Revenue Management in High-Density Urban Parking Districts: Modeling and Evaluation

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ABSTRACT

This thesis explores how revenue management (RM) principles would integrate into a parking system, and how advanced reservation-making, coupled with dynamic pricing (based on booking limits) could be used to maximize parking revenue. Detailed here is a comprehensive RM strategy for the parking industry, and an integer programming formulation that maximizes parking revenue over a system of garages is presented. Furthermore, an intelligent parking reservation model is developed that uses an artificial neural network procedure for online reservation decision-making.

Next, the work evaluates whether the implementation of a parking RM system in a dense urban parking district (and thus avoiding "trial-and-error" behaviors exhibited by drivers) mitigates urban congestion levels. In order to test this hypothesis, a parallel modeling structure was developed that uses a real-time decision-making model that either accepts or rejects requests for parking via a back-propagation neural network. Coupled with the real-time decision-making model is a micro-simulation model structure used to evaluate the policy's effects on network performance. It is clear from the results that the rate at which parkers renege is a primary determinant of the value of the implementation of RM. All other things being equal, the RM model in which the majority of parkers is directed to their precise parking spot via the most direct route is much more robust to the random elements within the network that can instigate extreme congestion.

The thesis then moves from micro-evaluation to macro-evaluation by measuring the performance of the urban parking system from the perspective of the set of relevant stakeholders using the hyperbolic DEA model within the context of the matrix DEA construct. The stakeholder models, including that of the provider, the user, and the community, have defined inputs/outputs to the hyperbolic DEA model, which allows for the inclusion of undesirable outputs such as network delay and incidence of extreme congestion. Another key contribution of this work is that of identifying design issues for current and future dense urban parking districts. Clearly, reneging rate and the tenacity of perspective parkers is a key consideration in cases where RM policy is not implemented.

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CHAPTER 1 Introduction

1.1 Problem Context

According to Robert G. Cross [12] in his seminal work, *Revenue Management*, the term *revenue management* is defined as "the application of disciplined tactics that predict consumer behavior at the micro-market level and optimize product availability and price to maximize revenue growth. In even simpler terms, revenue management ensures that companies will sell the right product to the right customer at the right time for the right price (pp.51-52)." The basic characteristics, as discussed by Cross and others, of industries to which revenue management concepts may be successfully applied are: (a) variable demand over time; (b) variable asset utilization; (c) perishable assets; (d) limited resource pool; (e) market segmentation; (f) the addition of new capacity is expensive, difficult, or impossible; (g) the direct cost per client is a negligible part of the total cost of making service available; (h) products are sellable in advance.

Although revenue management has its roots in the airline and hotel industries, applications are possible in all of the industries that possess the characteristics listed above. As detailed by Teodorović and Lučić [49], parking systems are ideal candidates for the application of revenue management principles. Consider the following:

- Parking demand is variable over time.
- Like hotel rooms, or restaurant chairs, parking spaces also have daily opportunities to be "sold".
- Any parking lot or garage has a limited number of parking spaces that can be used by drivers.
- Market segmentation means that different customers are willing to pay different prices for the same asset (hotel room, airline seat). For example, a working professional wanting to park a car near a meeting point 15 minutes before the meeting would be ready to pay higher parking fees than a pensioner who makes a reservation four days in advance.
- Building new garages and/or parking lots is expensive and difficult.
- Parking may be easily reserved in advance.

Although revenue management in and of itself cares nothing about the rising problem of urban traffic congestion (it only seeks to increase a business' revenue), introducing and implementing a well-developed parking reservation system (using the internet or cell phones as a means of requesting service) could significantly improve the urban congestion caused by the "trial and error" searches of prospective parkers.

Congestion is one of the most prevalent transport problems in larger urban areas. The diffusion of the automobile has increased the demand for transport infrastructures, but the supply of infrastructures has often not been able to keep up with the growth of mobility. Since vehicles spend the majority of the time parked, motorization has expanded the demand for parking space, which has created a space consumption problem, particularly in central areas. Pollution, generated by the high population of automobiles has become a serious impediment to the quality of life and health of urban populations. Additionally, energy consumption (and therefore, dependency on petroleum fuel) by many transportation providers has dramatically increased.

Congestion occurs when transport demand exceeds transport supply in a specific section of the transport system. Congestion can be perceived as an unavoidable consequence of the usage of scarce transport resources, particularly if there is no demand management strategy (e.g., congestion pricing) in place. The building of additional supply has largely proved ineffectual to combat this problem, and it has created a vicious cycle of congestion that supports the construction of additional road capacity and automobile dependency [35].

In the case of a parking system, congestion not only occurs when there is excess demand for the parking resource itself, but also in and around the surrounding road network due to the parking search process (or the "trial and error" search of prospective parkers). This congestion observed around high-density parking districts can be considered from the perspective of a variety of stakeholders. For instance, the parking provider likely considers congestion to either be neutral (especially, if parking resources are completely consumed) or an impediment to steady flow, and therefore, consumption of the parking resource being

sold. The parking consumer always views congestion negatively. It is a generator of delay, impeding him from reaching the destination.

An intelligent parking reservation system is indispensible to the effective segmentation of the parking market in accordance with revenue management, and therefore, the implementation of revenue management strategies could likely have an effect on driving behavior. The magnitude of this improvement (if any) in congestion levels and the extent of intelligent parking infrastructure required to see improvement is a key pursuit within this dissertation.

1.2 Research Contributions

As is detailed in **Chapter 2**, the current body of literature addressing the intersection of both parking systems and revenue management research is not overwhelmingly large. Many of the papers indicate the considerable amount of work left to be done. In particular, no paper has yet to explore how revenue management principles would fully integrate into a parking system or how advanced reservations, coupled with dynamic pricing (based on "booking limits") could be used to maximize parking revenue. This dissertation addresses the specific literature gap of developing a detailed implementation strategy for revenue management within parking systems, and demonstrates the suitability (and potential profitability) of revenue management principles for this application.

Furthermore, no investigation has been made into measuring if and how much the application of revenue management in the parking industry and within urban parking districts might mitigate traffic congestion in a downtown area. The testing of the principal research hypothesis of this thesis, that implementation of parking revenue management will mitigate urban traffic congestion, is accomplished through first developing the concept of parking revenue management and then testing the hypothesis through parallel mathematical programming and micro-simulation modeling.

Additionally, this dissertation seeks to evaluate the effects of intelligent parking/revenue management on urban congestion from the perspective of the three key stakeholders within the system: the parking provider, the parking consumer, and the surrounding community. In order to do this, this thesis introduces the concept of matrix data envelopment analysis (DEA) to compare changes in network conditions across stakeholder perspectives. It is also intended to provide insight into key system design issues for high-density urban parking districts. The resolution of these unanswered issues in the literature will be addressed by and will be the chief contributions of this thesis.

1.3 Organization of Dissertation

The dissertation has three main parts. The structure of the dissertation is shown in *Figure 1.1* below.

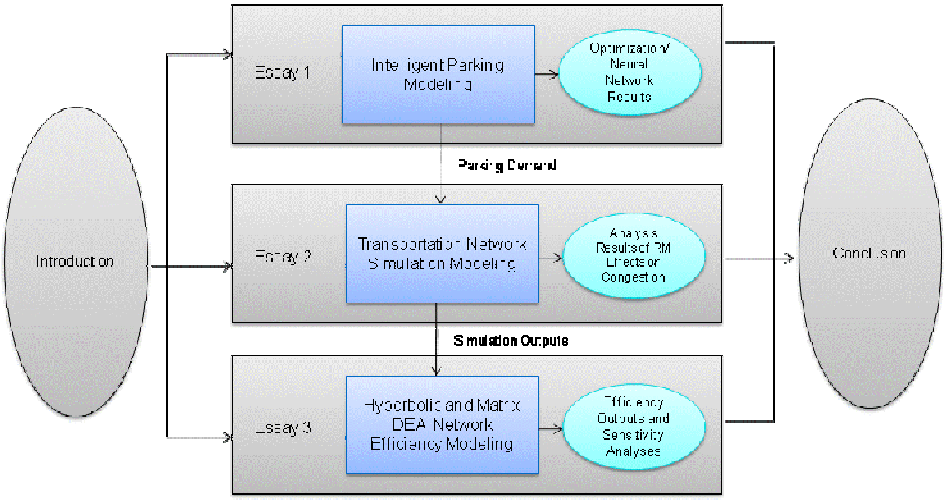

Figure 1.1 Thesis Structure and Modeling Interactions

Chapter 2 will provide a review of literature that is related to the research but is not covered in the three essays. In **Chapters 3, 4, 5**, the first, the second and the third essay will be presented, respectively. In **Chapter 6**, the results of the three essays will be summarized and along with opportunities for future work.

Additional modeling detail, along with any programming code supporting the three essays, is included as an appendix at the end of this document.

Essay One (**Chapter 3**) presents a comprehensive revenue management strategy for the parking industry, focusing on a single-garage scenario. In addition, an integer programming formulation that maximizes parking revenue over a system of garages is presented. Furthermore, an intelligent parking reservation model is developed that uses an artificial neural network procedure for online reservation decision-making. It is concluded that the parking industry is a good candidate for RM strategy implementation, and this chapter fully develops the formulation, tools, and modeling to operate an online decision-making system that isolates micro-markets and maximizes revenue.

Essay Two (**Chapter 4**) evaluates whether the establishment of a parking revenue management system in a dense urban parking district (and thus avoiding "trial-and-error" behaviors exhibited by parkers) mitigates urban congestion levels. In order to test this hypothesis, the intelligent parking model from Essay One is run alongside a VISSIM micro-simulation model to evaluate the policy's effects on network performance.

The primary purpose of Essay Three (**Chapter 5**) is to evaluate the performance of the urban parking system from the perspective of the set of relevant stakeholders using the hyperbolic DEA model within the context of the matrix DEA construct. The stakeholder models, including that of the parking provider, the parking customer, and the surrounding community, had defined inputs and outputs to the hyperbolic DEA model, which allows for the inclusion of undesirable outputs such as network delay and incidence of extreme congestion. DMUs are defined within two matrices: one designated for performance evaluation within the non-RM model (Base Case) and one designated for evaluation within the model where RM policy was in place (Alternative Case).

CHAPTER 2 Literature Review

2.1 Parking Modeling Literature

As described in **Chapter 1**, the principal aim of this research is to examine revenue management within the parking industry and its impact on urban traffic congestion. The body of urban parking-related research is fairly extensive, and although most of the body of literature would not be considered a direct predecessor of this research, much of it can guide or frame the research in light of previous findings, and therefore, in a more effective way.

The first and most common theme within the body of literature is that of survey-based research, including stated preference parking choice or mode choice research. In this literature, data is primarily gathered by means of polling or surveying a relevant population and allowing them to state their preferences based on a scenario or a given set of data. The results are analyzed by a variety of means to draw conclusions regarding parking or modal split. In the cases when the transportation mode choice is being examined, each of these research initiatives uses parking pricing, supply, or demand as variables within the model formulations.

Caicedo et al. [8], Centeno and Rojas [9], Hunt and Teply [24], and Van der Goot [59] all use the survey-based method (among others, in some cases) to evaluate the process or effects of parking space selection. Caicedo et al. [8] consider the special case of underground parking structures and the particular considerations for this environment. Hunt and Teply [24] employ a nested logit model of individual parking location choice. Van der Goot [59] performs a logit analysis of variables including walking time, parking charges, and occupation rates gathered by means of a survey.

The researchers that use a stated preference method to determine the transportation mode selection (with parking being a key variable) include Hensher and King [22]; Shiftan and Burd-Eden [41]; Thompson and Richardson [55]; and Washbrook et al. [62]. Hensher and King [22] consider transportation mode choice

based specifically on supply, pricing, and the choice of parking. Shiftan's and Burd-Eden's work [41] uses the survey-based method to examine the effects of changes in urban parking policy. The research of Thompson and Richardson [55] indicates that long-term experience with the parking environment within a particular urban area may not lead to better decision-making, and Washbrook et al. [62] demonstrate that parking price plays a pivotal role in transportation mode selection.

Several components of the body of parking-related literature address the issue of parking demand modeling. It is clear from this work that assigning a particular parking demand function to a specific functional form, apart from the demand assumptions adopted in the majority of the literature, is not trivial. Steiner [44]; Tong et al. [57]; Tong et al. [56]; and Wong et al. [65] all develop some variation of a parking demand model.

Steiner [44] evaluates the popular New Urbanist land development model. Specifically, she tests the hypothesis that a neighborhood typical of the New Urbanist movement that contains the "essentials" for everyday life (i.e. residences, shopping, post office, basic services) along with infrastructure to encourage pedestrian travel will reduce congestion and the need for parking in that neighborhood. In short, the neighborhood will generate fewer trips and lower parking demand. Her findings, however, show the opposite. By examining several of these types of neighborhoods within the Oakland/Berkeley area, Steiner [44] shows that newly constructed shops, services and development within the New Urbanist area generate additional trips from outside the neighborhood that offset the reduction in trips within the neighborhood.

Tong et al. [56] derive a demand/supply equilibrium model for the Hong Kong urban area that aids in evaluating the adequacy of existing parking facilities. In addition, Tong et al. [57] amass parking data from a variety of venues throughout Hong Kong to develop an impressive parking demand model for Hong Kong, including parking accumulation profiles from various zones of the city.

Another prevalent topic among the literature is that of evaluating the role and effectiveness of urban parking information systems. Although quite common in Europe and some parts of Asia, parking guidance

or parking information systems are relatively rare in the United States. Several large cities either have plans to or have already implemented one of these systems. The literature reflects this growing interest in parking guidance systems. Hae Don et al. [21]; Spencer and West [43]; Teng et al. [47]; and Waterson et al. [63] all address aspects of automated parking guidance. The issue of automated parking information systems is significant to the central problem of this research. If advanced parking reservations are allowed and encouraged, then a mechanism to direct these parkers holding a reservation to their space must be in place. One option to direct parkers is by means of a parking information system.

Hae Don et al. [21] researched a technology concept to direct parkers to available parking areas. They call the system the Nearest Available Parking Lot Application or NAPA. Spencer and West [43] describe the planned parking guidance system for the San Jose, California area and they derive a means to assess its effectiveness. Similarly, Teng et al. [47] use an ordered probit model to analyze the needs and anticipated effectiveness of a planned parking information system in New York City. To evaluate the performance and potential travel time savings from parking guidance systems, Waterson et al. [63] consider several operational parking information systems. Among their conclusions is that parking guidance aids in spreading demand more evenly over a parking stock.

Two research groups consider parking problems using a game theory perspective. Hollander et al. [23] consider a Stackelberg game between the government players and the prospective travelers to the urban core. In particular, they address the common belief that abundant parking must be made available within the urban core in order to attract visitors and foster strength and growth. Their research considers scenarios with varying parking price structures, parking availability, and transit availability/use.

Tsai and Chu [58] consider another set of games. In these, the government and private firms move to control and operate groups of parking supply. In each scenario, they set prices on their respective inventory, and travelers to the urban core choose their parking locations. Although the government and private firms (to a certain degree) will strive to maximize their own welfare, the overall objective function is to maximize public welfare.

Research at several institutions centers on performance measurement and evaluation of parking facilities and systems. Since this research will both examine and evaluate parking systems under revenue management scenarios, this branch of research is particularly relevant.

Randhawa et al. [34] model parking areas (based on actual sites) and then evaluate their performance using parameters such as average time spent waiting, number of cars waiting at entries and exits, and number of cars waiting within the parking area. An interesting note here is that the modelers use Poisson arrivals to the parking area and use several previous papers to set the precedence for this assumption.

The ARENA simulation package is used by Robert Saltzman [38] to evaluate performance measures in one particular on-street parking arrangement, and changes a host of his modeling assumptions to perform sensitivity analyses. For instance, Saltzman varies the amount of enforcement, the parking meter price structure, and the average time spent parked to look at the effect on measures such as delay, amount of illegal parking, level of service, and others.

Swanson [45] evaluates the effect of influencing factors on parking rates. In particular, the researcher compares the parking meter conventions in both the United States and Canada, and proposes that a national coinage structure, along with a meter's ability to accept a wide range of coins has a profound effect on the ability of meters to levy the appropriate parking price, and can influence whether or not parkers choose to park illegally.

The body of parking research includes a significant percentage of papers that examine the impact of parking policy on parking demand, supply, pricing, and several other defining characteristics. A key delineating factor among this family of research is that some investigators look at how parking policy "trickles down" to affect supply, demand, performance, and delay. Others look at how the current supply, demand, performance, and other elements impact the parking policy development process.

Meyer [29] examines the economics and policy of travel demand management in light of parking systems. In particular, he examines social concerns and the dilemma of making the true cost of travel (and parking a vehicle) visible to the traveler. Migliore [30] implies that using parking pricing in lieu of road pricing could be an effective alternative. Verhoef et al. [60] evaluate parking policies as a direct substitute for road pricing. In addition, they study the use of parking fees versus parking supply restrictions. "The former is found to be superior for three reasons: an information argument, a temporal efficiency argument and an intertemporal efficiency argument (p. 141)." Using a survey-based method, Shiftan and Burd-Eden [41] measure the effects of parking policy. The first sentence in the abstract of this work reads, "Parking policy is one of the most powerful means urban planners and policy makers can use to manage travel demand and traffic in city centers."

Shoup [42] looks at the availability of free parking and how conventions have encouraged vehicle use. In particular, he discredits conventional sources used to determine minimum parking requirements in specific use urban parking areas. Schank [39] observes the delicate balance of providing adequate parking at rail stations while accounting for social concerns and community pressures to limit parking structure height and prevalence.

There are several research groups that tackle various specialized parking modeling or reservation system pursuits. Arnott and Rowse [1] build a parking congestion model that captures individual drivers' searches for a parking space. The inherent nonlinearities, as described by the team, create multiple equilibria and make parking fee determination complex. Dell'Orco et al. [14] introduce an agent-based modeling approach to explore the complexities of parking systems and behaviors.

Maximum car ownership under the constraints of road capacity and parking space supply is examined by Tam and Lam [46]. This research group uses two-level programming to capture complexities of trip distribution, trip assignment, route choice, and destination choice. It is a unique perspective and frames the issue of excessive vehicle ownership well. Rojas and Centeno [36] provide a keen insight and introduction

to neural networks and how they can be used to evaluate parking systems. Their work includes a basic example to illustrate the principle.

Fantoni et al. [17] provide a broad review of premium airport parking supply, mechanics, and existing conventions within the United States. This is particularly pertinent to a study of revenue management within parking systems because it isolates a key market segment. In fact, this paper indicates that premium parking services is a comparatively easy way for airport parking management to "maximize net parking revenues (p.1)." Additionally, Javid et al. [26] derive rules of thumb for determining the needed supply of parking at high-volume airports.

Several research teams focus on the issue of advanced parking reservation systems. A group at Nippon Telegraph and Telephone Corporation (NTT) Service Integration Lab developed an internet parking reservation-making system that includes entry to facilities using smart cards. Inaba et al. [27] leverage existing technologies at NTT and tailor their concepts to streamline the parking and parking reservation-making process. Similarly, Mouskos et al. [31] present the idea of a parking reservation system and propose congestion reducing effects. Likewise, Ramirez [33] proposes an e-Parking system. This effort is a specific development for a planned parking business implementation. The desired effect is system transparency and efficiency.

One interesting area of research received significant attention in the late 1980's and early 1990's. In particular, teams at the University of Melbourne received funding from sources that included the Western Australia Department of Transport (WADoT) to develop parking software that would aid in urban planning in the central business district of Perth.

Thompson and Richardson [55] developed the concept of an early parking search model or choice model. One of their chief insights was that the long-term experience in parking within a certain area did not necessarily lead to better decision-making. Young et al. [66] developed the CENCIMM[1] software program

[1] Central City Movement Model

that was specifically designed for the Perth downtown project. Thompson and Collins [53][54] developed both PARKINFO and MICROPARK to provide an early parking management tool (software package).

2.2 Revenue Management

Several research groups grapple with the issues surrounding revenue management decision-making using various methods. Lin [28] examines dynamic pricing with real-time system learning. In other words, a system is developed to optimize a dynamic pricing scheme that adjusts within the sales window as actual demand information arrives. De Boer et al. [13] compare deterministic approximation methods of determining revenue management pricing structures versus the more sophisticated probabilistic and dynamic methods. The group conducts a trade-off analysis of time and resources required to conduct the more intricate algorithms versus the payoff in increased gross revenue. Secomandi et al. [40] also address general revenue management modeling topics and incorporate software to more effectively segment the market.

Teodorović et al. [50] introduce the concept of using fuzzy rules and logic (based on actual collected demand data) to make revenue-maximizing decisions within the airline industry. Grossman and Brandeau [20] look at ways to evenly allocate demand by charging according to the amount of delay a customer imposes on others (time cost). This approach results in net subsidies to entities/suppliers with less demand and revenue sharing from entities/suppliers with greater demand.

As mentioned earlier, the field and study of revenue management has its beginnings in the airline industry and has been applied to various others. Belobaba [4] conducted seminal research within this field, the results of which are guiding principles of universal yield management application. His analysis developed decision rules for airlines and structures for inventory control. Brumelle and McGill [7] build on the work of Belobaba [4] by extending decision rules to account for multiple, nested fare classes for flight legs. Bodily and Weatherford [5] address special issues in early yield management analysis. In particular, they propose methodologies to incorporate overbooking, multiple fare cases, and continuous resources. In this

way, they more closely approach the reality of modern airline business practices. Cross [12], a revolutionary figure within the field, published a widely read book entitled *Revenue Management* that narrates the airline industry's struggles and issues with the concept and implementation of revenue management.

In the late 1990's the idea of revenue management became prevalent within another travel-related industry--the hotel industry. Badinelli [2] published an approach for dynamic yield management for hotels that addressed variables such as time of arrival, day of the week, and number of vacancies at any particular moment. Lai and Ng [27] added a dimension peculiar to hotels: length of stay. Airline flights have a set duration, but hotel guests can stay lengths of time that vary greatly. They use a stochastic optimization approach that accounts for the random nature of a particular guest's length of stay.

2.3 Revenue Management in the Parking Industry and Intelligent Parking Systems

In reviewing the body of parking- and revenue-management-related literature, it is clear that the amount of research devoted to applying revenue management principles to the parking industry is quite limited. There are two key papers that have introduced the new research direction. Centeno and Rojas [9] [10] have studied the topic of parking systems from a variety of perspectives. This literature review already discussed two research efforts by Centeno and Rojas, and this duo also introduced the ground-breaking idea of revenue management in the parking industry at the Institute of Industrial Engineers Symposium in 2005. The work presented at the symposium introduces how revenue management might be applied to parking structures and provides basic modeling techniques, with astute insights into opportunities for future work. It discusses the dynamic pricing nature inherent in revenue management systems, but does not seek to clearly model the time series elements or the dynamic nature of the problem. It also does not fully discuss relationships between parking and urban traffic congestion, or the how mitigation of congestion might impact business revenue levels.

The second paper specifically addressing revenue management within the parking industry is that published by Teodorović and Lučić [49]. This research leverages the work of that ground-breaking paper. In it, the research team characterizes the elements of the parking industry that make it suitable for revenue management application. This is also the first paper that combines the ideas of intelligent (online) reservation decision-making in parking systems with the idea of market segmentation and revenue management principles.

2.4 Artificial Neural Networks

An artificial neural network is a mathematical model or computational model based on biological neural networks. It consists of an interconnected group of artificial neurons, and processes information using a connectionist approach to computation. In most cases a neural network is an adaptive system that changes its structure based on external or internal information that flows through the network during the training and testing phases. Neural networks can be used to model complex relationships between inputs and outputs or to find patterns in data. A graphical representation of a neural network is given in *Figure 2.1*.

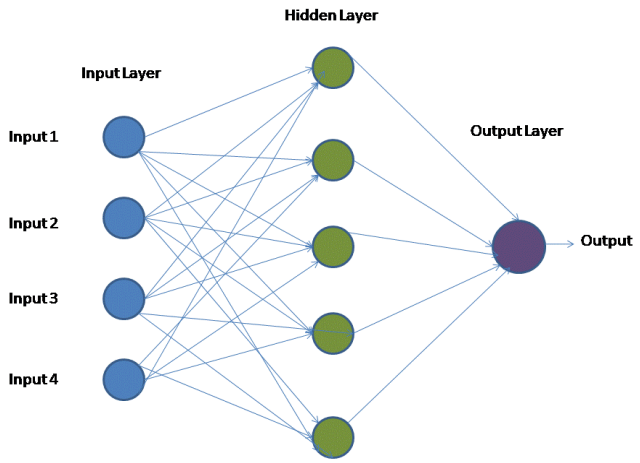

Figure 2.1: Artificial Neural Network

In order to train and test a neural network, meaningful inputs must be developed that will be used by the artificial network to make its real-time decision. An artificial neuron has properties similar to a biological

neuron, receiving inputs, processing the inputs, and delivering outputs (*Figure 2.2*). The neurons in an artificial neural network are also called processing elements (PEs). The summation function of the output gives the weighted average of all the inputs to the neuron. Then the output is modified to a reasonable value (avoiding extreme output values) through the transfer function.

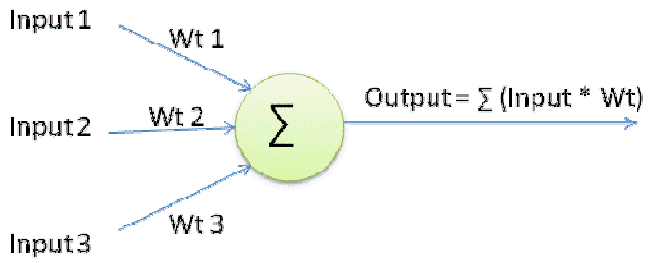

Figure 2.2: The Structure of an Artificial Neuron

A good treatment on the modeling background and assumptions associated with neural networks can be found in a text by Teodorović and Vukadinovic entitled *Traffic Control and Transport Planning: A Fuzzy Sets and Neural Networks Approach* [52]. According to this source, there are five characteristics that can be used to characterize a neural network. They are: the number of processing elements, connectivity of the processing elements, the rule of information propagation through the network, transfer functions, and learning rules.

Processing elements (or artificial neurons) are the basic functional units of a neural network, and are usually organized into layers with particular functionalities. In some types of neural networks, the neurons may not be arranged in layers, but it is always true that each processing element within the network simply multiplies an input by a set of weights to generate an output value. Neural networks often address complex problems, but do so with an abundance of very simple processing elements. The second characteristic used to characterize artificial neural networks is the connectivity of the processing elements. Each neuron in a layer of the network is connected with the neurons in other layers by a synapse, and these layers can be

fully connected or partially connected. The choice of this connectivity structure is fundamental to the network, because after the network is built, it will learn and adapt by adjusting the weights associated with these connections. The third characteristic, the rule of information propagation through the network, refers to how information flows through the network. The simplest form is feed-forward, where the information flows in one direction from input layer to hidden layer to output layer. No direct loop is formed. Both single-layer perceptron and multi-layer perceptron fall into this category. Apart from the feed-forward information flow, data can also be propagated from later layers to earlier layers within the network via bi-directional flow. Transfer functions (the fourth characteristic), also called activation or transformation functions, ensure the output value of the network falls in a reasonable, non-extreme, range. The fifth characteristic, learning rules, modifies the network parameters (weights) to improve neural network performance. These rules are generally classified as being either supervised (for example, minimizing error using gradient descent) or unsupervised (error function is pre-determined).

The use of artificial neural networks for the purposes of problem-solving and real-time decision-making has flourished over the past thirty years. Application areas include system identification and control (vehicle control, process control), quantum chemistry, game-playing, pattern recognition (radar systems and face identification), medical diagnosis, and data mining. It has also been more recently applied to transportation demand management engineering problems.

Teodorović [52] provides a fairly comprehensive literature review of the use of neural networks in transportation research. Applications specific to transportation modeling include demand forecasting, and continuous, real-time estimation of origin-destination matrices for dynamic routing models. The capability of neural networks to model complex functions, learn from historical data, and adapt to changing situations makes it a suitable tool for these problems. Researchers have applied artificial neural networks to a variety of transportation problems.

Edara [16] developed a transportation mode choice model using neural networks as the decision-making mechanism. The article compares the neural network approach to traditional models, including the logit

model and regression method, and concludes that the neural network produces the best results. Edara [15] also has applied artificial neural networks to a highway space inventory control problem, where real-time reservation decisions are made for highway capacity using a neural network.

Teodorović et al. [51] developed an intelligent intersection signal control model where neural networks (along with dynamic programming) served as the decision-making mechanism. The system made real-time decisions about the extension of current green time, which is the amount of time a traffic signal remains green during its cycle. Teodorović and Edara [48] applied neural networks to a real-time road pricing system that used neural networks to make dynamic decisions about toll values in response to congestion levels on those roadways.

2.5 Transportation and Micro-Simulation

The term simulation typically refers to the imitation of some real thing, state of affairs, or process. The act of simulating something generally entails representing certain key characteristics or behaviors of a selected physical or abstract system. Since the advent of computers with suitable capability, traffic simulation has become a powerful tool to enable transportation researchers and professionals make decisions in transportation planning that require the observation of detailed conditions and characteristics of the system under consideration.

Microscopic simulation (in contrast to macroscopic simulation techniques) attempts to model the movements and interactions of each individual vehicle or transportation element. Gross measures such as speed, volume and density are not model variables in microscopic simulation. Instead, they are typically outputs of the model derived from the interactions of all vehicles during the simulation run. The car-following model and the lane-changing model are key aspects of transportation network microscopic simulation. Route choice modeling is also important, describing how drivers make decisions regarding which network links to take from origin to destination.

There are several transportation micro-simulation packages currently available for use, including the two most prevalent ones, CORSIM (Corridor Simulation) and VISSIM. Micro-simulation models require a large amount of detail when modeling a road network, as well as effort to calibrate the large number of model parameters. Micro-simulation also requires significant computer processing time and storage capacity. These constraints can limit aspects of the modeling effort such as the size of the network, the number of simulation runs, or the complexity/granularity of the underlying parameters.

Boxill and Yu [6] provide a comprehensive list of the microscopic traffic simulation software. Clearly, each of these models has advantages and disadvantages. Selection of a software package in a simulation project depends on the problem to be solved and the resource availability. The modeling within this thesis uses the VISSIM software package. Many state and federal transportation agencies use VISSIM for transportation planning including the Missouri, New York, and Virginia Departments of Transportation. VISSIM has also been used in significant instances of Master and Doctoral thesis research, including the previously mentioned Edara thesis investigating highway reservation systems [15].

According to the VISSIM User's Guide [61], "VISSIM is a microscopic, time-step, behavior-based simulation model developed to model urban traffic and public transit operations." The program can analyze traffic operations under constraints such as lane configuration, traffic composition, and traffic signals, thus making it a useful tool for the evaluation of various alternatives based on measures of effectiveness associated with transportation engineering and planning.

The simulation package VISSIM consists of two primary modules that work in tandem. The first is the traffic simulator, which is a microscopic traffic flow simulation model including car following and lane change logic. The second element is the signal state generator, which is signal-control software polling detector information from the traffic simulator on a discrete time step basis. It then determines the signal status for the following time step and returns this information to the traffic simulator.

The accuracy of a traffic simulation model is mainly dependent on the quality of the vehicle modeling, e.g. the methodology of moving vehicles through the network [61]. In contrast to less complex models using constant speeds and deterministic car following logic, VISSIM uses the psycho-physical driver behavior model developed by Wiedemann in 1974 [64].

2.6 Data Envelopment Analysis and Macro-Evaluation

Performance evaluation is not only an important component of any policy, program and project, but it also helps to assess how the system progresses toward achieving predetermined goals. Inappropriate performance measures can result in inadequately assessing systems and resources, and transportation systems are no exception. Moreover, performance measures help to enhance communication between different stakeholders. A key aspect of performance measurement for transportation systems is the measurement of congestion. This type of measurement is particularly useful in the evaluation of congestion mitigation policies. There are many ways to measure congestion. For instance, one might measure congestion in terms of average travel speed, travel time, vehicle delay, cost (however it may be defined), or others.

The literature contains hundreds of papers addressing the issues related to performance measurement and systems efficiency. When considering matters of productivity or efficiency, most engineers will readily recognize the expression “outputs divided by inputs” to be a common method of evaluation. Whether it be a thermodynamic expression such as work per unit energy or a retail measure such as sales per labor hour, societal understanding of the word efficiency can be summarized by this general ratio.

Data Envelopment Analysis (DEA), first proposed in 1978 by Charnes, Cooper, and Rhodes [11], is a commonly used tool to evaluate the relative efficiency of what is termed decision-making units (DMUs). A DMU can be any number of things from a diesel engine to a non-profit charity organization. In short, DMUs are anything with quantifiable inputs and outputs that can be compared with other analogous entities. In contrast to statistical approaches that use central tendency approaches and evaluate DMUs

relative to a hypothetical "average" unit, DEA, also known as frontier analysis, is an extreme point method that compares each organization (for instance) with only the "best performers". DEA identifies the DMUs that most efficiently convert inputs to outputs and compares all others to their standard.

After identifying one or more efficient DMUs from a larger set of DMUs, DEA then measures the efficiency of all other items in the set relative to the efficient subset or what is also known as the efficient frontier. A fundamental assumption behind this extreme point method is that if a given DMU, A, is capable of producing O(A) units of output with I(A) units of input, then other DMUs within the analogous set should be able to do the same if they were operating efficiently. One of the great strengths of the DEA method is that set weights for the comparison of inputs is not required. The weights are variable so as to maximize the efficiency given the DMU-specific data. Also, it does not require prescribing the functional forms that are needed in statistical regression approaches to the same sorts of problems.

