity assumption at the 95 percent level of significance. However, since these tests were done by changing the part quantities only in the part group under consideration while holding all the other part-group quantities at their maximum level, nonlinearity may be more prevalent than these results indicate. Assuming that the part-group quantity - yield relationship found by these tests is an indicator of the part quantity - yield relationship under more complex settings (i.e. part quantity in several part groups is changed), a linear relationship may indeed not be appropriate. The results obtained for part group L_2W_2, the only part group where all results were found to be significantly different from a linear relationship, indeed do not show a linear behavior. This relationship could be more appropriately modeled by a quadratic equation. A first order least squares equation to fit the results of part group L_2W_2 would have the form of

$$yield = 68.83 + 162x \tag{6.5}$$

and its R^2 would be 0.85. A second order least squares estimation equation would assume the form

$$yield = 68.55 - 2.23x^2 + 3.85x \tag{6.6}$$

and would match the data observed much better as indicated by its value for R^2 of 0.99. Figure 6.1 displays the results obtained for these observations on part group L_2W_2.

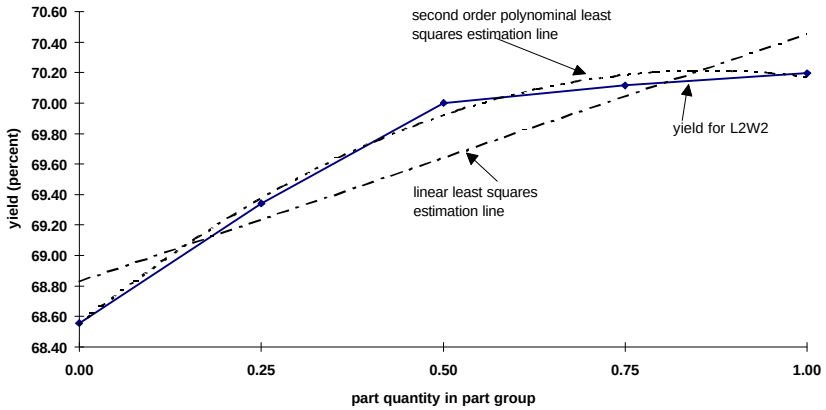


Figure 6.1: Yield for part group L_2W_2 and linear and quadratic least squares estimation lines

However, even though part group L_2W_2 did result in the largest error from linearity observed, the shape of its yield-response curve is a simplistic one. Would the yield responses for all possible part quantity combinations follow a similar curve as the one shown in Figure 6.1, employing a three factor factorial design would help to significantly increase the accuracy of a least squares estimation model. The yield-response curve for part groups L_5W_1, L_3W_3, and L_3W_4, for example, have a much more complex shape. Figure 6.2 displays the shape of the yield results of these three part groups. Whereas it is true that these tests, except for one case involving part group L_3W_4, did not turn out to be significantly different from a linear relationship at the 95 percent significance level, the yield errors from linearity may be more severe when more than one part group's quantity is manipulated. Therefore, one can take these curves as an indicator of what may be observed for the case when several part groups ask for quantities less than the maximum.

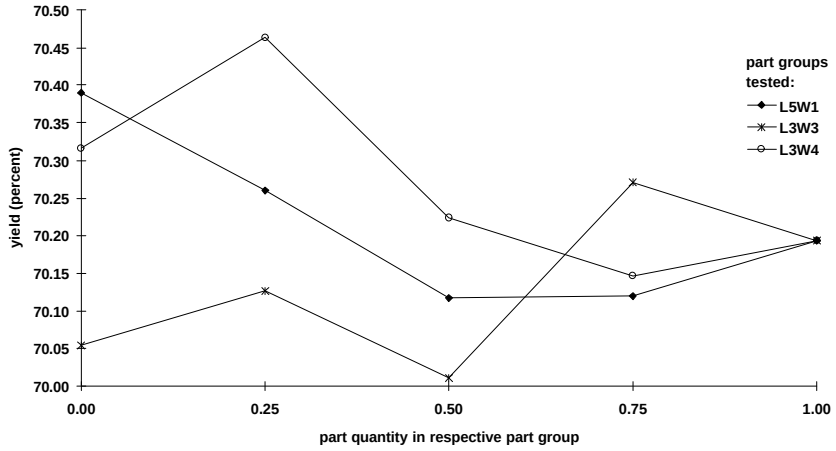


Figure 6.2: Part-group quantity - yield relationship for part groups L_5W_1, L_3W_3, and L_3W_4

To model curves like the ones displayed in Figure 6.2 using least squares estimation, would require higher order polynomial least squares equations. For example, the results for part group L_5W_1 could be modeled as a second order polynomial, that would achieve a R^2 of 0.97. The results for part group L_3W_4 would require a third degree polynomial to achieve a R^2 above 0.90. However, trying to fit a third degree polynomial least squares equation to the results of part group L_3W_3, would yield a R^2 of 0.47. A fourth degree polynomial equation, which could account for each single point observed, would be required to obtain a completely specified curve.

If the yield response for part-quantity settings other than the ones researched is as irregular as presented in Figure 6.1 and in Figure 6.2, modeling the cutting bill - yield relationship accurately by the method of least squares becomes almost impossible.

6.5.3 Least squares yield estimation model

As was discussed previously, estimating expected yield is a difficult endeavor. Even when eliminating the influence of the cut-up system and the lumber, estimating yield based on cutting bill requirements alone is difficult.

Creating a least squares estimation model that estimates expected yield for the case where the cutting bill requirements are similar to those on which the model presented in this study is based, proved

to be quite successful. As was shown in Section 6.4.1, the maximum yield deviation from the yield obtained by the simulation software (Thomas 1995a and 1995b) and the least squares model was found to be 4.27 percent when only maximum or zero quantities were used for the 20 part groups. When uniform, random part quantities were assigned to all the part groups, the maximum yield deviation was found to be 2.89 percent, as was shown in Section 6.4.2, whereas the average deviation was 2.19 percent. However, when trying to estimate the expected yield for "real" cutting bills, shown in Section 6.4.3, the error increased considerably. The average error due to the model for the five tests conducted was 7.62 percent and the maximum deviation was 14.68 percent. The following sections will explain the reasons for this rather large inaccuracy of the least squares yield estimation model and show possible ways for a model with improved accuracy. Each of the three sources for errors - clustering, scaling, and due to the model - will be discussed separately.

6.5.3.1 Error due to clustering of parts

The clustering of the parts contained in the "real" cutting bills contributed, on average of the five tests, 1.82 percent to the total estimation error observed. However, since one of the errors (cutting bill A) was negative, the average error of 1.82 percent understates the real error due to clustering of the parts. The absolute average error due to clustering was found to be 3.25 percent with a standard deviation of 3.12 percent. Table 6.8 displays the yields obtained for the "real" and the clustered cutting bills in ascending order according to the magnitude of the absolute error observed. Also shown are the number of

Table 6.8: Yield estimation errors due to clustering, number of part sizes, total parts required, and part groups used for the five "real" cutting bills

Cutting bill	Yield of "real" cutting bill	Yield of clustered cutting bill	Error due to clustering	# of parts required	# of part sizes	# of part groups used
E	72.39%	70.16%	2.23%*	1080	36	16
D	65.47%	62.64%	2.82%**	6840	8	7
B	67.34%	64.18%	3.16%**	2000	12	7
A	64.40%	67.97%	-3.57%**	840	7	6
C	68.48%	64.00%	4.48%**	1362	36	7

notation: * = significant at 95 percent level
** = significant at 99 percent level

different part sizes, the total number of parts in the cutting bill (total part quantity), and the number of different part groups to which the parts belonged when clustered. Z-tests (Schulman 1995) were used to establish the significance of the errors observed.

The errors due to clustering can be attributed to three sources. One is the different number of part sizes to be cut between the "real" and the clustered cutting bill. The second source of error is the difference between the true part length as given by the "real" cutting bill and the length the parts assume when clustered to the midpoints of their respective part groups. The third source is the difference in width between the real parts and the parts when clustered. However, because these cutting bills were not specifically designed to enable the separation of the error (i.e. orthogonal design in respect to the three errors under consideration), no exact magnitude of the individual error can be derived.

The first observation, to be discussed, was made between cutting bill E (lowest error) and cutting bill C (largest error). Both cutting bills required 36 different part sizes to be cut in their original form what made them the most easily comparable of all five cutting bills. The most obvious observation between these two cutting bills is, that cutting bill E has its part sizes spread over 16 part groups, whereas cutting bill C's part sizes are spread over only 7 part groups. Figure 6.3 shows the distribution of the 36 different part sizes over the respective part groups for both cutting bills. The pattern indicates the quantities of parts required for a particular part group. Maximum quantity (i.e. 100 percent) is when the maximum amount of parts is required according to the part quantities established based on the study by Araman et al. (1982) [see Table 4.7]. Hundred percent part quantity is thus always a different quantity of parts for each part group.

Figure 6.3 shows that cutting bill E's parts are dispersed over 16 different part groups. Also, in six of the 16 part groups, more than 33 percent of the respective maximum part quantity is required to be cut. Cutting bill C's 36 different part sizes are only dispersed over seven different part groups, with four part groups requiring more than 33 percent of the respective maximum part quantity. As was shown previously, (Table 5.11) the number of different parts to be cut influences yield. Therefore, a rather large part of the difference in errors between cutting bill C and E can be attributed to the different number of

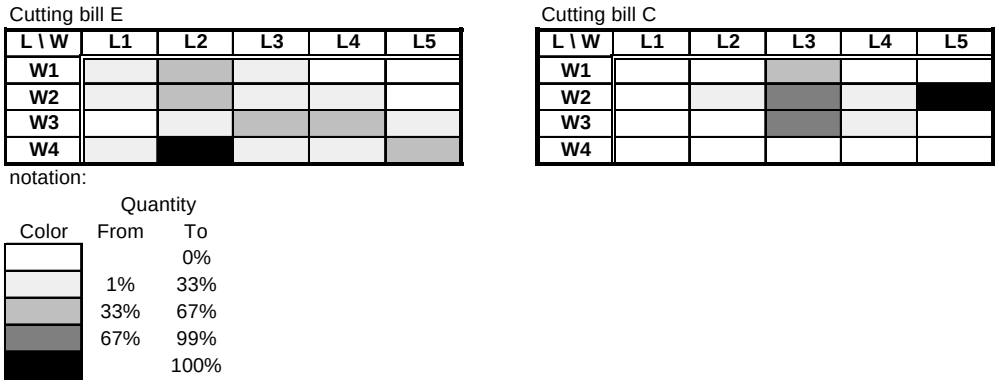


Figure 6.3: Distribution of part sizes and approximate part group quantities for cutting bills E and C

parts to be cut for the clustered cutting bill. The same observation is made between cutting bills D and B. Cutting bill D has eight different parts to be cut and seven when the parts are clustered. Cutting bill B has 12 different parts to be cut and seven when the parts are clustered to their respective part groups. The error of cutting bill B is 0.34 percent higher than the one for cutting bill D.

Cutting bill B has the smaller error despite the deviation between the part lengths in the "real" cutting bill and in the clustered cutting bill are higher than the one for cutting bill D. The absolute deviation in length between the "real" part length and the length used when the parts were clustered to their respective part group midpoints are shown in

Table 6.9. The cutting bills are in ascending order of the error size, as used for Table 6.8. Two measures were taken, the first one representing the absolute average deviation per part between the real part lengths and the clustered lengths for each length group and the second one being the average deviation per part for each length group. The second measure allows to obtain information about the spread of the real part lengths around the length group midpoints. For example, when the average absolute deviation is high but the average deviation is low, then the parts are spread quite evenly on both sides of the length group midpoints. Length group L_3 of cutting bill C is such a case. Also, Table 6.9 displays the average deviation per part for all length groups as well as the total deviation for all length groups. Total deviation is the sum of all parts' deviation times their respective quantity for a given cutting bill. The main point observable in Table 6.9 is that the magnitude of the error due to clustering is not

correlated with the deviation of the real part length to the part-group midpoint. The absolute average deviation of parts from their respective part-group midpoints is not highest for the cutting bill with the largest yield error due to clustering. The error due to clustering of the parts cannot be attributed to the parts being located on only one side of the midpoint, either. The cutting bill whose parts are located most

Table 6.9: Deviations of lengths in inches between "real" cutting bill and clustered cutting bill for the five cutting bills used

	length 1	length 2	length 3	length 4	length 5	all lengths	
cutting bill	average absolute deviation per part					average	total all parts
E	3.50	1.24	3.78	5.25	6.50	2.55	2757.50
D	no parts	0.50	3.83	6.98	6.96	4.88	33390.00
B	4.50	1.17	6.21	6.44	3.00	4.41	8825.00
A	4.25	2.00	3.45	3.38	4.75	3.17	2660.00
C	no parts	1.45	4.12	3.69	6.56	4.05	5514.00
	average deviation per part					average	total all parts
E	3.50	-0.71	-2.08	0.75	-6.50	-0.49	-532.50
D	no parts	0.50	-3.50	-6.98	-6.96	-4.62	-31590.00
B	4.50	0.17	-6.21	-1.44	3.00	-1.81	-3625.00
A	-4.25	2.00	-3.45	-3.38	4.75	-0.74	-620.00
C	no parts	1.45	0.19	-2.37	0.21	0.05	71.00

extremely on one side of the part-group midpoints, i.e. cutting bill D (with the highest total deviation), does not result in the largest error due to clustering but to the second smallest error observed.

Hence, according to the observations discussed above, the largest source of error due to clustering is the decrease in number of parts to be cut between the "real" cutting bill and the clustered cutting bill. This confirms the appropriateness of the part groups created and shows that cutting bill yield is less dependent on incremental changes in part size as opposed to the distribution of part sizes and part quantities. Minimizing the errors observed would imply to introduce more part groups, which would lead to a lower difference in number of parts to be cut in the real cutting bill and in the clustered cutting bill. Also, it would make the difference in part sizes to be cut between the "real" and the clustered cutting bill smaller as it would decrease the average absolute and non-absolute error as well. However, more part groups would make the analytical work more difficult.

Clustering of the parts is, as stated earlier, the second largest error observed and requires thus

attention. Smaller in magnitude, the scaling of part quantities required by cutting bills influence the accuracy of the yield estimation model, too. Its influence on yield is discussed in the next section.

6.5.3.2 Error due to scaling part quantities

As discussed in the Section 6.2.2.3, scaling the part quantities required by the "real" cutting bill is necessary to make these quantities adhere to the framework under which the least squares yield estimation model was developed. Quantities may be scaled up from less than maximum part quantity in a part group such that at least one part group reaches the maximum part quantity, or scaled down such that no part group exceeds its maximum part quantity.

The average error due to scaling was found to be 0.85 percent with a standard deviation of 0.77 percent. Table 6.10 shows the yields from the simulation runs obtained for the five cutting bills for the clustered and the clustered and scaled version of the "real" cutting bills. Also shown are the yield errors due to scaling, the scaling factors used and the number of part groups used. The cutting bills are sorted in ascending order according to the magnitude of their error.

The results shown in Table 6.10, indicates that the more part groups do require parts to be cut by a cutting bill, the larger the error due to scaling becomes. Also, it can be hypothesized that the more the scaling factor is different from 1.00 the larger the error could become. However, the data presented in Table 6.10 does not support these claims very well, mainly because not enough observations are available.

Table 6.10: Results of the analysis of yield errors due to scaling for the five cutting bills used for the validation of the model

Cutting bill	Yield of clustered cutting bill	Yield of clustered and scaled cutting bill	Error due to scaling	Scaling factor	# of part groups used
B	64.18%	64.18%	0.00%	0.78	7
D	62.64%	62.09%	0.55%*	2.33	7
A	67.97%	67.39%	0.58%	1.25	6
C	64.00%	62.90%	1.10%*	0.54	7
E	70.16%	68.13%	2.04%	0.57	16

notation: * = significant at 95 percent level
** = significant at 99 percent level

Another surprise is that the cutting bills with a scaling factor above 1.00 do not produce a negative error. Theoretically, one would expect that for cutting bills with factors larger than 1.00, the clustered and scaled cutting bill should result in higher yield than the clustered cutting bill, thus producing a negative error. This is, because the more boards are processed, the higher the yield achieved should be, at least up to 177 boards processed as established earlier. Even above 177 boards a slight increase, although not significant, could be expected. However, this was not observed for the five cutting bills used.

As was shown, the scaling of the cutting bill does introduce another source of error to the model. However, it is, on average, the smallest error contributing to the inaccuracy of the yield estimation model. The 2.04 percent error observed for cutting bill E should be close to the upper bound of the possible error. This can be interfered because cutting bill E requires parts in 16 part groups. Since the number of part groups is considered to be the major determinant of the magnitude of the error due to scaling, this cutting bill is not far away from the maximum of 20 part groups that possibly can require parts. Compared to the error due to the inaccuracy of the least squares model, the error due to scaling is, on average, tenfold smaller. Therefore, the next section will discuss the sources and possible remedies for the error due to the least squares model.

6.5.3.3 Error due to the least squares model

The results obtained from the comparison of the data from the 512 tests (3 replicates) based on the resolution V fractional factorial design, indicated that the linear least squares model did not fit the data perfectly. However, given the complexity of the cutting bill - yield interrelationship, the model achieves an acceptable accuracy. As shown before, 450 out of 512 results had an error of less than one percent. For these comparison, only the inaccuracy of the model can be attributed to be responsible for the error observed. No error due to clustering or scaling occurs since these 512 data points are based on cutting bills that conform to the framework of the model. Also, the within part group linearity assumption is not tested, since only either zero or maximum quantity for a given part group were used for these tests.

To gain a better understanding of the partitioning of the sources of the errors observed, a lack

of fit test was performed (Neter et al. 1996). The lack of fit test breaks the overall error down into two components, one being the noise from the differences in yield obtained between the three replicates and the other one being the error due to the least squares model not being perfect. More specifically, it computes the squared error for each of the 1536 data points obtained (512 tests with 3 replicates each) according to the following formula:

$$\sum_{k=1}^{k=3}\sum_{j=1}^{j=4}\sum_{i=1}^{i=5}(Y_{ijk}-\hat{Y}_{ij})^2=\sum_{k=1}^{k=3}\sum_{j=1}^{j=4}\sum_{i=1}^{i=5}(Y_{ijk}-\overline{Y}_{ij})^2+\sum_{i=1}^{i=4}\sum_{j=1}^{j=5}(\overline{Y}_{ij}-\hat{Y}_{ij})^2 \qquad (6.7)$$

where Y_{ijk} is the yield-result of replicate ijk, $\hat{Y}_{ij}$ is the estimated value ij, and $\overline{Y}_{ij}$ is the average yield obtained of the three replicates. The lack of fit test therefore breaks down the total squared error into two components: 1) the squared error of the system (i.e. the noise in the system) and 2) the squared error due to the model (i.e. the lack of fit). The results of this test are shown in Table 6.11.

Table 6.11: Results of the lack of fit test based on the 512 tests (3 replicates) done

Source	SS	DF	MS	F-Value	Probability (p)
Lack of Fit	841.32	301	2.80	23.09	0.0001
Pure Error	123.99	1024	0.12		
Total Error	965.31	1325	0.73		

As can be seen in Table 6.11, the squared error due to lack of fit is almost seven times larger than the squared error due to the noise in the system. Lack of fit thus is a highly significant ($\alpha < 0.01$) contributor to the total error observed as indicated by the p-value of 0.0001. This indicates that the variability of the average yield from the three replicates is not captured perfectly by the model.

Residual analyses did not reveal a pattern that would allow to conclusively state a source or sources of the errors observed. The most obvious information gained from plots of the residual versus the number of part groups requiring parts, is that the large deviations occur mainly when only a few part groups or many part groups require parts to be cut. When 9 to 16 part groups require parts, the residual is smaller. Figure 6.4 shows the residual plot created.

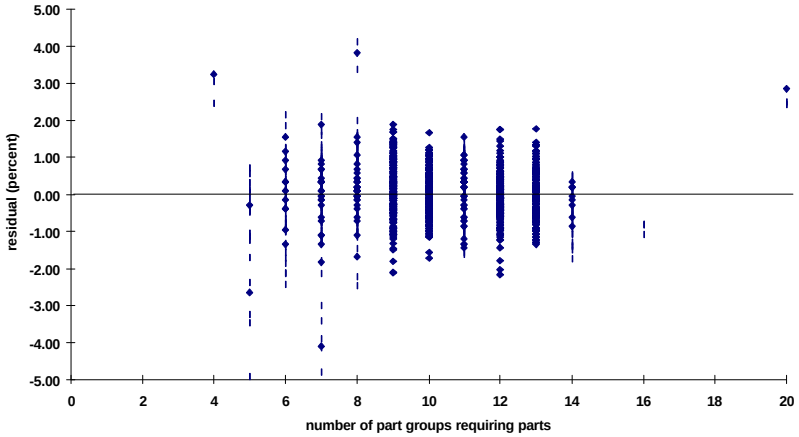


Figure 6.4: Residual plot for the 512 tests (3 replicates, i.e. 1536 replicates shown)

Relatively few residuals exceed two percent error, as was stated earlier. Also, one has to be aware that the residuals shown in Figure 6.4 are based on the individual observations (i.e. the replicates) and not on the average of the three replicates, to which the model was fitted. When analyzing the errors of the average yield from the three replicates versus the estimated value of the model, only eight observations out of 512 were larger than 2.00 percent. Thus, despite the lack of fit of the model, the least squares estimation model was able to estimate the expected yield quite accurately. Also, as stated previously, the model was able to estimate expected yield for cutting bills based on the 20 part groups with random quantities with an average error of 2.19 percent. Given the complexity of the interaction of cutting bills characteristics and yield, this can be considered a good value.

However, as was shown in section 6.3, when estimating the expected yield for “real” cutting bills, the error term became considerably larger. It was therefore concluded to focus on the analysis and, if possible, the minimization of these errors. For this purpose, 66 new “real” cutting bills, including the 40 presented earlier in section 4.2.3.1, were introduced, for a total of 71 cutting bills. To avoid errors stemming from clustering and scaling to occur, these cutting bills were clustered and scaled before the simulation was performed. Therefore, the error that was then observed between yield obtained from using the simulation tool (Thomas 1995a and 1995c) and the estimated yield from the least squares model could entirely be attributed to the model. Table 6.12 shows the number of observations where the estimated yield

was within the range of error given in the first column.

Table 6.12: Number of observations that fall within the specified range of error

	# of observations
# of errors <=2.0%	10
# of errors 2.0%>E<=5.0%	29
# of errors 5.0%>E<=10.0%	24
# of errors >10.0%	8

Fifty five percent (39 out of 71) of all cutting bills whose yield was estimated by the least squares model were within five percent of the yield obtained by the simulation runs (Thomas 1995a and 1995b). The best estimation from the yield estimation model misstated the expected yield by as little as 0.24 percent. Ten cutting bills had an error between yield obtained and yield estimated of equal or less than two percent. However, on the other hand, eight cutting bills resulted in an error above ten percent. The largest error observed was more than 18 percent. Based on the results shown in Table 6.12, one could expect that approximately 50 percent of real cutting bills whose yield is estimated will have an error equal to or lower than five percent yield.

The average yield for the 71 "real" cutting bills obtained by the simulation program (Thomas 1995a and 1995b) was 62.32 percent, whereas the average yield estimated by the model was 56.70 percent. Table 6.13 shows the summary statistic for the yield results obtained from performing the simulation and from employing the estimation model. The average, maximum, and minimum yield level observed for the simulation tool are shown in the second column, whereas the fourth column presents these data as obtained by the least squares model. The last column, column six, shows the absolute errors observed for any two sets (simulation versus estimation model) of data. This numbers are thus not attainable by subtracting the data in columns two and four.

Table 6.13: Summary statistics for the tests on 71 "real" cutting bills

	ROMI RIP		Model		absolute
	Yield	Std. Dev.	Yield	Std. Dev.	Error
average	62.32%	4.51%	56.70%	56.70%	5.62%
maximum	72.78%	0.29%	64.72%		18.18%
minimum	48.79%	0.37%	49.42%		0.24%

On average of the 71 cutting bills tested, the yield estimation model understates yield by 5.62 percent. An observation made throughout the validation work done for this study was, that the model did underestimate expected yield. A reason for this might be, as discussed earlier, that small quantities of parts influence yield in a nonlinear fashion. Since 15 out of the 20 part groups contribute positively to yield, this underestimating of small part quantities required by cutting bills leads to yield estimates that are lower than achieved by the simulation tool (Thomas 1995a and 1995b).

Pattern search for the errors observed using the 71 cutting bills was quite revealing. For this purpose, the quantity of parts required was analyzed according to length group by magnitude of the error observed. Table 6.14 shows the percentages of part quantities required by the five length groups compared to the magnitude of the error observed. The magnitude of the error was grouped in four groups, as shown in column one of Table 6.14. The numbers in the columns entitled "Quantity of parts in length group" are the average quantities of parts that are required by the 71 cutting bills.

Table 6.14: Average part-group quantity for length groups according to magnitude of error observed

	Quantity of parts in Length group					
Magnitude of Error (E)	**Length 1**	**Length 2**	**Length 3**	**Length 4**	**Length 5**	**# of obser.**
E<=2.0%	0%	14%	41%	32%	15%	10
2.0%>E<=5.0%	2%	13%	37%	33%	14%	29
5.0%>E<=10.0%	8%	13%	36%	30%	15%	24
E>10.0%	42%	33%	16%	8%	2%	8

There are distinct trends to be observed in Table 6.14. For example, the yield estimation model estimates yield with an error smaller than two percent when there are no parts required by length group L_1 and approximately 40 percent of the parts required are in length group L_3. However, when length group L_1 requires approximately 40 percent of the total part quantity in a cutting bill combined with one third required by length group L_2, the error becomes larger than ten percent. The close correlation between particular length group quantities and estimation error becomes more evident when looking at the correlation between the two factors. Correlation coefficients between part quantity by length group and magnitude of error were found to be 0.75, 0.38, -0.31, -0.36, and -0.26 for part groups L_1, L_2, L_3, L_4, and L_5, respectively. All correlation coefficients found were highly significant ($\alpha = 0.01$). These

correlation coefficients are consistent with the observations stated before that the magnitude of the error increases when part quantities in length groups L_1 and L_2 increases. Similar observations as were made for the length groups were made for the width groups. However, these relationships were not as distinguished, and are therefore not presented here.

Analyzing the individual part groups, reveals the correlation of the part group quantities and the estimation error observed. For example, the correlation coefficient for part group L_1W_1 between part group quantity and magnitude of error was found to be 0.51. On the other hand, the correlation coefficient for part group L_3W_2 turned out to be -0.52. As one can see, the part quantities actually required by cutting bills in different part groups influence the magnitude of the estimation error. A cutting bill with low error, thus would require no parts from part group L_1W_1, but maximum part for part group L_3W_2. Similar interpretations can be made for all the correlation coefficients shown in Table 6.15. However, one has always to be aware that these correlation coefficients do not convey any information about the relationship between cutting bill requirements and lumber yield. All they say is as to how part quantities in particular part groups influence the magnitude of the estimation error. Furthermore, the values presented are an average of all the 71 “real” cutting bills researched, individual cutting bills may contradict the findings shown in Table 6.15.

The numbers in Table 6.15 can be interpreted to a certain degree. However, the ability to make conclusive statements is restricted since higher order interactions are not taken into account. A positive correlation coefficient transmits the information that, when the error increased, part quantity in this part

Table 6.15: Correlation coefficients for part quantity of individual part groups versus magnitude of error

L \ W	W1	W2	W3	W4
L1	0.51**	0.46**	0.31**	0.37**
L2	0.34**	-0.25**	0.42**	0.16**
L3	-0.17**	-0.52**	0.00	0.00
L4	-0.04	-0.47**	-0.13**	0.06*
L5	-0.06*	-0.31**	0.04	0.09**

notation: * = significant at 95 percent level
** = significant at 99 percent level

group increased, too. When the coefficient is negative, the error increased when part quantity in this particular part group decreased.

Seventy out of 71 cutting bills tested resulted in yield estimates that were lower than the actual yield achieved. This indicates that the model cannot appropriately account for the increase in yield when smaller than maximum part quantities are required by a cutting bill. As it appears, small quantities of parts required to be cut by the small-size part groups have a disproportionate positive effect on yield. Thus, a linear representation of the yield increase, as it was used for this model, would not be appropriate. However, such a behavior could possibly be accounted for by transformation of the data (Draper and Smith 1981, Neter et al. 1996). Another problem may be the large amount of variables in the model. Because the parameter estimates are an average value of the part quantity - yield relationship as obtained from the 512 tests, the model calculates a somewhat “blurred” yield respond.

Unfortunately, attempts to improve the accuracy of the model as suggested by Draper and Smith (1981) and Neter et al. (1996) by either (a) using a higher order polynomial model or (b) transformation, failed. Polynomial models up to the third order for the main effects were tested with no significant improvement of the lack of fit term. Transformation of the data was not more successful, either. The following transformations were tested: natural log, exponential, square root, logit, reciprocal, power k, and combinations of them. However, none of them did reduce the lack of fit significantly.

As it appears, there is no detectable systematic effect in the interaction between the independent variable (settings of part groups) and the dependent variable (yield) for the many possible combinations of part groups and quantity. Possibly, a higher order polynomial model, based on more factors, or a nonlinear model could capture the relationship of cutting bill requirements and yield more appropriately. However, such a model would not only be preventive due to the necessary simulation tests to derive the data (a three factor factorial design has more than three trillion possible combinations), but would moreover result in a model having so many variables that its accuracy would be questionable. Unless a satisfactory way of improving the accuracy of the existing model can be found, the present model requires cutting bills that adhere to the framework on which the model was derived. Other techniques, to

be discussed in Section 7.4, may be of more benefit to be employed to solve the lumber yield estimation problem. However, as was shown in this study, the problem of estimating yield based on cutting bill characteristics is truly a challenge due to its complex nature.

6.6 SUMMARY

This chapter explained the least squares model that was developed based on the observations obtained from the tests of the fraction factorial design. This model, which contained 210 variables, namely 20 main effects and 190 secondary interactions, was then validated using three different sets of data. The first test compared the performance of the model in estimating yield based on the 512 cutting bills used in the fractional factorial design. It was found that 88 percent of all estimated yields were within one percent accuracy. The maximum estimation error observed was 4.27 percent. The second test used the 20 part groups but assigned random part quantities to each part group. The average estimation error observed for these five tests was found to be 2.19 percent. The maximum error was found to be 2.78 percent and the minimum error was 1.62 percent. The model ranked the cutting bills according to levels of yield quite successfully. Errors of larger magnitude, however, were observed when the model was tested using "real" cutting bills. The total error observed, on average of the five "real" cutting bills tested, was 10.30 percent. This error could be partitioned into three parts, namely, errors due to clustering, scaling, and limitations of the model. The error due to the model being not perfect was 7.62 percent, on average of the five cutting bills tested. Clustering and scaling contributed 1.82 and 0.85 percent, respectively, to the total error.

Analysis of the error due to the model revealed that the magnitude of the error is correlated with the part quantities in particular part groups. For example, the correlation coefficient between part quantity required by part group L_1W_1 and the magnitude of the error was found to be 0.51. Thus as the part quantity in part group L_1W_1 increased, the magnitude of the error increased, too. Unfortunately, though, there was not a distinct trend in the correlation of part group quantity and magnitude of error. A distinct trend would have lead to a transformation of the data that would have increased the accuracy of the model. Nonetheless, several transformations of the data were tried, however, none did increase the

accuracy of the model significantly. Also, including second and third order polynomial terms for the main effects into the model did not lead to a decrease in estimation error.

CHAPTER 7

7. SUMMARY AND CONCLUSIONS

There has been a substantial amount of research on lumber yield improvements in rough mills in recent years. However, the impact of cutting bill part sizes and quantities on yield was not the focus of this research, despite the fact that large differences in lumber yield can be attributed to cutting bill requirements (Buehlmann 1998a, Thomas 1996b). Understanding the underlying phenomena of cutting bill requirements on yield therefore is essential to profit improvement.

Also, today, yield estimates are based on post hoc heuristics or pre-calculated yield tables (Suter and Calloway 1994, Wengert and Lamb 1994b), which one may call rudimentary at best (Thomas et al. 1996, Wiedenbeck and Scheerer 1996, Manalan et al. 1980). The search for a new approach to a consistent and accurate yield estimation model is, and continues to be, a high priority for the scientific community and the secondary wood products industry.

This study's goals were to gain a better understanding of the physical phenomena relating cutting bill requirements and yield. By better understanding the marginal contribution of different part sizes and quantities to yield, cutting bills could be designed such that higher yield is achieved. Also, using this knowledge and the data derived, a yield estimation model based on the method of least squares could be constructed.

7.1 SUMMARY

The relationship between cutting bill requirements and lumber yield is a truly complex problem. The true function that governs the cutting bill – yield relationship must be of a daunting complexity. This research was a first approach to gain a better understanding of this relationship. Significant new knowledge to the understanding of the relationship between cutting bill requirements and lumber yield was obtained. The statistical approach can be used to observe and quantify the interactions

that distinguish cutting bills achieving low yield from cutting bills achieving high yield. This is highly relevant knowledge, since up to date, this relationship was never explicitly established. Existing yield estimation models and simulation programs act as a “black box”, that returns yield estimates without providing information from which to observe and quantify parameters responsible for a specific result.

Part groups used to standardize cutting bills were found to be a viable concept in decreasing the complexity of the cutting bill requirement - yield relationship. Two significant findings resulted from the development of part groups: First, parts can be clustered within their respective part groups without sacrificing too much yield accuracy. The average error due to clustering observed was 1.82 percent. There are indications that this error is mainly due to the decrease in number of different part sizes to be cut, rather than due to the incremental changes in part size when parts are reset to their respective part group midpoint. Second, part groups allow to decrease the complexity of cutting bills, because they reduce the number of factors considerably. Future research can be substantially simplified with the concept of part groups.

The marginal contribution of individual part groups to yield established is another piece of important knowledge gained from this study. This information can be used to compose cutting bills with parts that are most beneficial to yield. The data derived also allows to account for secondary interactions between two parts. Thus, yield losses can be minimized by not designing cutting bills where two parts that have a negative effect on yield when combined, are required simultaneously. Such parts can be separated into two unrelated cutting bills. However, knowledge of the marginal contribution of parts is not only helpful in composing cutting bills and planning rough mill production schedules, but hopefully will also influence the design of secondary wood products, such as furniture and cabinets. Parts for these products should be designed such that their sizes are most beneficial for yield. Since no quantitative data for the marginal contribution to yield of part sizes has been available to date, designers could not incorporate these parameters into their work. Furthermore, as it was shown, small parts do not benefit yield when they cannot be produced in large quantities. For such dispositions, it was shown that medium sized parts are more beneficial for yield. This is because medium sized parts use the remaining clear areas of boards more

effectively after the large parts have been cut than do small parts. Since clear areas in lower grade lumber are smaller, however, small parts may be more effectively used when processed using such lumber since medium sized parts may not fit the remaining clear areas as well as found in this study for the better grade lumber. Even though this idea was not researched, theoretical reasoning requires further investigation.

The least squares yield estimation model developed, although limited in its scope, is able to indicate trends of yield levels to be expected. For cutting bills that conform to the framework established in this study, cutting bills can be ranked in respect to expected yield correctly with 88 percent accuracy and a maximum error of +/- one percent. When part quantities are assigned randomly, the model ranked five cutting bills quite accurately as to their potential for yield. The model identified the two cutting bills with highest yield and the two cutting bills with lowest yield correctly, although for both cases in reverse order. This was not surprising, since the yield increment for the cutting bills in the same group was rather small (below 0.50 percent). This model thus is a helpful tool to establish relationships of cutting bill requirements and yield under specific settings. Expected yield of "real"[9] cutting bills, since they are beyond the framework established in this study, cannot be estimated reliably.

The following sections summarize the findings from this study and draws the conclusions possible. First, in Section 7.1.1, the observations from the derivation of the part groups, that were used to facilitate the statistical analysis of the cutting bill requirement - yield relationship, are presented. In the second section of this chapter, Section 7.1.2, the relationship between cutting bill requirements and lumber yield is summarized. This section is followed by Section 7.1.3, which does present the findings from the derivation of a least squares yield estimation model. Section 7.2 lists the conclusions made from this research project. Section 7.3 then explains the limitations that apply for the work presented. This chapter is concluded by Section 7.4, which shows some possible areas for future research that might be word undertaking.

[9] "Real" cutting bills, defined in Section 3.2, are cutting bills that were obtained from industrial operations

7.1.1 Part groups

Part groups, a theoretical construct that tries to describe “real" cutting bills in a standardized format, were employed in this study to make the statistical analyses of the cutting bill requirement - yield relationship possible. The cutting bill part size range, i.e. the range of part sizes that a cutting bill can require to be produced, was determined as ranging from 5 to 85 inches in length, and from 1.00 to 4.75 inches in width. This size range was then partitioned into 5 length groups and 4 width groups that formed a 5 by 4 part-group matrix. Part sizes were found by using the midpoint of each part group as the size of the standardized parts. Thus, the part-group midpoint is a representative of all parts that fall within a particular part-group range, i.e. parts were clustered within part groups. The sum of the quantities of individual part sizes required by “real” cutting bills that lie within a part-group range, was the quantity assigned to this part group’s midpoint. However, since “real” cutting bills can have an almost unlimited variability of requirements with respect to part quantity, average part quantities were derived based on a study done by Araman et al. (1982).

Iterative tests helped establish the ranges of all part groups. These tests assured that the influence on yield of any part size within a part group was similar for all part groups. This minimized the error that occurs due to the clustering of parts within a part group range. This way, the error due to the clustering of parts within its respective part group range was made small. The average error due to clustering parts when comparing yields from “real” cutting bills and yields from cutting bills whose parts were clustered to the part-group midpoints, was found to be 1.82 percent. The maximum error observed was 4.48 percent.

The ranges of part groups differed widely in length. The length range of the part groups was found to be from 5 to 25 inches. The shorter part ranges, i.e. group L_1, L_2, and L_3, which, as Buehlmann et al. (1998c) found, have a more pronounced influence on yield than longer parts, had length ranges not exceeding 15 inches. The longer part ranges, i.e. group L4 and L5, both had length ranges of 25 inches. Group L_2 had a length range of only five inches, emphasizing the high influence of this length range on

yield. However, the importance of a part group is not only determined by its length range, but also by the quantity of parts that is required for this range. The length range that group L_2 encompasses, i.e. from 15 to 20 inches, is the one where the highest quantities of parts per unit length are required by an average cutting bill.

Width does influence yield less than does length, given that the maximum width considered is 4.75 inches (Buehlmann et al. 1998c). This was confirmed by the width ranges found. Three width groups were found to be one inch, and one was found to be 0.75 inches.

7.1.2 Yield contribution of part groups

Using the part group matrix developed, an analysis of the marginal contribution of each part group to yield could be done. An orthogonal, 2^{20-11} fractional factorial design was used to test 512 cutting bills with different part group combinations requiring parts. This way, the average contribution of each part group to yield could be established. Also, the correlation of a particular part group to high yield could be obtained.

Analysis of Variance of the 512 tests performed, revealed that all main effects (i.e. part groups) were significant ($\alpha = 0.05$). One hundred and thirteen secondary interactions out of a total of 190 were also found to be significant ($\alpha = 0.05$). The average yield observed for the 512 tests performed was 65.09 percent, with a standard deviation of 3.59 percent. The maximum yield found was 70.81 percent, whereas the minimum was found to be 48.63 percent.

A central question in all dimension-part operations is related to determining the cutting bill requirements that maximizes yield. This question was discussed in three different aspects: (1) which parts add the most to high yield, (2) which parts in a existing cutting bill are most closely correlated to high yield, and (3) how important are the number of parts cut simultaneously for high yield?

To answer the first question, i.e. which parts are the best ones to be added to a cutting bill to achieve high yield, parameter estimates derived for the least squares estimation model were employed. The most positive effect on yield can be achieved by adding parts with a part size ranging from 15 to 20

inches in length and 2.00 to 3.00 inches in width. This part group had the steepest positive slope (i.e. largest parameter estimate) of all part groups. In general, all part groups whose length was not longer than 35 inches, contributed positively to yield. On the other hand, four part groups were found to affect yield negatively. All these part groups required the longest length to be cut, except one, which required the second longest length combined with the widest width to be cut. The negative influence of long length is increased when the part is also wide. The part group requiring parts with the longest length and the widest width, i.e. parts ranging in size from 60 to 85 inches in length and 3.75 to 4.75 inches in width, had the most negative slope, meaning they were lowering yield the most when added to a cutting bill. However, the statements above are only a simplification of the true cutting bill requirements - yield relationship, because these observations are based on the main effects in isolation, and do not account for the secondary interactions. Therefore, if one would account for these effects, the statements above may be slightly different.

The second question, where the correlation of part groups with high yield was established, found that the part group ranging from 15 to 20 inches in length and from 2.00 to 3.00 inches in width, was most positively correlated with high yield. The part group requiring the largest parts, i.e. the part group ranging form 60 to 85 inches in length and from 3.75 to 4.75 inches in width, was again the one that was found to be most negatively correlated with high yield. However, the part groups with the shortest length, i.e. the part groups ranging in lengths from 5 to 15 inches, were found to be negatively correlated with high yield. This contradicts the findings made for the case when these lengths are added to a cutting bill (as measured by the parameter estimates), where it was found that this length group contributes positively to yield. Now, as shown by the negative correlation coefficient, these lengths have a negative influence on yield. This can be explained by the two different viewpoints used to derive the parameter estimates and the correlation coefficients. For the parameter estimates, the marginal contribution of adding a part to a cutting bill (i.e. enlarging the cutting bill requirements by one part) is researched. For the correlation coefficients, the effect of the parts that are contained in a cutting bill (i.e. the cutting bill requirements are not changed) is researched. Thus, given that no more parts can be added to a cutting bill,

the shortest parts influence yield negatively because a higher yield could be achieved by cutting parts from longer part ranges such as L_2 and L_3 . Therefore, the correlation coefficient for the shortest part group was negative. Also, assuming that a cutting bill would require parts from all part groups, it was shown that having too many large parts and only a small amount of small parts is detrimental to yield. Whenever possible, large parts should be combined with as many small parts as possible, such that yield does not suffer too much. In fact, when large parts are combined with enough small parts, yield does not decrease significantly.

The answer for question three, the influence of the number of different part sizes cut simultaneously, showed that yield increases when the number of parts to be cut increases. However, for yield to maximally benefit from an increased number of different sizes to be cut, one should strive to select part sizes from groups that are of different size than the ones already in a cutting bill. Also, statistical tests performed did not show a significant ($\alpha = 0.05$) yield increase when more than 11 different part sizes are cut simultaneously. Having a large number of parts to be cut simultaneously and diverse part sizes in a cutting bill, the highest possible yield is achieved.

7.1.3 Yield estimation

Using the data obtained from the fractional factorial design, a least squares yield estimation model was contrived. The parameter estimates for the 20 main effect and for the 190 secondary interactions were obtained using the method of least squares. A least squares estimation model was then constructed using different techniques such as the forward, the backward and the stepwise procedure. However, the model containing all the main effects and all the secondary interactions was ultimately selected. This model's adjusted R^2 was 0.94.

The validation of the least squares yield estimation model was done using three different sets of tests. First, the model was tested against the data that was used for its derivation. This was done to observe if a least squares model was able to cope with the many variables in the model. Second, five cutting bills were constructed whose part quantities for all part groups were derived as a uniform random

numbers. Third, five “real” cutting bills obtained from industrial operations were tested.

The first test, that compared estimated yield from the model with the data obtained from the fractional factorial design, revealed a maximum estimation error of 4.27 percent. However, 450 out of 512 estimated values (88 percent) were within one percent accuracy. This results showed that a least squares model is not able to precisely capture the cutting bill requirement - yield relationship, but is able to explain general trends of this relationship. Lack of fit tests (Neter et al. 1996) revealed significant lack of fit ($\alpha = 0.05$) of the model. This indicated that the error observed did indeed come from the model and not from other sources of noise.

Testing the model using cutting bills whose part quantities were determined as a random uniform number, showed a maximum yield difference between the model and actual values obtained from simulation of 2.89 percent. The lowest difference found was 1.62 percent. These yield differences, even though quite large, are still within the expectations set forth in the model and well below the accuracy of other prediction models (Manalan et al. 1980, Englerth and Schumann 1969). Also, despite having an average yield estimation error of 2.19 percent, the model ranked the cutting bills correctly with a resolution of 0.50 percent. The model is thus able to show trends in yield due to changes in cutting bill requirements.

Testing the model on five “real” cutting bills allowed to determine not only the accuracy of the least squares yield estimation model, but also the influence of clustering the parts within their respective part group and the influence of the scaling of the part quantity to fit the model’s framework. The overall average estimation error between the yield estimation model and the actual results obtained from the rough mill simulator (Thomas 1995a and 1995b) was found to be 10.30 percent. Thereof, 1.82 percent, on average of the five cutting bills used, were attributable to the clustering of the parts and another 0.85 percent were found to come from the scaling of the part quantities. The average error of the yield estimation model thus could be quantified as being 7.62 percent. This large error occurred for two reasons: First, as the lack of fit test (Neter et al. 1996) showed, the model is not able to perfectly capture

the cutting bill requirements - yield relationship. Second, the “real” cutting bills do not conform to the framework under which the model was derived. Thus, the model has to predict data that is not part of the sample data, which leads to poor estimation (Lynch and Clutter 1998).

7.2 CONCLUSIONS

Three objectives were set forth for this study. In particular, the study’s objectives were to create part groups such that parts within each part group have a similar influence on yield for all part groups, the determination of the marginal contribution of these part groups on yield, and the development of a yield estimation model based on the method of least squares. The conclusions of this study are as follows:

(1) Part groups can be used to standardize cutting bills such that their complexity for analytical purposes decreases. However, part groups introduce a yield difference between “real” and standardized cutting bills. The average error from clustering parts within part groups was found to be 1.82 percent. The major source of error is believed to be due to the decrease in the number of parts to be cut simultaneously. Nonetheless, the concept of part groups to standardize cutting bills is important, since it allows to decrease the complexity of cutting bills and thus makes analyses easier attainable.

(2) Medium sized parts with a size of 17.50 inches in length and 2.50 inches in width were found to be the most beneficial part size for high yield. Limited quantities of such medium sized parts use the remaining clear area in boards more efficiently than limited quantities of part sizes smaller than the medium sized parts. Large parts, such as parts with size 72.50 by 4.25 inches, are detrimental to high yield. Large clear areas necessary for such parts are limited, such that large quantities of these parts cannot be obtained. Also, yield losses from salvage operations are large from wide strips, because often, the strips have to be cut to smaller widths. If shorter lengths of the same width can be cut, yield benefits substantially, as indicated by the high secondary interaction terms between these part groups.

(3) The number of different part sizes required by a cutting bill to be cut simultaneously influences yield significantly. However, no significant yield increase was observed between 11 and more different part

sizes to be cut simultaneously. Since the clear areas available in boards are of different sizes, a cutting bill requiring more different sizes to be cut simultaneously allows to better match the clear area and the part area. Yield thus increases. However, to benefit the most of the different part sizes required by a cutting bill, part sizes should be diverse and not similar.

(4) Least squares estimation of yield based on cutting bill requirements is a viable concept given that the cutting bills conform with the framework (i.e. part groups and part quantities) employed in this study. Within this framework, cutting bill yield can be estimated within one percent accuracy for 450 of 512 cutting bills researched (88 percent). Also, the model is able to rank cutting bills with random part quantities in order of expected level of yield correctly within 0.50 percent, despite an average error of 2.19 percent. Due to the complexity of the problem, however, extrapolation of the model by predicting yield for "real" cutting bills is dangerous, because the cutting bill requirement - yield relationship is too complex to allow such an extrapolation. The estimation error for "real" cutting bills thus becomes large in some cases.

7.3 LIMITATIONS

The results obtained are limited in applicability because of the restrictions imposed on the variables for this study. Limitations occur for (1) rough mill settings, (2) lumber, and (3) part sizes and part qualities. However, these limitations were necessary to be able to research the hypothesis-related questions. Also, and probably most importantly, the use of the ROMI RIP simulation software (Thomas 1995a and 1995b) opens the questions of the amount of distortion this study experienced as compared to actual results from rough mills. Therefore, the results of this study cannot be generalized to all cutting bill settings, rough mills, and all lumber species and grades.

ROMI RIP (Thomas 1995a and 1995b) was never truly validated (Thomas 1998). However, work done by Widoyoko and Kline(Widoyoko 1996, Kline et al. 1997) allow to compare the performance of ROMI RIP (Thomas 1995a and 1995b) to an actual operation. These authors found that the simulation obtained 3.50 percentage points higher yield compared to the rough mill. Simulation yield was found to be

69.10 percent compared to rough mill yield of 65.60 percent. However, several restrictions exist to make the study by Widoyoko and Kline fully applicable to the results found in this study. One major difference between this two studies are the rough mill settings. Whereas Widoyoko and Kline employed a Fixed-Blade-Best-Feed arbor (Thomas 1995a and 1995b) the study at hand used an All-Blades-Movable arbor. Also, the lumber used for both studies is different. Therefore, the question remains as to how the results found in the study at hand relate to actual rough mill operations.