Using the DEA method, an inefficient DMU can be compared with its virtual efficient self. This virtual DMU is an improved version of the original created by either making more outputs using the same inputs or making the same outputs with less input. The method by which we find the best DMU (and therefore the best virtual DMUs for those that are inefficient) within the peer set is linear programming. Each DMU has its own linear programming formulation that is solved.

According to most experts, the first proposed DEA formulation was what is referred to as the CCR model, set forth in the seminal work by Charnes, Cooper, and Rhodes [11]. In 1984, Banker et al. [3] proposed an alternative formulation that has its production frontiers spanned by the convex hull of the existing DMUs. This new formulation, known as the Banker, Charnes, and Cooper (BCC) model (see *Figure 2.3*), has become the most prevalently used DEA model.

$$
\begin{aligned}
&\text{minimize } \Theta, \\
&\text{s.t.} \\
&\quad \Theta x_0 - X\vec{\lambda} \geq 0, \\
&\quad Y\vec{\lambda} \geq y_0, \\
&\quad \mathbf{e}\vec{\lambda} = 1, \\
&\quad \lambda_i \geq 0
\end{aligned}
$$

Figure 2.3: Banker, Charnes, and Cooper Output-Oriented DEA Formulation

This is known as the input-oriented formulation due to the fact that the first constraint forces the virtual DMU to produce at least as many outputs as the studied DMU. The second constraint discovers how much less input the virtual DMU would need. Lambda (**λ**) is a vector of non-negative scalars that records the percentages of other peer DMUs used to construct what can be referred to as the corresponding efficient virtual DMU A.

X is the input data matrix, and *Y* is the output data matrix. When the vector lambda is multiplied by *X*, it yields the input vector for DMU A, with a similar operation on *Y* yielding the output vector. The value of theta (Θ) denotes the efficiency of DMU A. This linear program must be solved for each of the DMUs in the peer set. Another well-known basic DEA model is the output-oriented BCC model. The output-oriented model is very similar to the input-oriented formulation as the first constraint forces the virtual DMU to use at least as many inputs as the studied DMU. The second constraint discovers how much more output the virtual DMU could produce.

Clearly, the DEA modeling framework could have wide and varied application within the field of transportation/network design and performance evaluation. Pasupathy [32] provides a rich literature review with regard to DEA applications within transportation systems.

As one can see from above, traditional DEA modeling carries with it certain restricting assumptions. For example, the BCC models assume that inputs are used by the production process to produce outputs, and

inputting more resource into the process will yield more output. Implicit here is that outputs are desirable, being either product or some other desirable measure, where more is better.

But, what happens when the outputs of the DMU are undesirable? This is often the case in transportation systems. For instance, transportation systems can produce outputs that are generally desirable like revenue, trips completed, customers served, and ridership. However, undesirable outputs are also common --- outputs like carbon dioxide emissions, vehicle delay, travel time, and network congestion.

Various techniques and alternative DEA formulations have been proposed to deal with this issue, as is laid out in detail by Pasupathy in his 2002 thesis [32]. Färe et al. [18] introduced a different approach to incorporate both the desirable and undesirable outputs in the model. This formulation, as detailed and applied in **Chapter 5** of this thesis, allows the desirable outputs to increase by a proportion, and at the same time allows the undesirable outputs to decrease by the same proportion.

CHAPTER 3 Revenue Management in the Parking Industry: A Single Garage Strategy and a Multiple Garage Intelligent Reservation Model

3.1 Contributions, Context, and the Relationship between Revenue Management for Parking and Traffic Congestion

This chapter develops a comprehensive RM strategy for the parking industry, looking at a single parking garage, without consideration for urban congestion. Furthermore, it expands the concepts introduced in [49] and details a multiple parking garage formulation for revenue maximization. This multiple garage formulation not only extends the scope from one parking venue to *n* parking venues, it also augments the formulation to align with RM principles by adding the dimension of dynamic pricing. Additionally, this chapter develops a model for the implementation of a multiple-garage intelligent reservation system (or *intelligent parking system*) necessary to make real-time decisions and to execute an effective RM parking strategy.

The development of a parking RM strategy is not only a significant contribution in a business sense, but it also fills a clear gap in the literature to date. Additionally, since most parking garages reside in high-density urban parking districts, the extension of a single garage revenue maximizing formulation to the multiple parking garage case is more applicable and realistic. Fully developing the RM intelligent parking reservation model is also a key contribution, in that without a parking demand management and reservation-making system, RM cannot be effectively implemented.

RM-based advanced reservation systems typically include dynamic pricing adjustments in order to isolate market segments. This inherent dynamic pricing element within RM poises it to be an effective travel demand management (TDM) strategy. TDM is the application of strategies and policies to influence traveler behavior with the aim of reducing automobile travel demand, or redistributing this demand in space or in time [19]. Parking pricing variability (based on demand) and directed travel for those who make reservations can ideally reduce demand and/or redistribute it in a congestion-mitigating way. Although RM

itself does not concern itself with peripheral issues such as traffic congestion, this postulated positive "side effect" is an interesting synergistic solution to boost business strength, increase efficiency of movement, and enhance overall public welfare. **Chapter 4** explores whether there is behavioral evidence to support these hypotheses.

3.2 Revenue Management Strategy for the Parking Industry: A Single Garage Perspective

3.2.1 The Nature of Parking Demand

The parking industry, like many other industries, has a demand that is stochastic in nature. It has peak periods and lulls, and the peaks often occur before and/or during large-scale events or at the beginning of a work day. The lulls typically occur during the mid-day or during the late night hours. Obviously, the periods of high demand are the periods in which the parking garage has the greatest opportunity for the generation of revenue. In fact, most garages are able to stay in business because of the revenue generated during these large-scale events or high demand periods.

With this assumption in mind, perhaps the most prudent strategy for parking garages (and other parking facilities) is to center their RM strategy on these peak periods and extend it from there. A suggested parking RM strategy will be presented in the form of an example of a parking garage positioning itself to maximize its revenue during one of these large-scale events. Specifically, this work examines a privately-owned parking garage located in an urban area within a few blocks of several concert venues to illustrate a basic RM strategy for parking systems.

3.2.2 Motivating Revenue Management for Parking

The core concepts of RM (according to Cross [12, p. 61]) are summarized as follows: (1) use price (that a given customer is willing to pay) rather than costs to balance supply and demand within the market; (2) sell

to segmented micro-markets, not to mass markets; (3) save your products for your most valuable customers; (4) exploit the product's value cycle; and (5) continually reevaluate your revenue opportunities.

RM is highly dependent on the effective segmentation of the market under consideration. What does this mean for the parking industry? What is the most effective strategy for segmenting the parking market in order to maximize revenue and save the product for the most valuable customers?

Consider our example of a privately-owned parking garage located in an urban area near several large-scale concert venues. There are many types of people who purchase concert tickets; they span the spectrum from low-income families treating themselves to a weekend event to businesses providing prospective clients premium seats. The same spectrum of customers also constitutes the market for parking nearby the concert location. Most existing parking garages and parking lots charge a flat daily or hourly parking fee to cars entering the lot. However, does this maximize the revenue that the parking garage/lot can generate? In light of the advanced reservation technology available in today's market, one would imagine not.

Let us assume that our parking garage's capacity is 300 parking spaces. If all spots are sold on a typical concert evening for $15 each, the total revenue is $4500. The $15 price may or may not be based on a market analysis of supply and demand, i.e., it may be based on either a cost plus profit combination or what the business believes it can get, or based on what the management feels is the price that the average customer arriving on the day of the concert is willing to pay. However, almost certainly there are people arriving at the garage that would be willing to pay more than $15 to park. Consider the business that is entertaining clients. It may be willing to pay a premium to make the concert event a convenient and thoroughly enjoyable experience for its guests.

So, what price on the day of the concert would yield the same amount of revenue that the garage normally makes? What if we set the price at $25 per car? Now, by admitting only 180 cars, the garage can make its normal level of revenue and there are 120 more units of capacity unfilled.

Now, let's consider a related industry, the air travel industry. RM began in the airline industry, and airlines make efficient use of an advance reservation in order to segment its markets and save its product for its most valuable customers, last-minute travelers willing to pay a relatively high price for the ability to travel immediately. One could also imagine that advanced reservations can also be made for parking via the internet or by cellular phone. Like the airline industry, using the technology of an advance reservation system and high-fidelity demand data, a parking garage (or a group of parking garages) could segment its markets and raise its revenue by understanding better what prices its various micro-markets are willing to pay.

Now, let us consider a small-scale market segmentation for our parking garage in the concert district. What if we offered advanced parking reservations for a concert event evening at $10 and let the price on the evening itself be $25? If our demand data says that there are usually 180 last-minute customers willing to pay $25 and 120 customers willing to reserve early in order to pay a lower tariff, then we can sell 120 reservations early and save 180 for the day of the concert. If we fill our total capacity, our revenue climbs from $4500 to $5700, or a 26.7 percent increase. Revenue increases at this magnitude may attract parking businesses to seriously consider incurring the cost of implementing the necessary technology to segment their markets.

3.2.3 A Proposed Revenue Management Strategy for Parking

Now that we have examined what RM might look like in the parking industry, let us consider one possible RM strategy that could be implemented or easily adapted to different markets, locations, or situations. Let's look again at our example of the parking garage in the concert district. It has been operating for many years using the standard parking model of drivers entering and paying at the moment that they wish to park. The garage is now planning to adopt an online reservation system in addition to their standard model, and they will need an initial market segmentation strategy (which they will augment or adapt as they start to collect more and higher-fidelity demand data). What type of segmentation scheme should it choose?

The first step is to identify the most valuable customers and what they want. For our garage, there are several important customer groups. First are the music enthusiasts that have not planned their attendance in advance. They would like to drive to the concert venue, park their car in a convenient spot and quickly make their way to the event. They are willing to pay a relatively higher price for the convenience of making last-minute plans and having a close parking spot. Another valuable customer group is businesses that entertain clients who wish to provide a "premium" parking spot in a convenient location with no restrictions. There are also busy professionals desiring a relaxing evening out that would want the same flexibility and privilege. These valuable customers groups are remarkably similar to the valuable customer groups in the airline industry: the business (or pleasure) traveler planning ahead who wants a ticket with flexibility and privilege, and the last-minute traveler (whether for business or pleasure) who needs to travel immediately and is willing to pay for the convenience.

How much would these two highly-valued customer groups be willing to pay for parking? This is difficult to determine without demand data, but a starting point can be chosen by any number of means and changed as the customer response to the price is observed. The key is to pick a price that maximizes revenue within these essential micro-markets. Once these micro-markets have been analyzed, these highly-valued customers will consume an average percentage of total capacity. The remaining capacity can also be sold as one or more classes of discounted advance reservations in order to generate additional revenue. One key to effective market segmentation is to balance the quantity of the identified micro-markets with the labor/cost to manage each micro-market. The parking garage would also like to make sure that there is the appropriate limited number of reservation options in order not to be confusing to the clientele base.

This paper proposes a parking RM strategy that has many similar characteristics of that of the air travel industry. Our parking garage selects an interval prior to the event date to release an initial opportunity for reserving parking for the premier concert event of the season. A logical date for release would be the same day that tickets for the concert are first released (in fact, there might even be opportunities for concert ticket/parking package deals and revenue sharing between the two businesses). There are two types of reservations with two sets of rules and privileges.

The first reservation type is analogous to coach class air reservations. The price is relatively low, and the payment is non-refundable. It may even be advantageous to require that regular ("coach") class reservations arrive at a non-peak time like an hour before the concert or just after the concert begins. This kind of reservation might be ideal for people having pre-concert dinner plans or that have a limited budget.

The second type of reservation is analogous to first class air reservations. The price for this premium reservation is significantly higher than the regular type, but comes with flexibility such as the ability to change reservations, and perhaps special amenities like the ability to arrive at any point in time, guaranteed covered parking, and parking locations closest to the venue.

The price for both regular and premium class parking reservations would likely increase with time in increments similar to those commonly used by airlines. One common practice is to increase airfares at approximately two weeks and then one week before the date of departure. These intervals of time coupled with a price increase could also be used with our parking garage. Another common practice with airlines is to respond to changes in the market or to a competitor's price changes. This would also be a concern for the parking facility, and the reservation system would need to have the flexibility to change its structure at a moment's notice.

Additionally, the parking garage would certainly want to monitor their reservation rates to make sure that adequate capacity is being reserved for the most valuable markets, the premium and last-minute demand. If too many discounted parking reservations are being booked or if they are being sold out very quickly, the management group would want to respond by perhaps changing the amount of discounted reservations available or by adjusting the regular class price.

Another opportunity for revenue generation that is commonly used in the airline industry is the practice of "overbooking". Many airlines sell more seats per airplane than actually exist onboard due to the fact that on any given flight, there is a certain percentage of customers on average who will not show up to board the

plane. In other words, for very high demand periods, more reservations are booked that there is actual capacity with the expectancy of some "no shows". For the vast majority of flights, this practice increases revenue with no negative repercussions. However, there are instances where all customers for a given flight show up to take the flight. In these cases, airlines must compensate by offering free flights or other products/amenities in order to adequately substitute for not honoring the original reservation. The percentage of overbooked seats is determined with great care by balancing the revenue added by booking a certain amount of extra seats versus the cost to the airline (multiplied by the probability of a "no show") for compensating the customers if they, in fact, show up for the flight.

This opportunity could be easily adapted for the parking industry. The parking garage in our example could estimate the percentage of reservations that they expect will not show up to park. This could be determined by considering analogous commodities (such as airline seats, or concert attendees versus number of tickets sold). They could overbook by some amount, starting conservatively at first. Then, as the parking garage becomes more familiar with the average percentage of "no shows" on the day of a big event, the overbooking process could be further refined to maximize the additional revenue received. If more customers arrive to park on the day of the concert than there are parking spots to accommodate them, the parking garage could adopt a common policy in the hotel industry of booking the client with a sister hotel and also providing a voucher for a free night's stay at some point in the future. This would clearly translate to booking the driver with another parking garage nearby and providing a voucher for free future parking.

Another opportunity for additional revenue that has been adopted by both the air travel and hotel industries is the last minute reselling of capacity. For the air travel industry, it translates into the "stand-by" policy; customers wishing to fly at the last minute can choose to fly "stand-by" in which case they can join the flight at the last minute for a standard fee if there happens to be an empty seat on the flight. If there are no extra seats, then the customer is turned away. They may then choose to leave the airport or try their luck at the next flight opportunity.

The parking garage in the concert district could also adopt this policy. Clearly, if a reservation has an arrival time window associated with it, and the customer does not show up at the expected time, that spot can be resold. Also, the garage might adopt a policy regarding the premium spots that if the customer does not show up by a certain time, perhaps a half hour after the concert begins (assuming there is only one large-scale event in progress), then the parking space could be resold. If the customer with the premium reservation (with the assumption that there is no required arrival time associated with the reservation) does show up at some point in the future, an adequate substitute similar to that used with the overbooking policy could be offered.

Incidentally, this introduces another reservation class possibility. It might be in the garage's best interest to offer a "super premium" class of reservation that could never be resold during the course of the day; in other words, it is always guaranteed to be open. This may be particularly appealing to businesses hosting clients who want the client to be able to arrive at any point in time before or during the concert and have a convenient, guaranteed parking space (and are willing to pay a significantly higher price for this privilege). Shuttle or limousine service to the concert door box office might also be offered.

There are many other issues to address that may be specific to a given garage. For instance, will the parking garage charge by the hour or by the day (or some combination of the two)? For our example, it may behoove the garage to charge by the hour up to a maximum daily charge (less than the length of a typical concert or large-scale event) and then have a flat daily rate for any greater length of time. For other garages, the best strategy might be to have a combination of monthly, weekly, daily, and hourly parking as is common at airports. Yet another strategy, particularly well-suited for our example, is a package price for a combination of evenings when concerts or other events are scheduled.

3.2.4 Potential Revenue Growth Using Revenue Management: A Numerical Illustration

As was briefly introduced in **Section 3.2.3**, revenue growth due to RM can sometimes be rather dramatic. Here, we will explore a more detailed numerical example that delves into parking industry-specific

characteristics. Let us assume that our parking garage with a capacity of 300 parking spots is presently charging $15 to park during a given concert event. They nearly always fill their entire capacity, which gives them a total revenue yield of $4500. *Figure 3.1* shows the parking demand and supply curves for the event period as observed by the garage.

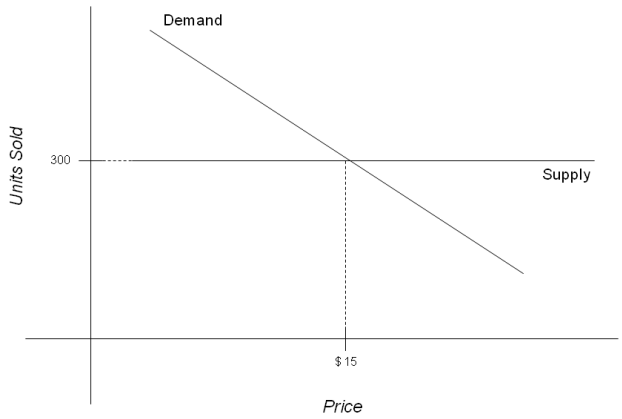

Figure 3.1: Parking Market Equilibrium pre-RM

Now, let us further assume that an estimated 65 percent of parkers would be willing to make an advanced reservation if it allowed them to get a better price, some set of amenities, or the assurance of having a parking space on the evening of the concert. When a reservation is made online, directions to the garage in which the reservation was made are given to the customer so that they can find the correct location when they arrive to park. Now, let us assume that a parking industry expert has estimated that a significant percentage of parkers that arrive at the garage on the evening of a concert are willing to pay more to park. In fact, the expert believes that they may be willing to pay as much as twice the original price. The garage, however, in the absence of any RM system demand data, will examine the predicted demand curves for each sub-market. The management would like to start with a conservative policy. Their strategy is detailed in *Table 3.1*.

	Regular	Premium
3 Months to Event	$5 (10%)	$15 (5%)
2 Weeks to Event	$10 (10%)	$20 (5%)
1 Week to Event	$12 (20%)	$20 (15%)

Concert Evening Price	$25 (35%)

Table 3.1: Parking Revenue Management Example

The strategy in *Table 3.1* is the proposed RM approach giving the various class prices and how they change with time. For instance, at three months before the scheduled event date until two weeks beforehand, the price for standard parking is $5 and for premium parking is $15. *Table 3.1* also provides (in parenthesis next to the price) the percentage of the market that is predicted to buy a reservation or parking location at that time and price. The table represents a starting point and does not take into account the dynamic and flexible nature of RM. As the booking cycle progresses, this will have to be easily adaptable in case of unpredicted market behaviors or a change in some characteristic of supply, demand, or customer base. However, let us assume in this case that our experts and predictions are identical to the actual outcome.

By performing the simple multiplication and addition of the various segments of revenue, we see that the total revenue generated in this case is $5595, which is a 24 percent increase over the previous amount of revenue generated on any particular event day. Although this increase in revenue is impressive, it likely not the maximum amount of revenue that could be made if more were known about the demand curves within each of the micro-markets. With time and a more sophisticated data-collection mechanism, the parking garage might be able to increase its revenue even more.

3.2.5 Iterative Improvement to a Garage-Specific Revenue Management (RM) Strategy and Extending to Multiple Garages

Clearly, the previously described RM strategy for a parking system is a starting point that utilizes the basic principles of RM theory. In order to obtain a near-optimal pricing and timing structure for advanced and

last-minute reservations, an iterative approach would be needed. As actual demand data in response to a given pricing structure is collected by the garage, then demand curves can be developed to allow parking management to adjust pricing in real time if demand behaves differently than originally predicted for a given event.

Now that we have developed the general parking RM strategy in the context of a single garage, it is important to note that these concepts can be easily extended to more complex scenarios. In many urban areas throughout the world, groups of garages are either privately/corporately owned, or are publically owned. It is fairly straightforward to see how the RM strategy developed for a single garage can be applied to multiple garages with varying locations, capacities, and pricing schemes. In the case of multiple garages within a close proximity to each other within a central business district, the implementation of a district-wide RM strategy more easily facilitates the study of RM's effects on urban congestion.

In the aforementioned principal source paper authored by Teodorović and Lučić [49], a single garage RM formulation is developed in the form of an integer program. The results of the integer program are used to develop fuzzy rules that are used to make real-time parking request decisions. This paper extends the single garage formulation, in that it develops a multiple garage integer programming formulation and adds dynamic pricing elements. Furthermore, the fuzzy rule approach is replaced by a back-propagation neural network model as a mechanism to make real-time decisions. The development of this multiple garage formulation will directly feed the future modeling and testing of the effects of RM on urban congestion. The formulation itself, data inputs, model outputs, and how it feeds neural network-based decision-making is described subsequently in **Section 3.3**.

3.3. Intelligent Parking Model for a Multiple Garage Scenario

3.3.1 Revenue Management Implementation and Modeling

The effective implementation of parking RM clearly requires an effective strategy and means of market segmentation. But as described earlier, the implementation of an *intelligent reservation system* is indispensible to the effective segmentation of the parking market, and therefore, the implementation of RM strategies will almost certainly have an effect on driving behavior. This chapter presents modeling details of a multiple-garage intelligent reservation system (or *intelligent parking system*) necessary to make real-time decisions and execute an effective RM parking strategy. Key aspects within this work that differ from that of [49] extend beyond the obvious move from single garage to multiple garage systems. The intelligent parking model developed here includes dynamic pricing, and demonstrates how back propagation neural networks can be used to make online parking sales decisions. Artificial neural networks are increasingly used within transportation science applications such as these, since they are a way of modeling human decision-making processes within a binary logic, computing environment. They are especially useful for problems such as these, where understanding of data relationships is still rudimentary and ease of use is particularly valuable.

3.3.2 The Multiple Garage Intelligent Parking Construct

Since parking RM does not exist in practice, in order to construct an intelligent parking model, one must evaluate how such a model would function. Inherent to this is the generation of assumptions based on how RM manifests itself within other industries (such as airline or hotel) and based on how parking systems currently operate. As described in **Section 3.2.1**, not only is parking demand stochastic, it is also specific to the location, network, and/or garage with which it is associated. The distribution of parking demand is a key assumption, as is how one defines parking classes (similar to airline ticket classes), dwell time, and a dynamic pricing structure.

To maintain a straightforward modeling structure, the authors assume a fixed demand distribution that is dynamic in the sense that it changes over time, from the time when parking reservations can first be made until the actual day/time of the parking event. Although this distribution is clearly not dynamic in the sense of the presence of feedback and adjustment, a true implementation of the intelligent parking model would use actual demand data collected over time to refine demand distributions and assumptions in real time. *Table 3.2* provides an example of an assumed demand distribution.

Demand	Week 1	Week 2	Week 3	Week 4	Actual Day
Basic	0.1	0.2	0.3	0.35	0.05
Premium	0.1	0.15	0.25	0.35	0.15

Total Demand by Class	
Basic	0.65
Premium	0.35

Overall Demand	Week 1	Week 2	Week 3	Week 4	Actual Day
Basic	0.065	0.13	0.195	0.2275	0.0325
Premium	0.035	0.0525	0.0875	0.1225	0.0525
Total	0.1	0.1825	0.2825	0.35	0.085
Cumulative Total	0.1	0.2825	0.565	0.915	1

Table 3.2: Intelligent Parking Model Assumed Demand Distribution for all Garages

As can be seen from *Table 3.2*, this intelligent parking model assumes only two classes of parking: basic and premium. Even though these classes aren't formally defined for the purposes of this model, one can assume that the premium class comes with amenities or a level of availability/certainty that the basic class does not. Furthermore, it is assumed that 65 percent of parkers will prefer basic class parking to premium class. The top portion of *Table 3.2* identifies the percentage of total demand within a class that falls within each time period. The bottom portion multiplies the demand within each tariff class with the demand break out by class. In general, it is assumed that the parking RM model has reached an equilibrium point, where the vast majority of parkers make a reservation as opposed to waiting until the actual day to reserve a scarce parking resource. Demand is captured from four weeks out until the parking day, with demand increasing in time, but falling away for the "actual day".

As is true within the RM school of thought, it assumed that as actual demand data is collected for the garage or garages being analyzed, that these demand distributions will be aligned accordingly.

Furthermore, it is clear that the parking garage owner or manager may choose to adjust their strategy by further segmenting their markets using additional parking classes or a finer/coarser pricing time period granularity, as detailed in **Section 3.2.3**.

Included within this intelligent parking model are four garages, each with a capacity of 65 parking spaces. The tariff structures are different for each garage, and a notional Garage One tariff structure (in US dollars per hour) is provided in *Table 3.3* below.

Garage 1 Tariff Per Hour (USD)	Week 1	Week 2	Week 3	Week 4	Actual Day
Basic	1	2	4	7	13
Premium	3	6	7.5	10.5	16

Table 3.3: Dynamic Pricing Structure Input for Garage One

The intelligent parking model generates individual parking requests using uniformly randomly generated numbers corresponding to the time periods within the demand distribution. Since the parking district is assumed to have high levels of demand throughout the day with both business and leisure parkers demanding parking, random numbers, within a uniform distribution, are used to generate arrival and departure times for each particular request. So, a request within the intelligent parking model consists of the time/date of the request, the hours or interval of parking requested, and the preferred parking class. From this data, a request then has an associated cost that corresponds to each garage's pricing structure, calculated by multiplying the request parking length (parking interval) by the cost per hour within the parking class and dynamic pricing period. For example, let's assume that a customer requests a premium class parking space four weeks from their requested parking date, and they wish to park from 12:00 until 3:00 pm. For Garage One, the cost calculated associated with this request would equal three dollars per hour multiplied by three hours, for a total price of nine dollars.

3.3.3 Multiple Garage RM Integer Programming Formulation

In order to allow for parking RM online decision-making, a mechanism must be prepared to do this work in real time. As mentioned previously, this is accomplished using a back propagation neural network approach. In order to train and test a neural network (as will be discussed in more detail in **Section 4.4**), parking requests coupled with their optimal decision sets must be collected for input.

The next step is to provide a mechanism to account for the multiple parking garage environment. We use an integer program that maximizes the revenue obtained within a multiple garage system, assuming that all requests for a given time period are known; in other words, this is the case when decisions are not made in real time, but are made once all request data is collected and available. Revenue is calculated by summing revenue across all requests, dynamic pricing periods, tariff classes, and parking garages.

It is important at this point to define some terminology used in the formulation that follows. When a customer accesses the intelligent parking model to make a parking reservation, this is referred to as a parking *request.* Each request has the potential to be assigned to one of the G garages. The possible manifestations of the request within the garage set, as indicated below, are the integer decision variables.

$$\text{MAX} \quad \sum_{g=1}^{G}\sum_{r=1}^{R}\sum_{l=1}^{L} C_g^{pt}(q_{lr})x_{rg}^{pt} \tag{1}$$

$$\textit{subject to} \quad \sum_{r=1}^{R} q_{lr} * x_{rg}^{pt} \le S_g, \forall l, \forall g, \tag{2}$$

$$\sum_{g=1}^{G} x_{rg}^{pt} \le 1, \forall r, \tag{3}$$

$$x_{rg}^{pt} = \{0,1\} \tag{4}$$

Decision Variables

x_{rg}^{pt} *: binary indicator of whether or not a particular request is accepted*

Indices and Superscripts

g: index of garages within parking system

t: index of tariff classes within a garage

p: index of dynamic pricing adjustments within a tariff class

r: index of parking reservation requests within a dynamic pricing adjustment period

l: index of equal-length time intervals during a garage opening

Parameters

q_{lr}*: binary indicator of whether or not a request includes time period l*

R: total number of parking requests

Constants

G: total number of garages in parking system

C_g^{pt} *: price within the* $p^{\underline{th}}$ *dynamic pricing adjustment within the* $t^{\underline{th}}$ *tariff class with the* $g^{\underline{th}}$ *garage*

S_g*: the capacity of garage g*

L: total number of time intervals in a reservation period

Each request *r* (and its potential manifestation within each garage, x_{rg}^{pt}) has a vector of q_{lr}'s associated with it that are parameter inputs to the integer program. This vector has one *q* for every equal-length time period (one for each hour of a day, for example). For the hours included in the individual reservation request *r*, q_{lr} has a value of one. Otherwise, it has a value of zero.

As shown above, this integer program maximizes total revenue across all garages *G*. This objective function multiplies parking cost per hour by the parking dwell time and the decision variable. This result is

summed across all garages, parking (or tariff) classes, dynamic pricing adjustments, requests, and equal-length time periods during which the garages operate. The objective function is constrained by a garage capacity constraint. It is assumed that there are a fixed number of equal length time intervals within a given parking day (or parking availability period). Garage capacity is enforced by evaluating garage fill within each equal length time interval l within each individual garage to ensure that capacity has not been exceeded. Furthermore, constraint (3) ensures that for each request, only one garage (at most) is chosen to meet that request.

Depending on the number of variables and dimensions, the IP could be solved using any of the commercially available computer packages, such as CPLEX or Microsoft Excel Solver. In the case of this particular intelligent reservation model, the IP was solved using the Risk Solver Platform add-on to Microsoft Excel Solver.

For the purposes of evaluating the intelligent parking model, notional inputs to the integer program were assumed. G for this problem was assumed to be four garages, and two tariff classes were assumed: basic and premium. Although specifics are not defined for the purposes of this paper, it is assumed that premium class parking would afford some privileges or amenities above and beyond that of the basic parking class, as is common practice in both the aviation and hotel industries. An example of this is that premium parking might be covered or in a preferable location within the garage, as was discussed in **Section 3.2.2**.

As is shown in *Table 3.3*, five dynamic pricing adjustment periods were assumed (each of the four weeks in advance of the date of parking, plus the actual parking date). C_g^{pt} are the prices within each of these periods, an example of which is also given in *Table 3.3*. S_g, the capacity of the individual garages, was assumed to be equal for all four garages, with the capacity being equal to 150 parking spaces.

Furthermore, L, the total number of time intervals in a reservation period, is assumed to be in hourly increments for the purpose of this modeling. Therefore, we assume that L is equal to 24; one l for each of the hours within a parking day. The q_{lr}, the binary indicator vector of whether or not a request includes

time period l, was generated using a uniform distribution to generate an arrival and departure time to the garage.

The formulation presented above reflects the specific modeling properties of the intelligent parking model within this chapter, but for the general form of the IP, many of the indices in the model are not required. The indices in the formulation above are a result of the fact that requests within the intelligent parking model are enumerated within each tariff class and pricing period. This is unique to this intelligent parking model, and similar models may choose to track requests without respect to tariff class or pricing period. In this case, the model does require this information in order to execute effectively. In the model below, for every parking request i we could determine the price p_i based on the request's attributes ahead of model execution. Our decision is to accept the request (and if so determine a garage) or reject the request.

$$\text{MAX} \quad \sum_{i \in R} \sum_{j \in G} p_i x_{ij} \tag{5}$$

$$\textit{subject to} \quad \sum_{i \in R} q_{it} * x_{ij} \leq S_j, \forall j \in G, t \in T \tag{6}$$

$$\sum_{j \in G} x_{ij} \leq 1, \forall i \in R, \tag{7}$$

$$x_{ij} \in \{0,1\}, \ \forall i \in R, \ j \in G$$

(8)

<u>Parameters and Sets</u>

q_{it}: indicator that equals 1 if request i includes time interval t, else 0, $\forall i \in R, \ t \in T$

p_t: total number of dynamic pricing adjustments (periods) in the tth tariff class

R: set of requests (includes all types)

G: set of garages

T: set of time intervals

S_j: the capacity of garage j, $j \in G$

Variables

x_{ij}: binary variable that equals 1 if request i is accepted in garage j, else 0, $\forall i \in R,\ j \in G$

Notional literal inputs to the integer program as well as sample results (for illustrative purposes) are given in *Table 3.4.* These results represent those that will be used to train and test the mechanism by which online decisions will be made through the artificial neural networks.

Intelligent Parking Model							
Request ID (r)	Garage (g)	Pricing Period (p)	Tariff Class (t)	Parked Time |q|	Tariff (C_{ptg})	Potential Revenue (q^*C_{ptg})	x_{rptg}
1	1	Week One	Basic	4	1	4	0
2	1	Week One	Basic	7	1	7	1
3	1	Week One	Basic	1	1	1	0
4	1	Week One	Basic	2	1	2	0
5	1	Week One	Basic	2	1	2	1
6	1	Week One	Basic	11	1	11	0
7	1	Week One	Basic	12	1	12	0
8	1	Week One	Basic	19	1	19	1
9	1	Week One	Basic	14	1	14	0
10	1	Week One	Basic	2	1	2	0
11	1	Week One	Basic	13	1	13	0
12	1	Week One	Basic	7	1	7	1
13	1	Week One	Basic	12	1	12	0
14	1	Week One	Basic	11	1	11	0
15	1	Week One	Basic	11	1	11	1
16	1	Week One	Basic	8	1	8	0
17	1	Week One	Basic	8	1	8	1
18	1	Week One	Basic	5	1	5	1
19	1	Week One	Basic	12	1	12	0
20	1	Week One	Basic	16	1	16	0

Table 3.4: Subset of Integer Programming Inputs and Results

In order to sufficiently train and test the artificial neural network, this IP was solved nine times. Each IP included 500 requests (and therefore 2000 garage alternatives/decision variables). The IP was solved in nine parts, due to restrictions in the number of integer variables (a maximum of 500 per integer program) that the Risk Solver Platform is able to process in any individual run. As detailed in **Section 3.3.4,** the defined neural network inputs are relative measures and not based on inputs sensitive to number of total requests. Solving these nine IPs provided a total data set of 18,000 intelligent parking model decisions that could be used to train and test the neural network. The training and testing procedure is detailed in the section below.