Thomas (1998) estimates that yield obtained by ROMI RIP (1995a and 1995b) is three to five percent above what actually is achieved in a rough mill. Reasons include that ROMI RIP does not produce any rejects, that operator mistakes (such as misfeeding the boards and strips, and errors when marking defective areas, etc.) do not occur. Also, the boards are optimized for length and width concurrently, instead of the two sequential approach (first rip, then crosscut) current rough mill use. The last point is of great importance. In the current rough mills, the strip saw operators are the single most important source for achieving high yield. Operators should override the computer at the rip saw, when they see a clear area within the board that would allow to cut the hard to obtain parts (i.e. long and/or wide parts). Obtaining these clear areas may imply to forego yield at the rip saw. However, overall the yield will improve since less waste will be produced to obtain the large (i.e. long and/or wide) parts. ROMI RIP (Thomas 1995a and 1995b) does take account of this opportunity since the boards are optimized for yield of parts (and not for yield from strips and then from parts).

Indeed, the observations made in this study are based on what the simulation software does, and not what happens in a real rough mill, as well as the yield estimation model tries to estimate expected yield that ROMI RIP (Thomas 1995a and 1995b) would achieve. However, the difference between simulation and real rough mill should be within five percent (Thomas 1998). Also, in the future, rough mills will use automatic machine vision systems to scan the boards for defects (Conners et al. 1997, Kline et al. 1997, Kline et al. 1993). Simulation software such as ROMI RIP (Thomas 1995a and 1995b) will be used to improve yield. Then, the observations from this study will converge with what happens in real rough mills.

Limitations imposed on this study for the rough mill operation, such as part quality, layback parts, random parts and others, too, restrict the applicability of the results. However, the observations from this study should still have relevance for real operations, since it is a major interest for rough mill operators to achieve high yield on primary parts. Given that, the observations from this study will help actual rough mills improve their operations, even though the operational settings may be different.

7.4 FUTURE RESEARCH

Since this study is only the first step in researching a complex and poorly understood phenomena, future research can be directed to several objectives. Major areas could be: 1) improvement of the yield estimation capabilities, 2) creation of algorithms to find the highest yielding cutting bill, 3) understanding the effects of changes in the rough mill settings, and 4) effects of different lumber grades and lumber grade mixes.

7.4.1 Yield estimation model

Improving the accuracy of the yield estimation capabilities of the existing model, or of a new model with different techniques, would be of high importance. A consistent and accurate yield estimation (Wiedenbeck and Scheerer 1996) is of great importance for dimension part producers (Wiedenbeck and Thomas 1995b, Manalan et al. 1980) since they have to be able to analyze and estimate the costs associated with a specific order. Furthermore, such a model would allow them to compose cutting bills that achieve highest yield. Therefore, efforts spend on the subject will be well appreciated. Improvements of the yield improvements capabilities can be recommended in three different areas: 1) improvement of the existing model, 2) development of a new model using other techniques, and 3) using simulation techniques.

The reduction or elimination of the errors found associated with the clustering and scaling of the cutting bill parts should be possible. Changing the sizes and locations of the parts groups and changing the part quantity range for individual parts should help achieve this goal. Moreover, boundaries

could be imposed to which a cutting bill to be examined has to conform. The improvement of the least squares model, on the other hand, could possibly be achieved by several different approaches. First, a more thoroughly developed higher order polynomial least squares model could be able to capture the variability observed better than the first order model employed in this study. Second, the model could be improved by adding third degree interactions, and, if necessary, higher order interactions. Third, a nonlinear model could be able to more accurately describe the variability observed. However, all these three approaches will result in a complex model with a significant number of variables involved. It may therefore be questioned if a significant increase in accuracy of the estimation can be derived. Having so many variables and interactions in a model will always make it a challenge to find a model that is accurate.

Other techniques to build an estimation model may prove to be more promising. Neural networks, introduced by McCulloch and Pitts in 1943 (Zurada 1990) offer a way to deal with nonlinear data. Also, neural networks are nonparametric models, i.e. they do not require a priori knowledge of the function being estimated (Atalla 1996). These two features of neural networks make them a superior candidate for solving the problem at hand. For the yield estimation problem, nonlinearity is at least partially present and the function which relates cutting bill characteristics to yield is unknown. Moreover, neural network can be trained to solve problems (Burke 1991).

Fuzzy systems, introduced by Zadeh in 1965 (Zadeh 1965), could also prove helpful to solve the yield estimation problem. As was observed when the errors due to the least squares estimation model were analyzed, there seems to be incidences where a small quantity of parts in a part group has an over-proportional influence on yield. Fuzzy systems offer a way to address nonlinearity and interactions implicit in a set of data. They do not, however, require the specification of a nonlinear dynamic system, the acquisition of a representative set of training samples and the following encoding of the training samples by repeated learning cycles as is the case for neural networks. Fuzzy systems require only a “rule matrix” be partially filled by an expert (Kosko 1992). Future research could show, if fuzzy systems would enable to capture the nonlinear response of the dependent variable (yield) from different levels of the

independent variables (part quantities).

Research done by Ramos-Nino et al. (1997) on the structure-activity relationship of chemical substances on microorganisms, which show a similar, nonlinear complexity of interactions between substances as does the cutting bill requirements - yield relationship, shows that the above suggestions have some merit. The authors compared the performance of multiple linear regression models by the method of least squares, artificial neural networks and fuzzy systems as to their ability to fit the biological activity surface describing the inhibition of microorganisms. They found that the coefficient of determination (R^2) was 0.96, 0.92, and 0.81 for the neural network, the fuzzy system and the multiple linear regression, respectively. This indicates the superiority of the two first mentioned methods over the last in the ability to capture complex relationships between dependent and independent data. However, one has to be aware that only the least squares method enabled the specification of average effects of part quantities on yield presented in this study. Neural networks and fuzzy systems are much harder, if not impossible, to interpret and individual effects to be quantified.

Another idea as to how the yield estimation problem may be solved is, given that a rather large amount of data points need to be produced for the derivation of any model, to work with similarities between cutting bills. Using a database with the cutting bill information and its associated yield, new cutting bills could be analyzed for similarities with existing ones (using classification schemes similar to Opitz or MultiClass for group technology [Groover 1987]).The estimated yield would then be the yield that the cutting bill that is most closely related to the one investigated. Once the cutting bill is processed, yield information could be fed to the database such that a new point of reference is obtained. This way, the yield prediction capability of the system would steadily improve.

Given the advent of ever faster and more powerful computers, a third avenue for future research could be to investigate the use of the existing simulation tools in establishing expected yield. Today, simulation takes too much time to set up, run, and interpret the data for the actual rough mill manager to be employed heavily. Also, to achieve an average value for the expected yield, several replicates from different lumber sets have to be obtained. By improving and facilitating the user interface,

the first mentioned obstacle could be overcome. The problem of obtaining an average value that is somewhat representative of the expected yield could be addressed by finding lumber board samples that reflect the average expected quality of the boards used reasonably well. Also, the effect of processing a rather small sample of boards could be investigated and its associated error specified. When only one replicate would have to be produced and the board sample to be processed would be small, simulation could produce results in minutes instead of hours. By using simulation, no part groups would have to be introduced, thus no error would occur from this source. Also, simulation would allow individual rough mill managers to mimic their own rough mill operations very closely.

7.4.2 Highest yielding cutting bills

At the core of the strive to understand the relationship between cutting bill requirements and cutting bill yield is the question what combination of parts for a cutting bill leads to the highest yield from a given set of lumber. A scenario would be that the parts required by the production schedule for a certain time span have to be allocated to a number of cutting bills to be processed. As this study showed, combining parts of different sizes to a cutting bill is correlated to achieving high yield. It can be hypothesized that by allocating parts to individual cutting bills such that maximum diversity in terms of size is achieved would lead to maximum overall yield. By maximizing the absolute distance between parts (taking in account quantities by multiplying distance by number of parts for each part) for any cutting bill, diversity of part sizes in any given cutting bill would be high. Thus, overall maximum yield could be achieved. However, this hypothesis needs further research.

Another aspect worthwhile to be researched would be from the design point of view. Knowing that parts in part group L_2W_2 help the most to achieve high yield, more parts required for a given product should be of this size. By changing design parameters, for example by interrupting long front parts, or by fingerjointing, the quantity of such parts could be increased.

7.4.3 Effects of the rough mill settings

This study used a specific rough mill setting throughout. This neglects the fact that the actual rough mill settings found in industry are different. Therefore, future research should be geared towards comparing the effects of different rough mill settings on yield. Findings presented in this study do not necessarily need to apply for different settings of the rough mill operation parameters. Especially the impact of employing an All-Blades-Movable arbor versus Fixed-Blades arbors could change the findings of this study significantly.

Another question would be to find out the applicability of the findings made in this study on crosscut-first mills. Even though rip-first rough mills are the predominant choice by industry today (Mullin 1990), a significant number of crosscut-first operations are still in use. Also, as Buehlmann et al (1998b) showed, crosscut-first rough mills may achieve higher yield for specific cutting bills and lumber grade mixes.

7.4.4 Effects of lumber grades and lumber grade mixes

The choice of the best lumber grade mix for optimum yield or least cost (Hoff 1997, Fortney 1994, Harding 1991, Timson and Martins 1990) is a widely researched topic. However, all these attempts assume a given cutting bill for which the optimum lumber grade mix has to be found. This is a simplistic approach, because there are interactions that would lead to a higher yield or lower cost when the cutting bill requirements and the lumber grade mix would be matched interactively. By better understanding the relationship between cutting bill requirements and lumber grade, further improvements as to the assignment of the “best” lumber grade or lumber grade mix to a specific cutting bill could be made.

Also, the question of the sequence of boards from different grades or of different geometrical data that is best to be fed to the rip saw is not researched at all. It can be hypothesized, that by, for example, first feeding some high quality boards with large clear areas that would yield many of the difficult to obtain parts (i.e. the long and/or wide parts), the overall yield could be increased. This is because often low yield is obtained when the yield optimization procedure has to look out for areas in the

boards that are large enough to accommodate the difficult to obtain parts. Until such boards are found, most of the smaller parts are already cut. This leads to a significant decrease in yield when the areas smaller than needed for the difficult to obtain parts cannot be used for smaller parts. Having good quality boards at the beginning of the cutting sequence may lessen this negative impact. Of course, in most rough mills, this decrease in yield is not observed since all the non-usable areas for primary parts are converted into random width, random length parts. However, primary parts are of highest value and therefore the more of them can be obtained with the least amount of lumber, the better.

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APPENDICES

Appendix A: Definition of cutting bill requirements

Cutting bill requirements describe part sizes, part quantities, and part size/quantity distribution as given by a cutting bill. Table A - 1 below shows an example cutting bill as actually used in a furniture rough mill. In particular the geometric characteristics of a cutting bill are:

Part Sizes

Three dimensions - length, width, and thickness - describe the actual body of a part. Thickness, for the work outlined in this paper, is not considered and assumed to be uniform. All the parts considered have a thickness of four quarters. Length and width are the two sole dimensions considered.

Part Quantities

Part quantities refers to the number of parts of a given size (length and width) asked for in the cutting bill. The number of parts of a given size is of importance to determine the weighted overall distribution of part sizes in cutting bills.

Table A - 1: Cutting bill containing 13 parts to be cut, sorted according to width of parts

Cutting Bill				
Nr.	**Quantity**	**Length**	**Width**	**Thickness**
	#	*inches*	*inches*	*inches*
1	40	45.75	1.00	4/4
2	80	21.00	1.50	4/4
3	40	24.25	1.75	4/4
4	40	42.50	1.75	4/4
5	80	77.25	1.75	4/4
6	160	24.00	2.25	4/4
7	160	5.75	2.75	4/4
8	320	19.50	3.25	4/4
9	80	21.00	4.25	4/4
10	40	44.50	4.25	4/4
11	80	22.75	4.50	4/4
12	40	40.00	4.50	4/4
13	40	48.25	4.50	4/4

Appendix B: Boards according to distribution by Wiedenbeck et al. (1996)

Table A - 2: Boards 1 to 100 according to distribution by Wiedenbeck et al. 1996[10]

Sequence Number	Board Number	Board Length	Board Width	Total Defects
#	#	inches	inches	units
1	1914	471	29	14
2	1595	484	24	9
3	1824	384	28	7
4	1555	196	23	0
5	1400	578	21	10
6	2318	580	52	17
7	1802	198	28	19
8	1823	384	28	4
9	2012	279	33	9
10	1524	580	22	12
11	1712	770	25	13
12	1502	494	22	3
13	1700	579	25	15
14	1687	483	24	8
15	1695	528	24	14
16	1483	387	22	7
17	1437	484	21	9
18	2254	486	45	19
19	2093	484	35	12
20	2024	390	32	13
21	2036	772	33	13
22	2100	288	37	12
23	2190	198	40	27
24	1941	235	30	15
25	1430	389	21	8
26	1478	336	22	11
27	1669	320	25	5
28	2087	385	35	8
29	1677	388	25	12
30	1401	579	20	10
31	2094	674	35	6
32	1466	291	22	9
33	2287	386	49	18
34	1612	580	23	3
35	1728	289	25	7
36	1398	496	20	5
37	1591	484	23	7
38	1666	297	24	9
39	1708	581	24	18
40	1625	675	24	9
41	1442	576	22	13
42	1472	296	23	10
43	1779	384	27	5
44	1491	392	22	4
45	1645	197	24	7
46	1773	296	27	27
47	1748	484	25	21
48	1945	300	30	8
49	1762	194	26	6
50	1497	486	22	3

continued

Sequence Number	Board Number	Board Length	Board Width	Total Defects
#	#	inches	inches	units
51	1449	674	22	28
52	1439	488	21	5
53	2235	579	42	5
54	1621	582	24	12
55	1960	484	31	19
56	1468	293	22	5
57	1325	391	16	8
58	1987	388	32	10
59	1410	769	21	12
60	1519	580	22	4
61	2014	290	33	13
62	2162	677	39	28
63	1934	194	30	9
64	2240	202	43	5
65	2015	291	33	19
66	2110	602	37	19
67	1584	482	24	13
68	1389	388	21	23
69	2069	387	35	29
70	1604	579	23	2
71	1723	226	26	4
72	2137	678	38	30
73	2201	435	40	11
74	1927	669	30	29
75	1565	294	23	7
76	2050	483	34	10
77	1386	384	20	4
78	2316	534	52	14
79	2236	579	42	22
80	1897	196	29	12
81	2066	344	34	21
82	1650	204	24	5
83	1765	207	27	12
84	1831	438	28	17
85	1409	679	20	3
86	2188	771	40	10
87	2145	203	39	9
88	1886	580	28	9
89	1882	579	29	15
90	1997	483	32	20
91	1791	572	26	20
92	2128	487	37	11
93	2242	298	43	51
94	2230	481	43	7
95	2000	579	31	69
96	2299	384	50	14
97	1832	470	28	12
98	2080	771	35	19
99	1582	387	23	2
100	2194	281	40	6

[10] The board numbers are consistent with the numbers used by Gatchell et al. (1998)

Table A - 2: Boards 101 to 200 according to distribution by Wiedenbeck et al. 1996, continued

Sequence Number	Board Number	Board Length	Board Width	Total Defects
#	#	inches	inches	units
101	2259	679	44	23
102	2283	674	47	9
103	1434	483	22	5
104	1574	345	24	24
105	1638	771	24	12
106	1998	484	31	31
107	2095	768	35	16
108	1647	198	25	10
109	1890	581	28	18
110	1749	484	26	10
111	1580	386	24	7
112	1607	580	23	5
113	1776	344	27	10
114	2129	578	37	6
115	1946	359	31	15
116	1956	482	31	18
117	2009	193	32	8
118	2133	581	38	18
119	2006	674	32	8
120	2063	199	34	9
121	1797	581	27	11
122	1822	336	27	5
123	1746	483	26	15
124	1498	487	23	11
125	2309	580	52	10
126	1560	291	23	5
127	1967	676	31	17
128	1615	580	24	7
129	1632	770	23	5
130	1959	484	31	27
131	2239	772	43	15
132	2223	774	41	18
133	1605	579	23	6
134	2257	673	45	18
135	1457	204	22	5
136	1815	291	27	10
137	2298	770	49	19
138	1888	580	29	7
139	1925	581	29	18
140	1880	523	28	14
141	2031	565	33	21
142	1309	502	15	1
143	1424	385	21	24
144	1949	388	30	13
145	1707	581	25	23
146	2305	677	51	17
147	2025	394	33	14
148	1496	484	22	11
149	2051	483	34	5
150	1725	247	25	6

continued

Sequence Number	Board Number	Board Length	Board Width	Total Defects
#	#	inches	inches	units
151	1721	206	25	8
152	1965	580	31	25
153	1387	387	21	15
154	1562	291	23	6
155	1402	581	21	12
156	1929	770	29	31
157	1412	228	21	4
158	2323	772	52	7
159	2264	292	45	16
160	1830	404	28	14
161	2077	770	35	13
162	2097	200	37	7
163	1785	483	27	15
164	2314	402	52	9
165	1453	193	22	2
166	1348	681	17	8
167	2086	297	36	16
168	2297	675	50	29
169	1594	484	24	13
170	1588	483	23	13
171	1393	392	20	4
172	1931	770	30	12
173	2155	486	38	18
174	1608	580	24	25
175	2148	384	38	1
176	1661	291	24	6
177	1619	581	24	19
178	1971	203	31	4
179	1701	580	24	6
180	2227	390	43	10
181	1518	580	22	11
182	1539	678	22	8
183	2258	678	45	29
184	2320	678	52	36
185	2301	388	50	12
186	1512	579	23	14
187	1626	675	23	13
188	2081	773	35	31
189	1601	578	24	12
190	2132	581	38	18
191	1336	202	17	0
192	1516	580	22	5
193	1761	771	26	16
194	1490	391	22	6
195	2176	485	40	11
196	1376	579	19	9
197	1431	390	22	11
198	2293	773	48	18
199	1624	674	23	17
200	1896	192	29	4

Table A - 2: Boards 201 to 300 according to distribution by Wiedenbeck et al. 1996, continued

Sequence Number	Board Number	Board Length	Board Width	Total Defects
#	#	inches	inches	units
201	2138	679	38	13
202	1446	580	22	17
203	1501	490	22	13
204	1715	197	25	19
205	1455	194	23	3
206	1547	771	23	19
207	2157	486	39	11
208	1754	576	26	6
209	2303	486	51	25
210	1646	197	24	12
211	2260	771	45	14
212	1537	677	23	19
213	1623	674	24	13
214	1633	771	23	2
215	771	657	9	0
216	1543	769	23	11
217	2037	194	33	3
218	1503	504	22	12
219	2219	487	42	10
220	1509	578	23	13
221	2146	336	39	6
222	2064	291	34	15
223	1905	291	29	30
224	1411	205	22	4
225	1718	199	25	4
226	1586	483	23	7
227	2005	674	32	10
228	1993	461	32	13
229	1996	482	31	7
230	2135	676	38	16
231	1508	576	22	6
232	1600	559	23	14
233	1970	200	31	6
234	2139	680	37	15
235	1416	293	22	12
236	1847	770	28	20
237	1789	520	27	20
238	2279	483	47	19
239	1796	580	26	20
240	1403	582	20	9
241	2253	483	44	35
242	1522	580	23	14
243	1441	501	21	12
244	1610	580	24	14
245	1343	392	18	12
246	2112	679	37	26
247	2034	581	32	21
248	1538	677	23	19
249	2120	384	37	2
250	2300	386	50	27

continued

Sequence Number	Board Number	Board Length	Board Width	Total Defects
#	#	inches	inches	units
251	1702	580	24	9
252	1690	484	25	25
253	1913	436	29	12
254	1531	675	22	13
255	1696	553	24	13
256	2140	683	37	13
257	2136	677	38	28
258	2149	386	38	11
259	1885	580	28	7
260	2060	770	33	21
261	2241	223	43	13
262	1760	770	25	36
263	1450	675	22	24
264	2164	770	38	8
265	1930	770	29	23
266	2312	581	51	21
267	1720	203	25	15
268	2306	206	51	7
269	1928	676	29	24
270	1603	579	24	11
271	1534	677	23	12
272	1486	389	22	4
273	2185	679	40	24
274	1919	484	30	28
275	2002	580	32	11
276	1857	204	28	3
277	2011	249	33	9
278	1839	579	28	9
279	1404	629	20	5
280	1445	580	21	13
281	1986	387	31	12
282	1923	580	29	8
283	2039	198	33	7
284	1877	483	29	14
285	1627	732	23	1
286	2161	676	38	17
287	1613	580	24	5
288	1371	484	20	25
289	2226	386	43	10
290	1709	768	24	8
291	2083	246	35	7
292	1614	580	23	5
293	1544	770	22	5
294	1333	583	17	17
295	2062	198	34	12
296	1933	773	29	15
297	2278	462	47	33
298	2182	675	39	13
299	1593	484	23	10
300	2208	486	41	22

Table A - 2: Boards 301 to 400 according to distribution by Wiedenbeck et al. 1996, continued

Sequence Number	Board Number	Board Length	Board Width	Total Defects
#	#	inches	inches	units
301	2169	384	39	4
302	2238	676	43	39
303	1589	483	23	14
304	1566	298	24	19
305	1917	484	30	16
306	1940	223	31	9
307	2265	292	45	3
308	2099	213	36	10
309	2216	384	41	7
310	2058	759	34	16
311	2033	580	32	8
312	2163	770	38	18
313	1337	252	18	7
314	2285	772	48	23
315	1898	196	29	7
316	1575	381	24	18
317	2079	770	34	41
318	2308	579	51	21
319	1590	483	23	10
320	2210	487	40	12
321	2244	390	43	22
322	1342	392	17	5
323	1443	576	22	24
324	2317	580	52	11
325	1448	582	22	16
326	2261	200	45	9
327	1530	645	23	24
328	1683	483	24	5
329	1415	292	21	8
330	1894	773	29	13
331	2184	678	39	22
332	2304	581	50	22
333	2189	192	41	8
334	2272	481	46	24
335	1536	677	22	8
336	1974	241	31	13
337	1631	770	23	18
338	2245	390	44	8
339	1413	240	21	10
340	1414	292	21	5
341	2228	391	43	11
342	1766	260	26	9
343	2007	677	31	16
344	1507	576	23	10
345	1373	508	20	8
346	1599	493	23	5
347	2313	676	52	22
348	2119	384	37	5
349	1526	581	23	10
350	2220	578	42	13

continued

Sequence Number	Board Number	Board Length	Board Width	Total Defects
#	#	inches	inches	units
351	1451	676	22	18
352	2186	770	39	32
353	1370	483	19	12
354	1506	573	23	22
355	1535	677	23	17
356	1515	580	22	15
357	1352	343	19	8
358	1306	493	16	10
359	2008	771	32	31
360	1456	199	22	2
361	1339	387	17	6
362	1606	580	24	21
363	2102	386	36	12
364	1372	504	19	5
365	1972	215	31	9
366	1365	387	19	8
367	1541	686	22	14
368	1900	244	29	9
369	2101	384	36	4
370	2061	194	34	3
371	1312	532	16	10
372	1597	487	24	13
373	1540	682	23	10
374	1975	247	32	6
375	2038	196	33	1
376	2059	770	34	11
377	1532	675	23	25
378	1335	587	16	5
379	1973	227	31	5
380	1542	692	23	20
381	2040	199	33	3
382	1937	211	30	19
383	1383	324	21	12
384	1510	578	22	16
385	2056	580	34	23
386	1334	587	17	9
387	2168	301	39	6
388	1382	291	20	10
389	2041	208	33	7
390	1598	491	23	3
391	1716	198	25	8
392	1300	387	15	4
393	1853	198	29	20
394	1360	624	19	14
395	1329	486	16	2
396	1287	392	14	3
397	1717	198	25	9
398	1767	288	26	10
399	1596	486	24	8
400	1289	393	15	6

Table A - 2: Boards 401 to 485 according to distribution by Wiedenbeck et al. 1996, continued

Sequence Number	Board Number	Board Length	Board Width	Total Defects
#	#	inches	inches	units
401	1316	583	16	8
402	1805	198	27	11
403	1545	770	22	11
404	1391	390	20	5
405	1359	587	19	13
406	1317	588	16	9
407	1308	496	15	7
408	1968	677	31	24
409	1294	492	15	4
410	1691	484	25	6
411	1719	202	26	14
412	1850	195	28	5
413	1323	388	16	3
414	1328	485	16	13
415	1533	676	23	19
416	1764	204	26	6
417	1932	771	29	9
418	1804	198	28	9
419	1706	580	24	8
420	1704	580	24	3
421	1505	539	23	13
422	1381	285	20	7
423	1321	384	17	6
424	1891	770	28	32
425	1340	388	17	2
426	1840	579	27	16
427	1697	578	25	7
428	1798	675	27	19
429	1800	193	27	8
430	1790	528	27	21
431	1447	580	22	13
432	1966	676	31	33
433	1351	299	19	7
434	1364	380	20	13
435	1763	199	26	17
436	1380	248	20	7
437	2004	636	32	24
438	1579	384	23	2
439	1887	580	28	10
440	1504	526	23	19
441	1319	295	16	1
442	1375	509	19	6
443	1795	580	26	15
444	1703	580	25	17
445	1699	579	25	21
446	1572	336	23	9
447	1837	577	28	8
448	1529	644	22	10
449	1630	770	23	15
450	1629	770	23	8

continued

Sequence Number	Board Number	Board Length	Board Width	Total Defects
#	#	inches	inches	units
451	1311	518	15	4
452	1338	290	17	2
453	1546	770	23	20
454	1384	333	21	7
455	1407	675	20	8
456	1527	586	23	17
457	1521	580	22	9
458	1554	194	24	5
459	1548	771	22	5
460	1298	582	14	0
461	1318	291	16	6
462	1361	291	20	9
463	1363	300	20	12
464	1353	390	19	9
465	1500	488	22	10
466	1354	390	18	7
467	1592	484	23	11
468	1618	581	23	5
469	1499	487	22	15
470	1378	770	20	16
471	1307	494	16	9
472	1895	774	29	12
473	1356	501	18	3
474	1477	315	22	7
475	1379	212	21	6
476	1345	488	17	5
477	1428	388	21	4
478	1464	291	22	4
479	1305	492	15	3
480	1326	393	17	5
481	1301	389	15	4
482	1313	578	16	5
483	1377	587	20	9
484	1299	382	16	17
485	1303	487	15	5

Appendix C: Part quantities according to Araman et al. (1982)

Table A - 3: Part quantity distribution in percent according to Araman et al. (1982) for length range 5 to 21 inches and for width range 1.00 to 4.75 inches

	Length groups															
Width groups	5.00-6.00	6.01-7.00	7.01-8.00	8.01-9.00	9.01-10.00	10.01-11.00	11.01-12.00	12.01-13.00	13.01-14.00	14.01-15.00	15.01-16.00	16.01-17.00	17.01-18.00	18.01-19.00	19.01-20.00	20.01-21.00
1.000-1.250	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.25	0.25	0.25	0.33	0.33
1.251-1.500	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.25	0.25	0.25	0.33	0.33
1.510-1.751	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.91	0.91	0.91	0.41	0.41
1.751-2.000	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.91	0.91	0.91	0.41	0.41
2.010-2.250	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.82	0.82	0.82	0.41	0.41
2.251-2.500	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.82	0.82	0.82	0.41	0.41
2.510-2.750	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.33	0.33	0.33	0.33	0.33
2.751-3.000	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.33	0.33	0.33	0.33	0.33
3.010-3.250	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.33	0.33	0.33	0.16	0.16
3.251-3.500	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.33	0.33	0.33	0.16	0.16
3.510-3.750	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.16	0.16	0.16	0.08	0.08
3.751-4.000	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.16	0.16	0.16	0.08	0.08
4.010-4.250	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.21	0.21	0.21	0.12	0.12
4.251-4.500	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.21	0.21	0.21	0.12	0.12
4.501-4.750	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.21	0.21	0.21	0.12	0.12

Table A - 4: Example of finding the part quantity in percent for part groups L_1W_1 , L_1W_2, L_1W_3, and L_1W_4 using the part quantity distribution shown in Table A - 4

	Length groups										
Width groups	5.00-6.00	6.01-7.00	7.01-8.00	8.01-9.00	9.01-10.00	10.01-11.00	11.01-12.00	12.01-13.00	13.01-14.00	14.01-15.00	Part quantity for part group
1.000-1.250	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	
1.251-1.500	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	
1.510-1.751	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	**L_1W_1**
1.751-2.000	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	**4.04**
2.010-2.250	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	
2.251-2.500	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	
2.510-2.750	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	**L_1W_2**
2.751-3.000	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	**4.49**
3.010-3.250	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	
3.251-3.500	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	**L_1W_3**
3.510-3.750	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	**1.35**
3.751-4.000	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	
4.010-4.250	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	
4.251-4.500	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	**L_1W_4**
4.501-4.750	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	**1.46**

Appendix D: Resolution V fractional factorial design and results

Table A - 5: Fractional factorial design, results from simulation (3 replicates), average yield and estimated yield in percent, cutting bills 1 to 52

#	L_1 W_1	L_2 W_1	L_3 W_1	L_4 W_1	L_5 W_1	L_1 W_2	L_2 W_2	L_3 W_2	L_4 W_2	L_5 W_2	L_1 W_3	L_2 W_3	L_3 W_3	L_4 W_3	L_5 W_3	L_1 W_4	L_2 W_4	L_3 W_4	L_4 W_4	L_5 W_4	Results Rep 1	Rep 2	Rep 3	Av.	Model
1	-	-	-	-	-	-	-	-	-	-	+	+	+	-	-	-	-	+	+	-	55.21	55.12	53.87	54.73	56.26
2	-	-	-	-	-	-	-	-	+	+	-	-	-	+	+	+	+	-	-	+	53.71	53.44	52.44	53.20	52.73
3	-	-	-	-	-	-	-	+	-	+	-	-	-	+	+	+	+	-	+	-	59.25	59.05	59.11	59.14	58.31
4	-	-	-	-	-	-	-	+	+	-	+	+	+	-	-	-	-	+	-	+	61.06	61.05	60.42	60.84	60.51
5	-	-	-	-	-	-	+	-	-	+	-	-	-	+	-	-	-	+	-	+	57.43	57.03	56.84	57.10	56.72
6	-	-	-	-	-	-	+	-	+	-	+	+	+	-	+	+	+	-	+	-	66.64	66.64	65.89	66.39	65.79
7	-	-	-	-	-	-	+	+	-	-	+	+	+	-	+	+	+	-	-	+	66.53	66.40	65.97	66.30	65.14
8	-	-	-	-	-	-	+	+	+	+	-	-	-	+	-	-	-	+	+	-	62.64	62.68	62.28	62.53	63.39
9	-	-	-	-	-	+	-	-	-	+	-	-	+	-	+	+	-	+	-	+	55.53	55.56	55.12	55.40	55.70
10	-	-	-	-	-	+	-	-	+	-	+	+	-	+	-	-	+	-	+	-	60.49	60.57	59.88	60.31	59.92
11	-	-	-	-	-	+	-	+	-	-	+	+	-	+	-	-	+	-	-	+	64.43	64.61	64.07	64.37	62.73
12	-	-	-	-	-	+	-	+	+	+	-	-	+	-	+	+	-	+	+	-	61.89	61.90	61.53	61.77	61.96
13	-	-	-	-	-	+	+	-	-	-	+	+	-	+	+	+	-	+	+	-	61.98	62.02	62.43	62.14	63.10
14	-	-	-	-	-	+	+	-	+	+	-	-	+	-	-	-	+	-	-	+	64.03	63.95	63.54	63.84	63.03
15	-	-	-	-	-	+	+	+	-	+	-	-	+	-	-	-	+	-	+	-	66.39	66.57	65.54	66.17	66.51
16	-	-	-	-	-	+	+	+	+	-	+	+	-	+	+	+	-	+	-	+	67.40	67.66	66.88	67.31	67.14
17	-	-	-	-	+	-	-	-	-	+	-	+	-	-	+	-	+	+	-	-	52.85	52.57	52.89	52.77	55.00
18	-	-	-	-	+	-	-	-	+	-	+	-	+	+	-	+	-	-	+	+	56.71	56.60	55.55	56.29	55.86
19	-	-	-	-	+	-	-	+	-	-	+	-	+	+	-	+	-	-	-	-	59.79	59.64	59.39	59.61	59.78
20	-	-	-	-	+	-	-	+	+	+	-	+	-	-	+	-	+	+	+	+	61.61	61.60	61.29	61.50	61.64
21	-	-	-	-	+	-	+	-	-	-	+	-	+	+	+	-	+	+	+	+	62.48	62.36	61.92	62.25	62.76
22	-	-	-	-	+	-	+	-	+	+	-	+	-	-	-	+	-	-	-	-	60.29	60.83	60.58	60.57	60.02
23	-	-	-	-	+	-	+	+	-	+	-	+	-	-	-	+	-	-	+	+	61.82	61.60	61.52	61.65	61.76
24	-	-	-	-	+	-	+	+	+	-	+	-	+	+	+	-	+	+	-	-	64.82	65.21	64.63	64.89	65.11
25	-	-	-	-	+	+	-	-	-	-	+	-	-	-	-	+	+	+	+	+	60.44	60.39	59.43	60.09	59.11
26	-	-	-	-	+	+	-	-	+	+	-	+	+	+	+	-	-	-	-	-	60.25	59.85	59.88	59.99	58.88
27	-	-	-	-	+	+	-	+	-	+	-	+	+	+	+	-	-	-	+	+	63.10	62.71	62.94	62.92	62.15
28	-	-	-	-	+	+	-	+	+	-	+	-	-	-	-	+	+	+	-	-	63.12	63.12	63.05	63.10	63.72
29	-	-	-	-	+	+	+	-	-	+	-	+	+	+	-	+	+	+	-	-	66.61	66.51	66.15	66.42	66.42
30	-	-	-	-	+	+	+	-	+	-	+	-	-	-	+	-	-	-	+	+	58.60	58.61	57.64	58.28	57.79
31	-	-	-	-	+	+	+	+	-	-	+	-	-	-	+	-	-	-	-	-	61.52	61.36	60.90	61.26	61.22
32	-	-	-	-	+	+	+	+	+	+	-	+	+	+	-	+	+	+	+	+	66.60	67.02	67.04	66.89	68.11
33	-	-	-	+	-	-	-	-	-	+	-	+	+	+	-	+	-	-	+	-	60.52	60.49	59.78	60.26	60.24
34	-	-	-	+	-	-	-	-	+	-	+	-	-	-	+	-	+	+	-	+	59.52	59.52	59.22	59.42	59.19
35	-	-	-	+	-	-	-	+	-	-	+	-	-	-	+	-	+	+	+	-	61.67	61.56	61.04	61.42	60.80
36	-	-	-	+	-	-	-	+	+	+	-	+	+	+	-	+	-	-	-	+	61.72	62.15	61.45	61.77	61.31
37	-	-	-	+	-	-	+	-	-	-	+	-	-	-	-	+	-	-	-	+	54.27	54.72	53.33	54.11	55.97
38	-	-	-	+	-	-	+	-	+	+	-	+	+	+	+	-	+	+	+	-	65.36	65.69	65.04	65.36	65.28
39	-	-	-	+	-	-	+	+	-	+	-	+	+	+	+	-	+	+	-	+	66.02	66.03	65.85	65.97	66.72
40	-	-	-	+	-	-	+	+	+	-	+	-	-	-	-	+	-	-	+	-	64.06	64.06	63.96	64.03	63.79
41	-	-	-	+	-	+	-	-	-	-	+	-	+	+	+	-	-	-	-	+	56.34	55.76	56.79	56.30	57.55
42	-	-	-	+	-	+	-	-	+	+	-	+	-	-	-	+	+	+	+	-	62.78	62.48	62.19	62.48	62.15
43	-	-	-	+	-	+	-	+	-	+	-	+	-	-	-	+	+	+	-	+	64.51	64.56	64.38	64.48	64.37
44	-	-	-	+	-	+	-	+	+	-	+	-	+	+	+	-	-	-	+	-	63.41	63.46	62.90	63.26	62.48
45	-	-	-	+	-	+	+	-	-	+	-	+	-	-	+	-	-	-	+	-	62.26	61.36	62.41	62.01	61.84
46	-	-	-	+	-	+	+	-	+	-	+	-	+	+	-	+	+	+	-	+	67.04	67.01	66.83	66.96	67.21
47	-	-	-	+	-	+	+	+	-	-	+	-	+	+	-	+	+	+	+	-	67.57	67.85	67.18	67.53	66.84
48	-	-	-	+	-	+	+	+	+	+	-	+	-	-	+	-	-	-	-	+	66.01	65.20	64.98	65.40	66.14
49	-	-	-	+	+	-	-	-	-	-	+	+	-	+	+	+	+	-	-	-	60.60	60.60	60.05	60.42	60.81
50	-	-	-	+	+	-	-	-	+	+	-	-	+	-	-	-	-	+	+	+	58.32	58.36	57.89	58.19	57.99
51	-	-	-	+	+	-	-	+	-	+	-	-	+	-	-	-	-	+	-	-	60.47	60.38	60.37	60.41	60.60
52	-	-	-	+	+	-	-	+	+	-	+	+	-	+	+	+	+	-	+	+	64.15	63.75	63.68	63.86	64.29

Table A - 5: Fractional factorial design, results from simulation (3 replicates), average yield and estimated yield in percent, cutting bills 53 to 104, continued

#	L_1 W_1	L_2 W_1	L_3 W_1	L_4 W_1	L_5 W_1	L_1 W_2	L_2 W_2	L_3 W_2	L_4 W_2	L_5 W_2	L_1 W_3	L_2 W_3	L_3 W_3	L_4 W_3	L_5 W_3	L_1 W_4	L_2 W_4	L_3 W_4	L_4 W_4	L_5 W_4	Results Rep 1	Rep 2	Rep 3	Av.	Model
53	-	-	-	+	+	-	+	-	-	+	-	-	+	-	+	+	+	-	+	+	64.24	64.17	63.93	64.11	63.77
54	-	-	-	+	+	-	+	-	+	-	+	+	-	+	-	-	-	+	-	-	64.43	64.38	64.11	64.31	64.01
55	-	-	-	+	+	-	+	+	-	-	+	+	-	+	-	-	-	+	+	+	63.47	63.99	63.52	63.66	63.02
56	-	-	-	+	+	-	+	+	+	+	-	-	+	-	+	+	+	-	-	-	65.52	65.60	65.40	65.51	65.08
57	-	-	-	+	+	+	-	-	-	+	-	-	-	+	-	-	+	-	+	+	58.54	58.77	57.87	58.39	58.68
58	-	-	-	+	+	+	-	-	+	-	+	+	+	-	+	+	-	+	-	-	64.38	64.31	64.39	64.36	64.81
59	-	-	-	+	+	+	-	+	-	-	+	+	+	-	+	+	-	+	+	+	64.42	64.20	64.06	64.23	65.03
60	-	-	-	+	+	+	-	+	+	+	-	-	-	+	-	-	+	-	-	-	62.61	62.55	62.00	62.39	62.13
61	-	-	-	+	+	+	+	-	-	-	+	+	+	-	-	-	+	-	-	-	65.41	65.44	65.17	65.34	65.43
62	-	-	-	+	+	+	+	-	+	+	-	-	-	+	+	+	-	+	+	+	62.49	62.54	61.79	62.27	62.94
63	-	-	-	+	+	+	+	+	-	+	-	-	-	+	+	+	-	+	-	-	65.82	66.03	65.66	65.84	65.15
64	-	-	-	+	+	+	+	+	+	-	+	+	+	-	-	-	+	-	+	+	67.22	67.21	67.02	67.15	67.35
65	-	-	+	-	-	-	-	-	-	+	+	-	-	-	+	-	-	-	+	+	52.82	52.56	52.10	52.49	52.48
66	-	-	+	-	-	-	-	-	+	-	-	+	+	+	-	+	+	+	-	-	65.01	65.03	64.15	64.73	65.61
67	-	-	+	-	-	-	-	+	-	-	-	+	+	+	-	+	+	+	+	+	65.61	65.95	65.39	65.65	66.42
68	-	-	+	-	-	-	-	+	+	+	+	-	-	-	+	-	-	-	-	-	60.17	60.33	60.17	60.22	60.09
69	-	-	+	-	-	-	+	-	-	-	-	+	+	+	+	-	-	-	-	-	65.56	65.27	64.86	65.23	65.18
70	-	-	+	-	-	-	+	-	+	+	+	-	-	-	-	+	+	+	+	+	66.07	66.10	65.85	66.01	66.22
71	-	-	+	-	-	-	+	+	-	+	+	-	-	-	-	+	+	+	-	-	66.43	66.16	66.01	66.20	66.36
72	-	-	+	-	-	-	+	+	+	-	-	+	+	+	+	-	-	-	+	+	66.29	66.29	66.01	66.20	66.88
73	-	-	+	-	-	+	-	-	-	-	-	+	-	-	-	+	-	-	-	-	64.69	64.49	63.88	64.35	61.44
74	-	-	+	-	-	+	-	-	+	+	+	-	+	+	+	-	+	+	+	+	63.24	63.35	63.06	63.22	63.84
75	-	-	+	-	-	+	-	+	-	+	+	-	+	+	+	-	+	+	-	-	65.78	65.78	65.10	65.55	65.10
76	-	-	+	-	-	+	-	+	+	-	-	+	-	-	-	+	-	-	+	+	63.99	63.48	63.22	63.56	64.25
77	-	-	+	-	-	+	+	-	-	+	+	-	+	+	-	+	-	-	+	+	64.68	65.76	64.23	64.89	64.09
78	-	-	+	-	-	+	+	-	+	-	-	+	-	-	+	-	+	+	-	-	67.48	67.34	67.21	67.34	67.67
79	-	-	+	-	-	+	+	+	-	-	-	+	-	-	+	-	+	+	+	+	67.84	67.76	67.54	67.71	67.79
80	-	-	+	-	-	+	+	+	+	+	+	-	+	+	-	+	-	-	-	-	68.44	68.29	67.93	68.22	68.50
81	-	-	+	-	+	-	-	-	-	-	-	-	+	-	-	-	+	-	-	+	60.73	60.23	60.06	60.34	60.17
82	-	-	+	-	+	-	-	-	+	+	+	+	-	+	+	+	-	+	+	-	62.69	62.62	62.38	62.56	62.96
83	-	-	+	-	+	-	-	+	-	+	+	+	-	+	+	+	-	+	-	+	65.03	65.06	64.67	64.92	64.44
84	-	-	+	-	+	-	-	+	+	-	-	-	+	-	-	-	+	-	+	-	63.67	63.59	63.46	63.57	64.71
85	-	-	+	-	+	-	+	-	-	+	+	+	-	+	-	-	+	-	+	-	66.24	66.08	66.03	66.12	65.74
86	-	-	+	-	+	-	+	-	+	-	-	-	+	-	+	+	-	+	-	+	65.23	65.00	65.35	65.19	65.64
87	-	-	+	-	+	-	+	+	-	-	-	-	+	-	+	+	-	+	+	-	65.25	65.65	65.38	65.43	65.50
88	-	-	+	-	+	-	+	+	+	+	+	+	-	+	-	-	+	-	-	+	67.10	67.32	66.91	67.11	67.77
89	-	-	+	-	+	+	-	-	-	+	+	+	+	-	+	+	+	-	+	-	66.83	66.64	66.24	66.57	66.18
90	-	-	+	-	+	+	-	-	+	-	-	-	-	+	-	-	-	+	-	+	61.17	61.72	60.88	61.26	61.78
91	-	-	+	-	+	+	-	+	-	-	-	-	-	+	-	-	-	+	+	-	63.51	63.34	62.21	63.02	63.18
92	-	-	+	-	+	+	-	+	+	+	+	+	+	-	+	+	+	-	-	+	66.27	66.39	65.90	66.19	66.13
93	-	-	+	-	+	+	+	-	-	-	-	-	-	+	+	+	+	-	-	+	65.26	64.82	64.93	65.00	64.22
94	-	-	+	-	+	+	+	-	+	+	+	+	+	-	-	-	-	+	+	-	67.61	67.18	66.31	67.03	67.00
95	-	-	+	-	+	+	+	+	-	+	+	+	+	-	-	-	-	+	-	+	67.85	67.90	67.53	67.76	67.16
96	-	-	+	-	+	+	+	+	+	-	-	-	-	+	+	+	+	-	+	-	68.14	67.93	67.63	67.90	67.70
97	-	-	+	+	-	-	-	-	-	-	-	-	-	+	+	+	-	+	+	+	60.07	59.64	59.42	59.71	58.54
98	-	-	+	+	-	-	-	-	+	+	+	+	+	-	-	-	+	-	-	-	62.26	62.08	62.11	62.15	62.37
99	-	-	+	+	-	-	-	+	-	+	+	+	+	-	-	-	+	-	+	+	65.48	65.72	65.38	65.53	65.18
100	-	-	+	+	-	-	-	+	+	-	-	-	-	+	+	+	-	+	-	-	63.24	63.10	63.00	63.11	63.28
101	-	-	+	+	-	-	+	-	-	+	+	+	+	-	+	+	-	+	-	-	66.43	66.38	66.31	66.37	66.54
102	-	-	+	+	-	-	+	-	+	-	-	-	-	+	-	-	+	-	+	+	64.99	65.02	64.79	64.93	65.10
103	-	-	+	+	-	-	+	+	-	-	-	-	-	+	-	-	+	-	-	-	65.15	65.12	64.94	65.07	65.94
104	-	-	+	+	-	-	+	+	+	+	+	+	+	-	+	+	-	+	+	+	66.17	65.95	66.57	66.23	66.25

Table A - 5: Fractional factorial design, results from simulation (3 replicates), average yield and estimated yield in percent, cutting bills 105 to 156, continued