3.3.4 Real-Time Decision-Making Using Neural Networks

As was previously introduced, neural networks are used in this intelligent parking model in order to enable real-time decision-making. An artificial neural network is a mathematical model or computational model based on biological neural networks. It consists of an interconnected group of artificial neurons, and processes information using a connectionist approach to computation. In most cases a neural network is an adaptive system that changes its structure based on external or internal information that flows through the network during the training and testing phases. Neural networks can be used to model complex, nonlinear relationships between inputs and outputs or to find patterns in data. A graphical representation of a neural network is given in *Figure 3.2*.

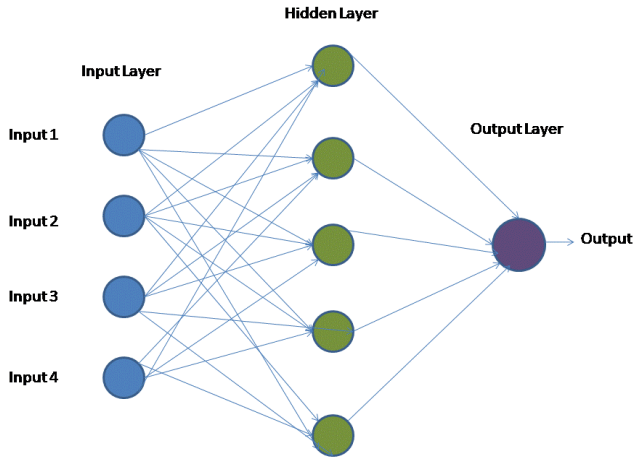

Figure 3.2: Artificial Neural Network

We know from the solutions of the integer program that each parking request is either accepted or rejected. These requests (or garage alternatives associated with a request) have a parking class associated with them. In this case, it is designated as either basic or premium. The neural networks are developed within each specific tariff class (or parking class). The modeling background and assumptions associated with neural networks are consistent with those described by Teodorović and Vukadinović [52].

In order to train and test a neural network, meaningful inputs must be developed that will be used by the artificial network to make its real-time decision [49, 52]. In all, five inputs were identified for use in the neural network.

$$X_1 = [1 - \frac{Maximum\ number\ of\ vehicles\ in\ garage\ during\ the\ parking\ time\ of\ the\ current\ request}{Capacity}(100)[\%]. \qquad (5).$$

This first of two input variables to the neural network represents the available amount of capacity within a particular garage at the time of the request. The variable looks across all time periods being requested and takes the largest percentage of capacity fill among all time periods being requested within that garage. In other words, if a customer requests parking from 10am until noon, this neural network input will check the garage for the 10-11am hour and the 11am-12pm hour to determine which hour has a higher number of vehicles within the garage. This number divided by the total garage capacity (subtracted from one) provides us with the available capacity within in the garage at the point of the parking request. This allows us to evaluate whether, if we grant this request, we will have additional capacity available later for our more valuable customers.

$$X_2 = \frac{A\ specific\ request's\ potential\ revenue\ contribution}{Maximum\ possible\ revenue\ from\ request}(100)[\%]. \qquad (6).$$

The second input variable to the neural network represents the relative revenue contribution for the request being considered. Here the numerator is the potential revenue to be gained from the current request, and the denominator is the maximum possible revenue that could be obtained for that request within all pricing periods within that request's tariff class. In other words, are we expecting better requests later that could produce more revenue? For example, if a request for three hours of parking is made during an early (and therefore, less expensive) pricing period, an hourly cost of two dollars per hour would yield a total price of six dollars. This value would be the X_2 numerator. Let us further suppose that the maximum rate within that tariff class is ten dollars per hour, for a total maximum price of \$30 for a three-hour reservation. Dividing the numerator of \$6 by the denominator, \$30, we obtain an X_2 of 20 percent.

$$X_3 = \frac{\textit{The hourly parking price applied to this request}}{\textit{The sum of all possible hourly parking prices within instance across all garages}}(100)[\%]. \quad (7).$$

The third input is the relative revenue for the request (as manifested in a particular garage) compared with the potential revenue of the request being offered within another garage. For example, if a request within the intelligent parking model will be offered within one of four garages, and the hourly tariffs for the four garages are \$1, \$1.50, \$2, and \$1 respectively, then X_3 for the first garage within the request would be calculated as follows:

$$X_3 = \frac{\$1}{\$1 + \$1.50 + \$2 + \$1} = 0.1818 \quad (8).$$

The fourth input is similar to third, but it is the rank order of the hourly revenue rate within all alternatives of a request. For our example above, the first garage potential manifestation within the request would be three (being tied with the fourth garage within the request). The fifth and final input is simply the week in which the request occurs. A request occurring in the first dynamic pricing period would be designated as a one.

These five inputs paired with the results of the integer program are used to train the neural network. A table of representative neural network inputs is given below in *Table 3.5*.

Intelligent Parking Model									% Cap Avail.	% Ptl Rev	Rel Rev Inst	Rnk Ordr Trf	Wk of Req
Request ID (r)	Garage (g)	Pricing Period (p)	Tariff Class (t)	Parked Time |q|	Tariff (C_{ptg})	Potential Revenue ($q*C_{ptg}$)	x_{rptg}	Rev. for Request	X1	X2	X3	X4	X5
1	1	Week One	Basic	4	1	4	0	0	1.0000	0.0128	0.3077	1	1
2	1	Week One	Basic	7	1	7	1	7	0.9839	0.0224	0.3077	1	1
3	1	Week One	Basic	1	1	1	0	0	1.0000	0.0032	0.3077	1	1
4	1	Week One	Basic	2	1	2	0	0	1.0000	0.0064	0.3077	1	1
5	1	Week One	Basic	2	1	2	1	2	0.9839	0.0064	0.3077	1	1
6	1	Week One	Basic	11	1	11	0	0	1.0000	0.0353	0.3077	1	1
7	1	Week One	Basic	12	1	12	0	0	1.0000	0.0385	0.3077	1	1
8	1	Week One	Basic	19	1	19	1	19	0.9677	0.0609	0.3077	1	1
9	1	Week One	Basic	14	1	14	0	0	1.0000	0.0449	0.3077	1	1
10	1	Week One	Basic	2	1	2	0	0	1.0000	0.0064	0.3077	1	1
11	1	Week One	Basic	13	1	13	0	0	1.0000	0.0417	0.3077	1	1
12	1	Week One	Basic	7	1	7	1	7	0.9516	0.0224	0.3077	1	1
13	1	Week One	Basic	12	1	12	0	0	1.0000	0.0385	0.3077	1	1
14	1	Week One	Basic	11	1	11	0	0	1.0000	0.0353	0.3077	1	1
15	1	Week One	Basic	11	1	11	1	11	0.9355	0.0353	0.3077	1	1
16	1	Week One	Basic	8	1	8	0	0	1.0000	0.0256	0.3077	1	1
17	1	Week One	Basic	8	1	8	1	8	0.9194	0.0256	0.3077	1	1
18	1	Week One	Basic	5	1	5	1	5	0.9032	0.0160	0.3077	1	1
19	1	Week One	Basic	12	1	12	0	0	1.0000	0.0385	0.3077	1	1
20	1	Week One	Basic	16	1	16	0	0	1.0000	0.0513	0.3077	1	1

Table 3.5: Sample Neural Network Input Data

For each of the tariff classes, the data resulting from the IP solutions is partitioned into data designated for training and data designated for testing. Clearly, the training set is much larger than the testing set, but both sets of data must be large enough to drive down the decision-making error within the neural network. Using the data package NeuroSolutions, breadboards (or palettes for building artificial neural networks) for both parking tariff classes were constructed and trained. After successful neural network training within each tariff class, the neural networks are tested for effectiveness using input data unpaired with output. The neural network predictions are then compared with the actual IP results to determine the effectiveness of the neural network. As shown in *Table 3.6* below, the models come within approximately 90 percent of optimal when measuring correct decision count and within 94 percent when comparing dollars of revenue.

	% of Optimal (Decision Count)	% of Optimal ($ of Revenue)
All Parking Classes	89.93%	93.59%

Table 3.6: Neural Network Output Quality Results

The performance measures shown in *Table 3.6* illustrate that optimality under revenue management can be approached in a way that could dramatically increase parking revenue.

3.4. Intelligent Parking Implementation

3.4.1 Making a Parking Reservation

In **Section 3.3**, we have described the development and mechanics of the intelligent parking and reservation model. However, this begs questions regarding how such a model can be implemented in practice. How would a prospective parking customer interact with such a reservation system? Clearly, upon approaching such a system, a customer likely has a particular parking need in mind. The technological manifestations of such as system (via the internet, cellular networks, or other means) will be discussed further in **Section 3.4.2**. Let us assume for the sake of this scenario, that the customer interacts with the reservation system via the internet.

Although there are several ways in which this system can interact with the customer to capture micro-markets and maximize revenue, one possibility is explored here. A customer could access a website that allows them to make a reservation in one of four garages within a particular compact urban district. In other words, all the garages available for reservation-making are close to destinations within the area. This simplifying assumption removes the requirement to enter a destination address. However, including this input would have fairly straightforward implications for the intelligent parking system, since many reservation systems include a destination input as a search criterion.

The customer logs onto the system and inputs their desired date and time period of parking. This action creates a *request* within the intelligent parking system. At this point, the system searches all of the garages to see if there is capacity available, and *alternatives* are generated. For each of these alternatives, the neural network inputs are generated, and the neural network decides whether or not an alternative should be accepted. The most acceptable alternative is displayed for consideration by the customer, including the parking location and price. The customer can then choose to accept the reservation or exit the system without making a reservation.

If a reservation is made by the customer, the parking location would likely be shown in more detail with driving directions provided. These driving directions are not only for convenience, but one of the means by which "trial-and-error" behavior in an individual parker is minimized.

3.4.2 Technology and Physical Manifestation of Intelligent Parking Model

Although the scenario described in **Section 3.4.1** assumed a customer interaction via the internet, it is also possible to imagine other ways that customers might make a parking reservation. Current technology allows access to the world wide web via cellular phones, which would permit making in-advance parking reservations en route to a destination. Also, cellular phone network technology permits such communication, even in the absence of internet browsing capability.

It is also important to observe intelligent parking model design and implementation issues at a more global level. As with any system design and development effort, it is advisable to use a rigorous approach including full attention to the systems engineering life cycle process. For the intelligent parking model, this would include system concept development, planning, requirements analysis, the actual design/development process, integration and test of the technology elements, implementation, operations and maintenance, and system disposal/disposition. **Section 3.2** of this chapter addresses concept development and a selection of planning/requirements analysis issues. Implementation, as well as integration/test and maintenance practices, would need to be tailored to an individual configuration of the intelligent parking model.

There are many possibilities and permutations of how the RM strategies and intelligent parking models might be implemented in practice, but the underlying principles remain the same: to segment the market into micro-markets (using intelligent reservation systems) that have the potential to dramatically increase revenue.

3.5. Conclusions and Future Research

After thoroughly reviewing the body of literature concerning parking systems and RM, it is clear that the topic is almost entirely unexplored. This chapter presented a strategy for how the principles of RM might be developed and implemented within the parking industry. This is illustrated with an example demonstrating how RM will function in a realistic parking scenario.

Furthermore, the single garage intelligent reservation formulation in [49] was extended to encompass a multiple-garage, dynamic-pricing environment. This formulation addresses a more realistic scenario. Also, an approach to use the IP solutions to train and test an artificial neural network in order to make online parking reservation decisions was proposed and results demonstrated. The neural network approach to make real-time decisions was found to be reasonable, even within the more complex multiple-garage environment.

Not only is the parking industry a good candidate for RM strategy implementation, this work fully develops the formulation, tools, and modeling to operate a sophisticated online decision-making system that isolates micro-markets and maximizes revenue. Opportunities for future work include further validation of the proposed intelligent parking modeling approach under various scenarios. One possibility would be to validate (prior to implementation) through the use of literal data sources such as existing garage capacity and volume data, survey data from both potential users and garage managers, and possibly the use of management flight simulation that can evaluate the sensitivity associated with model parameters. Furthermore, it would also be advisable to validate the system after implementation is complete. Clearly, verifying that revenue management policy coupled with the intelligent parking construct yields significant revenue increases would further validate the approach.

Additionally, it would interesting to investigate how some of the more subtle strategy elements presented in **Section 3.2** of this chapter might be explicitly modeled within the intelligent parking system. For instance, implementing the ability to overbook a garage for a given time period in response to data indicating how

many customers, on average, are no-shows. Another possible augmentation is to implement the ability within the intelligent parking model to dynamically adjust pricing in response to unexpected fluctuations in demand (as is often seen in the airline industry).

It is proposed that by implementing an advance-reservation system for parking (that almost always coincides with the adoption of RM strategies) that provides garage information and directions to the parking location, the level of congestion in the urban core could be significantly reduced. This inherent dynamic pricing element within RM poises it to be an effective travel demand management (TDM) strategy. Parking pricing variability (based on demand) and directed travel for those who make reservations can ideally reduce demand and/or redistribute it in a congestion-mitigating way. RM itself does not concern itself with peripheral issues such as traffic congestion, this postulated positive "side effect" is an interesting synergistic solution to boost business strength, increase efficiency of movement, and enhance overall public welfare. In **Chapter 4**, the multiple garage intelligent reservation system will be used to evaluate impact on urban traffic congestion using transportation micro-simulation modeling. The research hypothesis will be tested that, if RM is implemented among parking garages, urban core traffic congestion could be significantly mitigated.

CHAPTER 4: Modeling the Effects of Parking Revenue Management and Intelligent Reservations on Urban Congestion Levels

4.1. Revenue Management, Intelligent Parking Systems, and Research Objectives

In order to test a primary hypothesis of this research, a two-element, parallel modeling structure has been developed. The first model element is a real-time, decision-making model that receives requests for parking reservations and determines, via a back-propagation neural network, whether the request for parking will be accepted or rejected. The neural network is trained with an integer programming formulation. More details on the integer programming formulation, the training and testing of the neural network, as well as demand data generation are provided in **Chapter 3**.

The second model element is a micro-simulation in the VISSIM software package. VISSIM is a microscopic, behavior-based, multi-purpose traffic simulation program. It is a state-of-the-art package that offers a variety of urban and highway applications. Even very complex traffic conditions are visualized in detail to precisely and accurately recreate realistic traffic models. Many state and federal transportation agencies use VISSIM for transportation planning including the Missouri, New York, and Virginia Departments of Transportation. VISSIM has also been used to evaluate Travel Demand Management strategies such as highway reservation systems [15].

In order to use the second model element to test the research hypothesis, a three-square-mile, parking-dense central business district based on an analogous location within the District of Columbia was coded. A base case that simulated normal conditions including "trial-and-error" parking behaviors is compared with an alternative case that takes demand and reservation results from the first model element described above, while otherwise maintaining normal conditions. The second model element is presented in greater detail in **Section 4.2** of this chapter.

4.2 VISSIM Model Structure, Inputs, Assumptions, and Parameters

As introduced earlier, the second model element is a micro-simulation using the VISSIM software package. According to the VISSIM User's Guide [61, p. 22], "VISSIM is a microscopic, time-step, behavior-based simulation model developed to model urban traffic and public transit operations." The program can analyze traffic operations under constraints such as lane configuration, traffic composition, and traffic signals, thus making it a useful tool for the evaluation of various alternatives based on transportation engineering and planning measures of effectiveness.

The simulation package VISSIM consists of two primary modules that work in tandem. The first is the traffic simulator, which is a microscopic traffic flow simulation model including car following and lane change logic. The second module is the signal state generator, which is signal-control software that polls detector information from the traffic simulator on a discrete time step basis. It then determines the signal status for the following time step and returns this information to the traffic simulator.

The accuracy of a traffic simulation model is mainly dependent on the quality of the vehicle modeling, e.g. the methodology of moving vehicles through the network [61]. In contrast to less complex models using constant speeds and deterministic car following logic, VISSIM uses the psycho-physical driver behavior model developed by Wiedemann in 1974 [64]. The basic concept of this model is that the driver of a faster-moving vehicle starts to decelerate as it reaches its individual perception threshold to a slower-moving vehicle. Since it cannot exactly determine the speed of that vehicle, its speed will fall below that vehicle's speed until it starts to slightly accelerate again, after reaching another perception threshold. This results in an iterative process of acceleration and deceleration. Stochastic distributions of speed and spacing thresholds replicate individual driver behavior characteristics. Periodical field measurements and their resulting updates of model parameters ensure that changes in driver behavior and vehicle improvements are accounted for [61].

VISSIM's traffic simulator not only allows drivers on multiple lane roadways to react to preceding vehicles (two by default), but also neighboring vehicles on the adjacent travel lanes are taken into account. Furthermore, a vehicle approaching a traffic signal gains a higher alertness for drivers at a distance of one hundred (100) meters or fewer in front of the stop line. VISSIM simulates the traffic flow by moving driver-vehicle units through a network. Drivers with their specific behavior characteristics are assigned to specific vehicles. As a consequence, the driving behavior corresponds to the technical capabilities of the individual's vehicle. Attributes characterizing each driver-vehicle unit can be discriminated into three categories. The first of these is the vehicle technical specifications such as length, maximum speed, potential acceleration, actual position in the network, or actual speed/acceleration. Behavior of the driver-vehicle unit is the second of these categories, which can include driver sensitivity thresholds, aggressiveness, driver memory, acceleration based on current speed, and acceleration based on driver's desired speed. The third category is the interdependence of driver-vehicle units, which includes attributes like references to leading and following vehicles on surrounding lanes, references to current links and next travel intersection, and references to upcoming traffic signals [61].

In order build and simulate a network in VISSIM, the modeler must code the minimum required set of network components. Detail on the actual coding and network-building process is given in the appendix.

Both the Base Case and the Alternative Case were built using standard VISSIM coding practices, and the foundation network of links and connectors, previously described as a network based on an approximately three square mile area of the District of Columbia, is identical. Furthermore, all base vehicle inputs, traffic signals, ordinary routing decisions, and parking structures are identical. It is also important to note that overall demand/volume, including parking volume, is held constant between the two models. A screen shot of the foundation (background network) is shown in *Figure 4.1 (Default View).*

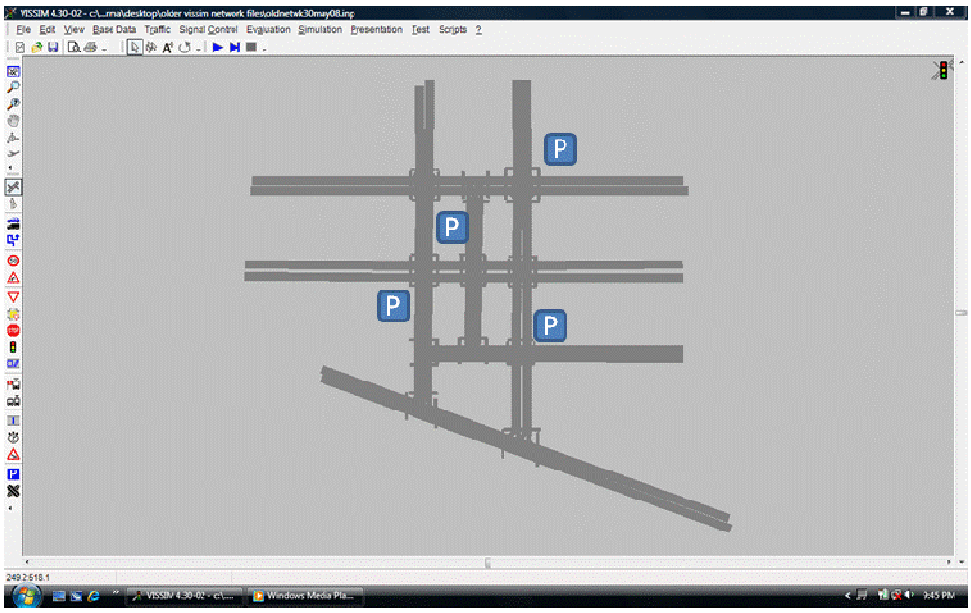

Figure 4.1: VISSIM Foundation Network (Default View)

The Base Case model includes both background traffic (through traffic) and traffic whose destination lies within the network. For the traffic whose destination is within the network area, these vehicles must select a location to park the vehicle. Routing decisions are included for vehicles seeking parking within the network. For each of these routing decisions, the vehicle will choose to park in the parking lot encountered, seek out other network parking lots, or leave the network (either reneging or seeking parking outside the network). These code elements simulate the "trial-and-error" behavior of vehicles in a dense parking district.

The Alternative Case VISSIM model has a few added features that allow it to test the revenue management - urban congestion research hypothesis. The first is additional vehicle classes and types are included so as to model the various types of parkers with reservations. This modeling feature allows VISSIM to simulate parkers arriving at specific times of the day for very specific reserved parking times. The second is adding routing decisions that take a parker with a parking reservation directly to his or her parking lot by the most direct route. The addition of these VISSIM model features allow one to evaluate the Alternative Case model to the revenue management and advanced parking reservation scenario.

Due to the fact that these models are being used to examine to what extent "trial-and-error" search behavior, caused by parking search, contributes to urban congestion, it is important to articulate the details of this modeling feature. As mentioned above, routing decisions are used to model parking behavior under revenue management by directing individual cars to a particular lot for a particular period of time using vehicle classes and types. However, "ordinary" parkers --- drivers seeking parking at the moment they would like to park --- are also modeled using routing decisions. A routing decision is specific to a particular point on the network. Also, the modeler defines what vehicle classes and types are bound by that routing decision (i.e. must make a decision regarding its next route when passing that point). A routing decision can be "fixed" in that all vehicles are bound by that decision and passing through will be directed in the same way.

However, a routing decision can also be probabilistic --- a modeler can define a group of routes that may be selected by the affected vehicles. This is accomplished through defining what fraction of traffic, on average, will take which route. The modeling feature not only allows "ordinary" parkers to randomly select a garage in which to attempt to park, it also allows for the modeling of a decision when a parker exits a garage after an unsuccessful search for parking. Within both the Base Case and Alternative Case VISSIM models, there are routing decisions at the exit of each garage that apply only to "ordinary" parkers. This decision either sends them to look for parking in one of the other garages, or it routes them off the network (or allows them to "give up" or renege).

The specific interaction and data flow between the first model element (the revenue management intelligent parking model) and the second model element (VISSIM Alternative Case) will be detailed in **Section 4.3**. Although observations and results will be fully discussed in **Section 4.4**, initial simulation screenshots are shown in *Figures 4.2 and 4.3*. VISSIM has both a two-dimensional and a three-dimensional simulation capability, and the Base Case model is shown being simulated in the figures below.

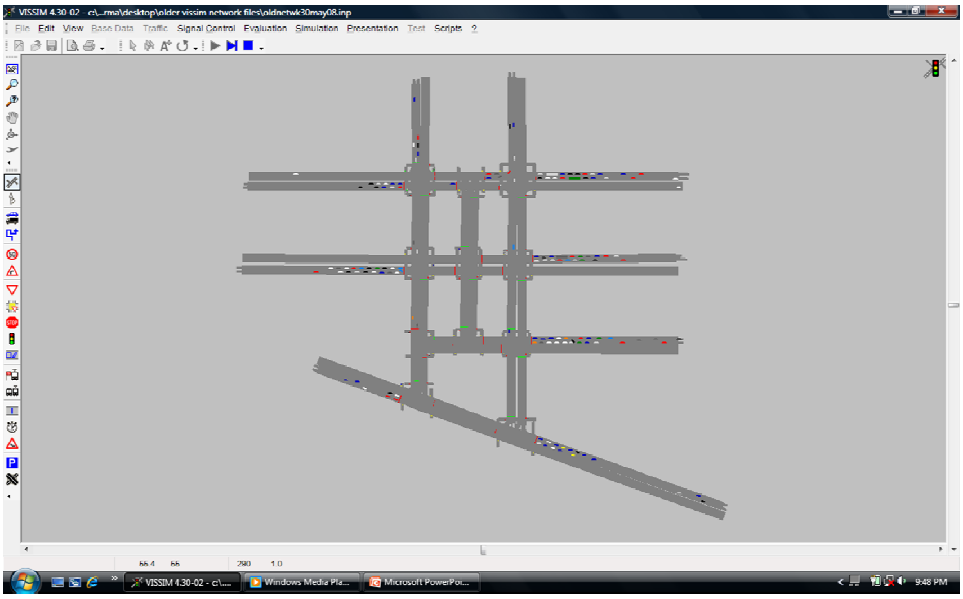

Figure 4.2: VISSIM Model Simulating Two-Dimensionally

Figure 4.3: VISSIM Model Simulating Three-Dimensionally

4.3 Interaction between the Intelligent Parking Model and the Micro-Simulation Model

As discussed in **Section 4.1**, the primary research hypothesis being tested using the parallel modeling structure (intelligent parking reservation model alongside a micro-simulation model) is that the implementation of revenue management within a central business parking district would reduce urban traffic congestion. The first model element is a revenue management intelligent parking model that makes real-time parking reservation decisions based on a trained and tested artificial neural network. The second model element is a VISSIM micro-simulation model that accepts the reservation set from the advanced reservation model and feeds the traffic volume into the urban micro-simulation network.

Once all reservation requests for a particular time period (one day, for example) are received and decided upon in the first model element, the demand is formatted and loaded into the second model element to be dispensed into the network. In order to accurately model this incoming reservation data, vehicle classes are created within VISSIM that correspond to specific parking entry times and dwell periods of specific vehicle types. Also, routing decisions at specific garage locations are created that dictate dwell times to the vehicle corresponding to a specific reservation.

The Base Case and Alternative Case VISSIM simulation models have identical through-traffic levels and identical volumes of total parking demand. The parking demand for the Base Case consists entirely of drivers that exhibit "trial-and-error" behavior while searching for a place to park the vehicle. The Alternative Case parker population, however, consists of both "typical" drivers exhibiting "trial-and-error" behavior and vehicles with a parking reservation that are routed directly to their parking lot. The Alternative Case model assumes a steady-state environment where the majority of parkers make a parking reservation in advance.

Once parking volume from the intelligent parking revenue management model feeds into the micro-simulation model, the simulation runs are used to evaluate the effects of revenue management parking

policies on overall levels of network congestion. Once the full simulation period is complete (twenty-four hours in this case), VISSIM outputs network performance metrics such as travel time over various network routes, total network delay, and average queue lengths in front of parking venues and at intersections. Since both the Base Case and Alternative Case VISSIM models are coded to output the same set of network performance metrics, these metrics can be compared to determine whether or not the implementation of parking revenue management impacts urban traffic congestion.

4.4 Parallel Model Results and Behavioral Sensitivity Analysis

4.4.1 Research Hypothesis Testing Results

For the primary research hypothesis test, the Base Case and Alternative Case VISSIM models were each run for thirty (30) twenty-four hour simulation periods. Because dense urban areas with city block structures such as Washington, DC often experience high-congestion conditions, it is important to note how the VISSIM simulation reacts to the these circumstances. In the case of moderate congestion, VISSIM continues to run, but slows in efficiency and pace. In the case of extreme gridlock, VISSIM runs extremely slowly and is prone to discontinue simulating if system demands become exceedingly high. In the case of most networks, if a gridlock situation occurs and demand remains fairly constant through the simulation, the network does not return to normal conditions. The congested situation continues and often worsens. In cases of extreme gridlock where VISSIM is running slower than actual time, the simulation is terminated, statistics are gathered, and output is earmarked as a gridlock simulation terminated at a certain time during the day.

Clearly, the key parameter in this pair of simulation models is that of what dictates the "trial-and-error" behavior of parkers that have not made an advanced reservation via the RM system. For the primary hypothesis test, each undirected parker exiting a parking lot in which he or she has unsuccessfully searched for parking has a twenty percent chance of reneging and leaving the network. This assumes that most parkers are motivated to continue driving and searching for parking close to their final destination rather

than changing their plans or looking for parking at a much greater distance from their destination. In order to test the sensitivity of this probability distribution, we also investigate situations in which we increase this percentage to thirty-three percent and when it falls to ten percent.

Overarching network performance measures were used to compare the models including total delay, total stopped delay, average speed, delay per vehicle, number of vehicles to leave network, and total travel time. Delay-based metrics were found to be most useful to compare total network congestion and its impacts. As is shown in *Table 4.1* below, the Base Case VISSIM model had a much higher incidence of congested conditions and simulation terminations due to gridlock. The Alternative Case model had only one incidence of a simulation stop due to gridlock.

	Percentage of Mid-Run Stops Due to Gridlock	Percentage of High Levels of Congestion
Base Case	23.33%	26.67%
Alternative Case	3.33%	3.33%

Table 4.1: Base and Alternative Case Congestion Conditions Results

Looking more closely at individual network performance metrics, *Table 4.2* shows the summarized results for all case runs that did not terminate due to gridlock conditions. It is clear from the total and individual vehicle delay results that overall levels of network congestion were significantly higher for the Base Case as compared to the Alternative Case. For instance, the average delay per vehicle within the network for the Base Case model is 26.68 seconds, while for the Alternative Case it is 23.40 seconds. This constitutes a reduction in delay per vehicle of 12.31 percent when a RM parking policy is in place. Furthermore, total network delay across the network is reduced by an average of 12.09 percent and total stop delay per vehicle is reduced by an average of 9.24 percent across the thirty simulation runs. Each of the results differences shown in *Table 4.2* is significant at the 98 percent confidence level (determined using the student's t-test for paired samples).

	Avg delay per veh [s]	Total delay time [h]	Avg stop delay per veh [s]	Total stopped delay [h]
Base Case	26.68	1527.61	23.22	1329.53
Alternative Case	23.40	1342.90	21.02	1206.72
Percent Difference	12.31%	12.09%	9.47%	9.24%

Table 4.2: Key Network Performance Results for Completed Base and Alternative Case Runs

It is also interesting to consider the situation where all significant congestion scenarios are removed (those that terminated the simulation and those that did not). In the case shown in *Table 4.3*, we see a much smaller, but still notable difference in average and total delays within the network. Again, each of the results differences shown in *Table 4.3* is significant at the 98 percent confidence level. The Base Case model averages 26.03 seconds of delay per vehicle, while the Alternative Case model averages 23.40 seconds. This equates to a 10.11 percent difference between the two scenarios. It can be concluded that within this network, the implementation of RM policies within parking venues relieves congestion even in non-extreme conditions. It is also clear that if statistics from the more prevalent terminated runs within the Base Case were included here, that the urban congestion mitigating effects of RM would be even more strongly demonstrated.

	Avg delay per veh [s]	Total delay time [h]	Avg stop delay per veh [s]	Total stopped delay [h]
Base Case	26.03	1490.17	22.56	1291.84
Alternative Case	23.40	1342.90	21.02	1206.72
Percent Difference	10.11%	9.88%	6.82%	6.59%

Table 4.3: Key Network Performance Results for Base and Alternative Case Runs under Normal Conditions

4.4.2 Model Sensitivity to Changes in Search Behavior

As mentioned earlier, in order to test the sensitivity of the reneging rate distribution, we also investigate situations in which the probability of a parker choosing to no longer search for parking increases to thirty-three percent and when it falls to ten percent. In other words, we want to observe how changes in parking search behavior affect overall network performance. For each of these sensitivity analyses, thirty runs of twenty-four hour days are examined.

For the case in which the probability of a parker reneging when exiting any particular parking lot after an unsuccessful search for a parking space is ten percent (10%), the results are somewhat startling. For the Base Case VISSIM model, eighty percent (80%) of the simulation runs were terminated at the point where the network became extremely congested to the point of running at a fraction of clock time. However, the Alternative Case had approximately ninety-seven percent (97%) normal runs. Although one might expect that since there was one high-congestion run for the case in which the reneging rate is twenty percent, that there might be more for the case in which the reneging rate is ten percent. Also, within the Alternative Case model, the reneging rate is assumed to not be nearly as influential as in the Base Case, and therefore would not likely affect the incidence of gridlock nearly as much. The congestion conditions results are given in *Table 4.4.*

	Percentage of Mid-Run Stops Due to Gridlock	Percentage of High Levels of Congestion
Base Case	80.00%	80.00%
Alternative Case	3.33%	3.33%

Table 4.4: Base and Alternative Case Congestion Conditions Results

(Sensitivity Case One: 10% Reneging Rate)

The resulting congestion metrics are shown in *Table 4.5 and 4.6.* It is clear that this change in parker behavior has a profound effect on network performance due to the occurrence of high congestion situations in the Base Case model. *Table 4.5* again shows a statistically significant difference (at the 99 percent confidence level) in congestion metrics between the Base Case and Alternative Case. The average delay per vehicle within the network for the Base Case model is 61.56 seconds, while for the Alternative Case it is 23.73 seconds. This constitutes a reduction in delay per vehicle of 61.45 percent when an intelligent parking revenue management parking policy is in place. Furthermore, total network delay across the network is reduced by an average of 54.38 percent and total stop delay per vehicle is reduced by an average of 54.29 percent across the thirty simulation runs. However, only twenty percent of the Base Case runs (in this case, only six runs) are included in the results that excluded terminated runs.

	Avg delay per veh [s]	Total delay time [h]	Avg stop delay per veh [s]	Total stopped delay [h]
Base Case	61.56	2985.41	55.78	2669.81
Alternative Case	23.73	1362.04	21.26	1220.33
Percent Difference	61.45%	54.38%	61.89%	54.29%

Table 4.5: Key Network Performance Results for Completed Base and Alternative Case Runs (Sensitivity Case One: 10% Reneging Rate)

In order to better represent the simulation results data, *Table 4.6* shows all results including terminated runs in order to show a more accurate performance scenario. Only one Alternative Case run was terminated, but eighty percent of Base Case runs were terminated. It is impossible to determine what the final metrics would have been if all simulations had completed their day-long runs, but it is clear that the Base Case results would have been quite a bit worse. Even at looking at the available data, it is clear that the Alternative Case vastly outperforms the Base Case. One can infer from these results that as the parker reneging rate decreases, the value of intelligent parking revenue management policies increases dramatically. The results shown in *Table 4.6* are significant at the 99 percent confidence level.

	Avg delay per veh [s]	Total delay time [h]	Avg stop delay per veh [s]	Total stopped delay [h]
Base Case	124.82	4674.26	120.14	4467.49
Alternative Case	27.19	1555.16	24.72	1413.70
Percent Difference	78.22%	66.73%	79.42%	68.36%

Table 4.6: Key Network Performance Results for Base and Alternative Case Runs Including Necessitated Run Terminations (Sensitivity Case One: 10% Reneging Rate)

For the case in which the probability of a parker reneging when exiting any particular parking lot after an unsuccessful search for a parking space is thirty-three percent (33%), or roughly one-third, the results are quite different. As in the previous sensitivity analysis case, thirty runs of twenty-fours each were run for the Base Case and the Alternative Case models. For both VISSIM networks, very few runs were terminated due to extreme congestion or gridlock conditions --- four in the Base Case model and only one in the Alternative Case model (as shown in *Table 4.7*). This is a drastic change from the case in which the

reneging rate was ten percent. Clearly, for the urban parking-dense network, parking search behavior has a significant effect on whether extreme urban congestion conditions develop.

	Percentage of Mid-Run Stops Due to Gridlock	Percentage of High Levels of Congestion
Base Case	13.33%	13.33%
Alternative Case	3.33%	3.33%

Table 4.7: Base and Alternative Case Congestion Conditions Results

(Sensitivity Case Two: 33% Reneging Rate)

The resulting congestion metrics for all completed runs within Sensitivity Case Two are shown in *Table 4.8*. *Table 4.8* shows a statistically significant (at the 99 percent confidence level), but much smaller difference in congestion metrics between the Base Case and Alternative Case. The average delay per vehicle within the network for the Base Case model is only 24.60 seconds, while for the Alternative Case it is 23.16 seconds. This constitutes a reduction in delay per vehicle of approximately 6 percent when an intelligent parking RM parking policy is in place. Furthermore, total network delay across the network is reduced by an average of 5.63 percent and total stop delay per vehicle is reduced by an average of 4.1 percent across the completed simulation runs.

	Avg delay per veh [s]	Total delay time [h]	Avg stop delay per veh [s]	Total stopped delay [h]
Base Case	24.60	1408.66	21.73	1244.26
Alternative Case	23.16	1329.33	20.84	1196.41
Percent Difference	5.87%	5.63%	4.09%	3.85%

Table 4.8: Key Network Performance Results for Completed Base and Alternative Case Runs

(Sensitivity Case Two: 33% Reneging Rate)

As with Sensitivity Case Two, in order to better represent the simulation results data, *Table 4.9* shows all results including terminated runs in order to show a more complete performance profile. Only one Alternative Case run was terminated, and four of the Base Case runs were terminated. As before, it is impossible to determine what the final metrics would have been if all simulations had completed, but it is likely that the performance results would have been at least somewhat worse. Looking at the output in *Table 4.9*, we see that the Alternative Case outperforms the Base Case, but the margin that is much smaller

than when the reneging rate is lower. It is interesting to note, that due to the sample variances, the results shown in *Table 4.9* were not determined to be statistically significant.

	Avg delay per veh [s]	Total delay time [h]	Avg stop delay per veh [s]	Total stopped delay [h]
Base Case	24.80	1424.69	21.90	1258.15
Alternative Case	23.31	1337.59	20.97	1203.94
Percent Difference	6.01%	6.11%	4.22%	4.31%

Table 4.9: Key Network Performance Results for Base and Alternative Case Runs Including Necessitated Run Terminations (Sensitivity Case Two: 33% Reneging Rate)

This sensitivity case provides further evidence that reneging rate is a key driver of urban congestion. These results demonstrate that as the parker reneging rate increases, RM policies become not as important to controlling congestion. Clearly, this rate of reneging is an important value to understand within any given urban parking district, due to the significance of its impact on congestion levels.

4.5 Summary, Conclusions, and Future Work

As detailed earlier, the primary research hypothesis of this work is that by implementing a revenue management strategy at parking venues within the urban central business district, urban traffic congestion can be mitigated. In order to test this hypothesis, a two-element, parallel modeling structure was developed. The first model element is a real-time, decision-making model that receives requests for parking reservations and determines, via a back-propagation neural network, whether the request for parking will be accepted or rejected. The second model element is a micro-simulation in the VISSIM microscope, behavior-based traffic simulation program. For the Base Case VISSIM model (or the control element of the experiment), reality-based inputs are used to build a foundation network. For the Alternative Case VISSIM model, however, the output from the first model element, the advanced reservations for a given day are imported into the model and constitute the majority of the day's parking demand. Both VISSIM models are identical in all facets except for the factors of advanced reservations and direct routing.

The primary hypothesis-testing experiment consisted of thirty twenty-four hour runs of each model with the likelihood of a parker exiting a garage after an unsuccessful search for parking being twenty percent (20%). The network performance statistics for each model were compared, and it became clear that the Base Case in which no intelligent parking revenue management policy was in place was much more prone to the development of extreme congestion and gridlock conditions. Furthermore, a comparison of network performance metrics showed a significant improvement under advanced reservations as indicated by measures such as delay per vehicle and total network delay.

In addition to the primary hypothesis-testing simulations, two sensitivity analyses were performed to evaluate the impact of changing the behavior of unreserved parkers. For the primary set of runs, the parker reneging rate was twenty percent. In the first sensitivity analysis, the rate was decreased to ten percent. Thirty runs of each model were executed. The Base Case completed only six of the thirty runs due to termination under heavy congestion conditions. The Alternative Case only terminated once. Furthermore, normal condition performance metrics between the two models differed significantly.

In the second sensitivity analysis, the parker reneging rate was increased to thirty-three percent (33%). In this case, the thirty runs for both the Base Case and the Alternative Case models encountered far fewer high congestion conditions. All completed their full runs successfully, with the exception of four within the Base Case model and one in the Alternative Case model. Furthermore, when examining network performance metrics such as total network delay, the difference was much smaller, ranging from a four to six percent improvement in performance for the Alternative Case in which intelligent parking revenue management policies are implemented.

One point is clear from these experiments. The rate at which parkers that do not have a parking reservation give up and search for parking outside the network or cancel their plans to visit the central business district is a primary driver of the value of the implementation of intelligent parking revenue management strategy. All other things being equal, the intelligent parking revenue management model in which the majority of parkers is directed to their precise parking spot via the most direct route (and thus avoids "trial-and-error"

behaviors) is much more robust to random elements and occurrences within the network that can instigate congestion. On the other hand, the control model is highly susceptible to high levels of congestion, especially when parkers are determined to find parking and have inflexible parking requirements.

Clearly, many other things can drive congestion development in urban networks. Future work could explore other sensitivity analyses including changes to background traffic volumes, swings in demand levels or distributions, changes to parking density or type, and many others. Furthermore, it would be interesting to look at the issue of parker reneging rate in greater detail. In particular, is there a parker reneging rate "tipping point" at which much higher levels of congestion develop within a particular network? A general result for this would be difficult to develop since this would depend highly on the properties of a specific urban area and its levels of travel and parking demand, but developing the principle more fully would be a worthy pursuit.

CHAPTER 5 Applying Hyperbolic DEA and Matrix DEA Constructs to the Performance Measurement of Revenue Management in the Parking Industry

5.1 Performance Measurement and Data Envelopment Analysis (DEA)

In **Chapters 3 and 4,** the modeling structure and results of this chapter's predecessor research were presented and detailed. In order to test the effects of implementing RM policies within a dense urban parking district, a parallel modeling structure was developed, composed of an intelligent parking model and a micro-simulation model. The intelligent parking model gathers and processes customer in-advance requests for parking. The requests are either accepted or rejected using a neural network decision-making mechanism. The VISSIM micro-simulation compares a high-density parking network without RM policies (and in-advance reservation-making) to the same network with RM. The results demonstrate that high-density parking districts benefit from RM policies and the subsequent relief from "trial-and-error" driver/parker behaviors.

Although these findings are certainly contributions in and of themselves, they do not address some of the central issues and questions of travel demand management. Particularly, we gain no direct insight into performance of the network from the viewpoint of key stakeholders such as the individual parker, the parking provider, or the community as a whole. In addition, this predecessor modeling does not evaluate the effect of changes to key network parameters such as changes in background traffic flows, changes in demand allocation among parkers with and without reservations, and changes in parker reneging rate.

In light of these observations, this paper intends to use a well-known macro-evaluation, performance measurement tool, data envelopment analysis (DEA), to evaluate urban parking systems from the perspective of the various stakeholders under both a current parking scenario and a revenue management scenario (previously and subsequently referred to as the Base Case and Alternative Case, respectively). Additionally, we will examine the effects on DEA-measured efficiency of changes in network parameters that tend to vary among individual parking districts. The idea here is, that since each parking-dense urban

area will be different, we would like to explore efficiency sensitivity to key network changes such as background traffic flows, changes in demand allocation among parkers with and without reservations, and changes in parker reneging rate. This will hopefully provide insight into what network characteristics drive performance, and therefore ought to be considered in urban or transit planning for a particular urban parking district.

Background information and literature review on the topic of DEA can be found in **Section 2.6** of this document. The DEA model has been applied to numerous scenarios. The most conventional application is to manufacturing production environments, but DEA is also commonly used to measure efficiency of non-profit entities and service industries. Furthermore, DEA has been expanded and augmented in a variety of ways to address specific performance measurement issues. For example, network DEA was developed to model not only a DMU in its entirety, but also its interior processes, so that insight might be gained into internal sources of inefficiency. Additionally, Färe et al. [18] introduced an approach to incorporate both desirable and undesirable outputs of DMUs called hyperbolic DEA. This technique is applied below to evaluate parking systems, and **Section 5.2** will provide more detail on this formulation and approach.

5.2 DEA Formulation and Parameters

5.2.1 Decision-Making Units

One of the first steps when implementing a frontier analysis formulation is to define the decision-making unit (DMU). As described in **Section 5.1,** DMUs are anything with quantifiable inputs and outputs that can be compared with other analogous entities. Since the purpose of this research is to evaluate parking systems from the perspective of various stakeholders under varying network and policy conditions, the DMU for this DEA formulation is defined as an instance of the parking network with certain defined characteristics. For example, a particular DMU may be an instance of the urban high-density parking district under revenue management with an increased level of background traffic (for modeling purposes, this level is specifically defined). Each individual DMU is defined in **Section 5.3.3**.

5.2.2 Hyperbolic DEA Model

Traditional DEA modeling carries with it certain restricting assumptions. For example, the Banker, Charnes, and Cooper (BCC) models assume that inputs are used by the production process to produce outputs, and inputting more resource into the process will yield more output under varying returns to scale. Implicit here is that outputs are desirable, being either product or some other desirable measure, where more is better.

But, what happens when the outputs of the DMU are undesirable? This is often the case in transportation systems. For instance, transportation systems can produce outputs that are generally desirable like revenue, trips completed, customers served, and ridership. However, undesirable outputs are also common --- outputs like carbon dioxide emissions, vehicle delay, travel time, and network congestion.

Various techniques and alternative DEA formulations have been proposed to deal with this issue, as is laid out in detail by Pasupathy in his 2002 thesis [32]. Färe, et al. [18] introduced a different approach to incorporate both the desirable and undesirable outputs in the model. This formulation allows the desirable outputs to increase by a proportion, and at the same time allows the undesirable outputs to decrease by the same proportion. The formulation is shown in *Figure 5.1* below.

$$\max \theta'$$

$$s.t.$$

$$\sum_{j=1}^{J} \propto_j p_{nj} \geq \theta' p_{njo} \quad \forall \; n = 1,2, \ldots . N$$

$$\sum_{j=1}^{J} \propto_j q_{rj} = q_{rjo}/\theta' \quad \forall \; r = 1,2, \ldots . R$$

$$\sum_{j=1}^{J} \propto_j x_{mj} \leq x_{mjo} \quad \forall \; m = 1,2, \ldots . M$$

$$j_o = 1, 2, \ldots . . J$$

$$\theta', \propto_j \geq 0 \; \forall \; j = 1,2, \ldots . J$$

Figure 5.1: Färe et.al Hyperbolic DEA Formulation [20]

It can be seen that θ' is the factor of increase of the desirable outputs and the decrease of undesirable outputs, and it is the resulting efficiency for a particular DMU. In this formulation, efficiency (θ') is maximized subject to constraints dictating proportionality between the undesirable input (q_{rj}) decreases and desirable output (p_{nj}) increases, across all desirable outputs N and undesirable outputs R. And, as with all traditional DEA formulations, the weighted inputs across all DMUs must be less than or equal to the input of the DMU for which the problem is being solved. The DEA problem is solved J times, which is the total number of DMUs.

Since the evaluation of the urban parking district developed here requires the analysis of undesirable outputs, we use the hyperbolic DEA formulation to model DMU efficiency. More detail on specific inputs and outputs of the DEA formulation for this problem are given in **Section 5.3.2**.

5.3 Matrix DEA Construct and Stakeholder Perspectives

5.3.1 Matrix DEA

Issues of transportation and demand management are inherently relevant to a broad range of stakeholders, including providers and users of the resources. In addition, issues of transportation and mobility are, on the whole, complex and dynamic. In order to effectively capture and communicate the multi-dimensionality of efficiency measurements within transportation systems, we introduce the concept of *matrix DEA*. Although using a matrix framework to communicate DEA multi-dimensionality can be configured in whatever way is most conducive to the problem at hand, this research uses two dimensions of stakeholders and DMUs, as shown in *Figure 5.2*.

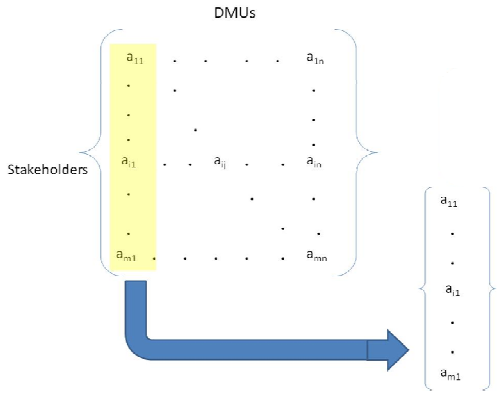

Figure 5.2: Matrix DEA Construct

Clearly, the strength of this method of display is that, for the stakeholders defined in **Section 5.3.2**, the parking provider, the parker district user, and the community/society, we can see, at a glance, the performance of that DMU, not only in comparison to the other DMUs, but also across the range of stakeholders. We can also take *efficiency vector* cuts across the matrix. These cuts can capture all aspects (dimensions) of efficiency for a given DMU, or efficiency across a particular stakeholder.

5.3.2 Stakeholder Models

As outlined in earlier sections, this work seeks to evaluate the efficiency of parking systems under varying conditions from the perspectives of a range of stakeholders. In this case, the relevant stakeholders are defined for urban parking systems to be the parking provider, the user of the parking district (parker or through-traveler), and the community/society that contains and experiences the conditions within the urban parking district. Each stakeholder model is detailed below with its specific DEA inputs and outputs.

The first stakeholder model is that of the parking provider, as show in *Figure 5.3* below.

Figure 5.3: Parking Provider Perspective DEA Model

As is clear from *Figure 5.3*, the parking provider model has as its inputs both parking supply (or garage capacities), and maintenance/labor costs. For the instances where reneging rate is being tested (see **Section 5.4.3**), reneging rate is also an input to the model. Revenue is the output. Parking supply is assumed within the VISSIM model and is constant across DMUs. Each parking lot contains 150 parking spaces, for a total capacity of 600 spaces. In addition, labor rate is constant, and is calculated by taking the average local labor rate (in this case, for the Washington, DC, US area) [37] in US dollars and multiplying by an assumed labor requirement. In this case, we assume two parking attendants per lot and one-half of a staff-year for garage maintenance. For the models in which the Base Case model (no RM policy in place) is being measured, revenue is calculated from VISSIM parker count output, segmented by parking class (either Basic or Premium) and reneging rate is assumed and provided as an input to the VISSIM micro-simulation. For the models in which the Alternative Case model (RM policy in place) is being measured,

revenue is calculated from the intelligent parking model output (revenue gathered from online reservation-makers) in addition to non-reserved parkers via parker count within VISSIM.

The second stakeholder model is that of the parking district user, as shown in *Figure 5.4* below.

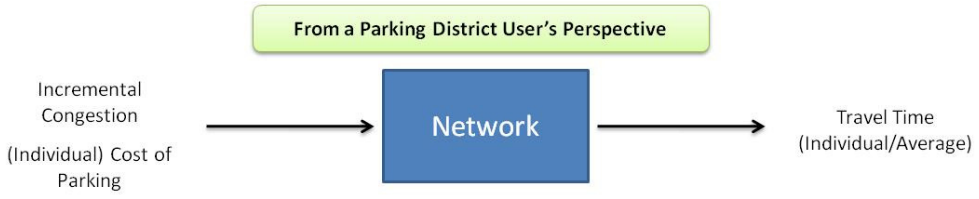

Figure 5.4: Parking District User's Perspective DEA Model

The parking district user model has as its inputs both incremental congestion and the individual cost of parking (average across all parkers). As before, for the instances where reneging rate is being tested, reneging rate is also an input to the model. User travel time is the output. *Incremental congestion* is defined as the average delay contribution per vehicle, which is an output of the VISSIM model; in other words, the amount of delay/congestion that an individual contributes to the network, on average. Under the Base Case model, individual cost of parking is calculated by taking a weighted average of parking prices across parking classes. For example, if we assume 35 percent of parkers are premium-class parkers at an average cost of $15 per hour, and 65 percent of parkers are basic-class parkers at a cost of $10 per hour, then the weighted hourly cost per parker is $11.75. Travel time is calculated by taking the average vehicle travel time over three cross-network routes, as shown in *Figure 5.5*, and is calculated from VISSIM-defined output.

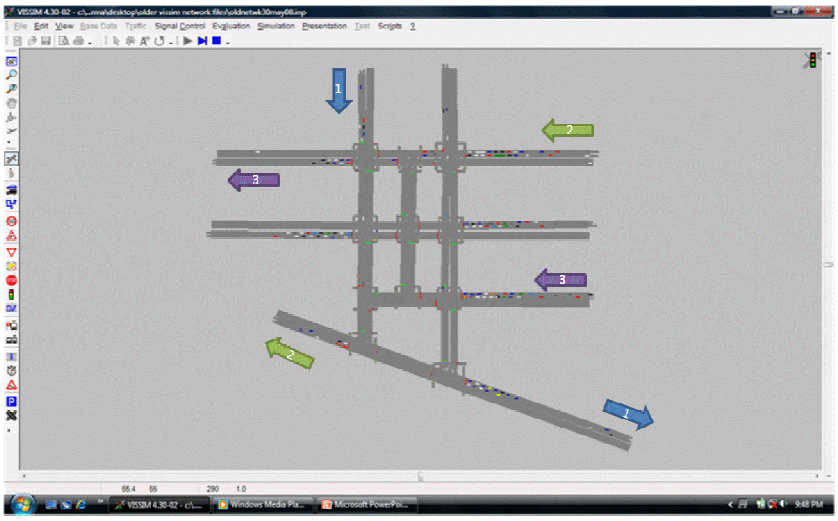

Figure 5.5: Travel Time Intervals across the Network

The third stakeholder model is that of the community or society, as shown in *Figure 5.6* below.

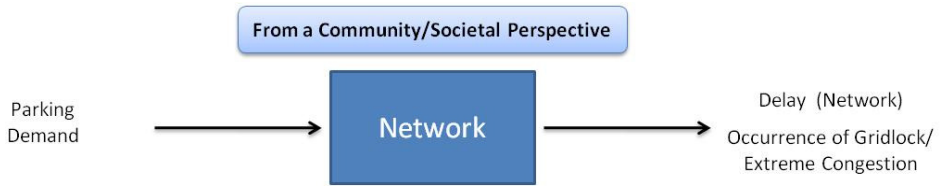

Figure 5.6: Community/Societal Perspective DEA Model

As is clear from *Figure 5.6,* the community/societal model has as its input parking demand. As before, for the instances where reneging rate is being tested, reneging rate is also an input to the model. Total network delay and occurrences of extreme congestion are outputs. For the Base Case model (no RM policy in place), parking demand is measured as the number of parkers input into the VISSIM model. This is due to the fact that since there is no RM policy in place, then there is no demand input coming from the intelligent parking model or, consequently, reservation-holding parkers. For the Alternative Case model (RM policy in place), parking demand is the combination of the total number of reservation requests within the Intelligent Parking model plus the unreserved parking population introduced into the VISSIM micro-simulation.

Network delay is an output of the VISSIM model that measures total delay across all vehicles within the network through the duration of the simulation, in this case, 24 hours. Occurrence of gridlock or extreme congestion is also an output of VISSIM. This is captured using a binary variable and is a count of how many VISSIM runs (out of the total of 30 runs for each DMU) experienced extreme congestion conditions. Extreme congestion is defined by network performance metric values (output of VISSIM) of 50 percent over normal.

5.3.3 DMU Definitions

As was articulated in **Section 5.3.1,** since the purpose of this research is to evaluate parking systems from the perspective of various stakeholders under varying network and policy conditions, the DMU for this DEA formulation is defined as an instance of the parking network with certain defined characteristics. This work seeks to look at network performance under both conditions where RM policy is in place and where RM policy is not in place. Furthermore, this work investigates performance from the perspective of the parking provider, the customer, and the community (as described in **Section 5.3.2).** Leveraging the concept of matrix DEA, as introduced in **Section 5.3.1**, two DEA matrices are proposed, each devoted to exploring network performance under a particular parking policy --- either with or without RM policy implemented.

The first matrix, which captures the DEA structure and model groups under the Base Case (or the "no RM" policy), is shown in *Figure 5.7*.

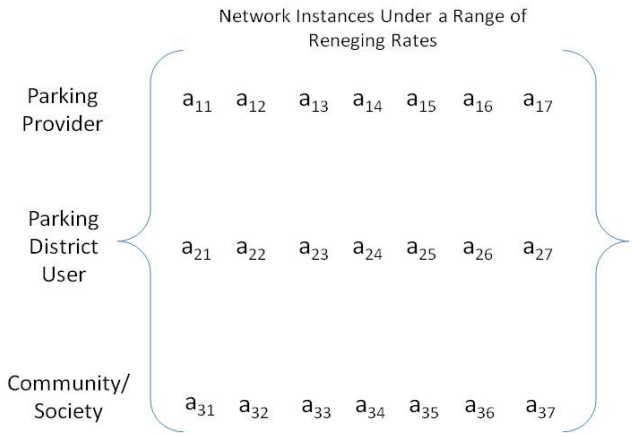

Figure 5.7: DEA Matrix under Networks Experiencing Different Rates of Reneging

One can observe that the matrix is composed of elements corresponding to one of the three stakeholders and to one of seven DMUs. The seven DMUs are network instances under differing rates of reneging, which is defined as the rate at which unsuccessful (unreserved) parkers leave the network. In **Chapter 4,** one of most compelling observations following the initial runs of the VISSIM micro-simulation model was that reneging rate seemed to have a significant impact on congestion levels and incidence of gridlock, as evidenced by a small set of sensitivity analyses. The motivation behind this DEA matrix is to not only increase the granularity of this reneging rate exploration, but to also use stakeholder-based DEA modeling to gain insight into who gets impacted and how. Since, initial runs demonstrated that as reneging rate decreases, congestion increases, and dramatic differences were observed between the 10 percent and 20 percent rates, more reneging rate DMUs were defined between these two values. The full DMU set is defined in *Table 5.1*.

Decision-Making Unit	Reneging Rate
DMU 1	10%
DMU 2	12%
DMU 3	15%
DMU 4	18%
DMU 5	20%
DMU 6	27%
DMU 7	33%

Table 5.1: *Base Case DEA Matrix DMU Definitions*

The second matrix, which captures the DEA structure and model groups under the Alternative Case (or with RM policy implemented), is shown in *Figure 5.8.*

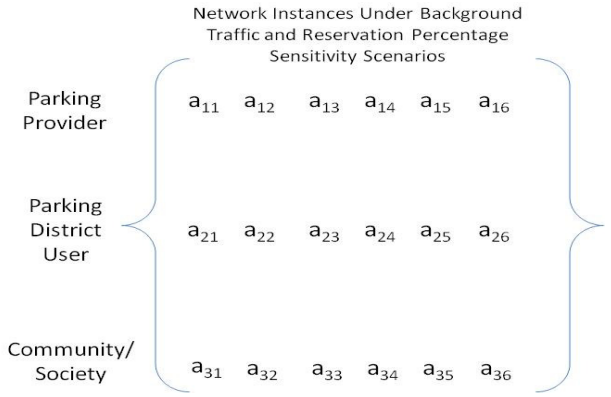

Figure 5.8: DEA Matrix under Networks Experiencing Varying Rates of Background Traffic and Reservation Rate

It is easily observed that the matrix above is composed of elements corresponding to one the three stakeholders and to one of six DMUs. The six DMUs are network instances under either varying rates of background traffic or varying reservation rates. Background traffic rate is defined as the amount of network traffic simply traveling on the network from one point to another and not seeking to linger on the network or park. Reservation rate is the relative amount of parkers within the model that reserve parking versus just searching for parking at the moment at which it is required.

It is a logical supposition that a large amount of ambient or background traffic on the network could affect system performance and efficiency. The intent of testing this in a hyperbolic, matrix DEA context is to test whether this research hypothesis holds true in practice and to what extent it affects performance from the viewpoint of the three key stakeholders. It is also an interesting consideration: does the relative rate of reservation-making versus "trial-and-error" (or conventional) parking search affect system performance? Since these network characteristics are readily measurable for a particular network, the intent of this DEA

matrix is to test the effects on system performance to changes in these key system design parameters. The full DMU set is defined in *Table 5.2*.

Decision-Making Unit	Network Characteristic
DMU 1	Initial
DMU 2	25% Increase in Background Traffic
DMU 3	25% Decrease in Background Traffic
DMU 4	50% Increase in Unreserved Parkers
DMU 5	100% Increase in Unreserved Parkers
DMU 6	50% Decrease in Unreserved Parkers

Table 5.2: Alternative Case DEA Matrix DMU Definitions

5.4 DEA Modeling Results/Observations

In **Section 5.3,** the model structure and the DMU definitions are defined. Since each of the stakeholder models requires VISSIM-generated output, and having a robust data set is critical to effective performance measurement, 30 24-hour runs for each DMU were ran within each defined DEA matrix. A 24-hour run in VISSIM takes approximately 45 minutes to run, so VISSIM processing time was approximately equal to approximately 292 hours or seven weeks.

Once VISSIM runs were complete, the hyperbolic DEA formulation was solved for each DMU for each stakeholder model within each of the two DEA matrices. These models were both formulated and solved using the MS Excel Solver tool, and the code is provided in the Appendix. Once these models were solved, the results were composed and analyzed.

Before summarizing the matrix of results for the DEA models within the Base Case, it is interesting to note the trends of the input/output data for each of the stakeholders. The parking provider stakeholder model is shown in *Figure 5.9,* and its input/output data is plotted in *Figure 5.10* below.

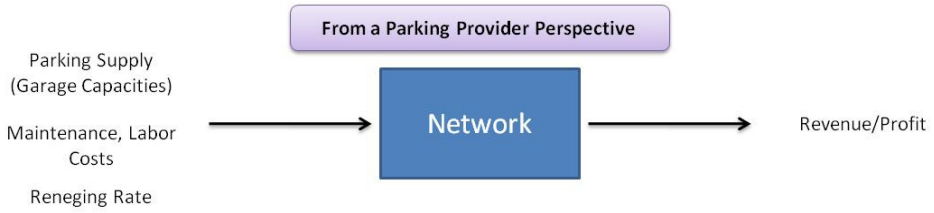

Figure 5.9: Parking Provider Perspective DEA Model

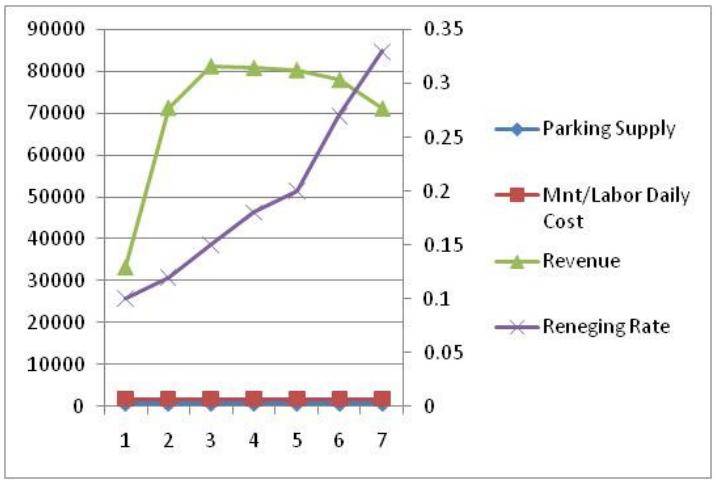

Figure 5.10: Parking Provider Stakeholder Input/Output Data across DMUs

Inputs to this model are parking supply, labor cost, and reneging rate; the output is revenue. It is interesting to note that as reneging rate climbs, we also see a climb in revenue through most of the DMUs. Since at 10 percent reneging rate, congestion is at a very high level, one can postulate that less revenue can be generated at these lower reneging rates due to parkers inability to access parking garages and congestion in and around the garages. However, when reneging rate is at the 15 percent level, one can see a peak in revenue generated. Then, as reneging rate continues to climb, revenue begins to tail off, due to a reduced amount of customers continuing parking searches after unsuccessful attempts.

The parking district user stakeholder model is shown in *Figure 5.11,* and its input/output data is plotted in *Figure 5.12* below.

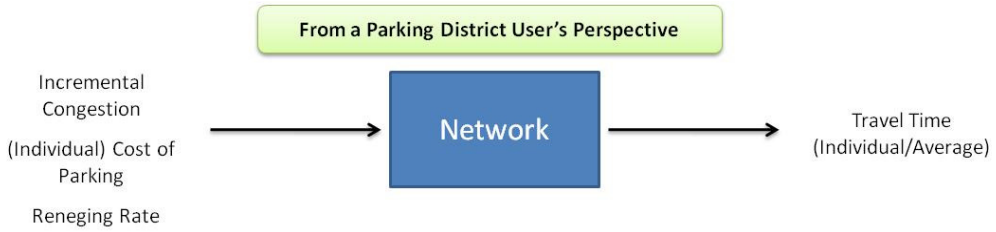

Figure 5.11: Parking District User Perspective DEA Model

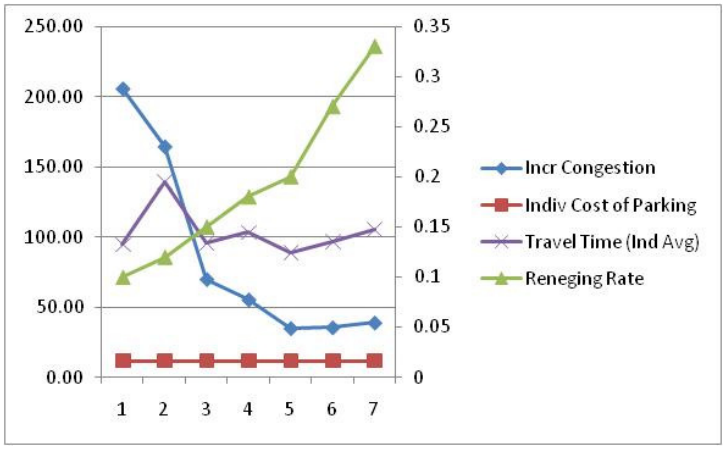

Figure 5.12: Parking District User Stakeholder Input/Output Data across DMUs

Inputs to this model are an individual vehicle's contribution to delay (incremental congestion), a parker's price to park, and reneging rate; the output is an individual user's average travel time. These stakeholder model input/output relationships are particularly interesting, since one can observe that as reneging rate increases along with incremental congestion decreasing, we see no clear change or trend in the output travel time.

The community/societal stakeholder model is shown in *Figure 5.13,* and its input/output data is plotted in *Figure 5.14* below.

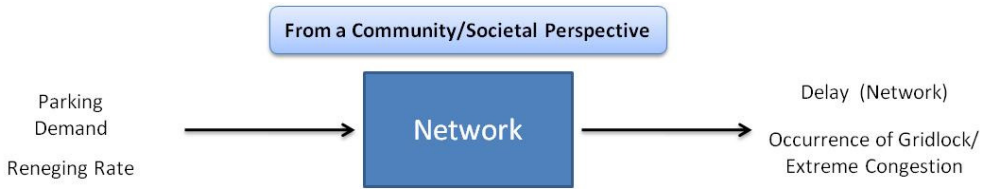

Figure 5.13: Community/Societal Perspective DEA Model

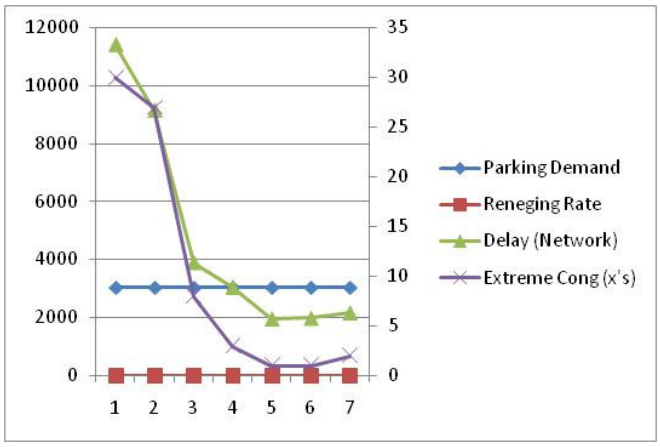

Figure 5.14: Community/Societal Stakeholder Input/Output Data across DMUs

Inputs to this model are parking demand and reneging rate; outputs are network delay and instances (within the thirty VISSIM runs) of extreme congestion as defined in **Section 5.3.2**. Although the reneging rate trend is not as visible as it is in *Figure 5.10* and *5.12,* it is identical. Parking demand remains constant, but as reneging rate increases, we see an interesting trend in the outputs. At very low reneging rates, we predictably see high incidence of extreme congestion and high levels of network delay. These high levels of delay and congestion decrease as reneging rate increases, and this continues through to the point where the reneging rate reaches 20 percent. Then, as reneging rate climbs to 27 percent and on to 33 percent, we see a slight increase in both delay and congestion incidence. After observing simulation runs, it is likely that the cause of this slight increase is due to congestion at the intersections near exits of the network, since a much higher level of vehicles are exiting the network after unsuccessful parking attempts.