#	L_1 W_1	L_2 W_1	L_3 W_1	L_4 W_1	L_5 W_1	L_1 W_2	L_2 W_2	L_3 W_2	L_4 W_2	L_5 W_2	L_1 W_3	L_2 W_3	L_3 W_3	L_4 W_3	L_5 W_3	L_1 W_4	L_2 W_4	L_3 W_4	L_4 W_4	L_5 W_4	Results Rep 1	Rep 2	Rep 3	Av.	Model
105	-	-	+	+	-	+	-	-	-	+	+	+	-	+	-	-	-	+	-	-	63.53	63.74	63.36	63.54	64.05
106	-	-	+	+	-	+	-	-	+	-	-	-	+	-	+	+	+	-	+	+	65.10	65.23	64.66	65.00	64.78
107	-	-	+	+	-	+	-	+	-	-	-	-	+	-	+	+	+	-	-	-	65.06	65.28	65.00	65.11	66.00
108	-	-	+	+	-	+	-	+	+	+	+	+	-	+	-	-	-	+	+	+	63.43	64.30	64.00	63.91	64.34
109	-	-	+	+	-	+	+	-	-	-	-	-	+	-	-	-	-	+	+	+	63.33	62.85	63.12	63.10	63.09
110	-	-	+	+	-	+	+	-	+	+	+	+	-	+	+	+	+	-	-	-	68.39	68.27	68.17	68.28	68.24
111	-	-	+	+	-	+	+	+	-	+	+	+	-	+	+	+	+	-	+	+	69.00	69.13	68.80	68.98	69.31
112	-	-	+	+	-	+	+	+	+	-	-	-	+	-	-	-	-	+	-	-	67.21	67.27	67.11	67.20	66.89
113	-	-	+	+	+	-	-	-	-	+	+	-	+	+	-	+	+	+	-	+	64.26	64.27	63.94	64.16	64.28
114	-	-	+	+	+	-	-	-	+	-	-	+	-	-	+	-	-	-	+	-	61.42	61.58	61.24	61.41	61.08
115	-	-	+	+	+	-	-	+	-	-	-	+	-	-	+	-	-	-	-	+	61.81	61.71	61.12	61.55	62.29
116	-	-	+	+	+	-	-	+	+	+	+	-	+	+	-	+	+	+	+	-	64.83	64.75	64.69	64.76	63.67
117	-	-	+	+	+	-	+	-	-	-	-	+	-	-	-	+	+	+	+	-	64.87	65.02	64.48	64.79	65.36
118	-	-	+	+	+	-	+	-	+	+	+	-	+	+	+	-	-	-	-	+	65.04	64.84	64.11	64.66	65.09
119	-	-	+	+	+	-	+	+	-	+	+	-	+	+	+	-	-	-	+	-	65.96	66.06	65.63	65.88	66.21
120	-	-	+	+	+	-	+	+	+	-	-	+	-	-	-	+	+	+	-	+	66.65	66.64	66.37	66.55	65.99
121	-	-	+	+	+	+	-	-	-	-	-	+	+	+	+	-	+	+	+	-	66.18	66.04	66.02	66.08	64.93
122	-	-	+	+	+	+	-	-	+	+	+	-	-	-	-	+	-	-	-	+	61.13	61.46	60.61	61.07	60.56
123	-	-	+	+	+	+	-	+	-	+	+	-	-	-	-	+	-	-	+	-	64.58	64.33	64.47	64.46	64.85
124	-	-	+	+	+	+	-	+	+	-	-	+	+	+	+	-	+	+	-	+	66.07	66.16	65.90	66.04	65.32
125	-	-	+	+	+	+	+	-	-	+	+	-	-	-	+	-	+	+	-	+	65.82	65.72	65.61	65.72	66.07
126	-	-	+	+	+	+	+	-	+	-	-	+	+	+	-	+	-	-	+	-	67.78	67.84	67.56	67.73	67.88
127	-	-	+	+	+	+	+	+	-	-	-	+	+	+	-	+	-	-	-	+	67.68	67.76	66.82	67.42	66.69
128	-	-	+	+	+	+	+	+	+	+	+	-	-	-	+	-	+	+	+	-	66.86	67.11	66.77	66.91	66.62
129	-	+	-	-	-	-	-	-	-	+	+	-	+	+	-	-	+	-	-	-	59.26	58.91	58.74	58.97	58.86
130	-	+	-	-	-	-	-	-	+	-	-	+	-	-	+	+	-	+	+	+	58.98	58.98	58.62	58.86	58.18
131	-	+	-	-	-	-	-	+	-	-	-	+	-	-	+	+	-	+	-	-	62.91	62.80	62.31	62.67	62.99
132	-	+	-	-	-	-	-	+	+	+	+	-	+	+	-	-	+	-	+	+	63.25	63.36	63.11	63.24	63.06
133	-	+	-	-	-	-	+	-	-	-	-	+	-	-	-	-	+	-	+	+	63.95	62.96	63.66	63.52	61.80
134	-	+	-	-	-	-	+	-	+	+	+	-	+	+	+	+	-	+	-	-	65.20	65.79	64.76	65.25	64.99
135	-	+	-	-	-	-	+	+	-	+	+	-	+	+	+	+	-	+	+	+	65.07	65.87	65.00	65.31	65.07
136	-	+	-	-	-	-	+	+	+	-	-	+	-	-	-	-	+	-	-	-	65.82	65.93	65.43	65.73	66.84
137	-	+	-	-	-	+	-	-	-	-	-	+	+	+	+	+	+	-	+	+	65.39	65.22	64.60	65.07	65.06
138	-	+	-	-	-	+	-	-	+	+	+	-	-	-	-	-	-	+	-	-	57.73	58.06	57.71	57.83	58.06
139	-	+	-	-	-	+	-	+	-	+	+	-	-	-	-	-	-	+	+	+	60.42	61.15	60.80	60.79	60.22
140	-	+	-	-	-	+	-	+	+	-	-	+	+	+	+	+	+	-	-	-	66.12	66.32	65.54	65.99	67.26
141	-	+	-	-	-	+	+	-	-	+	+	-	-	-	+	+	+	-	-	-	61.66	60.54	60.30	60.83	62.78
142	-	+	-	-	-	+	+	-	+	-	-	+	+	+	-	-	-	+	+	+	65.76	65.56	64.82	65.38	65.21
143	-	+	-	-	-	+	+	+	-	-	-	+	+	+	-	-	-	+	-	-	68.64	68.96	68.35	68.65	69.04
144	-	+	-	-	-	+	+	+	+	+	+	-	-	-	+	+	+	-	+	+	68.08	68.25	67.62	67.98	67.64
145	-	+	-	-	+	-	-	-	-	-	-	-	-	+	+	-	-	-	+	-	52.14	52.11	52.30	52.18	52.59
146	-	+	-	-	+	-	-	-	+	+	+	+	+	-	-	+	+	+	-	+	64.10	63.99	64.05	64.05	62.88
147	-	+	-	-	+	-	-	+	-	+	+	+	+	-	-	+	+	+	+	-	66.51	66.57	66.26	66.45	65.79
148	-	+	-	-	+	-	-	+	+	-	-	-	-	+	+	-	-	-	-	+	59.90	59.48	58.25	59.21	58.30
149	-	+	-	-	+	-	+	-	-	+	+	+	+	-	+	-	-	-	-	+	61.81	61.72	59.70	61.08	61.81
150	-	+	-	-	+	-	+	-	+	-	-	-	-	+	-	+	+	+	+	-	66.55	66.41	66.19	66.38	66.67
151	-	+	-	-	+	-	+	+	-	-	-	-	-	+	-	+	+	+	-	+	67.02	66.75	66.57	66.78	67.51
152	-	+	-	-	+	-	+	+	+	+	+	+	+	-	+	-	-	-	+	-	67.43	67.57	67.34	67.45	67.64
153	-	+	-	-	+	+	-	-	-	+	+	+	-	+	-	+	-	-	-	+	56.64	57.26	57.22	57.04	58.73
154	-	+	-	-	+	+	-	-	+	-	-	-	+	-	+	-	+	+	+	-	64.20	64.27	63.65	64.04	62.87
155	-	+	-	-	+	+	-	+	-	-	-	-	+	-	+	-	+	+	-	+	65.63	65.57	65.03	65.41	65.56
156	-	+	-	-	+	+	-	+	+	+	+	+	-	+	-	+	-	-	+	-	65.98	65.82	65.53	65.78	65.09

Table A - 5: Fractional factorial design, results from simulation (3 replicates), average yield and estimated yield in percent, cutting bills 157 to 208, continued

#	L_1 W_1	L_2 W_1	L_3 W_1	L_4 W_1	L_5 W_1	L_1 W_2	L_2 W_2	L_3 W_2	L_4 W_2	L_5 W_2	L_1 W_3	L_2 W_3	L_3 W_3	L_4 W_3	L_5 W_3	L_1 W_4	L_2 W_4	L_3 W_4	L_4 W_4	L_5 W_4	Results Rep 1	Rep 2	Rep 3	Av.	Model
157	-	+	-	-	+	+	+	-	-	-	-	-	+	-	-	+	-	-	+	-	67.44	66.32	65.48	66.41	65.35
158	-	+	-	-	+	+	+	-	+	+	+	+	-	+	+	-	+	+	-	+	68.21	68.40	68.41	68.34	68.12
159	-	+	-	-	+	+	+	+	-	+	+	+	-	+	+	-	+	+	+	-	68.63	68.88	68.63	68.71	68.66
160	-	+	-	-	+	+	+	+	+	-	-	-	+	-	-	+	-	-	-	+	67.45	67.28	66.55	67.09	67.57
161	-	+	-	+	-	-	-	-	-	-	-	-	+	-	-	+	+	+	-	-	66.49	66.52	66.24	66.42	65.25
162	-	+	-	+	-	-	-	-	+	+	+	+	-	+	+	-	-	-	+	+	58.76	58.97	59.08	58.94	59.69
163	-	+	-	+	-	-	-	+	-	+	+	+	-	+	+	-	-	-	-	-	64.93	65.10	65.10	65.04	64.64
164	-	+	-	+	-	-	-	+	+	-	-	-	+	-	-	+	+	+	+	+	64.78	65.24	64.90	64.97	65.88
165	-	+	-	+	-	-	+	-	-	+	+	+	-	+	-	+	+	+	+	+	68.45	67.97	67.97	68.13	67.34
166	-	+	-	+	-	-	+	-	+	-	-	-	+	-	+	-	-	-	-	-	66.76	66.44	66.54	66.58	65.73
167	-	+	-	+	-	-	+	+	-	-	-	-	+	-	+	-	-	-	+	+	65.14	65.09	64.59	64.94	65.15
168	-	+	-	+	-	-	+	+	+	+	+	+	-	+	-	+	+	+	-	-	68.80	68.87	68.58	68.75	67.88
169	-	+	-	+	-	+	-	-	-	+	+	+	+	-	+	-	+	+	+	+	66.44	66.58	66.09	66.37	66.38
170	-	+	-	+	-	+	-	-	+	-	-	-	-	+	-	+	-	-	-	-	62.07	62.52	61.71	62.10	63.03
171	-	+	-	+	-	+	-	+	-	-	-	-	-	+	-	+	-	-	+	+	63.36	63.59	63.49	63.48	63.49
172	-	+	-	+	-	+	-	+	+	+	+	+	+	-	+	-	+	+	-	-	66.95	67.05	66.53	66.84	66.34
173	-	+	-	+	-	+	+	-	-	-	-	-	-	+	+	-	+	+	-	-	66.47	66.27	66.09	66.28	66.28
174	-	+	-	+	-	+	+	-	+	+	+	+	+	-	-	+	-	-	+	+	66.69	67.24	66.60	66.84	67.53
175	-	+	-	+	-	+	+	+	-	+	+	+	+	-	-	+	-	-	-	-	70.31	70.13	69.85	70.10	70.76
176	-	+	-	+	-	+	+	+	+	-	-	-	-	+	+	-	+	+	+	+	67.24	67.51	67.16	67.30	67.04
177	-	+	-	+	+	-	-	-	-	+	+	-	-	-	+	+	-	+	+	-	59.90	59.86	58.96	59.57	59.86
178	-	+	-	+	+	-	-	-	+	-	-	+	+	+	-	-	+	-	-	+	65.00	64.94	64.81	64.92	64.65
179	-	+	-	+	+	-	-	+	-	-	-	+	+	+	-	-	+	-	+	-	66.06	65.39	65.63	65.69	66.72
180	-	+	-	+	+	-	-	+	+	+	+	-	-	-	+	+	-	+	-	+	62.89	63.52	62.75	63.05	63.07
181	-	+	-	+	+	-	+	-	-	-	-	+	+	+	+	+	-	+	-	+	67.19	67.37	66.01	66.86	66.72
182	-	+	-	+	+	-	+	-	+	+	+	-	-	-	-	-	+	-	+	-	66.28	66.39	66.13	66.27	65.92
183	-	+	-	+	+	-	+	+	-	+	+	-	-	-	-	-	+	-	-	+	66.81	66.95	66.74	66.83	66.48
184	-	+	-	+	+	-	+	+	+	-	-	+	+	+	+	+	-	+	+	-	66.96	66.52	66.56	66.68	66.35
185	-	+	-	+	+	+	-	-	-	-	-	+	-	-	-	-	-	+	-	+	61.62	61.74	61.29	61.55	61.98
186	-	+	-	+	+	+	-	-	+	+	+	-	+	+	+	+	+	-	+	-	65.02	65.24	64.81	65.02	65.97
187	-	+	-	+	+	+	-	+	-	+	+	-	+	+	+	+	+	-	-	+	67.20	67.09	67.05	67.11	67.28
188	-	+	-	+	+	+	-	+	+	-	-	+	-	-	-	-	-	+	+	-	64.58	64.72	63.98	64.43	64.37
189	-	+	-	+	+	+	+	-	-	+	+	-	+	+	-	-	-	+	+	-	66.48	65.56	65.87	65.97	65.57
190	-	+	-	+	+	+	+	-	+	-	-	+	-	-	+	+	+	-	-	+	69.98	69.58	69.38	69.65	69.14
191	-	+	-	+	+	+	+	+	-	-	-	+	-	-	+	+	+	-	+	-	69.93	69.86	69.61	69.80	70.45
192	-	+	-	+	+	+	+	+	+	+	+	-	+	+	-	-	-	+	-	+	67.17	67.39	67.21	67.26	67.13
193	-	+	+	-	-	-	-	-	-	-	+	+	-	+	+	-	+	+	-	+	66.05	66.03	65.66	65.91	65.77
194	-	+	+	-	-	-	-	-	+	+	-	-	+	-	-	+	-	-	+	-	61.71	61.90	61.79	61.80	63.03
195	-	+	+	-	-	-	-	+	-	+	-	-	+	-	-	+	-	-	-	+	62.57	62.56	62.90	62.68	62.79
196	-	+	+	-	-	-	-	+	+	-	+	+	-	+	+	-	+	+	+	-	66.76	66.70	66.21	66.56	66.14
197	-	+	+	-	-	-	+	-	-	+	-	-	+	-	+	-	+	+	+	-	66.68	66.35	66.31	66.45	66.37
198	-	+	+	-	-	-	+	-	+	-	+	+	-	+	-	+	-	-	-	+	67.68	67.94	65.50	67.04	66.50
199	-	+	+	-	-	-	+	+	-	-	+	+	-	+	-	+	-	-	+	-	68.84	68.61	68.48	68.64	69.16
200	-	+	+	-	-	-	+	+	+	+	-	-	+	-	+	-	+	+	-	+	67.69	67.20	67.25	67.38	67.73
201	-	+	+	-	-	+	-	-	-	+	-	-	-	+	-	+	+	+	+	-	66.26	65.86	65.42	65.85	66.02
202	-	+	+	-	-	+	-	-	+	-	+	+	+	-	+	-	-	-	-	+	64.08	64.18	63.97	64.08	65.17
203	-	+	+	-	-	+	-	+	-	-	+	+	+	-	+	-	-	-	+	-	68.41	68.66	68.08	68.38	68.58
204	-	+	+	-	-	+	-	+	+	+	-	-	-	+	-	+	+	+	-	+	67.11	66.82	66.23	66.72	67.06
205	-	+	+	-	-	+	+	-	-	-	+	+	+	-	-	+	+	+	-	+	69.64	69.49	69.39	69.51	70.54
206	-	+	+	-	-	+	+	-	+	+	-	-	-	+	+	-	-	-	+	-	65.24	65.62	65.05	65.30	64.88
207	-	+	+	-	-	+	+	+	-	+	-	-	-	+	+	-	-	-	-	+	67.25	66.98	67.03	67.09	65.88
208	-	+	+	-	-	+	+	+	+	-	+	+	+	-	-	+	+	+	+	-	70.43	70.36	70.03	70.27	69.40

Table A - 5: Fractional factorial design, results from simulation (3 replicates), average yield and estimated yield in percent, cutting bills 209 to 260, continued

#	L_1 W_1	L_2 W_1	L_3 W_1	L_4 W_1	L_5 W_1	L_1 W_2	L_2 W_2	L_3 W_2	L_4 W_2	L_5 W_2	L_1 W_3	L_2 W_3	L_3 W_3	L_4 W_3	L_5 W_3	L_1 W_4	L_2 W_4	L_3 W_4	L_4 W_4	L_5 W_4	Results Rep 1	Rep 2	Rep 3	Av.	Model
209	-	+	+	-	+	-	-	-	-	+	-	+	+	+	-	-	-	+	+	+	63.36	63.40	62.47	63.08	63.08
210	-	+	+	-	+	-	-	-	+	-	+	-	-	-	+	+	+	-	-	-	63.95	63.79	63.34	63.69	63.81
211	-	+	+	-	+	-	-	+	-	-	+	-	-	-	+	+	+	-	+	+	65.90	65.99	65.81	65.90	65.82
212	-	+	+	-	+	-	-	+	+	+	-	+	+	+	-	-	-	+	-	-	65.60	65.64	65.34	65.53	64.69
213	-	+	+	-	+	-	+	-	-	-	+	-	-	-	-	-	-	+	-	-	65.54	65.48	65.03	65.35	64.88
214	-	+	+	-	+	-	+	-	+	+	-	+	+	+	+	+	+	-	+	+	68.80	68.73	68.57	68.70	69.32
215	-	+	+	-	+	-	+	+	-	+	-	+	+	+	+	+	+	-	-	-	68.69	68.35	68.35	68.46	68.26
216	-	+	+	-	+	-	+	+	+	-	+	-	-	-	-	-	-	+	+	+	66.42	66.76	66.42	66.53	66.50
217	-	+	+	-	+	+	-	-	-	-	+	-	+	+	+	+	-	+	-	-	67.05	67.06	66.85	66.99	66.54
218	-	+	+	-	+	+	-	-	+	+	-	+	-	-	-	-	+	-	+	+	64.88	65.08	65.08	65.01	65.05
219	-	+	+	-	+	+	-	+	-	+	-	+	-	-	-	-	+	-	-	-	67.07	66.92	66.66	66.88	66.86
220	-	+	+	-	+	+	-	+	+	-	+	-	+	+	+	+	-	+	+	+	64.61	65.56	65.16	65.11	65.37
221	-	+	+	-	+	+	+	-	-	+	-	+	-	-	+	+	-	+	+	+	67.38	66.92	66.22	66.84	66.85
222	-	+	+	-	+	+	+	-	+	-	+	-	+	+	-	-	+	-	-	-	69.78	69.64	69.39	69.60	70.24
223	-	+	+	-	+	+	+	+	-	-	+	-	+	+	-	-	+	-	+	+	69.64	69.70	69.31	69.55	69.86
224	-	+	+	-	+	+	+	+	+	+	-	+	-	-	+	+	-	+	-	-	69.59	69.68	69.25	69.51	69.68
225	-	+	+	+	-	-	-	-	-	+	-	+	-	-	+	+	+	-	-	+	63.87	64.17	62.79	63.61	63.16
226	-	+	+	+	-	-	-	-	+	-	+	-	+	+	-	-	-	+	+	-	64.22	63.98	62.95	63.72	63.70
227	-	+	+	+	-	-	-	+	-	-	+	-	+	+	-	-	-	+	-	+	65.24	65.24	65.42	65.30	65.35
228	-	+	+	+	-	-	-	+	+	+	-	+	-	-	+	+	+	-	+	-	66.26	66.70	65.74	66.23	66.08
229	-	+	+	+	-	-	+	-	-	-	+	-	+	+	+	+	+	-	+	-	67.86	67.87	67.72	67.82	68.56
230	-	+	+	+	-	-	+	-	+	+	-	+	-	-	-	-	-	+	-	+	67.02	66.98	65.85	66.62	66.55
231	-	+	+	+	-	-	+	+	-	+	-	+	-	-	-	-	-	+	+	-	67.07	67.27	66.79	67.04	67.31
232	-	+	+	+	-	-	+	+	+	-	+	-	+	+	+	+	+	-	-	+	68.52	68.51	68.37	68.47	67.20
233	-	+	+	+	-	+	-	-	-	-	+	-	-	-	-	-	+	-	+	-	65.93	65.79	65.69	65.80	65.59
234	-	+	+	+	-	+	-	-	+	+	-	+	+	+	+	+	-	+	-	+	66.80	67.09	66.53	66.81	66.14
235	-	+	+	+	-	+	-	+	-	+	-	+	+	+	+	+	-	+	+	-	67.29	67.29	67.24	67.27	67.77
236	-	+	+	+	-	+	-	+	+	-	+	-	-	-	-	-	+	-	-	+	67.02	66.64	66.42	66.69	67.35
237	-	+	+	+	-	+	+	-	-	+	-	+	+	+	-	-	+	-	-	+	69.16	68.84	68.65	68.88	69.29
238	-	+	+	+	-	+	+	-	+	-	+	-	-	-	+	+	-	+	+	-	68.05	67.82	67.60	67.82	67.62
239	-	+	+	+	-	+	+	+	-	-	+	-	-	-	+	+	-	+	-	+	68.71	68.38	68.52	68.54	67.84
240	-	+	+	+	-	+	+	+	+	+	-	+	+	+	-	-	+	-	+	-	69.33	69.15	69.03	69.17	68.22
241	-	+	+	+	+	-	-	-	-	-	+	+	+	-	-	+	-	-	+	+	65.54	65.82	65.40	65.59	64.70
242	-	+	+	+	+	-	-	-	+	+	-	-	-	+	+	-	+	+	-	-	64.05	63.71	63.67	63.81	63.95
243	-	+	+	+	+	-	-	+	-	+	-	-	-	+	+	-	+	+	+	+	64.86	65.06	66.04	65.32	66.31
244	-	+	+	+	+	-	-	+	+	-	+	+	+	-	-	+	-	-	-	-	66.88	66.85	66.53	66.75	66.75
245	-	+	+	+	+	-	+	-	-	+	-	-	-	+	-	+	-	-	-	-	66.31	66.46	66.16	66.31	66.21
246	-	+	+	+	+	-	+	-	+	-	+	+	+	-	+	-	+	+	+	+	68.25	68.34	68.05	68.21	68.88
247	-	+	+	+	+	-	+	+	-	-	+	+	+	-	+	-	+	+	-	-	68.62	68.76	67.94	68.44	67.32
248	-	+	+	+	+	-	+	+	+	+	-	-	-	+	-	+	-	-	+	+	67.26	67.02	66.99	67.09	67.07
249	-	+	+	+	+	+	-	-	-	+	-	-	+	-	+	-	-	-	-	-	65.36	65.38	65.06	65.27	64.36
250	-	+	+	+	+	+	-	-	+	-	+	+	-	+	-	+	+	+	+	+	68.64	68.48	68.29	68.47	68.60
251	-	+	+	+	+	+	-	+	-	-	+	+	-	+	-	+	+	+	-	-	69.45	69.64	69.55	69.55	69.99
252	-	+	+	+	+	+	-	+	+	+	-	-	+	-	+	-	-	-	+	+	65.60	65.62	65.44	65.55	65.83
253	-	+	+	+	+	+	+	-	-	-	+	+	-	+	+	-	-	-	+	+	66.75	66.49	67.15	66.80	66.93
254	-	+	+	+	+	+	+	-	+	+	-	-	+	-	-	+	+	+	-	-	69.53	69.49	69.31	69.44	69.60
255	-	+	+	+	+	+	+	+	-	+	-	-	+	-	-	+	+	+	+	+	69.18	68.91	68.81	68.97	69.25
256	-	+	+	+	+	+	+	+	+	-	+	+	-	+	+	-	-	-	-	-	69.65	69.73	69.60	69.66	70.09
257	+	-	-	-	-	-	-	-	-	+	+	+	-	-	-	+	+	-	-	+	49.00	48.80	48.09	48.63	52.90
258	+	-	-	-	-	-	-	-	+	-	-	-	+	+	+	-	-	+	+	-	56.47	56.27	56.01	56.25	55.73
259	+	-	-	-	-	-	-	+	-	-	-	-	+	+	+	-	-	+	-	+	59.02	59.09	58.71	58.94	58.81
260	+	-	-	-	-	-	-	+	+	+	+	+	-	-	-	+	+	-	+	-	61.46	61.19	60.86	61.17	60.69

Table A - 5: Fractional factorial design, results from simulation (3 replicates), average yield and estimated yield in percent, cutting bills 261 to 312, continued

#	L_1 W_1	L_2 W_1	L_3 W_1	L_4 W_1	L_5 W_1	L_1 W_2	L_2 W_2	L_3 W_2	L_4 W_2	L_5 W_2	L_1 W_3	L_2 W_3	L_3 W_3	L_4 W_3	L_5 W_3	L_1 W_4	L_2 W_4	L_3 W_4	L_4 W_4	L_5 W_4	Results Rep 1	Rep 2	Rep 3	Av.	Model
261	+	-	-	-	-	-	+	-	-	-	-	-	+	+	-	+	+	-	+	-	63.46	63.22	62.50	63.06	63.13
262	+	-	-	-	-	-	+	-	+	+	+	+	-	-	+	-	-	+	-	+	62.64	62.75	62.66	62.68	61.24
263	+	-	-	-	-	-	+	+	-	+	+	+	-	-	+	-	-	+	+	-	63.95	63.74	63.51	63.73	64.01
264	+	-	-	-	-	-	+	+	+	-	-	-	+	+	-	+	+	-	-	+	64.92	65.07	64.84	64.94	65.23
265	+	-	-	-	-	+	-	-	-	-	-	-	-	-	+	-	+	-	+	-	49.54	47.87	49.31	48.91	52.78
266	+	-	-	-	-	+	-	-	+	+	+	+	+	+	-	+	-	+	-	+	62.68	62.34	62.01	62.34	61.42
267	+	-	-	-	-	+	-	+	-	+	+	+	+	+	-	+	-	+	+	-	65.63	64.82	64.25	64.90	65.60
268	+	-	-	-	-	+	-	+	+	-	-	-	-	-	+	-	+	-	-	+	59.32	59.71	59.13	59.39	58.77
269	+	-	-	-	-	+	+	-	-	+	+	+	+	+	+	-	+	-	-	+	66.85	66.89	65.90	66.55	65.34
270	+	-	-	-	-	+	+	-	+	-	-	-	-	-	-	+	-	+	+	-	61.51	61.72	61.73	61.65	62.15
271	+	-	-	-	-	+	+	+	-	-	-	-	-	-	-	+	-	+	-	+	64.57	64.15	63.83	64.18	63.30
272	+	-	-	-	-	+	+	+	+	+	+	+	+	+	+	-	+	-	+	-	68.27	68.52	67.61	68.13	68.90
273	+	-	-	-	+	-	-	-	-	-	-	+	+	-	+	+	-	-	+	+	56.39	55.98	56.21	56.19	56.15
274	+	-	-	-	+	-	-	-	+	+	+	-	-	+	-	-	+	+	-	-	58.73	58.66	58.49	58.63	58.25
275	+	-	-	-	+	-	-	+	-	+	+	-	-	+	-	-	+	+	+	+	62.49	62.58	62.47	62.51	62.11
276	+	-	-	-	+	-	-	+	+	-	+	+	-	+	+	-	-	-	-	-	62.07	62.12	61.80	62.00	62.13
277	+	-	-	-	+	-	+	-	-	+	+	-	-	+	+	+	-	-	-	-	58.97	58.48	58.11	58.52	57.50
278	+	-	-	-	+	-	+	-	+	-	-	+	+	-	-	-	+	+	+	+	65.05	65.22	64.82	65.03	65.14
279	+	-	-	-	+	-	+	+	-	-	-	+	+	-	-	-	+	+	-	-	65.65	65.57	65.40	65.54	65.32
280	+	-	-	-	+	-	+	+	+	+	+	-	-	+	+	+	-	-	+	+	62.92	62.82	61.84	62.53	63.05
281	+	-	-	-	+	+	-	-	-	+	+	-	+	-	-	-	-	-	-	-	53.76	53.61	53.48	53.62	55.33
282	+	-	-	-	+	+	-	-	+	-	-	+	-	+	+	+	+	+	+	+	64.18	64.00	63.64	63.94	63.41
283	+	-	-	-	+	+	-	+	-	-	-	+	-	+	+	+	+	+	-	-	66.12	66.16	65.89	66.06	65.92
284	+	-	-	-	+	+	-	+	+	+	-	+	-	-	-	-	-	-	+	+	61.49	61.89	61.58	61.65	60.63
285	+	-	-	-	+	+	+	-	-	-	-	+	-	+	-	-	-	-	+	+	57.74	58.50	58.41	58.22	59.43
286	+	-	-	-	+	+	+	-	+	+	+	-	+	-	+	+	+	+	-	-	67.37	67.48	67.49	67.45	67.13
287	+	-	-	-	+	+	+	+	-	+	+	-	+	-	+	+	+	+	+	+	67.93	67.99	67.45	67.79	68.86
288	+	-	-	-	+	+	+	+	+	-	-	+	-	+	-	-	-	-	-	-	66.80	67.10	66.99	66.96	66.86
289	+	-	-	+	-	-	-	-	-	-	-	+	-	+	-	-	+	+	-	+	62.40	62.52	62.27	62.40	61.38
290	+	-	-	+	-	-	-	-	+	+	+	-	+	-	+	+	-	-	+	-	60.16	59.94	59.77	59.96	59.75
291	+	-	-	+	-	-	-	+	-	+	+	-	+	-	+	+	-	-	-	+	61.43	61.50	60.35	61.09	60.64
292	+	-	-	+	-	-	-	+	+	-	-	+	-	+	-	-	+	+	+	-	64.00	63.90	63.63	63.84	62.86
293	+	-	-	+	-	-	+	-	-	+	+	-	+	-	-	-	+	+	+	-	65.54	64.84	64.45	64.94	64.88
294	+	-	-	+	-	-	+	-	+	-	-	+	-	+	+	+	-	-	-	+	62.91	64.26	62.50	63.22	63.36
295	+	-	-	+	-	-	+	+	-	-	-	+	-	+	+	+	-	-	+	-	66.41	66.63	66.17	66.40	66.16
296	+	-	-	+	-	-	+	+	+	+	+	-	+	-	-	-	+	+	-	+	66.44	66.56	66.29	66.43	67.13
297	+	-	-	+	-	+	-	-	-	+	+	-	-	+	+	+	+	+	+	-	63.58	63.15	62.99	63.24	62.24
298	+	-	-	+	-	+	-	-	+	-	-	+	+	-	-	-	-	-	-	+	59.67	59.59	59.07	59.44	60.43
299	+	-	-	+	-	+	-	+	-	-	-	+	+	-	-	-	-	-	+	-	65.41	65.02	65.19	65.21	64.51
300	+	-	-	+	-	+	-	+	+	+	+	-	-	+	+	+	+	+	-	+	64.42	64.30	64.37	64.36	64.93
301	+	-	-	+	-	+	+	-	-	-	-	+	+	-	+	+	+	+	-	+	67.96	68.07	67.78	67.94	68.14
302	+	-	-	+	-	+	+	-	+	+	+	-	-	+	-	-	-	-	+	-	63.83	63.80	63.06	63.56	63.22
303	+	-	-	+	-	+	+	+	-	+	+	-	-	+	-	-	-	-	-	+	64.61	65.76	63.84	64.74	64.88
304	+	-	-	+	-	+	+	+	+	-	-	+	+	-	+	+	+	+	+	-	68.60	68.82	68.33	68.58	67.86
305	+	-	-	+	+	-	-	-	-	+	+	+	+	+	+	-	-	+	+	+	62.01	61.75	61.47	61.74	61.46
306	+	-	-	+	+	-	-	-	+	-	-	-	-	-	-	+	+	-	-	-	58.48	58.53	58.09	58.37	58.74
307	+	-	-	+	+	-	-	+	-	-	-	-	-	-	-	+	+	-	+	+	62.25	62.53	61.82	62.20	61.26
308	+	-	-	+	+	-	-	+	+	+	+	+	+	+	+	-	-	+	-	-	63.69	63.90	63.64	63.74	64.01
309	+	-	-	+	+	-	+	-	-	-	-	-	-	-	+	-	-	+	-	-	59.63	59.47	58.15	59.08	59.51
310	+	-	-	+	+	-	+	-	+	+	+	+	+	+	-	+	+	-	+	+	66.75	66.60	66.55	66.63	67.00
311	+	-	-	+	+	-	+	+	-	+	+	+	+	+	-	+	+	-	-	-	67.29	67.19	67.22	67.23	67.00
312	+	-	-	+	+	-	+	+	+	-	-	-	-	-	+	-	-	+	+	+	63.04	62.84	62.79	62.89	62.93

Table A - 5: Fractional factorial design, results from simulation (3 replicates), average yield and estimated yield in percent, cutting bills 313 to 364, continued

#	L_1 W_1	L_2 W_1	L_3 W_1	L_4 W_1	L_5 W_1	L_1 W_2	L_2 W_2	L_3 W_2	L_4 W_2	L_5 W_2	L_1 W_3	L_2 W_3	L_3 W_3	L_4 W_3	L_5 W_3	L_1 W_4	L_2 W_4	L_3 W_4	L_4 W_4	L_5 W_4	Results Rep 1	Rep 2	Rep 3	Av.	Model
313	+	-	-	+	+	+	-	-	-	-	-	-	+	+	-	+	-	+	-	-	62.96	62.86	62.84	62.89	62.93
314	+	-	-	+	+	+	-	-	+	+	+	+	-	-	+	-	+	-	+	+	61.84	61.49	61.48	61.60	61.89
315	+	-	-	+	+	+	-	+	-	+	+	+	-	-	+	-	+	-	-	-	65.15	65.31	65.32	65.26	64.12
316	+	-	-	+	+	+	-	+	+	-	-	-	+	+	-	+	-	+	+	+	62.81	63.53	62.68	63.01	62.69
317	+	-	-	+	+	+	+	-	-	+	+	+	-	-	-	+	-	+	+	+	64.33	63.63	63.46	63.81	63.52
318	+	-	-	+	+	+	+	-	+	-	-	-	+	+	+	-	+	-	-	-	66.01	65.42	65.73	65.72	65.75
319	+	-	-	+	+	+	+	+	-	-	-	-	+	+	+	-	+	-	+	+	67.02	66.79	66.51	66.77	66.45
320	+	-	-	+	+	+	+	+	+	+	+	+	-	-	-	+	-	+	-	-	68.35	68.14	67.76	68.08	67.64
321	+	-	+	-	-	-	-	-	-	-	+	-	+	-	+	+	+	+	-	-	66.57	66.17	65.95	66.23	64.57
322	+	-	+	-	-	-	-	-	+	+	-	+	-	+	-	-	-	-	+	+	58.79	58.80	58.11	58.57	58.74
323	+	-	+	-	-	-	-	+	-	+	-	+	-	+	-	-	-	-	-	-	63.50	63.56	63.61	63.56	63.48
324	+	-	+	-	-	-	-	+	+	-	+	-	+	-	+	+	+	+	+	+	65.86	65.87	65.27	65.67	66.25
325	+	-	+	-	-	-	+	-	-	+	-	+	-	+	+	+	+	+	+	+	67.58	67.52	66.96	67.35	67.04
326	+	-	+	-	-	-	+	-	+	-	+	-	+	-	-	-	-	-	-	-	66.91	67.34	66.70	66.98	65.79
327	+	-	+	-	-	-	+	+	-	-	+	-	+	-	-	-	-	-	+	+	65.69	65.68	65.62	65.66	64.69
328	+	-	+	-	-	-	+	+	+	+	-	+	-	+	+	+	+	+	-	-	68.41	68.22	67.26	67.96	67.94
329	+	-	+	-	-	+	-	-	-	+	-	+	+	-	-	-	+	+	+	+	65.14	65.47	64.88	65.16	64.70
330	+	-	+	-	-	+	-	-	+	-	+	-	-	+	+	+	-	-	-	-	61.94	61.12	61.77	61.61	62.15
331	+	-	+	-	-	+	-	+	-	-	+	-	-	+	+	+	-	-	+	+	62.62	61.99	61.60	62.07	62.66
332	+	-	+	-	-	+	-	+	+	+	-	+	+	-	-	-	+	+	-	-	66.01	65.94	65.66	65.87	65.37
333	+	-	+	-	-	+	+	-	-	-	+	-	-	+	-	-	+	+	-	-	68.49	68.49	67.82	68.27	67.99
334	+	-	+	-	-	+	+	-	+	+	-	+	+	-	+	+	-	-	+	+	67.40	67.91	67.11	67.47	67.47
335	+	-	+	-	-	+	+	+	-	+	-	+	+	-	+	+	-	-	-	-	68.86	69.15	68.30	68.77	69.87
336	+	-	+	-	-	+	+	+	+	-	+	-	-	+	-	-	+	+	+	+	68.33	68.34	68.03	68.23	68.95
337	+	-	+	-	+	-	-	-	-	+	-	-	-	-	-	+	-	+	+	-	59.30	59.24	59.70	59.41	59.38
338	+	-	+	-	+	-	-	-	+	-	+	+	+	+	+	-	+	-	-	+	65.93	66.04	65.68	65.88	65.71
339	+	-	+	-	+	-	-	+	-	-	+	+	+	+	+	-	+	-	+	-	66.86	67.03	66.97	66.95	67.47
340	+	-	+	-	+	-	-	+	+	+	-	-	-	-	-	+	-	+	-	+	63.46	63.41	63.02	63.30	62.80
341	+	-	+	-	+	-	+	-	-	-	+	+	+	+	-	+	-	+	-	+	67.03	67.13	66.50	66.89	66.87
342	+	-	+	-	+	-	+	-	+	+	-	-	-	-	+	-	+	-	+	-	65.61	65.28	65.29	65.39	64.28
343	+	-	+	-	+	-	+	+	-	+	-	-	-	-	+	-	+	-	-	+	65.67	65.57	65.52	65.59	64.59
344	+	-	+	-	+	-	+	+	+	-	+	+	+	+	-	+	-	+	+	-	68.15	67.97	67.58	67.90	67.45
345	+	-	+	-	+	+	-	-	-	-	+	+	-	-	+	-	-	+	-	+	63.29	63.60	63.14	63.34	62.70
346	+	-	+	-	+	+	-	-	+	+	-	-	+	+	-	+	+	-	+	-	65.51	65.55	65.12	65.39	65.88
347	+	-	+	-	+	+	-	+	-	+	-	-	+	+	-	+	+	-	-	+	66.60	66.51	66.37	66.49	66.47
348	+	-	+	-	+	+	-	+	+	-	+	+	-	-	+	-	-	+	+	-	66.14	66.23	65.62	66.00	65.79
349	+	-	+	-	+	+	+	-	-	+	-	-	+	+	+	-	-	+	+	-	65.68	65.71	64.70	65.36	64.89
350	+	-	+	-	+	+	+	-	+	-	+	+	-	-	-	+	+	-	-	+	69.38	69.37	68.92	69.22	68.59
351	+	-	+	-	+	+	+	+	-	-	+	+	-	-	-	+	+	-	+	-	69.32	69.52	69.05	69.30	70.14
352	+	-	+	-	+	+	+	+	+	+	-	-	+	+	+	-	-	+	-	+	66.20	66.44	66.07	66.24	67.42
353	+	-	+	+	-	-	-	-	-	+	-	-	+	+	+	-	+	-	-	-	61.80	61.58	61.49	61.62	61.92
354	+	-	+	+	-	-	-	-	+	-	+	+	-	-	-	+	-	+	+	+	62.06	62.41	62.02	62.16	61.96
355	+	-	+	+	-	-	-	+	-	-	+	+	-	-	-	+	-	+	-	-	65.13	65.34	64.74	65.07	65.89
356	+	-	+	+	-	-	-	+	+	+	-	-	+	+	+	-	+	-	+	+	64.05	64.03	64.02	64.03	64.28
357	+	-	+	+	-	-	+	-	-	-	+	+	-	-	+	-	+	-	+	+	66.59	66.16	65.95	66.23	65.52
358	+	-	+	+	-	-	+	-	+	+	-	-	+	+	-	+	-	+	-	-	66.94	66.75	66.45	66.71	67.10
359	+	-	+	+	-	-	+	+	-	+	-	-	+	+	-	+	-	+	+	+	65.54	66.16	65.11	65.60	65.66
360	+	-	+	+	-	-	+	+	+	-	+	+	-	-	+	-	+	-	-	-	67.73	67.76	67.57	67.69	67.94
361	+	-	+	+	-	+	-	-	-	-	+	+	+	+	-	+	+	-	+	+	68.29	68.51	67.90	68.23	68.02
362	+	-	+	+	-	+	-	-	+	+	-	-	-	-	+	-	-	+	-	-	61.97	61.88	62.13	61.99	61.96
363	+	-	+	+	-	+	-	+	-	+	-	-	-	-	+	-	-	+	+	+	63.77	63.89	63.51	63.72	63.18
364	+	-	+	+	-	+	-	+	+	-	+	+	+	+	-	+	+	-	-	-	67.95	67.96	67.43	67.78	67.94

Table A - 5: Fractional factorial design, results from simulation (3 replicates), average yield and estimated yield in percent, cutting bills 365 to 416, continued

#	L_1 W_1	L_2 W_1	L_3 W_1	L_4 W_1	L_5 W_1	L_1 W_2	L_2 W_2	L_3 W_2	L_4 W_2	L_5 W_2	L_1 W_3	L_2 W_3	L_3 W_3	L_4 W_3	L_5 W_3	L_1 W_4	L_2 W_4	L_3 W_4	L_4 W_4	L_5 W_4	Results Rep 1	Rep 2	Rep 3	Av.	Model
365	+	-	+	+	-	+	+	-	-	+	-	-	-	-	-	+	+	-	-	-	67.17	66.76	66.24	66.72	66.11
366	+	-	+	+	-	+	+	-	+	-	+	+	+	+	+	-	-	+	+	+	67.01	67.53	67.60	67.38	67.28
367	+	-	+	+	-	+	+	+	-	-	+	+	+	+	+	-	-	+	-	-	69.46	69.36	69.16	69.33	69.58
368	+	-	+	+	-	+	+	+	+	+	-	-	-	-	-	+	+	-	+	+	68.68	68.61	68.24	68.51	68.27
369	+	-	+	+	+	-	-	-	-	-	+	-	-	+	-	-	-	-	+	-	59.84	60.60	60.04	60.16	59.92
370	+	-	+	+	+	-	-	-	+	+	-	+	+	-	+	+	+	+	-	+	65.18	64.99	64.91	65.03	65.31
371	+	-	+	+	+	-	-	+	-	+	-	+	+	-	+	+	+	+	+	-	66.64	66.62	66.27	66.51	66.05
372	+	-	+	+	+	-	-	+	+	-	+	-	-	+	-	-	-	-	-	+	62.84	63.16	62.76	62.92	63.26
373	+	-	+	+	+	-	+	-	-	+	-	+	+	-	-	-	-	-	-	+	63.97	64.74	64.06	64.26	64.03
374	+	-	+	+	+	-	+	-	+	-	+	-	-	+	+	+	+	+	+	-	67.48	67.16	66.91	67.18	67.30
375	+	-	+	+	+	-	+	+	-	-	+	-	-	+	+	+	+	+	-	+	67.04	66.70	66.92	66.89	67.62
376	+	-	+	+	+	-	+	+	+	+	-	+	+	-	-	-	-	-	+	-	66.92	67.20	66.72	66.95	67.03
377	+	-	+	+	+	+	-	-	-	+	-	+	-	+	+	+	-	-	-	+	63.66	63.47	62.66	63.26	63.71
378	+	-	+	+	+	+	-	-	+	-	+	-	+	-	-	-	+	+	+	-	66.06	66.12	65.70	65.96	65.99
379	+	-	+	+	+	+	-	+	-	-	+	-	+	-	-	-	+	+	-	+	66.70	67.04	66.75	66.83	67.69
380	+	-	+	+	+	+	-	+	+	+	-	+	-	+	+	+	-	-	+	-	66.00	65.94	65.70	65.88	67.00
381	+	-	+	+	+	+	+	-	-	-	+	-	+	-	+	+	-	-	+	-	66.89	66.73	66.59	66.74	67.35
382	+	-	+	+	+	+	+	-	+	+	-	+	-	+	-	-	+	+	-	+	68.23	68.44	67.90	68.19	69.15
383	+	-	+	+	+	+	+	+	-	+	-	+	-	+	-	-	+	+	+	-	68.28	68.51	67.85	68.21	68.04
384	+	-	+	+	+	+	+	+	+	-	+	-	+	-	+	+	-	-	-	+	68.28	68.37	68.05	68.23	67.96
385	+	+	-	-	-	-	-	-	-	-	+	-	-	+	-	+	-	+	+	+	56.83	56.32	56.36	56.50	56.57
386	+	+	-	-	-	-	-	-	+	+	-	+	+	-	+	-	+	-	-	-	60.98	60.94	60.76	60.89	60.57
387	+	+	-	-	-	-	-	+	-	+	-	+	+	-	+	-	+	-	+	+	65.57	65.41	65.07	65.35	64.35
388	+	+	-	-	-	-	-	+	+	-	+	-	-	+	-	+	-	+	-	-	63.56	63.36	62.98	63.30	63.73
389	+	+	-	-	-	-	+	-	-	+	-	+	+	-	-	+	-	+	-	-	68.09	68.21	67.56	67.95	66.55
390	+	+	-	-	-	-	+	-	+	-	+	-	-	+	+	-	+	-	+	+	63.33	62.66	62.20	62.73	63.26
391	+	+	-	-	-	-	+	+	-	-	+	-	-	+	+	-	+	-	-	-	66.01	66.20	65.86	66.02	65.86
392	+	+	-	-	-	-	+	+	+	+	-	+	+	-	-	+	-	+	+	+	67.14	67.64	66.42	67.07	66.89
393	+	+	-	-	-	+	-	-	-	+	-	+	-	+	+	-	-	+	-	-	61.20	60.86	60.73	60.93	61.41
394	+	+	-	-	-	+	-	-	+	-	+	-	+	-	-	+	+	-	+	+	64.96	65.19	64.80	64.98	64.46
395	+	+	-	-	-	+	-	+	-	-	+	-	+	-	-	+	+	-	-	-	69.64	69.32	69.26	69.41	68.07
396	+	+	-	-	-	+	-	+	+	+	-	+	-	+	+	-	-	+	+	+	62.59	62.62	62.70	62.64	63.19
397	+	+	-	-	-	+	+	-	-	-	+	-	+	-	+	-	-	+	+	+	63.12	62.46	62.88	62.82	63.10
398	+	+	-	-	-	+	+	-	+	+	-	+	-	+	-	+	+	-	-	-	69.92	70.35	69.80	70.02	69.21
399	+	+	-	-	-	+	+	+	-	+	-	+	-	+	-	+	+	-	+	+	70.58	70.56	70.15	70.43	70.68
400	+	+	-	-	-	+	+	+	+	-	+	-	+	-	+	-	-	+	-	-	68.64	68.89	68.59	68.71	68.99
401	+	+	-	-	+	-	-	-	-	+	-	-	+	+	+	+	+	+	-	+	62.63	62.72	62.23	62.53	62.80
402	+	+	-	-	+	-	-	-	+	-	+	+	-	-	-	-	-	-	+	-	58.69	57.94	56.90	57.84	58.16
403	+	+	-	-	+	-	-	+	-	-	+	+	-	-	-	-	-	-	-	+	59.68	59.76	57.65	59.03	59.79
404	+	+	-	-	+	-	-	+	+	+	-	-	+	+	+	+	+	+	+	-	64.54	64.26	64.18	64.33	64.31
405	+	+	-	-	+	-	+	-	-	-	+	+	-	-	+	+	+	+	+	-	68.36	68.63	67.91	68.30	67.57
406	+	+	-	-	+	-	+	-	+	+	-	-	+	+	-	-	-	-	-	+	63.45	63.05	61.36	62.62	63.17
407	+	+	-	-	+	-	+	+	-	+	-	-	+	+	-	-	-	-	+	-	66.04	66.16	65.46	65.89	66.43
408	+	+	-	-	+	-	+	+	+	-	+	+	-	-	+	+	+	+	-	+	69.33	68.81	68.78	68.97	69.41
409	+	+	-	-	+	+	-	-	-	-	+	+	+	+	-	-	+	+	+	-	67.94	67.67	67.31	67.64	67.19
410	+	+	-	-	+	+	-	-	+	+	-	-	-	-	+	+	-	-	-	+	56.68	56.69	55.78	56.38	56.34
411	+	+	-	-	+	+	-	+	-	+	-	-	-	-	+	+	-	-	+	-	63.48	63.50	62.71	63.23	62.24
412	+	+	-	-	+	+	-	+	+	-	+	+	+	+	-	-	+	+	-	+	67.86	68.21	67.49	67.85	68.02
413	+	+	-	-	+	+	+	-	-	+	-	-	-	-	-	-	+	+	-	+	67.49	67.23	66.86	67.19	65.75
414	+	+	-	-	+	+	+	-	+	-	+	+	+	+	+	+	-	-	+	-	70.90	70.56	69.89	70.45	70.32
415	+	+	-	-	+	+	+	+	-	-	+	+	+	+	+	+	-	-	-	+	70.42	70.66	69.39	70.16	70.03
416	+	+	-	-	+	+	+	+	+	+	-	-	-	-	-	-	+	+	+	-	68.16	68.28	67.49	67.98	68.66

Table A - 5: Fractional factorial design, results from simulation (3 replicates), average yield and estimated yield in percent, cutting bills 417 to 468, continued