The resultant matrix for the DEA models within the Base Case model (no RM policy in place) model is shown in *Figure 5.15*.

	10%	12%	15%	18%	20%	27%	33%
Parking Provider	1.00	4.35	3.40	2.99	2.73	1.79	1.00
Parking District User	2.96	3.63	2.00	1.79	1.39	1.08	1.00
Community/ Society	4.00	1.00	1.95	2.52	1.34	1.00	1.00

Figure 5.15: DEA Result Matrix under Networks Experiencing Different Rates of Reneging

It is important to note when looking at the results in *Figure 5.15* and later in this section, a DMU on the efficient frontier (within a particular stakeholder, in this case) will have a value of one. From a relative standpoint, these DMUs operate the most efficiently. The larger the value within the matrix, the further the DMU is from the efficient frontier, and thus the less efficient it is.

Likewise, for the Alternative Case model (RM policy in place), before summarizing the matrix of results for the DEA models, we note the trends of the input/output data for each of the stakeholders. The parking provider stakeholder model input/output data is plotted in *Figure 5.16* below.

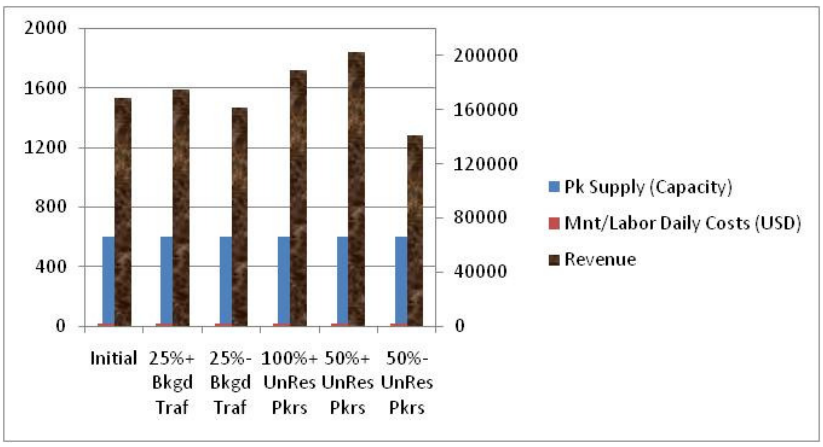

Figure 5.16: Parking Provider Stakeholder Input / Output Data across DMUs (RM Case)

As seen in *Figure 5.16*, both inputs of parking supply and labor cost are held constant, but the state of the network (DMU) changes as indicated in the horizontal chart axis. It is clear that even substantive changes in background traffic do not seem to affect revenue, when compared with the initial case DMU. This seems logical, since in the Alternative Case model, the majority of parkers are reserved parkers, and therefore, increases in background traffic do not necessarily equate to increases in the parking population. However, increases in numbers of unreserved parkers do raise revenue levels generated. Predictably, revenue decreases when the unreserved parking population is decreased by 50 percent.

The parking district user stakeholder model input/output data is plotted in *Figure 5.17* below.

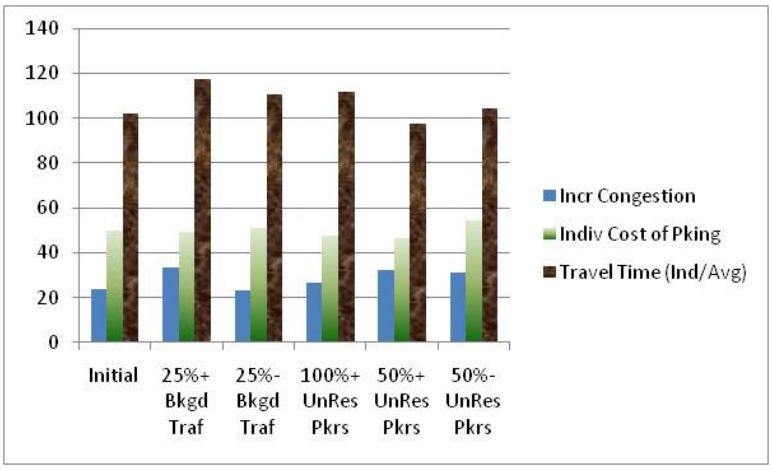

Figure 5.17: Parking District User Stakeholder Input / Output Data across DMUs (RM Case)

Inputs to this model are incremental congestion and the individual cost of parking; the output is travel time. In this model, since we are looking at an RM policy implementation, individual cost of parking fluctuates slightly across the DMUs. When looking at the DMU where there is a 25 percent increase in background traffic and increased incremental congestion, we predictably see an increase in travel time. Furthermore, we see a decrease in travel time when background traffic decreases and incremental congestion decreases.

However, under certain circumstances, we can observe travel time fluctuate under conditions which seem counterintuitive. For instance, when the unreserved parking population is increased by 100 percent and incremental congestion increases slightly, we see a slight corresponding increase in travel time. However, when the unreserved parking population increases by 50 percent (instead of 100 percent), we actually see a decrease in travel time when compared with the "Initial" DMU. It is possible that the small magnitude of this difference indicates that the unreserved parking population is still small enough to not appreciably affect overall travel times under a comprehensive RM policy.

The community/societal stakeholder model input/output data is plotted in *Figure 5.18* below.

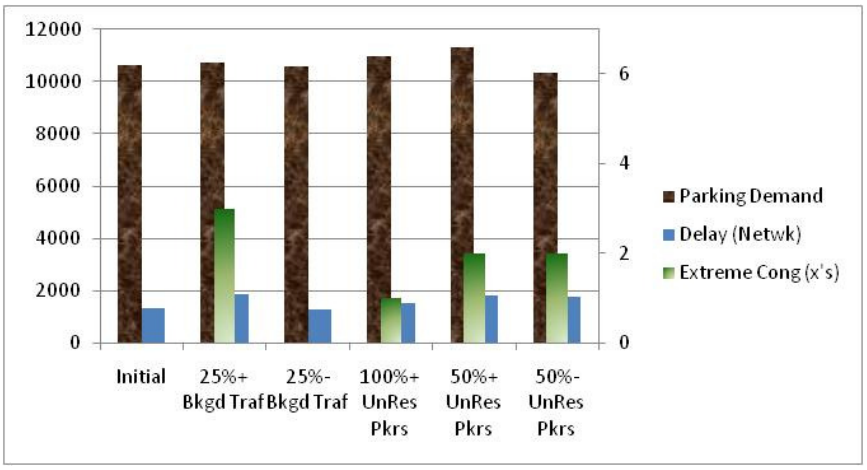

Figure 5.18: Community/Societal Stakeholder Input / Output Data across DMUs (RM Case)

The input to this model is parking demand and, of course, the characteristics of the DMU itself; outputs are network delay and instances (within the thirty VISSIM runs) of extreme congestion as defined in **Section 5.3.2**. Parking demand remains constant, but we can observe changes in network delay and incidence of extreme congestion as the conditions of the network change. For instance, we see that under a 25 percent increase in background traffic, total network delay rises slightly, and we see 10 percent of the VISSIM runs experience extreme congestion, as compared with zero under the initial case. Under a 25 percent reduction in background traffic, extreme congestion returns to zero and network delay decreases.

Under changes in the unreserved parker population, however, we see slightly counterintuitive results. A large increase (100 percent) in unreserved parkers leaves network delay virtually unchanged, but introduces one instance of extreme congestion. This is especially puzzling when compared to the case in which the unreserved parking population only increases by 50 percent. In this case, extreme congestion increases to two instances and network delay increase slightly over the initial case. The results are nearly identical for the case in which unreserved parker population is decreased by 50 percent. These last two behaviors are interesting in that they do not adhere to conventional behavioral expectation. Further modeling and observation would need to be completed, as well as further experimentation, to fully understand whether these are statistical anomalies (observable because of the insignificance of the unreserved parker population

as compared to the total effect of the parking population) or if there is something unique about that particular population level and ratio that produces the behavior observed.

The resultant matrix for the DEA models within the Alternative Case model (RM policy in place) model is shown in *Figure 5.19* below.

	Initial	25% Reduction in Background Traffic	25% Increase in Background Traffic	50% Increase in Unreserved Parkers	100% Increase in Unreserved Parkers	50% Decrease in Unreserved Parkers
Parking Provider	1.20	1.16	1.25	1.07	1.00	1.44
Parking District User	1.00	1.20	1.00	1.00	1.00	1.06
Community/ Society	1.03	1.00	1.00	1.03	1.25	1.00

Figure 5.19: DEA Result Matrix under Alternative Case Network DMUs

5.5 Summary, Conclusions, and Future Work

The primary purpose (and therefore the salient contribution) of this chapter was to evaluate the performance of the urban parking system from the perspective of the set of relevant stakeholders using the hyperbolic DEA model within the context of the matrix DEA construct. The stakeholder models, including that of the parking provider, the parking district user, and the surrounding community, had defined inputs and outputs to the hyperbolic DEA model, which allowed for the inclusion of undesirable outputs such as network delay and incidence of extreme congestion.

DMUs were defined within two matrices: one designated for performance evaluation within the non-RM model (Base Case) and one designated for evaluation within the model where RM policy was in place (Alternative Case). For the Base Case model, a range of reneging rate (the rate at which unsuccessful parkers renege and leave the network) values were tested (from 10 percent to 33 percent), based on earlier modeling evidence that this was a key driver of interesting network behavior (and not an influential factor under RM). Looking that resulting matrix, we see that the sum across all stakeholders is minimized (and therefore, efficiency is maximized) at 33 percent reneging rate. This makes sense for the district user and the community, but seems as if it would not always be optimal for the provider, since potential revenue is leaving the network. However, we do see another point of efficiency at the 10 percent reneging rate as well.

For the Alternative Case model, DMUs were defined as to evaluate conditions under which one would suspect network performance would be affected under a RM policy. These conditions included both adjustments to the levels of background traffic (non-parkers) within the network, and adjustments to the relative (to reserved parkers) and total number of unreserved parkers within the network. If, again, we look at the minimum sum across the stakeholders within each DMU (or the *efficiency vector* for each DMU), we do not see large differences among the DMUs evaluated. This is likely due to the overall performance of the system under revenue management and its robustness to even significant changes to other inputs.

Another key contribution of this work is that of identifying design issues for current and future dense urban parking districts. Clearly, reneging rate and the tenacity of perspective parkers is a key consideration in cases where RM policy is not implemented. However, designers can effectively remove the effect of reneging rate and its negative effects on congestion by encouraging or supplementing parking vendors to implement a RM parking strategy. We also learn from this performance evaluation that it is likely that parking districts with RM policies in-place are more robust to changes in background traffic levels and increases in last-minute, unreserved parkers. In other words, unanticipated changes in network conditions can have a more predictable effect on day-to-day traffic congestions through the implementation of parking revenue management.

CHAPTER 6 Conclusions and Future Directions

6.1 Research Methods and Findings

This thesis explored how revenue management principles would integrate into a parking system, and how advanced reservation-making, coupled with dynamic pricing (based on booking limits) might be used to maximize parking revenue. A revenue management strategy for the parking industry was presented, as well as an integer programming formulation that maximizes parking revenue over a system of garages. Furthermore, an intelligent parking reservation model is developed that uses an artificial neural network procedure for online reservation decision-making. Next, implementation of a parking revenue management system in a dense urban parking district (and thus avoiding "trial-and-error" behaviors exhibited by drivers searching for a parking space) is examined for any effects in mitigating urban congestion levels. All other things being equal, the revenue management model in which the majority of parkers is directed to their precise parking spot via the most direct route (and thus avoids "trial-and-error" behaviors) is much more resilient to random elements and occurrences within the network that can instigate extreme congestion situations. This work then used macro-evaluation techniques to model the performance of the urban parking system from the perspective of the set of relevant stakeholders using the hyperbolic DEA model within the context of the matrix DEA construct.

The over-arching modeling techniques used within this thesis and their relationships are shown in *Figure 6.1* below.

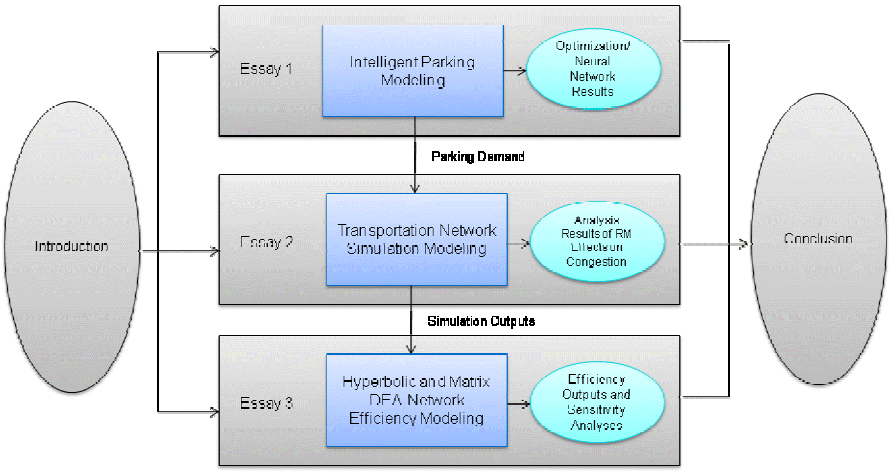

Figure 6.1: Thesis Structure and Modeling Interactions

Essay One (**Chapter 3**) presented a comprehensive revenue management strategy for the parking industry, focusing on a single-garage scenario. With the overarching strategy established, the chapter extended the work of [49] by presenting an integer programming formulation that maximizes parking revenue over a system of garage. Furthermore, an intelligent parking reservation model is developed that uses an artificial neural network procedure for online reservation decision-making. It is concluded that the parking industry is a good candidate for RM strategy implementation, and this chapter fully develops the formulation, tools, and modeling to operate an online decision-making system that isolates micro-markets and maximizes revenue.

Essay Two (**Chapter 4**) evaluates whether the establishment of a parking revenue management system in a dense urban parking district (and thus avoiding "trial-and-error" behaviors exhibited by parkers) mitigates urban congestion levels. In order to test this hypothesis, the intelligent parking model from Essay One is run in conjunction with a VISSIM micro-simulation model to evaluate the policy's effects on network performance. It is clear from the results of the simulation experiments that the rate at which parkers renege and abandon their parking search is a primary driver of the value of the implementation of an intelligent parking system. All other things being equal, the intelligent parking system model in which the majority of parkers are directed to their precise parking spot via the most direct route is much more robust to random elements and occurrences within the network that can instigate extreme congestion situations. On the other

hand, the real time control model that is part of the intelligent parking system is highly susceptible to high levels of congestion, especially when parkers are determined to find parking and have inflexible parking requirements.

The primary purpose of Essay Three (**Chapter 5**) was to evaluate the performance of the urban parking system from the perspective of the set of relevant stakeholders using the hyperbolic DEA model within the context of the matrix DEA construct. The stakeholder models, including that of the parking provider, the parking customer, and the surrounding community, had defined inputs and outputs to the hyperbolic DEA model, which allowed for the inclusion of undesirable outputs such as network delay and incidence of extreme congestion. DMUs were defined within two matrices: one designated for performance evaluation within the non-RM model (Base Case) and one designated for evaluation within the model where RM policy was in place (Alternative Case). Looking at the resulting Base Case matrix, we see that the sum across all stakeholders is minimized (and therefore, efficiency is maximized) at the highest and lowest evaluated reneging rates. For the Alternative Case model, DMUs were defined as to evaluate conditions under which one would suspect network performance would be affected under a revenue management policy. These conditions included both adjustments to the levels of background traffic (non-parkers) within the network, and adjustments to the relative (to reserved parkers) and total number of unreserved parkers within the network. If, again, we look at the minimum sum across the stakeholders within each DMU (or the *efficiency vector* for each DMU), we do not see large differences among the DMUs evaluated. This is likely due to the overall performance of the system under revenue management and its robustness to even significant changes to other inputs.

6.2 Applications and Design Implications of Modeling Results

In many respects, the conclusions within this thesis bring to bear results that have implications and applications for parking providers, parking systems, as well as urban parking districts, as a whole. For instance, the RM strategy for parking systems presented in **Chapter 3** demonstrates how dramatically a parking vendor's revenue could increase with the adoption of RM strategies. This was demonstrated using

a simple numerical example, but in an environment where actual parking demand data for a particular garage (or group of garages) is available and continuously updated to maximize revenue, and there is an intelligent parking model in place, this revenue increase could be even more dramatic.

Additionally, the VISSIM results in **Chapter 4** and DEA modeling results in **Chapter 5** suggest that reneging rate and the tenacity of perspective parkers is a key consideration in cases where RM policy is not implemented within a high-density urban parking district. However, designers can effectively remove the impact of reneging rate and its negative effects on congestion by encouraging or supplementing parking vendors to implement a revenue management parking strategy. We also learn from this performance evaluation that it is likely that parking districts with RM policies in-place are more robust to changes in background traffic levels and increases in last-minute, unreserved parkers. In other words, unanticipated changes in network conditions can have a more predictable effect on day-to-day traffic congestions through the implementation of parking revenue management.

6.3 Future Research Directions

Opportunities for future work include further validation of the proposed intelligent parking modeling approach, as well as the VISSIM micro-simulation model, under various scenarios. One possibility would be to validate (prior to implementation) through the use of literal data sources such as existing garage capacity and volume data, survey data from both potential users and garage managers, and possibly the use of management flight simulation that can evaluate the sensitivity associated with model parameters. Furthermore, it would also be advisable to validate the system after implementation is complete. Clearly, verifying that revenue management policy coupled with the intelligent parking construct yields significant revenue increases would further validate the approach.

Additionally, it would be interesting to investigate how some of the more subtle RM strategy elements presented in **Chapter 3** might be explicitly modeled within the intelligent parking system. For instance, implementing the ability to overbook a garage for a given time period in response to data indicating how

many customers, on average, are no-shows. Another possible augmentation is to implement the ability within the intelligent parking model to dynamically adjust pricing in response to unexpected fluctuations in demand (as is often seen in the airline industry).

Another useful research pursuit would be to expand the matrix DEA structure presented in **Chapter 5** to test other drivers of urban congestion such as changes in number of parking lots, structure, or network configuration, as well as other aspects of RM implementation, such as vehicle count or occupancy.

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Appendix

Chapter 3 of this dissertation presented a multiple-garage, dynamic-pricing environment integer programming formulation, generating results used to train and test artificial neural networks. Shown below in *Figure A.1* is the MS Excel Solver Risk Platform code for solving the integer program (corresponding to the formulation found in **Chapter 3**).

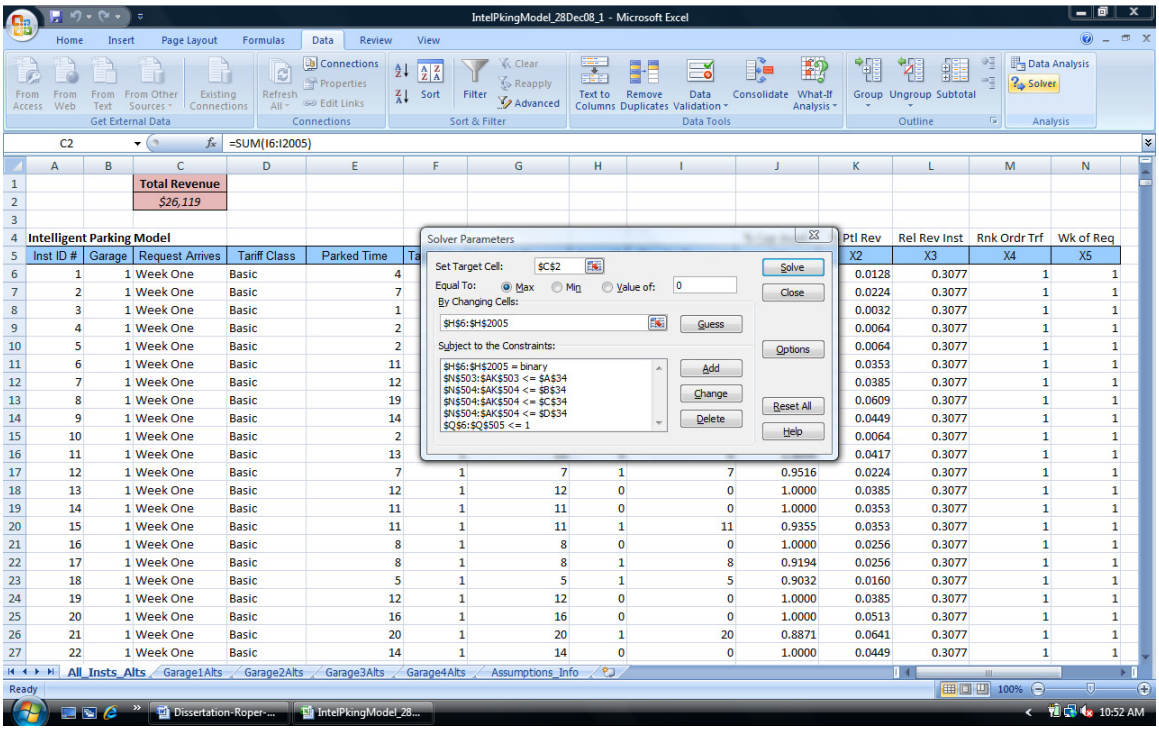
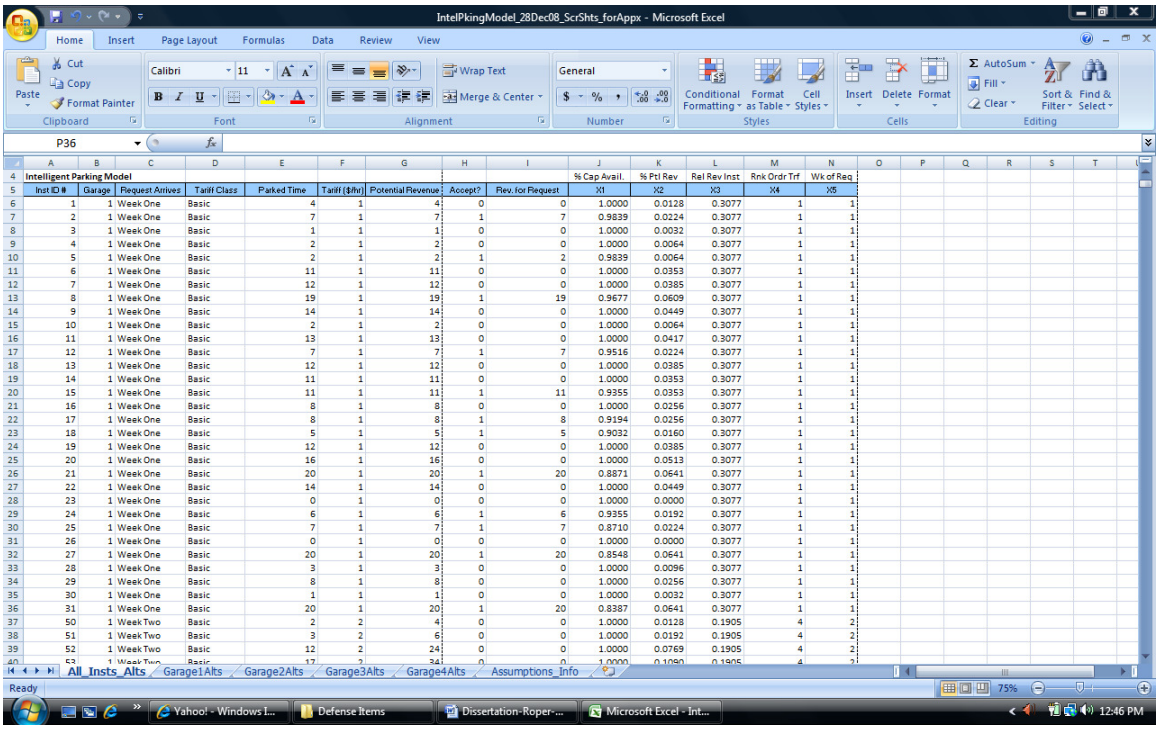


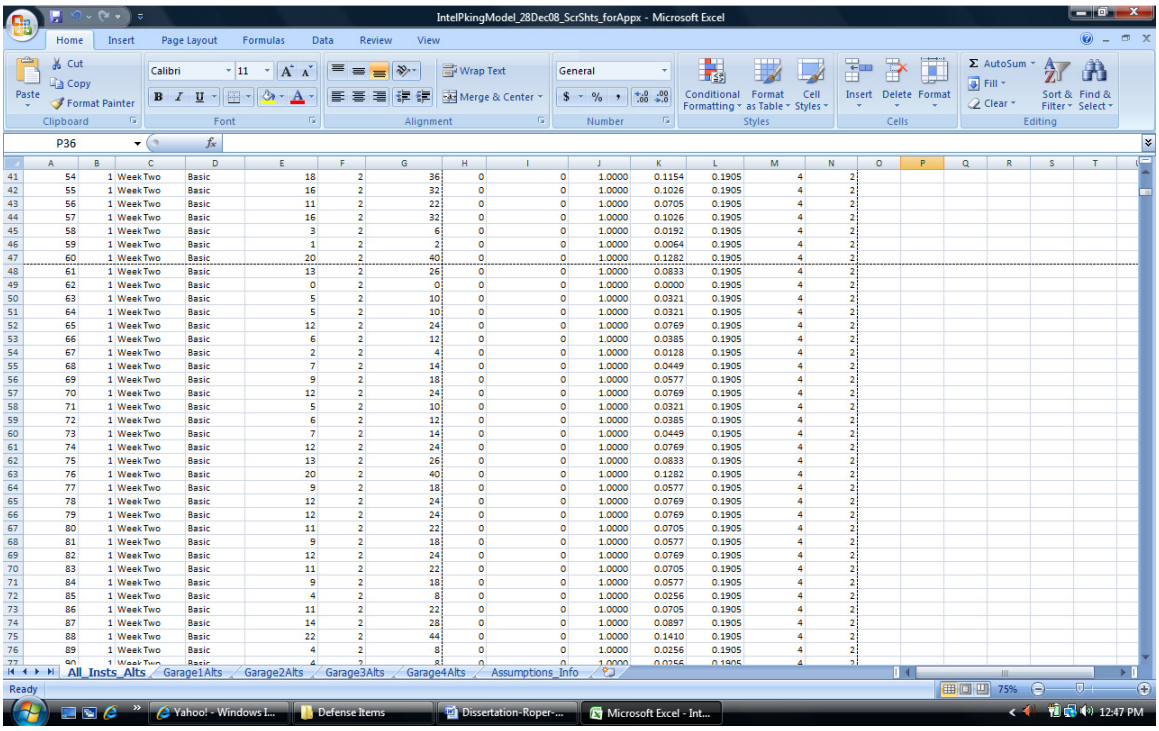
Figure A.1: MS Excel Solver Risk Platform IP Code

Furthermore, a complete data set for one of the nine IP models referenced in **Chapter 4** is given below in *Figures A.2* through *A.57*. This is representative of the data used in the intelligent parking model (and thus used to train/test the neural network) and the actual data used to populate the VISSIM model. Additional detail and datasets can be obtained by contacting the candidate.



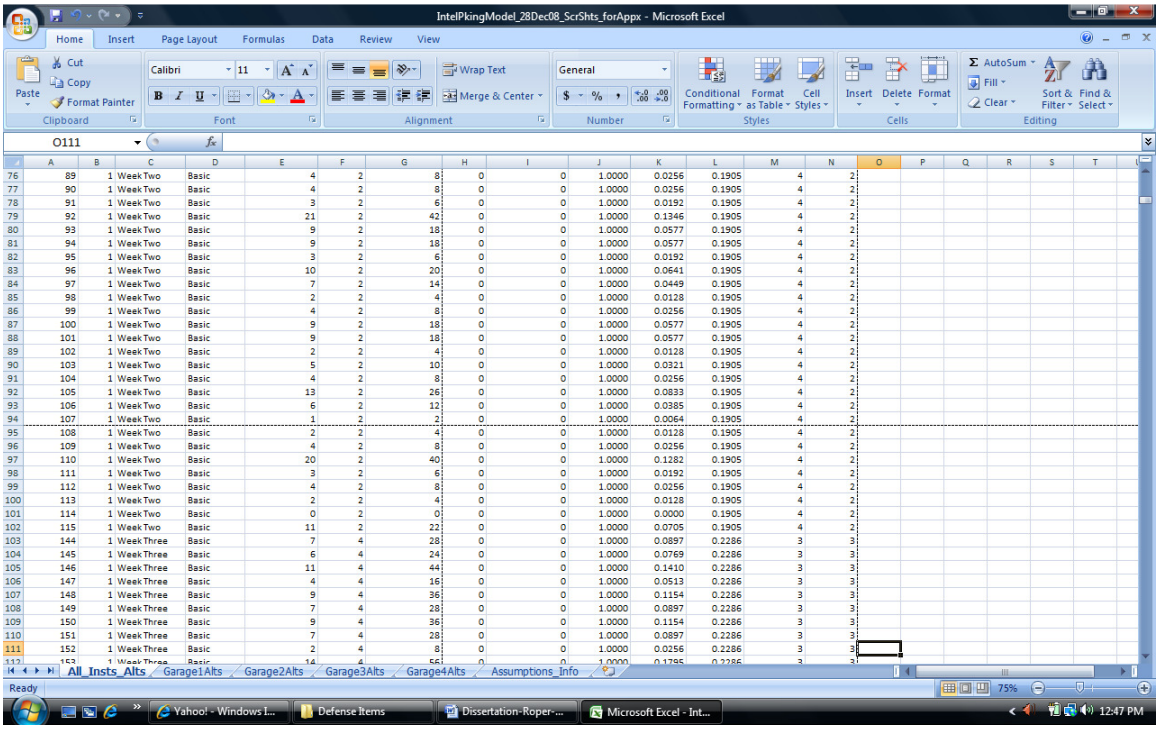
Intelligent Parking Model									% Cap Avail.	% Ptl Rev	Rel Rev Inst	Rnk Ordr Trf	Wk of Req
Inst ID #	Garage	Request Arrives	Tariff Class	Parked Time	Tariff ($/hr)	Potential Revenue	Accept?	Rev. for Request	X1	X2	X3	X4	X5
1	1	Week One	Basic	4	1	4	0	0	1.0000	0.0128	0.3077	1	1
2	1	Week One	Basic	7	1	7	1	7	0.9839	0.0224	0.3077	1	1
3	1	Week One	Basic	1	1	1	0	0	1.0000	0.0032	0.3077	1	1
4	1	Week One	Basic	2	1	2	0	0	1.0000	0.0064	0.3077	1	1
5	1	Week One	Basic	2	1	2	1	2	0.9839	0.0064	0.3077	1	1
6	1	Week One	Basic	11	1	11	0	0	1.0000	0.0353	0.3077	1	1
7	1	Week One	Basic	12	1	12	0	0	1.0000	0.0385	0.3077	1	1
8	1	Week One	Basic	19	1	19	1	19	0.9677	0.0609	0.3077	1	1
9	1	Week One	Basic	14	1	14	0	0	1.0000	0.0449	0.3077	1	1
10	1	Week One	Basic	2	1	2	0	0	1.0000	0.0064	0.3077	1	1
11	1	Week One	Basic	13	1	13	0	0	1.0000	0.0417	0.3077	1	1
12	1	Week One	Basic	7	1	7	1	7	0.9516	0.0224	0.3077	1	1
13	1	Week One	Basic	12	1	12	0	0	1.0000	0.0385	0.3077	1	1
14	1	Week One	Basic	11	1	11	0	0	1.0000	0.0353	0.3077	1	1
15	1	Week One	Basic	11	1	11	1	11	0.9355	0.0353	0.3077	1	1
16	1	Week One	Basic	8	1	8	0	0	1.0000	0.0256	0.3077	1	1
17	1	Week One	Basic	8	1	8	1	8	0.9194	0.0256	0.3077	1	1
18	1	Week One	Basic	5	1	5	1	5	0.9032	0.0160	0.3077	1	1
19	1	Week One	Basic	12	1	12	0	0	1.0000	0.0385	0.3077	1	1
20	1	Week One	Basic	16	1	16	0	0	1.0000	0.0513	0.3077	1	1
21	1	Week One	Basic	20	1	20	1	20	0.8871	0.0641	0.3077	1	1
22	1	Week One	Basic	14	1	14	0	0	1.0000	0.0449	0.3077	1	1
23	1	Week One	Basic	0	1	0	0	0	1.0000	0.0000	0.3077	1	1
24	1	Week One	Basic	6	1	6	1	6	0.9355	0.0192	0.3077	1	1
25	1	Week One	Basic	7	1	7	1	7	0.8710	0.0224	0.3077	1	1
26	1	Week One	Basic	0	1	0	0	0	1.0000	0.0000	0.3077	1	1
27	1	Week One	Basic	20	1	20	1	20	0.8548	0.0641	0.3077	1	1
28	1	Week One	Basic	3	1	3	0	0	1.0000	0.0096	0.3077	1	1
29	1	Week One	Basic	8	1	8	0	0	1.0000	0.0256	0.3077	1	1
30	1	Week One	Basic	1	1	1	0	0	1.0000	0.0032	0.3077	1	1
31	1	Week One	Basic	20	1	20	1	20	0.8387	0.0641	0.3077	1	1
50	1	Week Two	Basic	2	2	4	0	0	1.0000	0.0128	0.1905	4	2
51	1	Week Two	Basic	3	2	6	0	0	1.0000	0.0192	0.1905	4	2
52	1	Week Two	Basic	12	2	24	0	0	1.0000	0.0769	0.1905	4	2

Figure A.2: MS Excel Solver Risk Platform IP Data Set (1)



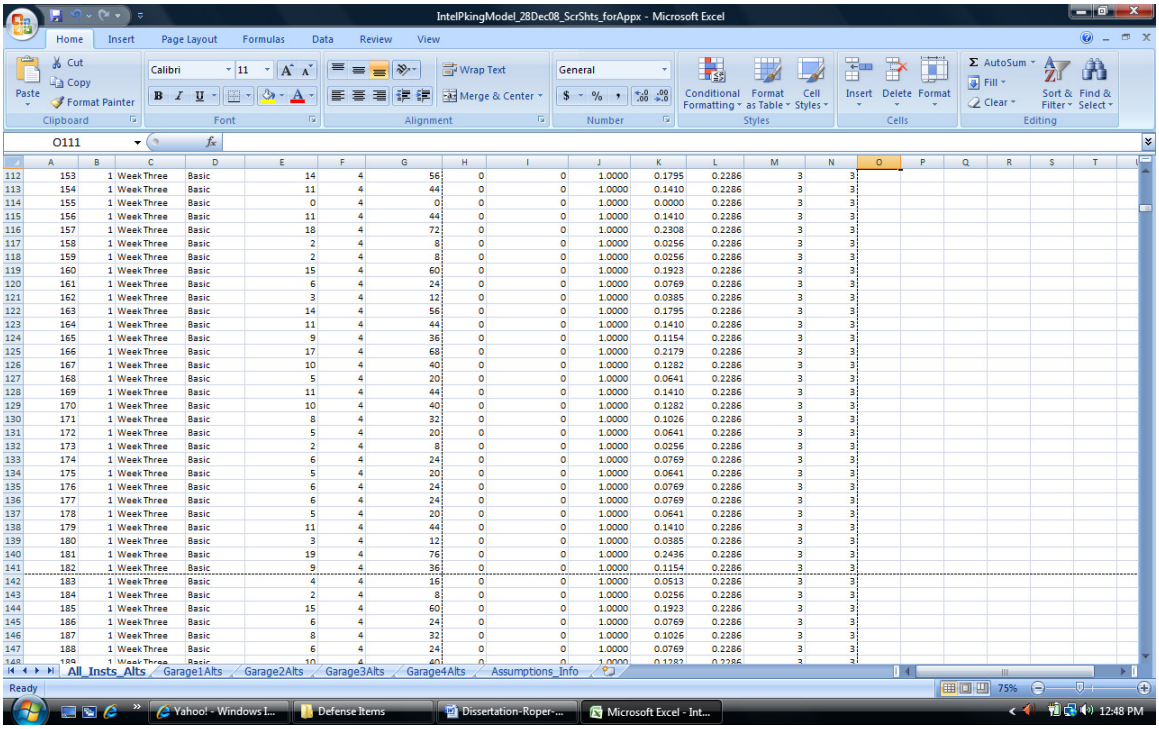
54	1	Week Two	Basic	18	2	36	0	0	1.0000	0.1154	0.1905	4	2
55	1	Week Two	Basic	16	2	32	0	0	1.0000	0.1026	0.1905	4	2
56	1	Week Two	Basic	11	2	22	0	0	1.0000	0.0705	0.1905	4	2
57	1	Week Two	Basic	16	2	32	0	0	1.0000	0.1026	0.1905	4	2
58	1	Week Two	Basic	3	2	6	0	0	1.0000	0.0192	0.1905	4	2
59	1	Week Two	Basic	1	2	2	0	0	1.0000	0.0064	0.1905	4	2
60	1	Week Two	Basic	20	2	40	0	0	1.0000	0.1282	0.1905	4	2
61	1	Week Two	Basic	13	2	26	0	0	1.0000	0.0833	0.1905	4	2
62	1	Week Two	Basic	0	2	0	0	0	1.0000	0.0000	0.1905	4	2
63	1	Week Two	Basic	5	2	10	0	0	1.0000	0.0321	0.1905	4	2
64	1	Week Two	Basic	5	2	10	0	0	1.0000	0.0321	0.1905	4	2
65	1	Week Two	Basic	12	2	24	0	0	1.0000	0.0769	0.1905	4	2
66	1	Week Two	Basic	6	2	12	0	0	1.0000	0.0385	0.1905	4	2
67	1	Week Two	Basic	2	2	4	0	0	1.0000	0.0128	0.1905	4	2
68	1	Week Two	Basic	7	2	14	0	0	1.0000	0.0449	0.1905	4	2
69	1	Week Two	Basic	9	2	18	0	0	1.0000	0.0577	0.1905	4	2
70	1	Week Two	Basic	12	2	24	0	0	1.0000	0.0769	0.1905	4	2
71	1	Week Two	Basic	5	2	10	0	0	1.0000	0.0321	0.1905	4	2
72	1	Week Two	Basic	6	2	12	0	0	1.0000	0.0385	0.1905	4	2
73	1	Week Two	Basic	7	2	14	0	0	1.0000	0.0449	0.1905	4	2
74	1	Week Two	Basic	12	2	24	0	0	1.0000	0.0769	0.1905	4	2
75	1	Week Two	Basic	13	2	26	0	0	1.0000	0.0833	0.1905	4	2
76	1	Week Two	Basic	20	2	40	0	0	1.0000	0.1282	0.1905	4	2
77	1	Week Two	Basic	9	2	18	0	0	1.0000	0.0577	0.1905	4	2
78	1	Week Two	Basic	12	2	24	0	0	1.0000	0.0769	0.1905	4	2
79	1	Week Two	Basic	12	2	24	0	0	1.0000	0.0769	0.1905	4	2
80	1	Week Two	Basic	11	2	22	0	0	1.0000	0.0705	0.1905	4	2
81	1	Week Two	Basic	9	2	18	0	0	1.0000	0.0577	0.1905	4	2
82	1	Week Two	Basic	12	2	24	0	0	1.0000	0.0769	0.1905	4	2
83	1	Week Two	Basic	11	2	22	0	0	1.0000	0.0705	0.1905	4	2
84	1	Week Two	Basic	9	2	18	0	0	1.0000	0.0577	0.1905	4	2
85	1	Week Two	Basic	4	2	8	0	0	1.0000	0.0256	0.1905	4	2
86	1	Week Two	Basic	11	2	22	0	0	1.0000	0.0705	0.1905	4	2
87	1	Week Two	Basic	14	2	28	0	0	1.0000	0.0897	0.1905	4	2
88	1	Week Two	Basic	22	2	44	0	0	1.0000	0.1410	0.1905	4	2
89	1	Week Two	Basic	4	2	8	0	0	1.0000	0.0256	0.1905	4	2

Figure A.3: MS Excel Solver Risk Platform IP Data Set (2)



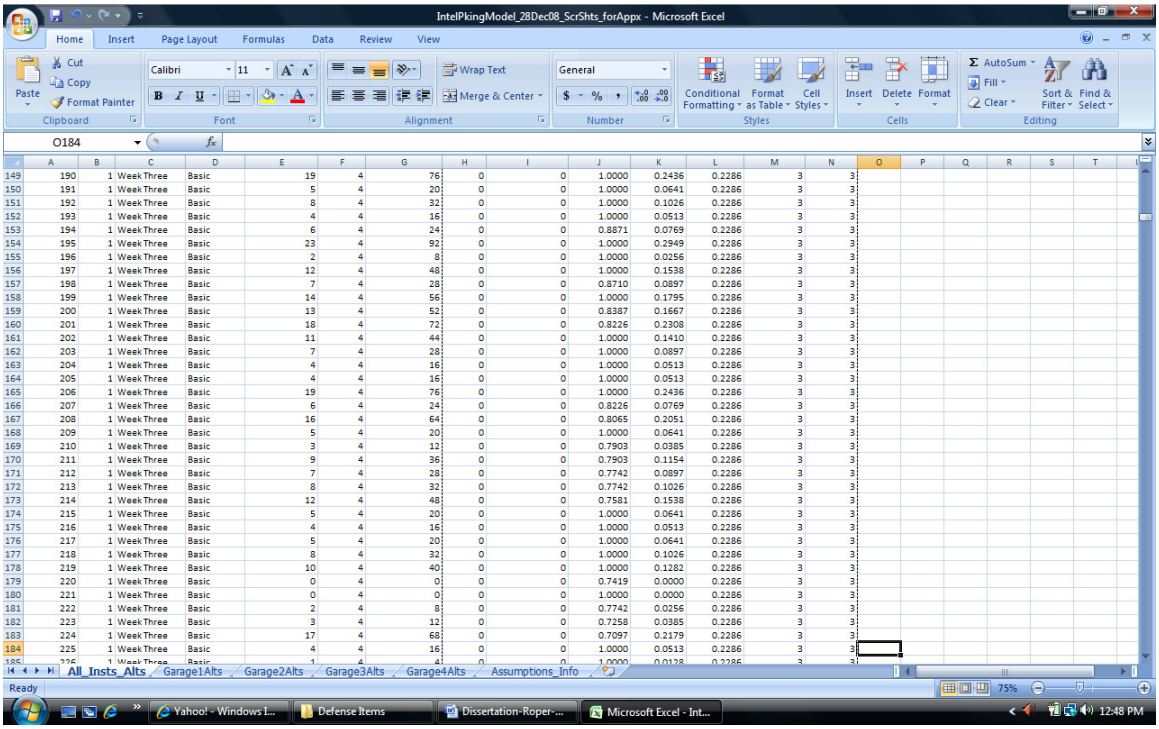
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
76	89	1	WeekTwo	Basic	4	2	8	0	0	1.0000	0.0256	0.1905	4	2
77	90	1	WeekTwo	Basic	4	2	8	0	0	1.0000	0.0256	0.1905	4	2
78	91	1	WeekTwo	Basic	3	2	6	0	0	1.0000	0.0192	0.1905	4	2
79	92	1	WeekTwo	Basic	21	2	42	0	0	1.0000	0.1346	0.1905	4	2
80	93	1	WeekTwo	Basic	9	2	18	0	0	1.0000	0.0577	0.1905	4	2
81	94	1	WeekTwo	Basic	9	2	18	0	0	1.0000	0.0577	0.1905	4	2
82	95	1	WeekTwo	Basic	3	2	6	0	0	1.0000	0.0192	0.1905	4	2
83	96	1	WeekTwo	Basic	10	2	20	0	0	1.0000	0.0641	0.1905	4	2
84	97	1	WeekTwo	Basic	7	2	14	0	0	1.0000	0.0449	0.1905	4	2
85	98	1	WeekTwo	Basic	2	2	4	0	0	1.0000	0.0128	0.1905	4	2
86	99	1	WeekTwo	Basic	4	2	8	0	0	1.0000	0.0256	0.1905	4	2
87	100	1	WeekTwo	Basic	9	2	18	0	0	1.0000	0.0577	0.1905	4	2
88	101	1	WeekTwo	Basic	9	2	18	0	0	1.0000	0.0577	0.1905	4	2
89	102	1	WeekTwo	Basic	2	2	4	0	0	1.0000	0.0128	0.1905	4	2
90	103	1	WeekTwo	Basic	5	2	10	0	0	1.0000	0.0321	0.1905	4	2
91	104	1	WeekTwo	Basic	4	2	8	0	0	1.0000	0.0256	0.1905	4	2
92	105	1	WeekTwo	Basic	13	2	26	0	0	1.0000	0.0833	0.1905	4	2
93	106	1	WeekTwo	Basic	6	2	12	0	0	1.0000	0.0385	0.1905	4	2
94	107	1	WeekTwo	Basic	1	2	2	0	0	1.0000	0.0064	0.1905	4	2
95	108	1	WeekTwo	Basic	2	2	4	0	0	1.0000	0.0128	0.1905	4	2
96	109	1	WeekTwo	Basic	4	2	8	0	0	1.0000	0.0256	0.1905	4	2
97	110	1	WeekTwo	Basic	20	2	40	0	0	1.0000	0.1282	0.1905	4	2
98	111	1	WeekTwo	Basic	3	2	6	0	0	1.0000	0.0192	0.1905	4	2
99	112	1	WeekTwo	Basic	4	2	8	0	0	1.0000	0.0256	0.1905	4	2
100	113	1	WeekTwo	Basic	2	2	4	0	0	1.0000	0.0128	0.1905	4	2
101	114	1	WeekTwo	Basic	0	2	0	0	0	1.0000	0.0000	0.1905	4	2
102	115	1	WeekTwo	Basic	11	2	22	0	0	1.0000	0.0705	0.1905	4	2
103	144	1	WeekThree	Basic	7	4	28	0	0	1.0000	0.0897	0.2286	3	3
104	145	1	WeekThree	Basic	6	4	24	0	0	1.0000	0.0769	0.2286	3	3
105	146	1	WeekThree	Basic	11	4	44	0	0	1.0000	0.1410	0.2286	3	3
106	147	1	WeekThree	Basic	4	4	16	0	0	1.0000	0.0513	0.2286	3	3
107	148	1	WeekThree	Basic	9	4	36	0	0	1.0000	0.1154	0.2286	3	3
108	149	1	WeekThree	Basic	7	4	28	0	0	1.0000	0.0897	0.2286	3	3
109	150	1	WeekThree	Basic	9	4	36	0	0	1.0000	0.1154	0.2286	3	3
110	151	1	WeekThree	Basic	7	4	28	0	0	1.0000	0.0897	0.2286	3	3
111	152	1	WeekThree	Basic	2	4	8	0	0	1.0000	0.0256	0.2286	3	3

Figure A.4: MS Excel Solver Risk Platform IP Data Set (3)



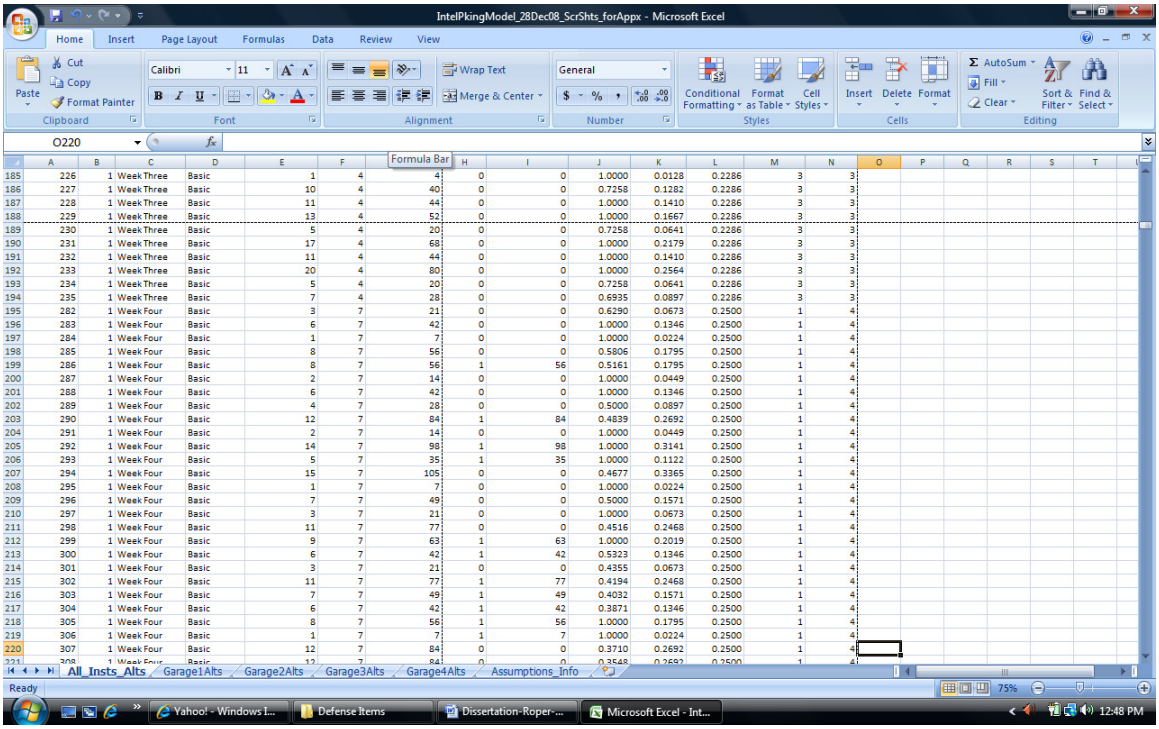
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
112	153	1	WeekThree	Basic	14	4	56	0	0	1.0000	0.1795	0.2286	3	3
113	154	1	WeekThree	Basic	11	4	44	0	0	1.0000	0.1410	0.2286	3	3
114	155	1	WeekThree	Basic	0	4	0	0	0	1.0000	0.0000	0.2286	3	3
115	156	1	WeekThree	Basic	11	4	44	0	0	1.0000	0.1410	0.2286	3	3
116	157	1	WeekThree	Basic	18	4	72	0	0	1.0000	0.2308	0.2286	3	3
117	158	1	WeekThree	Basic	2	4	8	0	0	1.0000	0.0256	0.2286	3	3
118	159	1	WeekThree	Basic	2	4	8	0	0	1.0000	0.0256	0.2286	3	3
119	160	1	WeekThree	Basic	15	4	60	0	0	1.0000	0.1923	0.2286	3	3
120	161	1	WeekThree	Basic	6	4	24	0	0	1.0000	0.0769	0.2286	3	3
121	162	1	WeekThree	Basic	3	4	12	0	0	1.0000	0.0385	0.2286	3	3
122	163	1	WeekThree	Basic	14	4	56	0	0	1.0000	0.1795	0.2286	3	3
123	164	1	WeekThree	Basic	11	4	44	0	0	1.0000	0.1410	0.2286	3	3
124	165	1	WeekThree	Basic	9	4	36	0	0	1.0000	0.1154	0.2286	3	3
125	166	1	WeekThree	Basic	17	4	68	0	0	1.0000	0.2179	0.2286	3	3
126	167	1	WeekThree	Basic	10	4	40	0	0	1.0000	0.1282	0.2286	3	3
127	168	1	WeekThree	Basic	5	4	20	0	0	1.0000	0.0641	0.2286	3	3
128	169	1	WeekThree	Basic	11	4	44	0	0	1.0000	0.1410	0.2286	3	3
129	170	1	WeekThree	Basic	10	4	40	0	0	1.0000	0.1282	0.2286	3	3
130	171	1	WeekThree	Basic	8	4	32	0	0	1.0000	0.1026	0.2286	3	3
131	172	1	WeekThree	Basic	5	4	20	0	0	1.0000	0.0641	0.2286	3	3
132	173	1	WeekThree	Basic	2	4	8	0	0	1.0000	0.0256	0.2286	3	3
133	174	1	WeekThree	Basic	6	4	24	0	0	1.0000	0.0769	0.2286	3	3
134	175	1	WeekThree	Basic	5	4	20	0	0	1.0000	0.0641	0.2286	3	3
135	176	1	WeekThree	Basic	6	4	24	0	0	1.0000	0.0769	0.2286	3	3
136	177	1	WeekThree	Basic	6	4	24	0	0	1.0000	0.0769	0.2286	3	3
137	178	1	WeekThree	Basic	5	4	20	0	0	1.0000	0.0641	0.2286	3	3
138	179	1	WeekThree	Basic	11	4	44	0	0	1.0000	0.1410	0.2286	3	3
139	180	1	WeekThree	Basic	3	4	12	0	0	1.0000	0.0385	0.2286	3	3
140	181	1	WeekThree	Basic	19	4	76	0	0	1.0000	0.2436	0.2286	3	3
141	182	1	WeekThree	Basic	9	4	36	0	0	1.0000	0.1154	0.2286	3	3
142	183	1	WeekThree	Basic	4	4	16	0	0	1.0000	0.0513	0.2286	3	3
143	184	1	WeekThree	Basic	2	4	8	0	0	1.0000	0.0256	0.2286	3	3
144	185	1	WeekThree	Basic	15	4	60	0	0	1.0000	0.1923	0.2286	3	3
145	186	1	WeekThree	Basic	6	4	24	0	0	1.0000	0.0769	0.2286	3	3
146	187	1	WeekThree	Basic	8	4	32	0	0	1.0000	0.1026	0.2286	3	3
147	188	1	WeekThree	Basic	6	4	24	0	0	1.0000	0.0769	0.2286	3	3

Figure A.5: MS Excel Solver Risk Platform IP Data Set (4)



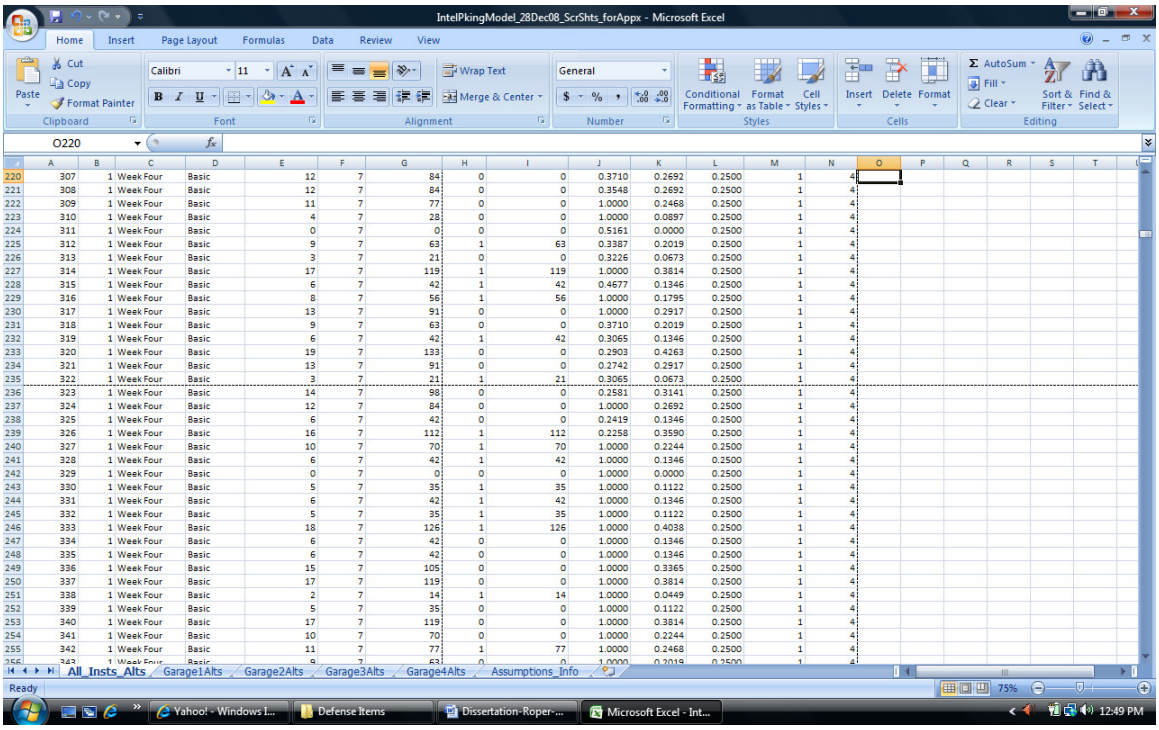
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
149	190	1	Week Three	Basic	19	4	76	0	0	1.0000	0.2436	0.2286	3	3
150	191	1	Week Three	Basic	5	4	20	0	0	1.0000	0.0641	0.2286	3	3
151	192	1	Week Three	Basic	8	4	32	0	0	1.0000	0.1026	0.2286	3	3
152	193	1	Week Three	Basic	4	4	16	0	0	1.0000	0.0513	0.2286	3	3
153	194	1	Week Three	Basic	6	4	24	0	0	0.8871	0.0769	0.2286	3	3
154	195	1	Week Three	Basic	23	4	92	0	0	1.0000	0.2949	0.2286	3	3
155	196	1	Week Three	Basic	2	4	8	0	0	1.0000	0.0256	0.2286	3	3
156	197	1	Week Three	Basic	12	4	48	0	0	1.0000	0.1538	0.2286	3	3
157	198	1	Week Three	Basic	7	4	28	0	0	0.8710	0.0897	0.2286	3	3
158	199	1	Week Three	Basic	14	4	56	0	0	1.0000	0.1795	0.2286	3	3
159	200	1	Week Three	Basic	13	4	52	0	0	0.8387	0.1667	0.2286	3	3
160	201	1	Week Three	Basic	18	4	72	0	0	0.8226	0.2308	0.2286	3	3
161	202	1	Week Three	Basic	11	4	44	0	0	1.0000	0.1410	0.2286	3	3
162	203	1	Week Three	Basic	7	4	28	0	0	1.0000	0.0897	0.2286	3	3
163	204	1	Week Three	Basic	4	4	16	0	0	1.0000	0.0513	0.2286	3	3
164	205	1	Week Three	Basic	4	4	16	0	0	1.0000	0.0513	0.2286	3	3
165	206	1	Week Three	Basic	19	4	76	0	0	1.0000	0.2436	0.2286	3	3
166	207	1	Week Three	Basic	6	4	24	0	0	0.8226	0.0769	0.2286	3	3
167	208	1	Week Three	Basic	16	4	64	0	0	0.8065	0.2051	0.2286	3	3
168	209	1	Week Three	Basic	5	4	20	0	0	1.0000	0.0641	0.2286	3	3
169	210	1	Week Three	Basic	3	4	12	0	0	0.7903	0.0385	0.2286	3	3
170	211	1	Week Three	Basic	9	4	36	0	0	0.7903	0.1154	0.2286	3	3
171	212	1	Week Three	Basic	7	4	28	0	0	0.7742	0.0897	0.2286	3	3
172	213	1	Week Three	Basic	8	4	32	0	0	0.7742	0.1026	0.2286	3	3
173	214	1	Week Three	Basic	12	4	48	0	0	0.7581	0.1538	0.2286	3	3
174	215	1	Week Three	Basic	5	4	20	0	0	1.0000	0.0641	0.2286	3	3
175	216	1	Week Three	Basic	4	4	16	0	0	1.0000	0.0513	0.2286	3	3
176	217	1	Week Three	Basic	5	4	20	0	0	1.0000	0.0641	0.2286	3	3
177	218	1	Week Three	Basic	8	4	32	0	0	1.0000	0.1026	0.2286	3	3
178	219	1	Week Three	Basic	10	4	40	0	0	1.0000	0.1282	0.2286	3	3
179	220	1	Week Three	Basic	0	4	0	0	0	0.7419	0.0000	0.2286	3	3
180	221	1	Week Three	Basic	0	4	0	0	0	1.0000	0.0000	0.2286	3	3
181	222	1	Week Three	Basic	2	4	8	0	0	0.7742	0.0256	0.2286	3	3
182	223	1	Week Three	Basic	3	4	12	0	0	0.7258	0.0385	0.2286	3	3
183	224	1	Week Three	Basic	17	4	68	0	0	0.7097	0.2179	0.2286	3	3
184	225	1	Week Three	Basic	4	4	16	0	0	1.0000	0.0513	0.2286	3	3

Figure A.6: MS Excel Solver Risk Platform IP Data Set (5)



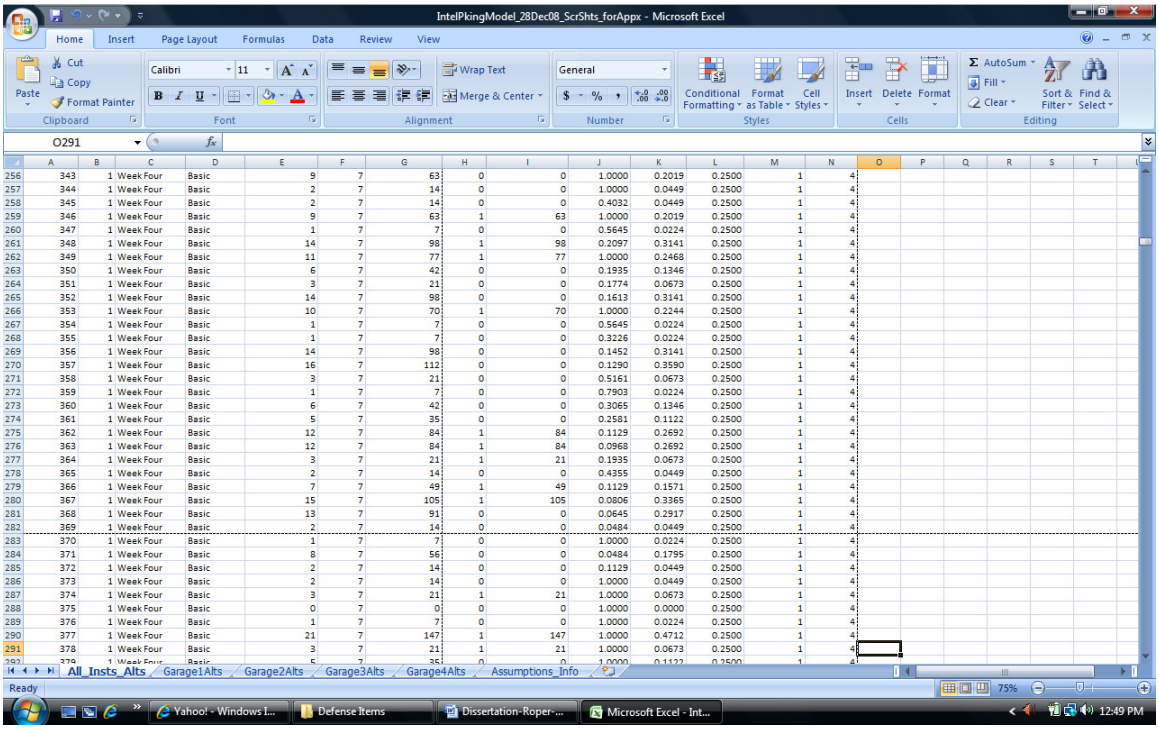
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
185	226	1	Week Three	Basic	1	4	4	0	0	1.0000	0.0128	0.2286	3	3
186	227	1	Week Three	Basic	10	4	40	0	0	0.7258	0.1282	0.2286	3	3
187	228	1	Week Three	Basic	11	4	44	0	0	1.0000	0.1410	0.2286	3	3
188	229	1	Week Three	Basic	13	4	52	0	0	1.0000	0.1667	0.2286	3	3
189	230	1	Week Three	Basic	5	4	20	0	0	0.7258	0.0641	0.2286	3	3
190	231	1	Week Three	Basic	17	4	68	0	0	1.0000	0.2179	0.2286	3	3
191	232	1	Week Three	Basic	11	4	44	0	0	1.0000	0.1410	0.2286	3	3
192	233	1	Week Three	Basic	20	4	80	0	0	1.0000	0.2564	0.2286	3	3
193	234	1	Week Three	Basic	5	4	20	0	0	0.7258	0.0641	0.2286	3	3
194	235	1	Week Three	Basic	7	4	28	0	0	0.6935	0.0897	0.2286	3	3
195	282	1	Week Four	Basic	3	7	21	0	0	0.6290	0.0673	0.2500	1	4
196	283	1	Week Four	Basic	6	7	42	0	0	1.0000	0.1346	0.2500	1	4
197	284	1	Week Four	Basic	1	7	7	0	0	1.0000	0.0224	0.2500	1	4
198	285	1	Week Four	Basic	8	7	56	0	0	0.5806	0.1795	0.2500	1	4
199	286	1	Week Four	Basic	8	7	56	1	56	0.5161	0.1795	0.2500	1	4
200	287	1	Week Four	Basic	2	7	14	0	0	1.0000	0.0449	0.2500	1	4
201	288	1	Week Four	Basic	6	7	42	0	0	1.0000	0.1346	0.2500	1	4
202	289	1	Week Four	Basic	4	7	28	0	0	0.5000	0.0897	0.2500	1	4
203	290	1	Week Four	Basic	12	7	84	1	84	0.4839	0.2692	0.2500	1	4
204	291	1	Week Four	Basic	2	7	14	0	0	1.0000	0.0449	0.2500	1	4
205	292	1	Week Four	Basic	14	7	98	1	98	1.0000	0.3141	0.2500	1	4
206	293	1	Week Four	Basic	5	7	35	1	35	1.0000	0.1122	0.2500	1	4
207	294	1	Week Four	Basic	15	7	105	0	0	0.4677	0.3365	0.2500	1	4
208	295	1	Week Four	Basic	1	7	7	0	0	1.0000	0.0224	0.2500	1	4
209	296	1	Week Four	Basic	7	7	49	0	0	0.5000	0.1571	0.2500	1	4
210	297	1	Week Four	Basic	3	7	21	0	0	1.0000	0.0673	0.2500	1	4
211	298	1	Week Four	Basic	11	7	77	0	0	0.4516	0.2468	0.2500	1	4
212	299	1	Week Four	Basic	9	7	63	1	63	1.0000	0.2019	0.2500	1	4
213	300	1	Week Four	Basic	6	7	42	1	42	0.5323	0.1346	0.2500	1	4
214	301	1	Week Four	Basic	3	7	21	0	0	0.4355	0.0673	0.2500	1	4
215	302	1	Week Four	Basic	11	7	77	1	77	0.4194	0.2468	0.2500	1	4
216	303	1	Week Four	Basic	7	7	49	1	49	0.4032	0.1571	0.2500	1	4
217	304	1	Week Four	Basic	6	7	42	1	42	0.3871	0.1346	0.2500	1	4
218	305	1	Week Four	Basic	8	7	56	1	56	1.0000	0.1795	0.2500	1	4
219	306	1	Week Four	Basic	1	7	7	1	7	1.0000	0.0224	0.2500	1	4
220	307	1	Week Four	Basic	12	7	84	0	0	0.3710	0.2692	0.2500	1	4