#	L_1 W_1	L_2 W_1	L_3 W_1	L_4 W_1	L_5 W_1	L_1 W_2	L_2 W_2	L_3 W_2	L_4 W_2	L_5 W_2	L_1 W_3	L_2 W_3	L_3 W_3	L_4 W_3	L_5 W_3	L_1 W_4	L_2 W_4	L_3 W_4	L_4 W_4	L_5 W_4	Results Rep 1	Rep 2	Rep 3	Av.	Model
417	+	+	-	+	-	-	-	-	-	+	-	-	-	-	-	-	-	-	+	+	53.60	54.38	53.49	53.82	54.39
418	+	+	-	+	-	-	-	-	+	-	+	+	+	+	+	+	+	+	-	-	67.45	67.69	67.32	67.49	69.49
419	+	+	-	+	-	-	-	+	-	-	+	+	+	+	+	+	+	+	+	+	68.47	68.56	68.11	68.38	69.85
420	+	+	-	+	-	-	-	+	+	+	-	-	-	-	-	-	-	-	-	-	61.47	61.91	61.30	61.56	61.58
421	+	+	-	+	-	-	+	-	-	-	+	+	+	+	-	-	-	-	-	-	70.01	69.96	69.43	69.80	69.33
422	+	+	-	+	-	-	+	-	+	+	-	-	-	-	+	+	+	+	+	+	66.46	66.91	66.43	66.60	66.79
423	+	+	-	+	-	-	+	+	-	+	-	-	-	-	+	+	+	+	-	-	67.33	67.24	67.57	67.38	67.76
424	+	+	-	+	-	-	+	+	+	-	+	+	+	+	-	-	-	-	+	+	68.37	68.44	68.07	68.29	67.94
425	+	+	-	+	-	+	-	-	-	-	+	+	-	-	+	+	-	-	-	-	70.57	70.27	69.83	70.22	66.45
426	+	+	-	+	-	+	-	-	+	+	-	-	+	+	-	-	+	+	+	+	65.13	64.85	65.06	65.01	64.87
427	+	+	-	+	-	+	-	+	-	+	-	-	+	+	-	-	+	+	-	-	67.00	66.72	66.82	66.85	67.58
428	+	+	-	+	-	+	-	+	+	-	+	+	-	-	+	+	-	-	+	+	67.07	66.72	66.13	66.64	67.03
429	+	+	-	+	-	+	+	-	-	+	-	-	+	+	+	+	-	-	+	+	65.99	66.15	66.34	66.16	65.81
430	+	+	-	+	-	+	+	-	+	-	+	+	-	-	-	-	+	+	-	-	70.70	70.70	70.14	70.51	71.30
431	+	+	-	+	-	+	+	+	-	-	+	+	-	-	-	-	+	+	+	+	69.96	69.82	69.36	69.71	70.40
432	+	+	-	+	-	+	+	+	+	+	-	-	+	+	+	+	-	-	-	-	69.06	69.12	68.72	68.97	69.47
433	+	+	-	+	+	-	-	-	-	-	+	-	+	-	+	-	+	-	-	+	66.28	66.07	65.76	66.04	64.39
434	+	+	-	+	+	-	-	-	+	+	-	+	-	+	-	+	-	+	+	-	63.55	63.48	63.34	63.46	63.71
435	+	+	-	+	+	-	-	+	-	+	-	+	-	+	-	+	-	+	-	+	65.76	66.29	65.63	65.89	65.56
436	+	+	-	+	+	-	-	+	+	-	+	-	+	-	+	-	+	-	+	-	66.09	66.34	65.34	65.92	66.92
437	+	+	-	+	+	-	+	-	-	+	-	+	-	+	+	-	+	-	+	-	68.15	67.80	67.73	67.89	67.46
438	+	+	-	+	+	-	+	-	+	-	+	-	+	-	-	+	-	+	-	+	67.42	67.91	67.44	67.59	68.14
439	+	+	-	+	+	-	+	+	-	-	+	-	+	-	-	+	-	+	+	-	68.00	68.11	67.67	67.93	68.31
440	+	+	-	+	+	-	+	+	+	+	-	+	-	+	+	-	+	-	-	+	68.00	68.16	67.66	67.94	68.75
441	+	+	-	+	+	+	-	-	-	+	-	+	+	-	-	+	+	-	+	-	68.25	68.43	68.09	68.26	68.66
442	+	+	-	+	+	+	-	-	+	-	+	-	-	+	+	-	-	+	-	+	64.03	64.42	64.09	64.18	63.91
443	+	+	-	+	+	+	-	+	-	-	+	-	-	+	+	-	-	+	+	-	65.27	65.66	64.81	65.25	65.09
444	+	+	-	+	+	+	-	+	+	+	-	+	+	-	-	+	+	-	-	+	67.05	67.20	66.65	66.97	67.11
445	+	+	-	+	+	+	+	-	-	-	+	-	-	+	-	+	+	-	-	+	70.11	69.75	69.50	69.79	69.22
446	+	+	-	+	+	+	+	-	+	+	-	+	+	-	+	-	-	+	+	-	68.51	68.45	68.28	68.41	68.53
447	+	+	-	+	+	+	+	+	-	+	-	+	+	-	+	-	-	+	-	+	69.66	69.71	69.17	69.51	69.54
448	+	+	-	+	+	+	+	+	+	-	+	-	-	+	-	+	+	-	+	-	71.09	71.00	70.21	70.77	70.93
449	+	+	+	-	-	-	-	-	-	+	+	+	+	+	+	+	-	-	+	-	67.26	67.48	67.33	67.36	66.92
450	+	+	+	-	-	-	-	-	+	-	-	-	-	-	-	-	+	+	-	+	64.43	64.48	63.70	64.20	63.94
451	+	+	+	-	-	-	-	+	-	-	-	-	-	-	-	-	+	+	+	-	66.19	66.12	65.01	65.77	65.37
452	+	+	+	-	-	-	-	+	+	+	+	+	+	+	+	+	-	-	-	+	66.56	65.86	66.14	66.19	65.94
453	+	+	+	-	-	-	+	-	-	-	-	-	-	-	+	+	-	-	-	+	57.33	57.76	56.61	57.23	60.75
454	+	+	+	-	-	-	+	-	+	+	+	+	+	+	-	-	+	+	+	-	69.52	69.43	68.86	69.27	69.80
455	+	+	+	-	-	-	+	+	-	+	+	+	+	+	-	-	+	+	-	+	68.86	69.50	69.25	69.20	70.02
456	+	+	+	-	-	-	+	+	+	-	-	-	-	-	+	+	-	-	+	-	68.06	68.08	67.80	67.98	66.76
457	+	+	+	-	-	+	-	-	-	-	-	-	+	+	-	-	-	-	-	+	62.19	62.21	60.57	61.66	62.41
458	+	+	+	-	-	+	-	-	+	+	+	+	-	-	+	+	+	+	+	-	67.78	67.91	67.77	67.82	68.05
459	+	+	+	-	-	+	-	+	-	+	+	+	-	-	+	+	+	+	-	+	69.47	69.89	69.40	69.59	69.52
460	+	+	+	-	-	+	-	+	+	-	-	-	+	+	-	-	-	-	+	-	67.06	66.73	66.50	66.76	65.78
461	+	+	+	-	-	+	+	-	-	+	+	+	-	-	-	-	-	-	+	-	68.73	69.47	67.00	68.40	67.79
462	+	+	+	-	-	+	+	-	+	-	-	-	+	+	+	+	+	+	-	+	70.32	70.11	69.74	70.06	69.68
463	+	+	+	-	-	+	+	+	-	-	-	-	+	+	+	+	+	+	+	-	69.99	70.37	69.93	70.10	68.60
464	+	+	+	-	-	+	+	+	+	+	+	+	-	-	-	-	-	-	-	+	69.33	68.97	68.48	68.93	69.28
465	+	+	+	-	+	-	-	-	-	-	-	+	-	+	-	+	+	-	-	-	68.60	68.37	68.15	68.37	67.20
466	+	+	+	-	+	-	-	-	+	+	+	-	+	-	+	-	-	+	+	+	63.78	63.55	62.89	63.41	63.85
467	+	+	+	-	+	-	-	+	-	+	+	-	+	-	+	-	-	+	-	-	65.75	65.99	65.84	65.86	66.28
468	+	+	+	-	+	-	-	+	+	-	-	+	-	+	-	+	+	-	+	+	68.05	68.06	67.66	67.92	67.67

Table A - 5: Fractional factorial design, results from simulation (3 replicates), average yield and estimated yield in percent, cutting bills 469 to 512, continued

#	L_1 W_1	L_2 W_1	L_3 W_1	L_4 W_1	L_5 W_1	L_1 W_2	L_2 W_2	L_3 W_2	L_4 W_2	L_5 W_2	L_1 W_3	L_2 W_3	L_3 W_3	L_4 W_3	L_5 W_3	L_1 W_4	L_2 W_4	L_3 W_4	L_4 W_4	L_5 W_4	Results Rep 1	Rep 2	Rep 3	Av.	Model
469	+	+	+	-	+	-	+	-	-	+	+	-	+	-	-	+	+	-	+	+	69.51	69.08	69.09	69.23	69.37
470	+	+	+	-	+	-	+	-	+	-	-	+	-	+	+	-	-	+	-	-	68.66	68.56	68.36	68.53	69.07
471	+	+	+	-	+	-	+	+	-	-	-	+	-	+	+	-	-	+	+	+	67.88	68.20	67.63	67.90	67.03
472	+	+	+	-	+	-	+	+	+	+	+	-	+	-	-	+	+	-	-	-	69.24	69.37	68.90	69.17	69.54
473	+	+	+	-	+	+	-	-	-	+	+	-	-	+	+	-	+	-	+	+	64.18	64.24	64.01	64.14	64.53
474	+	+	+	-	+	+	-	-	+	-	-	+	+	-	-	+	-	+	-	-	68.74	68.75	68.40	68.63	69.38
475	+	+	+	-	+	+	-	+	-	-	-	+	+	-	-	+	-	+	+	+	67.46	68.04	67.26	67.59	67.98
476	+	+	+	-	+	+	-	+	+	+	+	-	-	+	+	-	+	-	-	-	66.90	66.95	66.66	66.84	66.50
477	+	+	+	-	+	+	+	-	-	-	-	+	+	-	+	-	+	-	-	-	69.85	69.70	69.18	69.58	70.34
478	+	+	+	-	+	+	+	-	+	+	+	-	-	+	-	+	-	+	+	+	68.33	68.80	68.66	68.60	68.47
479	+	+	+	-	+	+	+	+	-	+	+	-	-	+	-	+	-	+	-	-	70.74	70.69	70.58	70.67	71.12
480	+	+	+	-	+	+	+	+	+	-	-	+	+	-	+	-	+	-	+	+	70.18	70.20	70.09	70.16	70.12
481	+	+	+	+	-	-	-	-	-	-	-	+	+	-	+	-	-	+	+	-	65.52	66.29	65.99	65.93	66.21
482	+	+	+	+	-	-	-	-	+	+	+	-	-	+	-	+	+	-	-	+	65.95	65.84	65.80	65.86	64.72
483	+	+	+	+	-	-	-	+	-	+	+	-	-	+	-	+	+	-	+	-	68.23	68.31	68.15	68.23	68.28
484	+	+	+	+	-	-	-	+	+	-	-	+	+	-	+	-	-	+	-	+	66.88	67.27	66.09	66.75	66.46
485	+	+	+	+	-	-	+	-	-	+	+	-	-	+	+	-	-	+	-	+	67.29	67.20	67.18	67.22	66.56
486	+	+	+	+	-	-	+	-	+	-	-	+	+	-	-	+	+	-	+	-	69.71	69.62	69.26	69.53	70.70
487	+	+	+	+	-	-	+	+	-	-	-	+	+	-	-	+	+	-	-	+	69.12	69.22	69.08	69.14	68.76
488	+	+	+	+	-	-	+	+	+	+	+	-	-	+	+	-	-	+	+	-	66.74	66.47	66.37	66.53	67.29
489	+	+	+	+	-	+	-	-	-	+	+	-	+	-	-	+	-	+	-	+	67.44	67.68	67.09	67.40	66.76
490	+	+	+	+	-	+	-	-	+	-	-	+	-	+	+	-	+	-	+	-	68.62	68.79	68.56	68.66	67.99
491	+	+	+	+	-	+	-	+	-	-	-	+	-	+	+	-	+	-	-	+	69.56	69.09	69.20	69.28	69.98
492	+	+	+	+	-	+	-	+	+	+	+	-	+	-	-	+	-	+	+	-	66.86	66.92	66.87	66.88	67.32
493	+	+	+	+	-	+	+	-	-	-	-	+	-	+	-	+	-	+	+	-	68.93	69.09	68.67	68.90	70.28
494	+	+	+	+	-	+	+	-	+	+	+	-	+	-	+	-	+	-	-	+	70.29	70.60	69.91	70.27	70.06
495	+	+	+	+	-	+	+	+	-	+	+	-	+	-	+	-	+	-	+	-	70.58	70.23	70.19	70.33	70.99
496	+	+	+	+	-	+	+	+	+	-	-	+	-	+	-	+	-	+	-	+	70.53	70.43	70.25	70.40	69.56
497	+	+	+	+	+	-	-	-	-	+	+	+	-	-	-	-	+	+	-	-	66.38	66.44	66.04	66.29	66.60
498	+	+	+	+	+	-	-	-	+	-	-	-	+	+	+	+	-	-	+	+	65.38	65.47	65.47	65.44	64.48
499	+	+	+	+	+	-	-	+	-	-	-	-	+	+	+	+	-	-	-	-	66.53	66.89	66.48	66.63	67.28
500	+	+	+	+	+	-	-	+	+	+	+	+	-	-	-	-	+	+	+	+	65.93	66.77	66.70	66.47	66.52
501	+	+	+	+	+	-	+	-	-	-	-	-	+	+	-	-	+	+	+	+	67.84	67.90	67.25	67.66	68.36
502	+	+	+	+	+	-	+	-	+	+	+	+	-	-	+	+	-	-	-	-	69.37	69.34	68.98	69.23	69.64
503	+	+	+	+	+	-	+	+	-	+	+	+	-	-	+	+	-	-	+	+	69.18	69.07	68.85	69.03	68.91
504	+	+	+	+	+	-	+	+	+	-	-	-	+	+	-	-	+	+	-	-	68.49	68.49	68.22	68.40	66.74
505	+	+	+	+	+	+	-	-	-	-	-	-	-	-	+	+	+	+	+	+	67.00	66.96	66.80	66.92	67.89
506	+	+	+	+	+	+	-	-	+	+	+	+	+	+	-	-	-	-	-	-	68.61	68.62	68.04	68.42	68.21
507	+	+	+	+	+	+	-	+	-	+	+	+	+	+	-	-	-	-	+	+	68.92	68.94	68.34	68.73	68.43
508	+	+	+	+	+	+	-	+	+	-	-	-	-	-	+	+	+	+	-	-	68.33	68.36	67.71	68.13	68.18
509	+	+	+	+	+	+	+	-	-	+	+	+	+	+	+	+	+	+	-	-	70.89	70.91	70.63	70.81	71.71
510	+	+	+	+	+	+	+	-	+	-	-	-	-	-	-	-	-	-	+	+	67.47	67.14	66.09	66.90	66.40
511	+	+	+	+	+	+	+	+	-	-	-	-	-	-	-	-	-	-	-	-	69.53	69.52	69.58	69.54	69.34
512	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	69.95	70.38	70.02	70.12	67.53

Appendix E: Significance and parameter estimates of secondary interactions

Table A - 6: Significance and parameter estimates of all 190 unique secondary interactions, interactions 1 - 50

#	Interaction between Part Group	Part Group	Parameter Estimate	t for H0	Probability (p)
1	L1W1	L1W2	0.01	0.67	0.5051
2	L1W3	L2W1	0.02	0.82	0.4153
3	L2W1	L3W4	-0.10	-4.76	0.0001
4	L2W4	L3W3	-0.11	-5.03	0.0001
5	L3W3	L5W3	0.07	3.20	0.0014
6	L1W1	L1W3	0.12	5.42	0.0001
7	L1W3	L2W2	-0.04	-1.75	0.0803
8	L2W1	L4W1	0.06	2.57	0.0103
9	L2W4	L3W4	-0.01	-0.61	0.5401
10	L3W3	L5W4	0.02	0.71	0.4754
11	L1W1	L1W4	0.02	0.98	0.3291
12	L1W3	L2W3	-0.03	-1.42	0.1559
13	L2W1	L4W2	-0.14	-6.60	0.0001
14	L2W4	L4W1	-0.13	-5.78	0.0001
15	L3W4	L4W1	-0.18	-8.34	0.0001
16	L1W1	L2W1	0.07	3.09	0.0021
17	L1W3	L2W4	0.03	1.20	0.2322
18	L2W1	L4W3	-0.08	-3.79	0.0002
19	L2W4	L4W2	-0.12	-5.62	0.0001
20	L3W4	L4W2	-0.08	-3.69	0.0002
21	L1W1	L2W2	0.00	0.19	0.8535
22	L1W3	L3W1	0.01	0.27	0.7870
23	L2W1	L4W4	-0.06	-2.61	0.0091
24	L2W4	L4W3	-0.01	-0.48	0.6321
25	L3W4	L4W3	-0.07	-3.30	0.0010
26	L1W1	L2W3	0.04	2.04	0.0418
27	L1W3	L3W2	-0.02	-0.84	0.4024
28	L2W1	L5W1	0.01	0.41	0.6848
29	L2W4	L4W4	0.15	7.08	0.0001
30	L3W4	L4W4	-0.19	-8.54	0.0001
31	L1W1	L2W4	0.00	-0.18	0.8558
32	L1W3	L3W3	0.01	0.66	0.5082
33	L2W1	L5W2	-0.07	-3.04	0.0024
34	L2W4	L5W1	0.02	1.13	0.2569
35	L3W4	L5W1	-0.02	-1.06	0.2912
36	L1W1	L3W1	0.00	-0.14	0.8921
37	L1W3	L3W4	0.01	0.24	0.8110
38	L2W1	L5W3	-0.04	-2.00	0.0457
39	L2W4	L5W2	-0.08	-3.72	0.0002
40	L3W4	L5W2	0.03	1.26	0.2084
41	L1W1	L3W2	-0.05	-2.50	0.0126
42	L1W3	L4W1	0.00	0.15	0.8850
43	L2W1	L5W4	-0.06	-2.67	0.0077
44	L2W4	L5W3	-0.06	-2.96	0.0031
45	L3W4	L5W3	0.01	0.30	0.7628
46	L1W1	L3W3	0.02	0.87	0.3835
47	L1W3	L4W2	-0.01	-0.58	0.5645
48	L2W2	L2W3	-0.10	-4.48	0.0001
49	L2W4	L5W4	0.27	12.53	0.0001
50	L3W4	L5W4	0.15	6.87	0.0001

Table A - 6: Significance and parameter estimates of all 190 unique secondary interactions, interactions 51 - 100, continued

#	Interaction between Part Group	Part Group	Parameter Estimate	t for H0	Probability (p)
51	L1W1	L3W4	0.04	2.00	0.0457
52	L1W3	L4W3	0.01	0.41	0.6835
53	L2W2	L2W4	-0.12	-5.34	0.0001
54	L3W1	L3W2	-0.35	-16.02	0.0001
55	L4W1	L4W2	-0.13	-6.02	0.0001
56	L1W1	L4W1	0.06	2.63	0.0087
57	L1W3	L4W4	-0.01	-0.30	0.7682
58	L2W2	L3W1	-0.32	-14.59	0.0001
59	L3W1	L3W3	-0.23	-10.54	0.0001
60	L4W1	L4W3	-0.07	-3.34	0.0009
61	L1W1	L4W2	-0.05	-2.49	0.0131
62	L1W3	L5W1	-0.01	-0.48	0.6308
63	L2W2	L3W2	-0.25	-11.58	0.0001
64	L3W1	L3W4	-0.15	-6.99	0.0001
65	L4W1	L4W4	-0.07	-2.99	0.0029
66	L1W1	L4W3	0.04	2.04	0.0417
67	L1W3	L5W2	-0.06	-2.62	0.0089
68	L2W2	L3W3	-0.15	-6.84	0.0001
69	L3W1	L4W1	-0.39	-17.98	0.0001
70	L4W1	L5W1	-0.09	-4.15	0.0001
71	L1W1	L4W4	-0.05	-2.20	0.0277
72	L1W3	L5W3	0.11	5.22	0.0001
73	L2W2	L3W4	-0.15	-7.01	0.0001
74	L3W1	L4W2	-0.10	-4.61	0.0001
75	L4W1	L5W2	0.01	0.62	0.5354
76	L1W1	L5W1	0.02	0.77	0.4389
77	L1W3	L5W4	-0.01	-0.68	0.4968
78	L2W2	L4W1	-0.25	-11.28	0.0001
79	L3W1	L4W3	-0.07	-2.99	0.0029
80	L4W1	L5W3	0.10	4.38	0.0001
81	L1W1	L5W2	0.00	0.20	0.8427
82	L1W4	L2W1	0.02	1.15	0.2515
83	L2W2	L4W2	0.13	5.85	0.0001
84	L3W1	L4W4	-0.02	-1.07	0.2866
85	L4W1	L5W4	0.04	1.86	0.0633
86	L1W1	L5W3	0.02	1.01	0.3113
87	L1W4	L2W2	-0.10	-4.77	0.0001
88	L2W2	L4W3	-0.07	-3.13	0.0018
89	L3W1	L5W1	-0.01	-0.30	0.7650
90	L4W2	L4W3	-0.10	-4.59	0.0001
91	L1W1	L5W4	-0.05	-2.11	0.0352
92	L1W4	L2W3	-0.01	-0.66	0.5074
93	L2W2	L4W4	-0.04	-1.87	0.0614
94	L3W1	L5W2	0.03	1.16	0.2461
95	L4W2	L4W4	-0.04	-1.87	0.0618
96	L1W2	L1W3	0.00	-0.02	0.9866
97	L1W4	L2W4	-0.03	-1.46	0.1453
98	L2W2	L5W1	-0.08	-3.83	0.0001
99	L3W1	L5W3	-0.02	-1.00	0.3185
100	L4W2	L5W1	0.01	0.45	0.6565

Table A - 6: Significance and parameter estimates of all 190 unique secondary interactions, interactions 101 - 150, continued

#	Interaction between Part Group	Part Group	Parameter Estimate	t for H0	Probability (p)
101	L1W2	L1W4	0.07	3.12	0.0018
102	L1W4	L3W1	-0.09	-3.90	0.0001
103	L2W2	L5W2	0.16	7.51	0.0001
104	L3W1	L5W4	0.02	0.84	0.4004
105	L4W2	L5W2	-0.05	-2.50	0.0125
106	L1W2	L2W1	-0.01	-0.56	0.5762
107	L1W4	L3W2	-0.11	-5.06	0.0001
108	L2W2	L5W3	-0.05	-2.25	0.0245
109	L3W2	L3W3	-0.27	-12.43	0.0001
110	L4W2	L5W3	0.02	0.82	0.4139
111	L1W2	L2W2	-0.09	-4.32	0.0001
112	L1W4	L3W3	-0.01	-0.56	0.5754
113	L2W2	L5W4	0.00	0.12	0.9063
114	L3W2	L3W4	-0.23	-10.60	0.0001
115	L4W2	L5W4	0.06	2.82	0.0049
116	L1W2	L2W3	0.04	1.81	0.0706
117	L1W4	L3W4	0.00	0.18	0.8586
118	L2W3	L2W4	-0.16	-7.15	0.0001
119	L3W2	L4W1	-0.26	-11.82	0.0001
120	L4W3	L4W4	-0.07	-3.34	0.0009
121	L1W2	L2W4	-0.02	-1.03	0.3026
122	L1W4	L4W1	-0.06	-2.84	0.0045
123	L2W3	L3W1	-0.12	-5.60	0.0001
124	L3W2	L4W2	-0.27	-12.49	0.0001
125	L4W3	L5W1	-0.03	-1.17	0.2420
126	L1W2	L3W1	-0.10	-4.62	0.0001
127	L1W4	L4W2	-0.05	-2.16	0.0309
128	L2W3	L3W2	-0.15	-7.01	0.0001
129	L3W2	L4W3	-0.10	-4.47	0.0001
130	L4W3	L5W2	0.02	0.90	0.3703
131	L1W2	L3W2	-0.04	-1.78	0.0759
132	L1W4	L4W3	-0.03	-1.16	0.2458
133	L2W3	L3W3	-0.13	-5.76	0.0001
134	L3W2	L4W4	0.04	1.71	0.0880
135	L4W3	L5W3	-0.06	-2.94	0.0033
136	L1W2	L3W3	-0.10	-4.70	0.0001
137	L1W4	L4W4	0.07	3.44	0.0006
138	L2W3	L3W4	-0.12	-5.66	0.0001
139	L3W2	L5W1	-0.09	-4.30	0.0001
140	L4W3	L5W4	0.02	1.10	0.2728
141	L1W2	L3W4	-0.09	-4.31	0.0001
142	L1W4	L5W1	0.02	0.86	0.3888
143	L2W3	L4W1	-0.10	-4.74	0.0001
144	L3W2	L5W2	0.08	3.76	0.0002
145	L4W4	L5W1	0.04	1.67	0.0959
146	L1W2	L4W1	-0.06	-2.96	0.0031
147	L1W4	L5W2	-0.05	-2.45	0.0146
148	L2W3	L4W2	-0.12	-5.36	0.0001
149	L3W2	L5W3	0.01	0.67	0.5047
150	L4W4	L5W2	0.17	7.97	0.0001

Table A - 6: Significance and parameter estimates of all 190 unique secondary interactions, interactions 151 - 190, continued

#	Interaction between Part Group	Part Group	Parameter Estimate	t for H0	Probability (p)
151	L1W2	L4W2	-0.07	-3.26	0.0012
152	L1W4	L5W3	0.01	0.30	0.7637
153	L2W3	L4W3	0.11	4.99	0.0001
154	L3W2	L5W4	0.11	5.05	0.0001
155	L4W4	L5W3	0.01	0.28	0.7778
156	L1W2	L4W3	-0.06	-2.88	0.0041
157	L1W4	L5W4	-0.10	-4.48	0.0001
158	L2W3	L4W4	0.00	0.15	0.8803
159	L3W3	L3W4	-0.18	-8.39	0.0001
160	L4W4	L5W4	0.03	1.21	0.2255
161	L1W2	L4W4	-0.07	-3.29	0.0010
162	L2W1	L2W2	-0.11	-4.95	0.0001
163	L2W3	L5W1	-0.12	-5.55	0.0001
164	L3W3	L4W1	-0.14	-6.58	0.0001
165	L5W1	L5W2	0.03	1.17	0.2432
166	L1W2	L5W1	-0.03	-1.25	0.2130
167	L2W1	L2W3	-0.03	-1.28	0.1997
168	L2W3	L5W2	-0.07	-3.24	0.0012
169	L3W3	L4W2	-0.13	-5.85	0.0001
170	L5W1	L5W3	0.02	0.89	0.3722
171	L1W2	L5W2	0.00	-0.21	0.8329
172	L2W1	L2W4	0.00	0.11	0.9096
173	L2W3	L5W3	0.19	8.92	0.0001
174	L3W3	L4W3	-0.17	-7.74	0.0001
175	L5W1	L5W4	0.10	4.43	0.0001
176	L1W2	L5W3	-0.05	-2.15	0.0317
177	L2W1	L3W1	-0.25	-11.33	0.0001
178	L2W3	L5W4	-0.03	-1.32	0.1858
179	L3W3	L4W4	0.03	1.51	0.1318
180	L5W2	L5W3	0.01	0.33	0.7387
181	L1W2	L5W4	-0.01	-0.56	0.5730
182	L2W1	L3W2	-0.19	-8.86	0.0001
183	L2W4	L3W1	-0.17	-7.73	0.0001
184	L3W3	L5W1	-0.06	-2.57	0.0102
185	L5W2	L5W4	0.05	2.24	0.0255
186	L1W3	L1W4	-0.03	-1.58	0.1136
187	L2W1	L3W3	-0.08	-3.70	0.0002
188	L2W4	L3W2	-0.23	-10.63	0.0001
189	L3W3	L5W2	-0.01	-0.49	0.6257
190	L5W3	L5W4	0.07	3.17	0.0015