Figure A.7: MS Excel Solver Risk Platform IP Data Set (6)



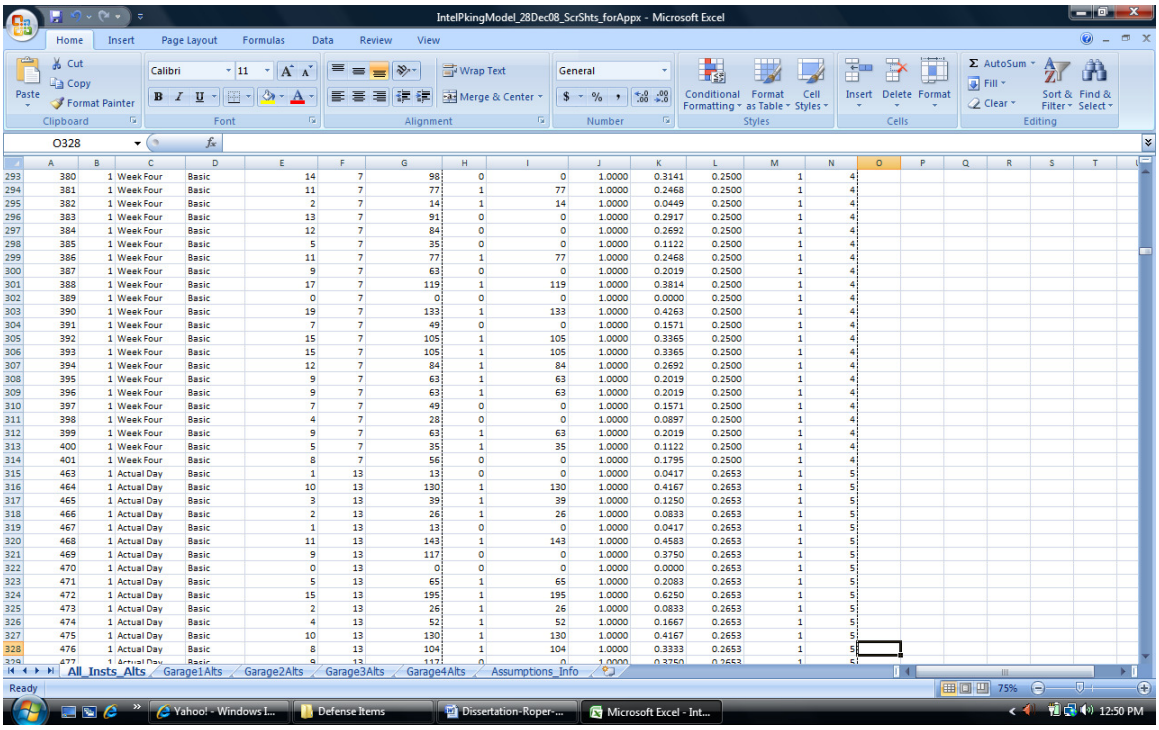
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
220	307	1	Week Four	Basic	12	7	84	0	0	0.3710	0.2692	0.2500	1	4
221	308	1	Week Four	Basic	12	7	84	0	0	0.3548	0.2692	0.2500	1	4
222	309	1	Week Four	Basic	11	7	77	0	0	1.0000	0.2468	0.2500	1	4
223	310	1	Week Four	Basic	4	7	28	0	0	1.0000	0.0897	0.2500	1	4
224	311	1	Week Four	Basic	0	7	0	0	0	0.5161	0.0000	0.2500	1	4
225	312	1	Week Four	Basic	9	7	63	1	63	0.3387	0.2019	0.2500	1	4
226	313	1	Week Four	Basic	3	7	21	0	0	0.3226	0.0673	0.2500	1	4
227	314	1	Week Four	Basic	17	7	119	1	119	1.0000	0.3814	0.2500	1	4
228	315	1	Week Four	Basic	6	7	42	1	42	0.4677	0.1346	0.2500	1	4
229	316	1	Week Four	Basic	8	7	56	1	56	1.0000	0.1795	0.2500	1	4
230	317	1	Week Four	Basic	13	7	91	0	0	1.0000	0.2917	0.2500	1	4
231	318	1	Week Four	Basic	9	7	63	0	0	0.3710	0.2019	0.2500	1	4
232	319	1	Week Four	Basic	6	7	42	1	42	0.3065	0.1346	0.2500	1	4
233	320	1	Week Four	Basic	19	7	133	0	0	0.2903	0.4263	0.2500	1	4
234	321	1	Week Four	Basic	13	7	91	0	0	0.2742	0.2917	0.2500	1	4
235	322	1	Week Four	Basic	3	7	21	1	21	0.3065	0.0673	0.2500	1	4
236	323	1	Week Four	Basic	14	7	98	0	0	0.2581	0.3141	0.2500	1	4
237	324	1	Week Four	Basic	12	7	84	0	0	1.0000	0.2692	0.2500	1	4
238	325	1	Week Four	Basic	6	7	42	0	0	0.2419	0.1346	0.2500	1	4
239	326	1	Week Four	Basic	16	7	112	1	112	0.2258	0.3590	0.2500	1	4
240	327	1	Week Four	Basic	10	7	70	1	70	1.0000	0.2244	0.2500	1	4
241	328	1	Week Four	Basic	6	7	42	1	42	1.0000	0.1346	0.2500	1	4
242	329	1	Week Four	Basic	0	7	0	0	0	1.0000	0.0000	0.2500	1	4
243	330	1	Week Four	Basic	5	7	35	1	35	1.0000	0.1122	0.2500	1	4
244	331	1	Week Four	Basic	6	7	42	1	42	1.0000	0.1346	0.2500	1	4
245	332	1	Week Four	Basic	5	7	35	1	35	1.0000	0.1122	0.2500	1	4
246	333	1	Week Four	Basic	18	7	126	1	126	1.0000	0.4038	0.2500	1	4
247	334	1	Week Four	Basic	6	7	42	0	0	1.0000	0.1346	0.2500	1	4
248	335	1	Week Four	Basic	6	7	42	0	0	1.0000	0.1346	0.2500	1	4
249	336	1	Week Four	Basic	15	7	105	0	0	1.0000	0.3365	0.2500	1	4
250	337	1	Week Four	Basic	17	7	119	0	0	1.0000	0.3814	0.2500	1	4
251	338	1	Week Four	Basic	2	7	14	1	14	1.0000	0.0449	0.2500	1	4
252	339	1	Week Four	Basic	5	7	35	0	0	1.0000	0.1122	0.2500	1	4
253	340	1	Week Four	Basic	17	7	119	0	0	1.0000	0.3814	0.2500	1	4
254	341	1	Week Four	Basic	10	7	70	0	0	1.0000	0.2244	0.2500	1	4
255	342	1	Week Four	Basic	11	7	77	1	77	1.0000	0.2468	0.2500	1	4

Figure A.8: MS Excel Solver Risk Platform IP Data Set (7)



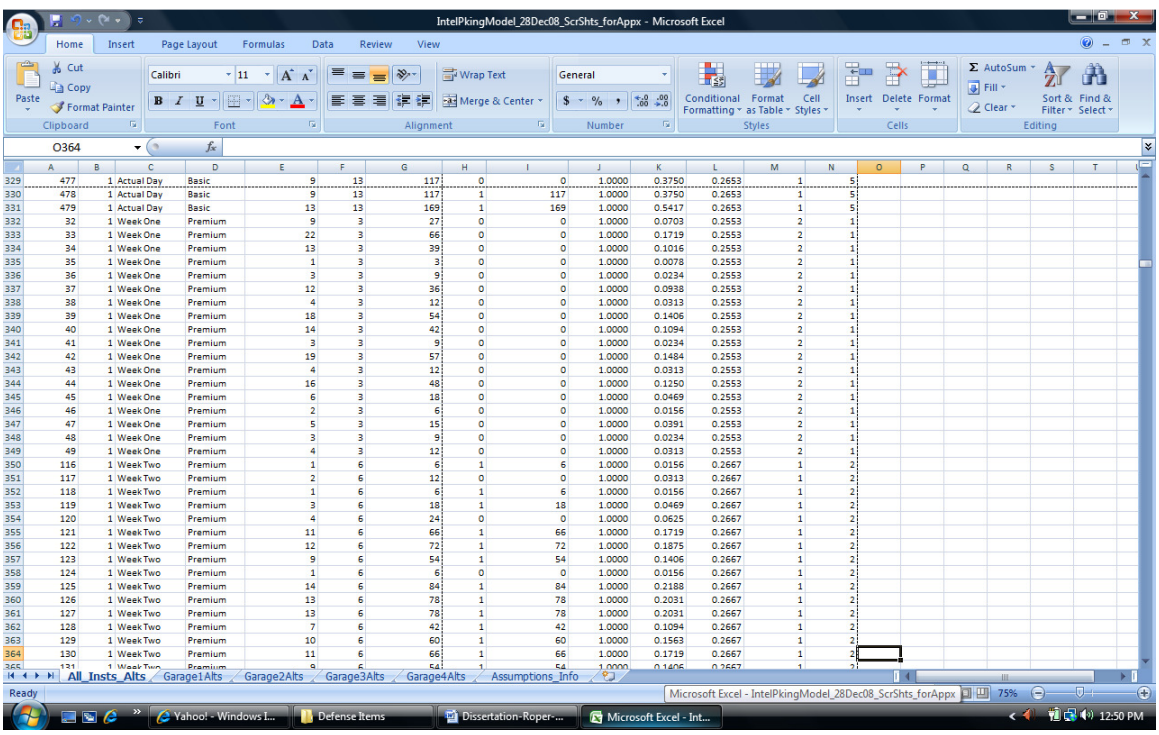
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
256	343	1	Week Four	Basic	9	7	63	0	0	1.0000	0.2019	0.2500	1	4
257	344	1	Week Four	Basic	2	7	14	0	0	1.0000	0.0449	0.2500	1	4
258	345	1	Week Four	Basic	2	7	14	0	0	0.4032	0.0449	0.2500	1	4
259	346	1	Week Four	Basic	9	7	63	1	63	1.0000	0.2019	0.2500	1	4
260	347	1	Week Four	Basic	1	7	7	0	0	0.5645	0.0224	0.2500	1	4
261	348	1	Week Four	Basic	14	7	98	1	98	0.2097	0.3141	0.2500	1	4
262	349	1	Week Four	Basic	11	7	77	1	77	1.0000	0.2468	0.2500	1	4
263	350	1	Week Four	Basic	6	7	42	0	0	0.1935	0.1346	0.2500	1	4
264	351	1	Week Four	Basic	3	7	21	0	0	0.1774	0.0673	0.2500	1	4
265	352	1	Week Four	Basic	14	7	98	0	0	0.1613	0.3141	0.2500	1	4
266	353	1	Week Four	Basic	10	7	70	1	70	1.0000	0.2244	0.2500	1	4
267	354	1	Week Four	Basic	1	7	7	0	0	0.5645	0.0224	0.2500	1	4
268	355	1	Week Four	Basic	1	7	7	0	0	0.3226	0.0224	0.2500	1	4
269	356	1	Week Four	Basic	14	7	98	0	0	0.1452	0.3141	0.2500	1	4
270	357	1	Week Four	Basic	16	7	112	0	0	0.1290	0.3590	0.2500	1	4
271	358	1	Week Four	Basic	3	7	21	0	0	0.5161	0.0673	0.2500	1	4
272	359	1	Week Four	Basic	1	7	7	0	0	0.7903	0.0224	0.2500	1	4
273	360	1	Week Four	Basic	6	7	42	0	0	0.3065	0.1346	0.2500	1	4
274	361	1	Week Four	Basic	5	7	35	0	0	0.2581	0.1122	0.2500	1	4
275	362	1	Week Four	Basic	12	7	84	1	84	0.1129	0.2692	0.2500	1	4
276	363	1	Week Four	Basic	12	7	84	1	84	0.0968	0.2692	0.2500	1	4
277	364	1	Week Four	Basic	3	7	21	1	21	0.1935	0.0673	0.2500	1	4
278	365	1	Week Four	Basic	2	7	14	0	0	0.4355	0.0449	0.2500	1	4
279	366	1	Week Four	Basic	7	7	49	1	49	0.1129	0.1571	0.2500	1	4
280	367	1	Week Four	Basic	15	7	105	1	105	0.0806	0.3365	0.2500	1	4
281	368	1	Week Four	Basic	13	7	91	0	0	0.0645	0.2917	0.2500	1	4
282	369	1	Week Four	Basic	2	7	14	0	0	0.0484	0.0449	0.2500	1	4
283	370	1	Week Four	Basic	1	7	7	0	0	1.0000	0.0224	0.2500	1	4
284	371	1	Week Four	Basic	8	7	56	0	0	0.0484	0.1795	0.2500	1	4
285	372	1	Week Four	Basic	2	7	14	0	0	0.1129	0.0449	0.2500	1	4
286	373	1	Week Four	Basic	2	7	14	0	0	1.0000	0.0449	0.2500	1	4
287	374	1	Week Four	Basic	3	7	21	1	21	1.0000	0.0673	0.2500	1	4
288	375	1	Week Four	Basic	0	7	0	0	0	1.0000	0.0000	0.2500	1	4
289	376	1	Week Four	Basic	1	7	7	0	0	1.0000	0.0224	0.2500	1	4
290	377	1	Week Four	Basic	21	7	147	1	147	1.0000	0.4712	0.2500	1	4
291	378	1	Week Four	Basic	3	7	21	1	21	1.0000	0.0673	0.2500	1	4

Figure A.9: MS Excel Solver Risk Platform IP Data Set (8)



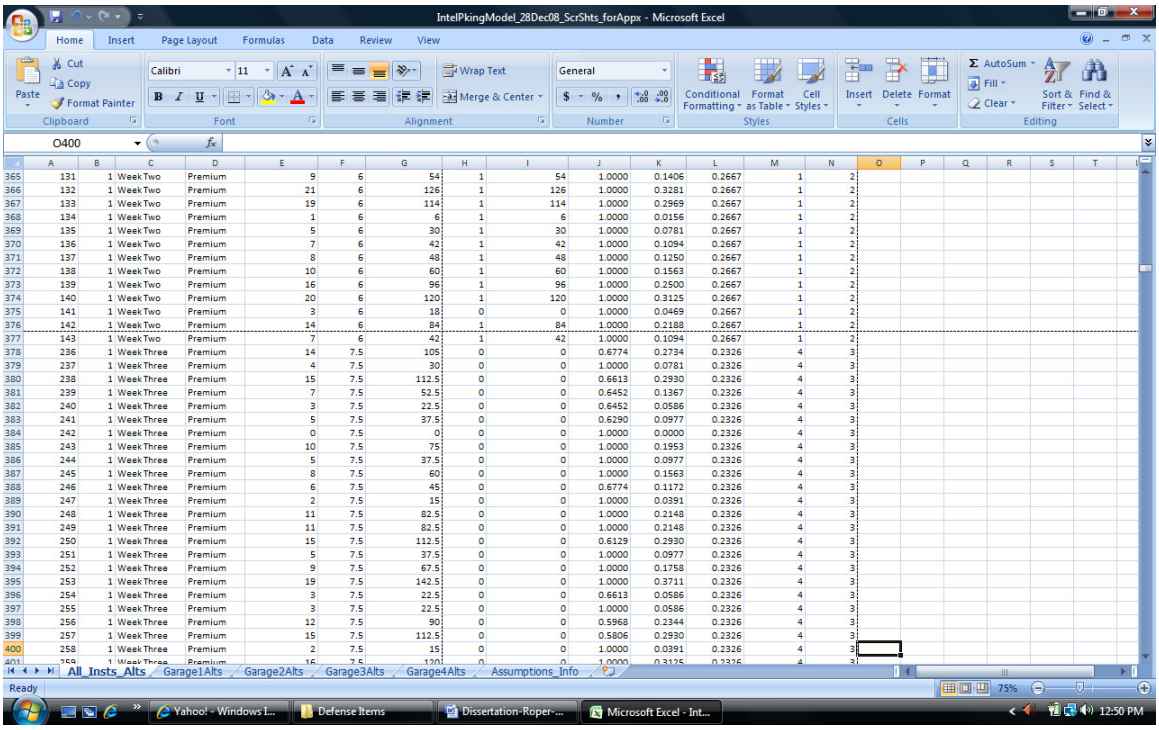
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
293	380	1	Week Four	Basic	14	7	98	0	0	1.0000	0.3141	0.2500	1	4
294	381	1	Week Four	Basic	11	7	77	1	77	1.0000	0.2468	0.2500	1	4
295	382	1	Week Four	Basic	2	7	14	1	14	1.0000	0.0449	0.2500	1	4
296	383	1	Week Four	Basic	13	7	91	0	0	1.0000	0.2917	0.2500	1	4
297	384	1	Week Four	Basic	12	7	84	0	0	1.0000	0.2692	0.2500	1	4
298	385	1	Week Four	Basic	5	7	35	0	0	1.0000	0.1122	0.2500	1	4
299	386	1	Week Four	Basic	11	7	77	1	77	1.0000	0.2468	0.2500	1	4
300	387	1	Week Four	Basic	9	7	63	0	0	1.0000	0.2019	0.2500	1	4
301	388	1	Week Four	Basic	17	7	119	1	119	1.0000	0.3814	0.2500	1	4
302	389	1	Week Four	Basic	0	7	0	0	0	1.0000	0.0000	0.2500	1	4
303	390	1	Week Four	Basic	19	7	133	1	133	1.0000	0.4263	0.2500	1	4
304	391	1	Week Four	Basic	7	7	49	0	0	1.0000	0.1571	0.2500	1	4
305	392	1	Week Four	Basic	15	7	105	1	105	1.0000	0.3365	0.2500	1	4
306	393	1	Week Four	Basic	15	7	105	1	105	1.0000	0.3365	0.2500	1	4
307	394	1	Week Four	Basic	12	7	84	1	84	1.0000	0.2692	0.2500	1	4
308	395	1	Week Four	Basic	9	7	63	1	63	1.0000	0.2019	0.2500	1	4
309	396	1	Week Four	Basic	9	7	63	1	63	1.0000	0.2019	0.2500	1	4
310	397	1	Week Four	Basic	7	7	49	0	0	1.0000	0.1571	0.2500	1	4
311	398	1	Week Four	Basic	4	7	28	0	0	1.0000	0.0897	0.2500	1	4
312	399	1	Week Four	Basic	9	7	63	1	63	1.0000	0.2019	0.2500	1	4
313	400	1	Week Four	Basic	5	7	35	1	35	1.0000	0.1122	0.2500	1	4
314	401	1	Week Four	Basic	8	7	56	0	0	1.0000	0.1795	0.2500	1	4
315	463	1	Actual Day	Basic	1	13	13	0	0	1.0000	0.0417	0.2653	1	5
316	464	1	Actual Day	Basic	10	13	130	1	130	1.0000	0.4167	0.2653	1	5
317	465	1	Actual Day	Basic	3	13	39	1	39	1.0000	0.1250	0.2653	1	5
318	466	1	Actual Day	Basic	2	13	26	1	26	1.0000	0.0833	0.2653	1	5
319	467	1	Actual Day	Basic	1	13	13	0	0	1.0000	0.0417	0.2653	1	5
320	468	1	Actual Day	Basic	11	13	143	1	143	1.0000	0.4583	0.2653	1	5
321	469	1	Actual Day	Basic	9	13	117	0	0	1.0000	0.3750	0.2653	1	5
322	470	1	Actual Day	Basic	0	13	0	0	0	1.0000	0.0000	0.2653	1	5
323	471	1	Actual Day	Basic	5	13	65	1	65	1.0000	0.2083	0.2653	1	5
324	472	1	Actual Day	Basic	15	13	195	1	195	1.0000	0.6250	0.2653	1	5
325	473	1	Actual Day	Basic	2	13	26	1	26	1.0000	0.0833	0.2653	1	5
326	474	1	Actual Day	Basic	4	13	52	1	52	1.0000	0.1667	0.2653	1	5
327	475	1	Actual Day	Basic	10	13	130	1	130	1.0000	0.4167	0.2653	1	5
328	476	1	Actual Day	Basic	8	13	104	1	104	1.0000	0.3333	0.2653	1	5

Figure A.10: MS Excel Solver Risk Platform IP Data Set (9)



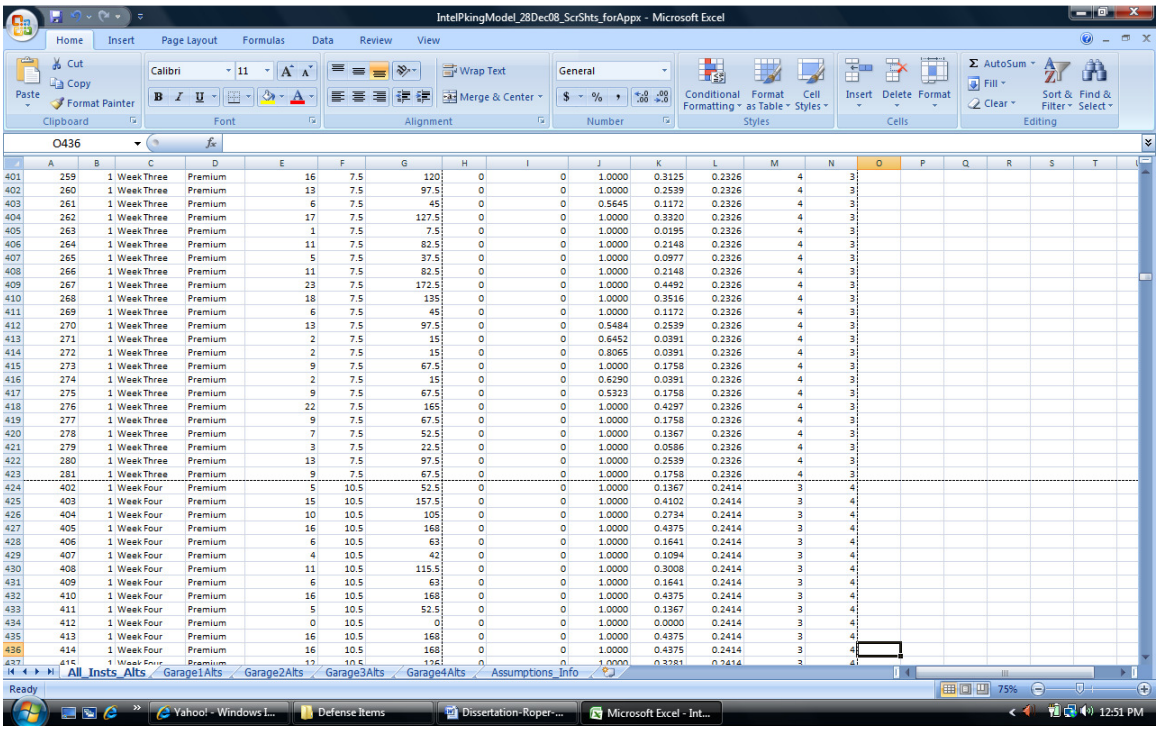
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
329	477	1	Actual Day	Basic	9	13	117	0	0	1.0000	0.3750	0.2653	1	5
330	478	1	Actual Day	Basic	9	13	117	1	117	1.0000	0.3750	0.2653	1	5
331	479	1	Actual Day	Basic	13	13	169	1	169	1.0000	0.5417	0.2653	1	5
332	32	1	Week One	Premium	9	3	27	0	0	1.0000	0.0703	0.2553	2	1
333	33	1	Week One	Premium	22	3	66	0	0	1.0000	0.1719	0.2553	2	1
334	34	1	Week One	Premium	13	3	39	0	0	1.0000	0.1016	0.2553	2	1
335	35	1	Week One	Premium	1	3	3	0	0	1.0000	0.0078	0.2553	2	1
336	36	1	Week One	Premium	3	3	9	0	0	1.0000	0.0234	0.2553	2	1
337	37	1	Week One	Premium	12	3	36	0	0	1.0000	0.0938	0.2553	2	1
338	38	1	Week One	Premium	4	3	12	0	0	1.0000	0.0313	0.2553	2	1
339	39	1	Week One	Premium	18	3	54	0	0	1.0000	0.1406	0.2553	2	1
340	40	1	Week One	Premium	14	3	42	0	0	1.0000	0.1094	0.2553	2	1
341	41	1	Week One	Premium	3	3	9	0	0	1.0000	0.0234	0.2553	2	1
342	42	1	Week One	Premium	19	3	57	0	0	1.0000	0.1484	0.2553	2	1
343	43	1	Week One	Premium	4	3	12	0	0	1.0000	0.0313	0.2553	2	1
344	44	1	Week One	Premium	16	3	48	0	0	1.0000	0.1250	0.2553	2	1
345	45	1	Week One	Premium	6	3	18	0	0	1.0000	0.0469	0.2553	2	1
346	46	1	Week One	Premium	2	3	6	0	0	1.0000	0.0156	0.2553	2	1
347	47	1	Week One	Premium	5	3	15	0	0	1.0000	0.0391	0.2553	2	1
348	48	1	Week One	Premium	3	3	9	0	0	1.0000	0.0234	0.2553	2	1
349	49	1	Week One	Premium	4	3	12	0	0	1.0000	0.0313	0.2553	2	1
350	116	1	Week Two	Premium	1	6	6	1	6	1.0000	0.0156	0.2667	1	2
351	117	1	Week Two	Premium	2	6	12	0	0	1.0000	0.0313	0.2667	1	2
352	118	1	Week Two	Premium	1	6	6	1	6	1.0000	0.0156	0.2667	1	2
353	119	1	Week Two	Premium	3	6	18	1	18	1.0000	0.0469	0.2667	1	2
354	120	1	Week Two	Premium	4	6	24	0	0	1.0000	0.0625	0.2667	1	2
355	121	1	Week Two	Premium	11	6	66	1	66	1.0000	0.1719	0.2667	1	2
356	122	1	Week Two	Premium	12	6	72	1	72	1.0000	0.1875	0.2667	1	2
357	123	1	Week Two	Premium	9	6	54	1	54	1.0000	0.1406	0.2667	1	2
358	124	1	Week Two	Premium	1	6	6	0	0	1.0000	0.0156	0.2667	1	2
359	125	1	Week Two	Premium	14	6	84	1	84	1.0000	0.2188	0.2667	1	2
360	126	1	Week Two	Premium	13	6	78	1	78	1.0000	0.2031	0.2667	1	2
361	127	1	Week Two	Premium	13	6	78	1	78	1.0000	0.2031	0.2667	1	2
362	128	1	Week Two	Premium	7	6	42	1	42	1.0000	0.1094	0.2667	1	2
363	129	1	Week Two	Premium	10	6	60	1	60	1.0000	0.1563	0.2667	1	2
364	130	1	Week Two	Premium	11	6	66	1	66	1.0000	0.1719	0.2667	1	2

Figure A.11: MS Excel Solver Risk Platform IP Data Set (10)



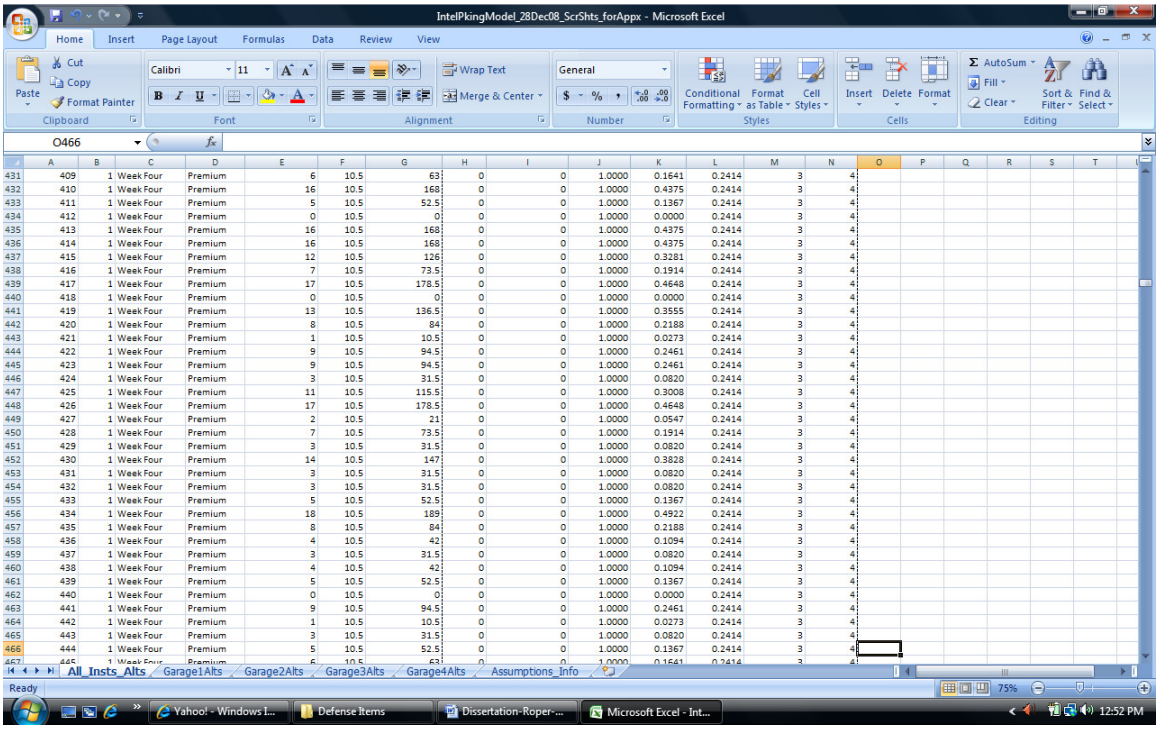
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
365	131	1	Week Two	Premium	9	6	54	1	54	1.0000	0.1406	0.2667	1	2
366	132	1	Week Two	Premium	21	6	126	1	126	1.0000	0.3281	0.2667	1	2
367	133	1	Week Two	Premium	19	6	114	1	114	1.0000	0.2969	0.2667	1	2
368	134	1	Week Two	Premium	1	6	6	1	6	1.0000	0.0156	0.2667	1	2
369	135	1	Week Two	Premium	5	6	30	1	30	1.0000	0.0781	0.2667	1	2
370	136	1	Week Two	Premium	7	6	42	1	42	1.0000	0.1094	0.2667	1	2
371	137	1	Week Two	Premium	8	6	48	1	48	1.0000	0.1250	0.2667	1	2
372	138	1	Week Two	Premium	10	6	60	1	60	1.0000	0.1563	0.2667	1	2
373	139	1	Week Two	Premium	16	6	96	1	96	1.0000	0.2500	0.2667	1	2
374	140	1	Week Two	Premium	20	6	120	1	120	1.0000	0.3125	0.2667	1	2
375	141	1	Week Two	Premium	3	6	18	0	0	1.0000	0.0469	0.2667	1	2
376	142	1	Week Two	Premium	14	6	84	1	84	1.0000	0.2188	0.2667	1	2
377	143	1	Week Two	Premium	7	6	42	1	42	1.0000	0.1094	0.2667	1	2
378	236	1	Week Three	Premium	14	7.5	105	0	0	0.6774	0.2734	0.2326	4	3
379	237	1	Week Three	Premium	4	7.5	30	0	0	1.0000	0.0781	0.2326	4	3
380	238	1	Week Three	Premium	15	7.5	112.5	0	0	0.6613	0.2930	0.2326	4	3
381	239	1	Week Three	Premium	7	7.5	52.5	0	0	0.6452	0.1367	0.2326	4	3
382	240	1	Week Three	Premium	3	7.5	22.5	0	0	0.6452	0.0586	0.2326	4	3
383	241	1	Week Three	Premium	5	7.5	37.5	0	0	0.6290	0.0977	0.2326	4	3
384	242	1	Week Three	Premium	0	7.5	0	0	0	1.0000	0.0000	0.2326	4	3
385	243	1	Week Three	Premium	10	7.5	75	0	0	1.0000	0.1953	0.2326	4	3
386	244	1	Week Three	Premium	5	7.5	37.5	0	0	1.0000	0.0977	0.2326	4	3
387	245	1	Week Three	Premium	8	7.5	60	0	0	1.0000	0.1563	0.2326	4	3
388	246	1	Week Three	Premium	6	7.5	45	0	0	0.6774	0.1172	0.2326	4	3
389	247	1	Week Three	Premium	2	7.5	15	0	0	1.0000	0.0391	0.2326	4	3
390	248	1	Week Three	Premium	11	7.5	82.5	0	0	1.0000	0.2148	0.2326	4	3
391	249	1	Week Three	Premium	11	7.5	82.5	0	0	1.0000	0.2148	0.2326	4	3
392	250	1	Week Three	Premium	15	7.5	112.5	0	0	0.6129	0.2930	0.2326	4	3
393	251	1	Week Three	Premium	5	7.5	37.5	0	0	1.0000	0.0977	0.2326	4	3
394	252	1	Week Three	Premium	9	7.5	67.5	0	0	1.0000	0.1758	0.2326	4	3
395	253	1	Week Three	Premium	19	7.5	142.5	0	0	1.0000	0.3711	0.2326	4	3
396	254	1	Week Three	Premium	3	7.5	22.5	0	0	0.6613	0.0586	0.2326	4	3
397	255	1	Week Three	Premium	3	7.5	22.5	0	0	1.0000	0.0586	0.2326	4	3
398	256	1	Week Three	Premium	12	7.5	90	0	0	0.5968	0.2344	0.2326	4	3
399	257	1	Week Three	Premium	15	7.5	112.5	0	0	0.5806	0.2930	0.2326	4	3
400	258	1	Week Three	Premium	2	7.5	15	0	0	1.0000	0.0391	0.2326	4	3

Figure A.12: MS Excel Solver Risk Platform IP Data Set (11)