Appendix F: Random part quantities cutting bills

Table A - 7: Cutting bills with uniform, random part quantities

Cutting bill 1				
#	Part Group	Quantity	Length	Width
1	L1W1	44	10.00	1.50
2	L2W1	600	17.50	1.50
3	L3W1	726	27.50	1.50
4	L4W1	437	47.50	1.50
5	L5W1	92	72.50	1.50
6	L1W2	69	10.00	2.50
7	L2W2	395	17.50	2.50
8	L3W2	1013	27.50	2.50
9	L4W2	88	47.50	2.50
10	L5W2	206	72.50	2.50
11	L1W3	18	10.00	3.50
12	L2W3	10	17.50	3.50
13	L3W3	76	27.50	3.50
14	L4W3	151	47.50	3.50
15	L5W3	81	72.50	3.50
16	L1W4	115	10.00	4.25
17	L2W4	110	17.50	4.25
18	L3W4	365	27.50	4.25
19	L4W4	43	47.50	4.25
20	L5W4	70	72.50	4.25

Cutting bill 2				
#	Part Group	Quantity	Length	Width
1	L1W1	15	10.00	1.50
2	L2W1	633	17.50	1.50
3	L3W1	627	27.50	1.50
4	L4W1	607	47.50	1.50
5	L5W1	215	72.50	1.50
6	L1W2	166	10.00	2.50
7	L2W2	173	17.50	2.50
8	L3W2	1196	27.50	2.50
9	L4W2	499	47.50	2.50
10	L5W2	3	72.50	2.50
11	L1W3	75	10.00	3.50
12	L2W3	242	17.50	3.50
13	L3W3	349	27.50	3.50
14	L4W3	165	47.50	3.50
15	L5W3	25	72.50	3.50
16	L1W4	72	10.00	4.25
17	L2W4	113	17.50	4.25
18	L3W4	89	27.50	4.25
19	L4W4	106	47.50	4.25
20	L5W4	63	72.50	4.25

Cutting bill 3				
#	Part Group	Quantity	Length	Width
1	L1W1	126	10.00	1.50
2	L2W1	347	17.50	1.50
3	L3W1	443	27.50	1.50
4	L4W1	424	47.50	1.50
5	L5W1	132	72.50	1.50
6	L1W2	251	10.00	2.50
7	L2W2	297	17.50	2.50
8	L3W2	936	27.50	2.50
9	L4W2	484	47.50	2.50
10	L5W2	85	72.50	2.50
11	L1W3	36	10.00	3.50
12	L2W3	245	17.50	3.50
13	L3W3	16	27.50	3.50
14	L4W3	32	47.50	3.50
15	L5W3	78	72.50	3.50
16	L1W4	121	10.00	4.25
17	L2W4	244	17.50	4.25
18	L3W4	172	27.50	4.25
19	L4W4	15	47.50	4.25
20	L5W4	18	72.50	4.25

Cutting bill 4				
#	Part Group	Quantity	Length	Width
1	L1W1	195	10.00	1.50
2	L2W1	536	17.50	1.50
3	L3W1	1045	27.50	1.50
4	L4W1	330	47.50	1.50
5	L5W1	36	72.50	1.50
6	L1W2	204	10.00	2.50
7	L2W2	687	17.50	2.50
8	L3W2	107	27.50	2.50
9	L4W2	552	47.50	2.50
10	L5W2	101	72.50	2.50
11	L1W3	93	10.00	3.50
12	L2W3	156	17.50	3.50
13	L3W3	139	27.50	3.50
14	L4W3	99	47.50	3.50
15	L5W3	73	72.50	3.50
16	L1W4	47	10.00	4.25
17	L2W4	50	17.50	4.25
18	L3W4	62	27.50	4.25
19	L4W4	46	47.50	4.25
20	L5W4	24	72.50	4.25

Table A - 7: Cutting bills with uniform, random part quantities, continued

Cutting bill 5				
#	Part Group	Quantity	Length	Width
1	L1W1	173	10.00	1.50
2	L2W1	649	17.50	1.50
3	L3W1	835	27.50	1.50
4	L4W1	209	47.50	1.50
5	L5W1	211	72.50	1.50
6	L1W2	305	10.00	2.50
7	L2W2	502	17.50	2.50
8	L3W2	834	27.50	2.50
9	L4W2	355	47.50	2.50
10	L5W2	49	72.50	2.50
11	L1W3	75	10.00	3.50
12	L2W3	71	17.50	3.50
13	L3W3	309	27.50	3.50
14	L4W3	71	47.50	3.50
15	L5W3	126	72.50	3.50
16	L1W4	14	10.00	4.25
17	L2W4	107	17.50	4.25
18	L3W4	273	27.50	4.25
19	L4W4	7	47.50	4.25
20	L5W4	42	72.50	4.25

Appendix G: "Real" cutting bills used for the validation of the model

Table A - 8: "Real" cutting bills from actual operations

Cutting bill A			
#	Quantity	Length	Width
1	40	45.75	1.00
2	40	24.25	1.75
3	40	42.50	1.75
4	80	77.25	1.75
5	160	24.00	2.25
6	160	5.75	2.75
7	320	19.50	3.25

Cutting bill B			
#	Quantity	Length	Width
1	200	19.25	2.00
2	200	16.00	2.25
3	100	57.50	2.25
4	200	17.75	2.50
5	100	21.50	2.50
6	100	75.50	2.50
7	200	14.50	2.75
8	200	23.25	2.75
9	100	42.25	2.75
10	200	42.25	3.00
11	200	20.00	3.50
12	200	20.50	3.50

Cutting bill C			
#	Quantity	Length	Width
1	32	21.00	1.50
2	88	21.50	1.50
3	40	21.75	1.50
4	14	30.50	1.50
5	38	24.25	1.75
6	14	29.75	1.75
7	36	18.50	2.00
8	14	19.75	2.00
9	80	22.00	2.00
10	14	26.75	2.00
11	74	27.25	2.00
12	14	28.25	2.00
13	30	28.50	2.00
14	18	29.75	2.00
15	54	30.75	2.00
16	14	32.75	2.00
17	36	33.75	2.00
18	30	34.25	2.00
19	20	42.50	2.00
20	14	48.75	2.00
21	8	57.50	2.00
22	6	66.75	2.00
23	14	76.25	2.00
24	100	19.00	2.25
25	40	21.75	2.25
26	36	27.25	2.25
27	52	28.50	2.25
28	20	31.25	2.25
29	20	40.25	2.25
30	38	47.50	2.25
31	38	63.25	2.25
32	40	70.25	2.25
33	52	81.25	2.50
34	20	47.50	2.75
35	176	33.25	3.00
36	28	40.25	3.25

Table A - 8: "Real" cutting bills from actual operations, continued

Cutting bill D			
#	Quantity	Length	Width
1	540	72.00	1.50
2	630	60.00	3.00
3	1170	44.00	1.50
4	900	36.00	3.00
5	900	28.00	1.50
6	900	24.00	1.50
7	900	20.00	3.00
8	900	18.00	1.50

Cutting bill E			
#	Quantity	Length	Width
1	20	13.50	1.25
2	40	14.75	1.25
3	190	15.75	1.25
4	30	16.25	1.25
5	10	18.25	1.25
6	20	25.50	1.25
7	20	13.50	2.00
8	10	30.00	2.00
9	10	56.25	2.00
10	20	12.25	2.50
11	20	15.75	2.50
12	60	17.00	2.50
13	80	18.25	2.50
14	40	19.50	2.50
15	40	23.00	2.50
16	20	47.50	2.50
17	20	20.25	3.00
18	20	23.00	3.00
19	20	28.00	3.00
20	20	34.25	3.00
21	10	43.00	3.00
22	20	45.00	3.00
23	20	56.25	3.00
24	40	16.25	3.25
25	20	24.50	3.25
26	10	54.00	3.25
27	10	60.50	3.25
28	20	12.25	4.00
29	10	26.50	4.00
30	20	38.75	4.00
31	10	50.75	4.00
32	20	68.75	4.00
33	20	15.75	4.75
34	60	16.25	4.75
35	60	17.75	4.75
36	20	24.50	4.75

Appendix H: "Real" cutting bills, parts clustered, unscaled and scaled

Table A - 9: "Real" cutting bills, parts clustered, unscaled and scaled quantities

Cutting bill A					
#	Part Group	Unscaled quantity	Scaled quantity	Length	Width
1	L3W1	40	32	27.50	1.50
2	L4W1	80	64	47.50	1.50
3	L5W1	80	64	72.50	1.50
4	L1W2	160	127	10.00	2.50
5	L3W2	160	127	27.50	2.50
6	L2W3	320	254	17.50	3.50

Cutting bill B					
#	Part Group	Unscaled quantity	Scaled quantity	Length	Width
1	L1W2	200	183	10.00	2.50
2	L2W2	600	548	17.50	2.50
3	L3W2	300	274	27.50	2.50
4	L4W2	200	183	47.50	2.50
5	L5W2	100	91	72.50	2.50
6	L3W3	400	365	27.50	3.50
7	L4W3	200	183	47.50	3.50

Cutting bill C					
#	Part Group	Unscaled quantity	Scaled quantity	Length	Width
1	L3W1	226	371	27.50	1.50
2	L2W2	150	246	17.50	2.50
3	L3W2	512	840	27.50	2.50
4	L4W2	120	197	47.50	2.50
5	L5W2	150	246	72.50	2.50
6	L3W3	176	289	27.50	3.50
7	L4W3	28	46	47.50	3.50

Cutting bill D					
#	Part Group	Unscaled quantity	Scaled quantity	Length	Width
1	L2W1	900	203	17.50	1.50
2	L3W1	1800	406	27.50	1.50
3	L4W1	1170	264	47.50	1.50
4	L5W1	540	122	72.50	1.50
5	L3W3	900	203	27.50	3.50
6	L4W3	900	203	47.50	3.50
7	L5W3	630	142	72.50	3.50

Cutting bill E					
#	Part Group	Unscaled quantity	Scaled quantity	Length	Width
1	L1W1	60	106	10.00	1.50
2	L2W1	230	407	17.50	1.50
3	L3W1	20	35	27.50	1.50
4	L1W2	40	71	10.00	2.50
5	L2W2	200	354	17.50	2.50
6	L3W2	50	89	27.50	2.50
7	L4W2	30	53	47.50	2.50
8	L2W3	40	71	17.50	3.50
9	L3W3	100	177	27.50	3.50
10	L4W3	60	106	47.50	3.50
11	L5W3	10	18	72.50	3.50
12	L1W4	20	35	10.00	4.25
13	L2W4	140	248	17.50	4.25
14	L3W4	30	53	27.50	4.25
15	L4W4	30	53	48	4.25
16	L5W4	20	35	73	4.25

Appendix I: Individual results of the tests with the five "real" cutting bills

Table A - 10: Individual results from the five "real" cutting bills

Line #	Observation	Cutting bill				
		A	B	C	D	E
1	**Simulation**	64.40	67.34	68.48	65.47	72.39
2	**Clustered simulation**	67.97	64.18	64.00	62.64	70.16
3	**Clustered and scaled simulation**	67.39	64.18	62.90	62.09	68.13
4	**LS Model**	52.71	59.33	58.98	55.35	60.20
5	**Simulation-clustered simulation [1-2]**	-3.57	3.16	4.48	2.82	2.23
6	**Simulation - clustered and scaled simulation [1-3]**	-2.99	3.16	5.58	3.37	4.26
7	**Clustered simulation - clustered and scaled simulation [2-3]**	0.58	0.00	1.10	0.55	2.04
8	**Simulation-LS Model [1-4]**	11.69	8.01	9.50	10.12	12.19
9	**Clustered simulation - LS Model [2-4]**	15.26	4.85	5.02	7.29	9.96
10	**Clustered and scaled simulation - LS Model [3-4]**	14.68	4.85	3.92	6.74	7.93
11	**# of parts in cutting bill**	7	12	36	8	36
12	**# of part groups used**	6	7	7	7	16

Appendix J: Resolution IV fractional factorial design and results

Table A - 11: Resolution IV fractional factorial design, results from simulation (3 replicates), average yield and estimated yield in percent, cutting bills 1 to 50

#	L_1 W_1	L_2 W_1	L_3 W_1	L_4 W_1	L_5 W_1	L_1 W_2	L_2 W_2	L_3 W_2	L_4 W_2	L_5 W_2	L_1 W_3	L_2 W_3	L_3 W_3	L_4 W_3	L_5 W_3	L_1 W_4	L_2 W_4	L_3 W_4	L_4 W_4	L_5 W_4	Results Rep 1	Rep 2	Rep 3	Av.	Model
1	-	-	-	-	-	-	+	+	+	+	+	+	+	+	-	+	-	+	-	-	66.07	66.34	65.63	66.01	66.03
2	-	-	-	-	-	+	-	-	-	-	-	-	-	+	-	-	+	+	-	-	58.02	57.46	57.27	57.58	57.42
3	-	-	-	-	+	-	-	-	-	-	-	-	+	-	-	+	-	-	+	-	53.79	53.19	53.00	53.33	53.31
4	-	-	-	-	+	+	+	+	+	+	+	+	-	-	-	-	+	-	+	-	66.18	66.53	66.04	66.25	66.37
5	-	-	-	+	-	-	-	-	-	-	+	+	-	-	+	-	-	-	-	-	55.53	55.55	56.31	55.80	55.88
6	-	-	-	+	-	+	+	+	+	+	-	-	+	-	+	+	+	-	-	-	67.09	67.12	66.68	66.96	66.88
7	-	-	-	+	+	-	+	+	+	+	-	-	-	+	+	-	-	+	+	-	62.51	62.93	62.34	62.59	62.53
8	-	-	-	+	+	+	-	-	-	-	+	+	+	+	+	+	+	+	+	-	66.32	66.24	65.85	66.14	66.24
9	-	-	+	-	-	-	-	-	+	+	-	-	-	-	-	-	-	-	-	+	53.59	53.58	52.54	53.24	53.27
10	-	-	+	-	-	+	+	+	-	-	+	+	+	-	-	+	+	-	-	+	69.39	69.29	69.03	69.24	69.10
11	-	-	+	-	+	-	+	+	-	-	+	+	-	+	-	-	-	+	+	+	65.91	66.06	65.22	65.73	65.72
12	-	-	+	-	+	+	-	-	+	+	-	-	+	+	-	+	+	+	+	+	64.89	64.69	64.14	64.57	64.73
13	-	-	+	+	-	-	+	+	-	-	-	-	+	+	+	+	-	+	-	+	66.17	66.06	65.57	65.93	65.98
14	-	-	+	+	-	+	-	-	+	+	+	+	-	+	+	-	+	+	-	+	65.05	65.12	64.66	64.94	64.86
15	-	-	+	+	+	-	-	-	+	+	+	+	+	-	+	+	-	-	+	+	63.06	62.89	62.78	62.91	62.82
16	-	-	+	+	+	+	+	+	-	-	-	-	-	-	+	-	+	-	+	+	66.42	66.31	65.85	66.19	66.29
17	-	+	-	-	-	-	-	+	-	+	-	+	-	-	+	+	+	+	+	+	64.64	64.54	64.27	64.48	64.52
18	-	+	-	-	-	+	+	-	+	-	+	-	+	-	+	-	-	+	+	+	64.51	64.94	63.94	64.46	64.57
19	-	+	-	-	+	-	+	-	+	-	+	-	-	+	+	+	+	-	-	+	66.55	66.28	65.53	66.12	66.05
20	-	+	-	-	+	+	-	+	-	+	-	+	+	+	+	-	-	-	-	+	64.82	64.59	63.35	64.25	64.22
21	-	+	-	+	-	-	+	-	+	-	-	+	+	+	-	-	+	-	+	+	67.56	67.57	67.60	67.58	67.59
22	-	+	-	+	-	+	-	+	-	+	+	-	-	+	-	+	-	-	+	+	64.61	64.03	63.54	64.06	64.05
23	-	+	-	+	+	-	-	+	-	+	+	-	+	-	-	-	+	+	-	+	65.39	65.59	65.08	65.35	65.36
24	-	+	-	+	+	+	+	-	+	-	-	+	-	-	-	+	-	+	-	+	67.58	67.11	67.71	67.47	67.43
25	-	+	+	-	-	-	+	-	-	+	+	-	+	+	+	-	+	-	+	-	67.59	67.07	67.03	67.23	67.26
26	-	+	+	-	-	+	-	+	+	-	-	+	-	+	+	+	-	-	+	-	67.52	67.89	67.27	67.56	67.63
27	-	+	+	-	+	-	-	+	+	-	-	+	+	-	+	-	+	+	-	-	66.14	66.40	65.94	66.16	66.08
28	-	+	+	-	+	+	+	-	-	+	+	-	-	-	+	+	-	+	-	-	67.61	67.78	66.58	67.32	67.26
29	-	+	+	+	-	-	-	+	+	-	+	-	-	-	-	+	+	+	+	-	66.90	66.82	66.48	66.73	66.77
30	-	+	+	+	-	+	+	-	-	+	-	+	+	-	-	-	-	+	+	-	68.16	67.30	67.13	67.53	67.53
31	-	+	+	+	+	-	+	-	-	+	-	+	-	+	-	+	+	-	-	-	67.30	67.51	67.34	67.38	67.42
32	-	+	+	+	+	+	-	+	+	-	+	-	+	+	-	-	-	-	-	-	67.98	67.71	67.35	67.68	67.65
33	+	-	-	-	-	-	-	+	+	-	+	-	+	+	+	-	+	-	+	+	62.26	62.38	61.76	62.13	62.20
34	+	-	-	-	-	+	+	-	-	+	-	+	-	+	+	+	-	-	+	+	61.00	60.68	60.43	60.70	60.78
35	+	-	-	-	+	-	+	-	-	+	-	+	+	-	+	-	+	+	-	+	64.65	64.79	64.05	64.50	64.42
36	+	-	-	-	+	+	-	+	+	-	+	-	-	-	+	+	-	+	-	+	61.81	61.95	61.32	61.69	61.66
37	+	-	-	+	-	-	+	-	-	+	+	-	-	-	-	+	+	+	+	+	64.52	65.13	64.67	64.77	64.81
38	+	-	-	+	-	+	-	+	+	-	-	+	+	-	-	-	-	+	+	+	63.62	63.53	63.22	63.46	63.42
39	+	-	-	+	+	-	-	+	+	-	-	+	-	+	-	+	+	-	-	+	64.37	64.27	63.70	64.11	64.11
40	+	-	-	+	+	+	+	-	-	+	+	-	+	+	-	-	-	-	-	+	62.97	63.35	63.08	63.13	63.09
41	+	-	+	-	-	-	+	-	+	-	-	+	-	-	+	+	+	+	+	-	67.54	67.17	67.31	67.34	67.37
42	+	-	+	-	-	+	-	+	-	+	+	-	+	-	+	-	-	+	+	-	64.31	65.11	64.68	64.70	64.77
43	+	-	+	-	+	-	-	+	-	+	+	-	-	+	+	+	+	-	-	-	64.36	64.07	64.07	64.17	64.06
44	+	-	+	-	+	+	+	-	+	-	-	+	+	+	+	-	-	-	-	-	69.26	69.12	69.12	69.17	69.13
45	+	-	+	+	-	-	-	+	-	+	-	+	+	+	-	-	+	-	+	-	66.40	66.35	66.05	66.27	66.31
46	+	-	+	+	-	+	+	-	+	-	+	-	-	+	-	+	-	-	+	-	68.18	68.18	68.00	68.12	68.12
47	+	-	+	+	+	-	+	-	+	-	+	-	+	-	-	-	+	+	-	-	66.71	66.80	66.44	66.65	66.66
48	+	-	+	+	+	+	-	+	-	+	-	+	-	-	-	+	-	+	-	-	65.78	65.83	65.86	65.82	65.81
49	+	+	-	-	-	-	+	+	-	-	-	-	-	-	-	-	-	-	-	-	67.24	66.82	66.46	66.84	66.69
50	+	+	-	-	-	+	-	-	+	+	+	+	+	-	-	+	+	-	-	-	64.18	64.02	63.98	64.06	64.07

Table A - 11: Resolution IV fractional factorial design, results from simulation (3 replicates), average yield and estimated yield in percent, cutting bills 51 to 64, continued

#	L_1	L_2	L_3	L_4	L_5	L_1	L_2	L_3	L_4	L_5	L_1	L_2	L_3	L_4	L_5	L_1	L_2	L_3	L_4	L_5	Results				
	W_1	W_1	W_1	W_1	W_1	W_2	W_2	W_2	W_2	W_2	W_3	W_3	W_3	W_3	W_3	W_4	W_4	W_4	W_4	W_4	Rep 1	Rep 2	Rep 3	Av.	Model
51	+	+	-	-	+	-	-	-	+	+	+	+	-	+	-	-	-	+	+	-	61.47	61.55	61.10	61.37	61.51
52	+	+	-	-	+	+	+	+	-	-	-	-	+	+	-	+	+	+	+	-	69.61	69.32	69.05	69.33	69.30
53	+	+	-	+	-	-	-	-	+	+	-	-	+	+	+	+	-	+	-	-	63.13	63.10	62.65	62.96	62.87
54	+	+	-	+	-	+	+	+	-	-	+	+	-	+	+	-	+	+	-	-	70.75	70.77	70.26	70.59	70.69
55	+	+	-	+	+	-	+	+	-	-	+	+	+	-	+	+	-	-	+	-	69.29	69.43	69.27	69.33	69.42
56	+	+	-	+	+	+	-	-	+	+	-	-	-	-	+	-	+	-	+	-	63.48	63.37	63.23	63.36	63.31
57	+	+	+	-	-	-	-	-	-	-	+	+	+	+	-	+	-	+	-	+	66.67	67.45	67.54	67.22	67.10
58	+	+	+	-	-	+	+	+	+	+	-	-	-	+	-	-	+	+	-	+	69.49	69.58	68.65	69.24	69.26
59	+	+	+	-	+	-	+	+	+	+	-	-	+	-	-	+	-	-	+	+	68.23	67.85	67.70	67.93	68.09
60	+	+	+	-	+	+	-	-	-	-	+	+	-	-	-	-	+	-	+	+	68.04	68.03	66.99	67.69	67.66
61	+	+	+	+	-	-	+	+	+	+	+	+	-	-	+	-	-	-	-	+	68.88	68.88	68.58	68.78	68.68
62	+	+	+	+	-	+	-	-	-	-	-	-	+	-	+	+	+	-	-	+	68.20	68.21	68.19	68.20	68.26
63	+	+	+	+	+	-	-	-	-	-	-	-	-	+	+	-	-	+	+	+	62.39	62.45	61.78	62.21	62.29
64	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	70.29	70.32	69.97	70.19	70.11

Appendix K: Significance and parameter estimates for main effects, resolution IV design

Table A - 12: Significance and parameter estimates of main effects, resolution IV design

#	Part Group	Parameter Estimate	t for H0	Probability (p)
0	Intercept	65.23	609.92	0.0001
1	L1W1	0.58	5.44	0.0001
2	L1W2	0.76	7.09	0.0001
3	L1W3	0.41	3.85	0.0002
4	L1W4	0.46	4.31	0.0001
5	L2W1	1.35	12.64	0.0001
6	L2W2	1.66	15.55	0.0001
7	L2W3	0.71	6.61	0.0001
8	L2W4	0.88	8.21	0.0001
9	L3W1	1.14	10.70	0.0001
10	L3W2	1.01	9.46	0.0001
11	L3W3	0.54	5.01	0.0001
12	L3W4	0.24	2.24	0.0267
13	L4W1	0.49	4.62	0.0001
14	L4W2	0.14	1.28	0.2008
15	L4W3	0.28	2.59	0.0104
16	L4W4	-0.04	-0.34	0.7332
17	L5W1	0.08	0.78	0.4338
18	L5W2	-0.32	-3.03	0.0029
19	L5W3	0.05	0.49	0.6259
20	L5W4	-0.15	-1.44	0.1520

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