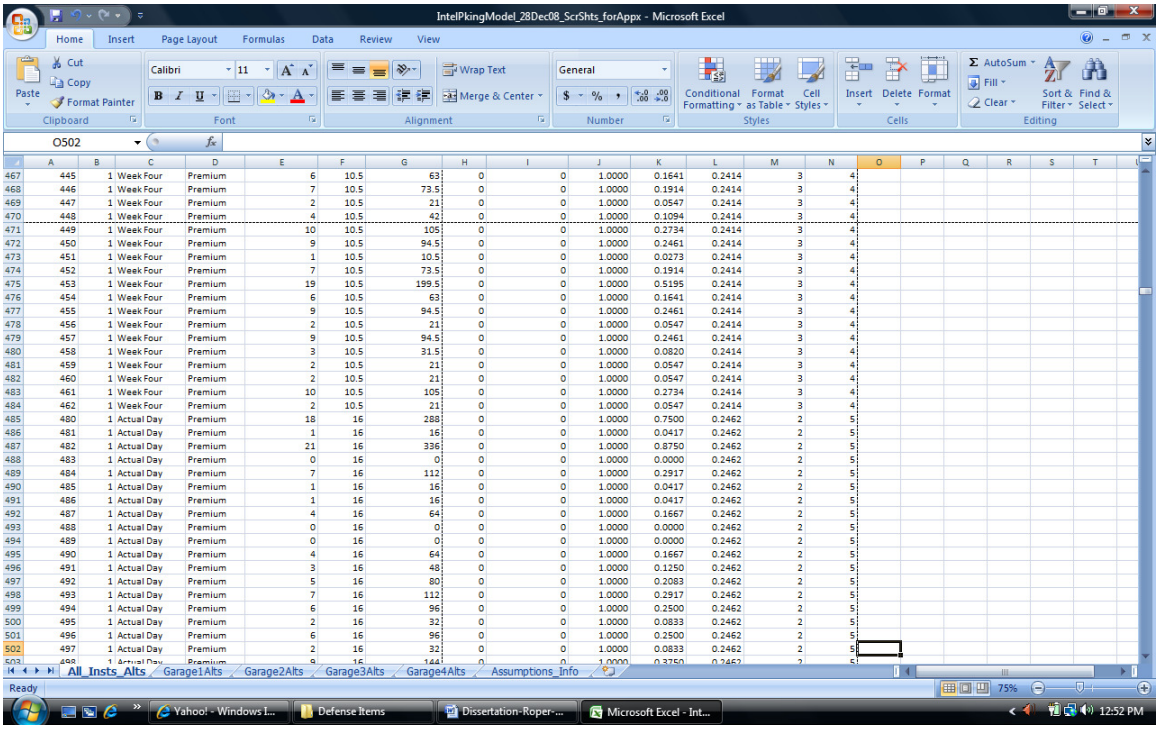
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
401	259	1	Week Three	Premium	16	7.5	120	0	0	1.0000	0.3125	0.2326	4	3
402	260	1	Week Three	Premium	13	7.5	97.5	0	0	1.0000	0.2539	0.2326	4	3
403	261	1	Week Three	Premium	6	7.5	45	0	0	0.5645	0.1172	0.2326	4	3
404	262	1	Week Three	Premium	17	7.5	127.5	0	0	1.0000	0.3320	0.2326	4	3
405	263	1	Week Three	Premium	1	7.5	7.5	0	0	1.0000	0.0195	0.2326	4	3
406	264	1	Week Three	Premium	11	7.5	82.5	0	0	1.0000	0.2148	0.2326	4	3
407	265	1	Week Three	Premium	5	7.5	37.5	0	0	1.0000	0.0977	0.2326	4	3
408	266	1	Week Three	Premium	11	7.5	82.5	0	0	1.0000	0.2148	0.2326	4	3
409	267	1	Week Three	Premium	23	7.5	172.5	0	0	1.0000	0.4492	0.2326	4	3
410	268	1	Week Three	Premium	18	7.5	135	0	0	1.0000	0.3516	0.2326	4	3
411	269	1	Week Three	Premium	6	7.5	45	0	0	1.0000	0.1172	0.2326	4	3
412	270	1	Week Three	Premium	13	7.5	97.5	0	0	0.5484	0.2539	0.2326	4	3
413	271	1	Week Three	Premium	2	7.5	15	0	0	0.6452	0.0391	0.2326	4	3
414	272	1	Week Three	Premium	2	7.5	15	0	0	0.8065	0.0391	0.2326	4	3
415	273	1	Week Three	Premium	9	7.5	67.5	0	0	1.0000	0.1758	0.2326	4	3
416	274	1	Week Three	Premium	2	7.5	15	0	0	0.6290	0.0391	0.2326	4	3
417	275	1	Week Three	Premium	9	7.5	67.5	0	0	0.5323	0.1758	0.2326	4	3
418	276	1	Week Three	Premium	22	7.5	165	0	0	1.0000	0.4297	0.2326	4	3
419	277	1	Week Three	Premium	9	7.5	67.5	0	0	1.0000	0.1758	0.2326	4	3
420	278	1	Week Three	Premium	7	7.5	52.5	0	0	1.0000	0.1367	0.2326	4	3
421	279	1	Week Three	Premium	3	7.5	22.5	0	0	1.0000	0.0586	0.2326	4	3
422	280	1	Week Three	Premium	13	7.5	97.5	0	0	1.0000	0.2539	0.2326	4	3
423	281	1	Week Three	Premium	9	7.5	67.5	0	0	1.0000	0.1758	0.2326	4	3
424	402	1	Week Four	Premium	5	10.5	52.5	0	0	1.0000	0.1367	0.2414	3	4
425	403	1	Week Four	Premium	15	10.5	157.5	0	0	1.0000	0.4102	0.2414	3	4
426	404	1	Week Four	Premium	10	10.5	105	0	0	1.0000	0.2734	0.2414	3	4
427	405	1	Week Four	Premium	16	10.5	168	0	0	1.0000	0.4375	0.2414	3	4
428	406	1	Week Four	Premium	6	10.5	63	0	0	1.0000	0.1641	0.2414	3	4
429	407	1	Week Four	Premium	4	10.5	42	0	0	1.0000	0.1094	0.2414	3	4
430	408	1	Week Four	Premium	11	10.5	115.5	0	0	1.0000	0.3008	0.2414	3	4
431	409	1	Week Four	Premium	6	10.5	63	0	0	1.0000	0.1641	0.2414	3	4
432	410	1	Week Four	Premium	16	10.5	168	0	0	1.0000	0.4375	0.2414	3	4
433	411	1	Week Four	Premium	5	10.5	52.5	0	0	1.0000	0.1367	0.2414	3	4
434	412	1	Week Four	Premium	0	10.5	0	0	0	1.0000	0.0000	0.2414	3	4
435	413	1	Week Four	Premium	16	10.5	168	0	0	1.0000	0.4375	0.2414	3	4
436	414	1	Week Four	Premium	16	10.5	168	0	0	1.0000	0.4375	0.2414	3	4

Figure A.13: MS Excel Solver Risk Platform IP Data Set (12)



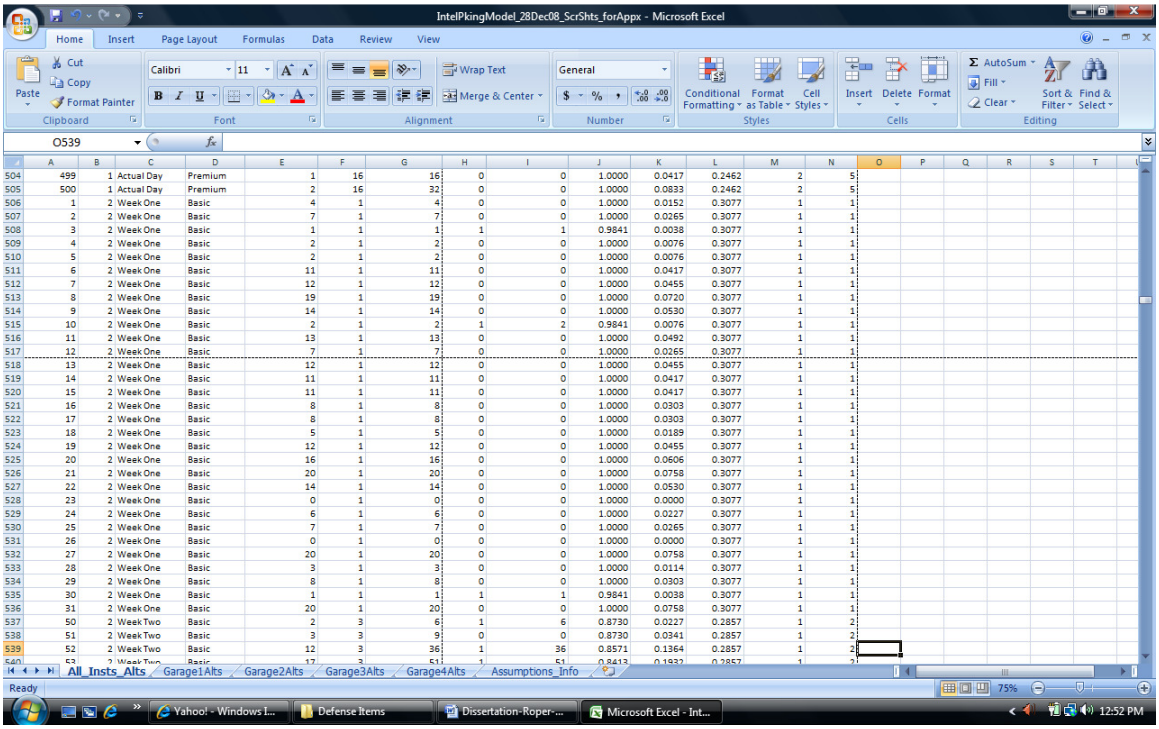
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
431	409	1	Week Four	Premium	6	10.5	63	0	0	1.0000	0.1641	0.2414	3	4
432	410	1	Week Four	Premium	16	10.5	168	0	0	1.0000	0.4375	0.2414	3	4
433	411	1	Week Four	Premium	5	10.5	52.5	0	0	1.0000	0.1367	0.2414	3	4
434	412	1	Week Four	Premium	0	10.5	0	0	0	1.0000	0.0000	0.2414	3	4
435	413	1	Week Four	Premium	16	10.5	168	0	0	1.0000	0.4375	0.2414	3	4
436	414	1	Week Four	Premium	16	10.5	168	0	0	1.0000	0.4375	0.2414	3	4
437	415	1	Week Four	Premium	12	10.5	126	0	0	1.0000	0.3281	0.2414	3	4
438	416	1	Week Four	Premium	7	10.5	73.5	0	0	1.0000	0.1914	0.2414	3	4
439	417	1	Week Four	Premium	17	10.5	178.5	0	0	1.0000	0.4648	0.2414	3	4
440	418	1	Week Four	Premium	0	10.5	0	0	0	1.0000	0.0000	0.2414	3	4
441	419	1	Week Four	Premium	13	10.5	136.5	0	0	1.0000	0.3555	0.2414	3	4
442	420	1	Week Four	Premium	8	10.5	84	0	0	1.0000	0.2188	0.2414	3	4
443	421	1	Week Four	Premium	1	10.5	10.5	0	0	1.0000	0.0273	0.2414	3	4
444	422	1	Week Four	Premium	9	10.5	94.5	0	0	1.0000	0.2461	0.2414	3	4
445	423	1	Week Four	Premium	9	10.5	94.5	0	0	1.0000	0.2461	0.2414	3	4
446	424	1	Week Four	Premium	3	10.5	31.5	0	0	1.0000	0.0820	0.2414	3	4
447	425	1	Week Four	Premium	11	10.5	115.5	0	0	1.0000	0.3008	0.2414	3	4
448	426	1	Week Four	Premium	17	10.5	178.5	0	0	1.0000	0.4648	0.2414	3	4
449	427	1	Week Four	Premium	2	10.5	21	0	0	1.0000	0.0547	0.2414	3	4
450	428	1	Week Four	Premium	7	10.5	73.5	0	0	1.0000	0.1914	0.2414	3	4
451	429	1	Week Four	Premium	3	10.5	31.5	0	0	1.0000	0.0820	0.2414	3	4
452	430	1	Week Four	Premium	14	10.5	147	0	0	1.0000	0.3828	0.2414	3	4
453	431	1	Week Four	Premium	3	10.5	31.5	0	0	1.0000	0.0820	0.2414	3	4
454	432	1	Week Four	Premium	3	10.5	31.5	0	0	1.0000	0.0820	0.2414	3	4
455	433	1	Week Four	Premium	5	10.5	52.5	0	0	1.0000	0.1367	0.2414	3	4
456	434	1	Week Four	Premium	18	10.5	189	0	0	1.0000	0.4922	0.2414	3	4
457	435	1	Week Four	Premium	8	10.5	84	0	0	1.0000	0.2188	0.2414	3	4
458	436	1	Week Four	Premium	4	10.5	42	0	0	1.0000	0.1094	0.2414	3	4
459	437	1	Week Four	Premium	3	10.5	31.5	0	0	1.0000	0.0820	0.2414	3	4
460	438	1	Week Four	Premium	4	10.5	42	0	0	1.0000	0.1094	0.2414	3	4
461	439	1	Week Four	Premium	5	10.5	52.5	0	0	1.0000	0.1367	0.2414	3	4
462	440	1	Week Four	Premium	0	10.5	0	0	0	1.0000	0.0000	0.2414	3	4
463	441	1	Week Four	Premium	9	10.5	94.5	0	0	1.0000	0.2461	0.2414	3	4
464	442	1	Week Four	Premium	1	10.5	10.5	0	0	1.0000	0.0273	0.2414	3	4
465	443	1	Week Four	Premium	3	10.5	31.5	0	0	1.0000	0.0820	0.2414	3	4
466	444	1	Week Four	Premium	5	10.5	52.5	0	0	1.0000	0.1367	0.2414	3	4

Figure A.14: MS Excel Solver Risk Platform IP Data Set (13)



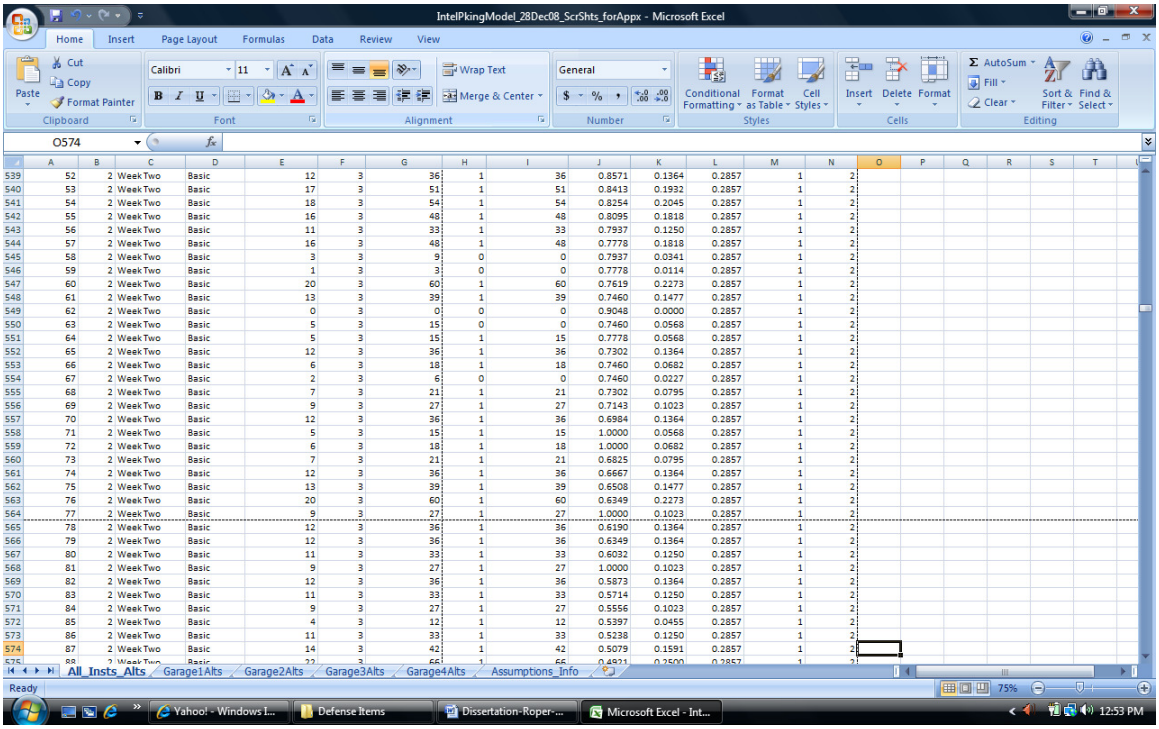
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
467	445	1	Week Four	Premium	6	10.5	63	0	0	1.0000	0.1641	0.2414	3	4
468	446	1	Week Four	Premium	7	10.5	73.5	0	0	1.0000	0.1914	0.2414	3	4
469	447	1	Week Four	Premium	2	10.5	21	0	0	1.0000	0.0547	0.2414	3	4
470	448	1	Week Four	Premium	4	10.5	42	0	0	1.0000	0.1094	0.2414	3	4
471	449	1	Week Four	Premium	10	10.5	105	0	0	1.0000	0.2734	0.2414	3	4
472	450	1	Week Four	Premium	9	10.5	94.5	0	0	1.0000	0.2461	0.2414	3	4
473	451	1	Week Four	Premium	1	10.5	10.5	0	0	1.0000	0.0273	0.2414	3	4
474	452	1	Week Four	Premium	7	10.5	73.5	0	0	1.0000	0.1914	0.2414	3	4
475	453	1	Week Four	Premium	19	10.5	199.5	0	0	1.0000	0.5195	0.2414	3	4
476	454	1	Week Four	Premium	6	10.5	63	0	0	1.0000	0.1641	0.2414	3	4
477	455	1	Week Four	Premium	9	10.5	94.5	0	0	1.0000	0.2461	0.2414	3	4
478	456	1	Week Four	Premium	2	10.5	21	0	0	1.0000	0.0547	0.2414	3	4
479	457	1	Week Four	Premium	9	10.5	94.5	0	0	1.0000	0.2461	0.2414	3	4
480	458	1	Week Four	Premium	3	10.5	31.5	0	0	1.0000	0.0820	0.2414	3	4
481	459	1	Week Four	Premium	2	10.5	21	0	0	1.0000	0.0547	0.2414	3	4
482	460	1	Week Four	Premium	2	10.5	21	0	0	1.0000	0.0547	0.2414	3	4
483	461	1	Week Four	Premium	10	10.5	105	0	0	1.0000	0.2734	0.2414	3	4
484	462	1	Week Four	Premium	2	10.5	21	0	0	1.0000	0.0547	0.2414	3	4
485	480	1	Actual Day	Premium	18	16	288	0	0	1.0000	0.7500	0.2462	2	5
486	481	1	Actual Day	Premium	1	16	16	0	0	1.0000	0.0417	0.2462	2	5
487	482	1	Actual Day	Premium	21	16	336	0	0	1.0000	0.8750	0.2462	2	5
488	483	1	Actual Day	Premium	0	16	0	0	0	1.0000	0.0000	0.2462	2	5
489	484	1	Actual Day	Premium	7	16	112	0	0	1.0000	0.2917	0.2462	2	5
490	485	1	Actual Day	Premium	1	16	16	0	0	1.0000	0.0417	0.2462	2	5
491	486	1	Actual Day	Premium	1	16	16	0	0	1.0000	0.0417	0.2462	2	5
492	487	1	Actual Day	Premium	4	16	64	0	0	1.0000	0.1667	0.2462	2	5
493	488	1	Actual Day	Premium	0	16	0	0	0	1.0000	0.0000	0.2462	2	5
494	489	1	Actual Day	Premium	0	16	0	0	0	1.0000	0.0000	0.2462	2	5
495	490	1	Actual Day	Premium	4	16	64	0	0	1.0000	0.1667	0.2462	2	5
496	491	1	Actual Day	Premium	3	16	48	0	0	1.0000	0.1250	0.2462	2	5
497	492	1	Actual Day	Premium	5	16	80	0	0	1.0000	0.2083	0.2462	2	5
498	493	1	Actual Day	Premium	7	16	112	0	0	1.0000	0.2917	0.2462	2	5
499	494	1	Actual Day	Premium	6	16	96	0	0	1.0000	0.2500	0.2462	2	5
500	495	1	Actual Day	Premium	2	16	32	0	0	1.0000	0.0833	0.2462	2	5
501	496	1	Actual Day	Premium	6	16	96	0	0	1.0000	0.2500	0.2462	2	5
502	497	1	Actual Day	Premium	2	16	32	0	0	1.0000	0.0833	0.2462	2	5

Figure A.15: MS Excel Solver Risk Platform IP Data Set (14)



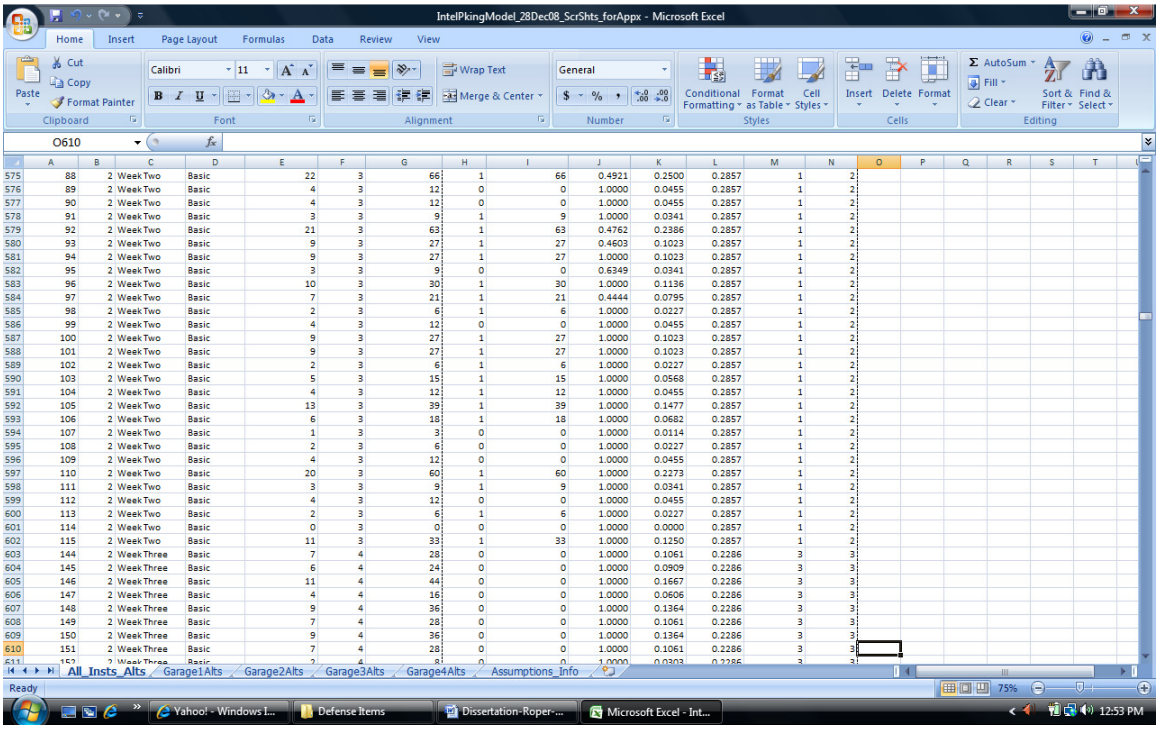
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
504	499	1	Actual Day	Premium	1	16	16	0	0	1.0000	0.0417	0.2462	2	5
505	500	1	Actual Day	Premium	2	16	32	0	0	1.0000	0.0833	0.2462	2	5
506	1	2	Week One	Basic	4	1	4	0	0	1.0000	0.0152	0.3077	1	1
507	2	2	Week One	Basic	7	1	7	0	0	1.0000	0.0265	0.3077	1	1
508	3	2	Week One	Basic	1	1	1	1	1	0.9841	0.0038	0.3077	1	1
509	4	2	Week One	Basic	2	1	2	0	0	1.0000	0.0076	0.3077	1	1
510	5	2	Week One	Basic	2	1	2	0	0	1.0000	0.0076	0.3077	1	1
511	6	2	Week One	Basic	11	1	11	0	0	1.0000	0.0417	0.3077	1	1
512	7	2	Week One	Basic	12	1	12	0	0	1.0000	0.0455	0.3077	1	1
513	8	2	Week One	Basic	19	1	19	0	0	1.0000	0.0720	0.3077	1	1
514	9	2	Week One	Basic	14	1	14	0	0	1.0000	0.0530	0.3077	1	1
515	10	2	Week One	Basic	2	1	2	1	2	0.9841	0.0076	0.3077	1	1
516	11	2	Week One	Basic	13	1	13	0	0	1.0000	0.0492	0.3077	1	1
517	12	2	Week One	Basic	7	1	7	0	0	1.0000	0.0265	0.3077	1	1
518	13	2	Week One	Basic	12	1	12	0	0	1.0000	0.0455	0.3077	1	1
519	14	2	Week One	Basic	11	1	11	0	0	1.0000	0.0417	0.3077	1	1
520	15	2	Week One	Basic	11	1	11	0	0	1.0000	0.0417	0.3077	1	1
521	16	2	Week One	Basic	8	1	8	0	0	1.0000	0.0303	0.3077	1	1
522	17	2	Week One	Basic	8	1	8	0	0	1.0000	0.0303	0.3077	1	1
523	18	2	Week One	Basic	5	1	5	0	0	1.0000	0.0189	0.3077	1	1
524	19	2	Week One	Basic	12	1	12	0	0	1.0000	0.0455	0.3077	1	1
525	20	2	Week One	Basic	16	1	16	0	0	1.0000	0.0606	0.3077	1	1
526	21	2	Week One	Basic	20	1	20	0	0	1.0000	0.0758	0.3077	1	1
527	22	2	Week One	Basic	14	1	14	0	0	1.0000	0.0530	0.3077	1	1
528	23	2	Week One	Basic	0	1	0	0	0	1.0000	0.0000	0.3077	1	1
529	24	2	Week One	Basic	6	1	6	0	0	1.0000	0.0227	0.3077	1	1
530	25	2	Week One	Basic	7	1	7	0	0	1.0000	0.0265	0.3077	1	1
531	26	2	Week One	Basic	0	1	0	0	0	1.0000	0.0000	0.3077	1	1
532	27	2	Week One	Basic	20	1	20	0	0	1.0000	0.0758	0.3077	1	1
533	28	2	Week One	Basic	3	1	3	0	0	1.0000	0.0114	0.3077	1	1
534	29	2	Week One	Basic	8	1	8	0	0	1.0000	0.0303	0.3077	1	1
535	30	2	Week One	Basic	1	1	1	1	1	0.9841	0.0038	0.3077	1	1
536	31	2	Week One	Basic	20	1	20	0	0	1.0000	0.0758	0.3077	1	1
537	50	2	Week Two	Basic	2	3	6	1	6	0.8730	0.0227	0.2857	1	2
538	51	2	Week Two	Basic	3	3	9	0	0	0.8730	0.0341	0.2857	1	2
539	52	2	Week Two	Basic	12	3	36	1	36	0.8571	0.1364	0.2857	1	2

Figure A.16: MS Excel Solver Risk Platform IP Data Set (15)



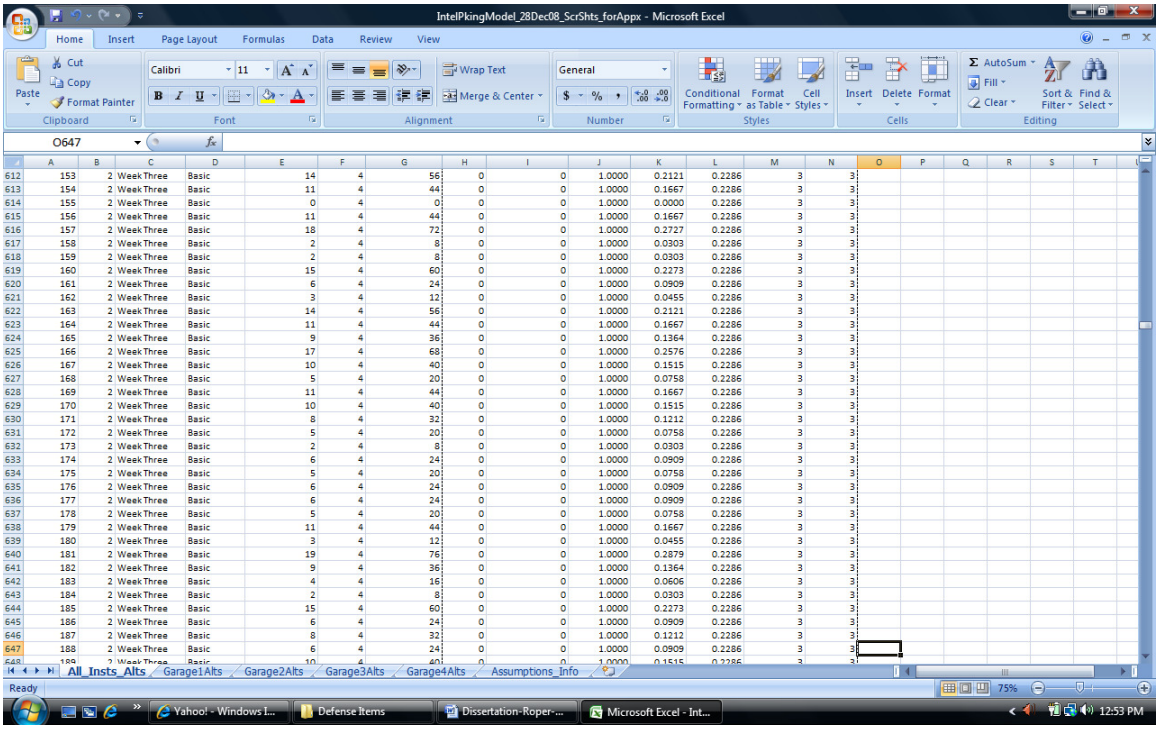
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
539	52	2	Week Two	Basic	12	3	36	1	36	0.8571	0.1364	0.2857	1	2
540	53	2	Week Two	Basic	17	3	51	1	51	0.8413	0.1932	0.2857	1	2
541	54	2	Week Two	Basic	18	3	54	1	54	0.8254	0.2045	0.2857	1	2
542	55	2	Week Two	Basic	16	3	48	1	48	0.8095	0.1818	0.2857	1	2
543	56	2	Week Two	Basic	11	3	33	1	33	0.7937	0.1250	0.2857	1	2
544	57	2	Week Two	Basic	16	3	48	1	48	0.7778	0.1818	0.2857	1	2
545	58	2	Week Two	Basic	3	3	9	0	0	0.7937	0.0341	0.2857	1	2
546	59	2	Week Two	Basic	1	3	3	0	0	0.7778	0.0114	0.2857	1	2
547	60	2	Week Two	Basic	20	3	60	1	60	0.7619	0.2273	0.2857	1	2
548	61	2	Week Two	Basic	13	3	39	1	39	0.7460	0.1477	0.2857	1	2
549	62	2	Week Two	Basic	0	3	0	0	0	0.9048	0.0000	0.2857	1	2
550	63	2	Week Two	Basic	5	3	15	0	0	0.7460	0.0568	0.2857	1	2
551	64	2	Week Two	Basic	5	3	15	1	15	0.7778	0.0568	0.2857	1	2
552	65	2	Week Two	Basic	12	3	36	1	36	0.7302	0.1364	0.2857	1	2
553	66	2	Week Two	Basic	6	3	18	1	18	0.7460	0.0682	0.2857	1	2
554	67	2	Week Two	Basic	2	3	6	0	0	0.7460	0.0227	0.2857	1	2
555	68	2	Week Two	Basic	7	3	21	1	21	0.7302	0.0795	0.2857	1	2
556	69	2	Week Two	Basic	9	3	27	1	27	0.7143	0.1023	0.2857	1	2
557	70	2	Week Two	Basic	12	3	36	1	36	0.6984	0.1364	0.2857	1	2
558	71	2	Week Two	Basic	5	3	15	1	15	1.0000	0.0568	0.2857	1	2
559	72	2	Week Two	Basic	6	3	18	1	18	1.0000	0.0682	0.2857	1	2
560	73	2	Week Two	Basic	7	3	21	1	21	0.6825	0.0795	0.2857	1	2
561	74	2	Week Two	Basic	12	3	36	1	36	0.6667	0.1364	0.2857	1	2
562	75	2	Week Two	Basic	13	3	39	1	39	0.6508	0.1477	0.2857	1	2
563	76	2	Week Two	Basic	20	3	60	1	60	0.6349	0.2273	0.2857	1	2
564	77	2	Week Two	Basic	9	3	27	1	27	1.0000	0.1023	0.2857	1	2
565	78	2	Week Two	Basic	12	3	36	1	36	0.6190	0.1364	0.2857	1	2
566	79	2	Week Two	Basic	12	3	36	1	36	0.6349	0.1364	0.2857	1	2
567	80	2	Week Two	Basic	11	3	33	1	33	0.6032	0.1250	0.2857	1	2
568	81	2	Week Two	Basic	9	3	27	1	27	1.0000	0.1023	0.2857	1	2
569	82	2	Week Two	Basic	12	3	36	1	36	0.5873	0.1364	0.2857	1	2
570	83	2	Week Two	Basic	11	3	33	1	33	0.5714	0.1250	0.2857	1	2
571	84	2	Week Two	Basic	9	3	27	1	27	0.5556	0.1023	0.2857	1	2
572	85	2	Week Two	Basic	4	3	12	1	12	0.5397	0.0455	0.2857	1	2
573	86	2	Week Two	Basic	11	3	33	1	33	0.5238	0.1250	0.2857	1	2
574	87	2	Week Two	Basic	14	3	42	1	42	0.5079	0.1591	0.2857	1	2

Figure A.17: MS Excel Solver Risk Platform IP Data Set (16)



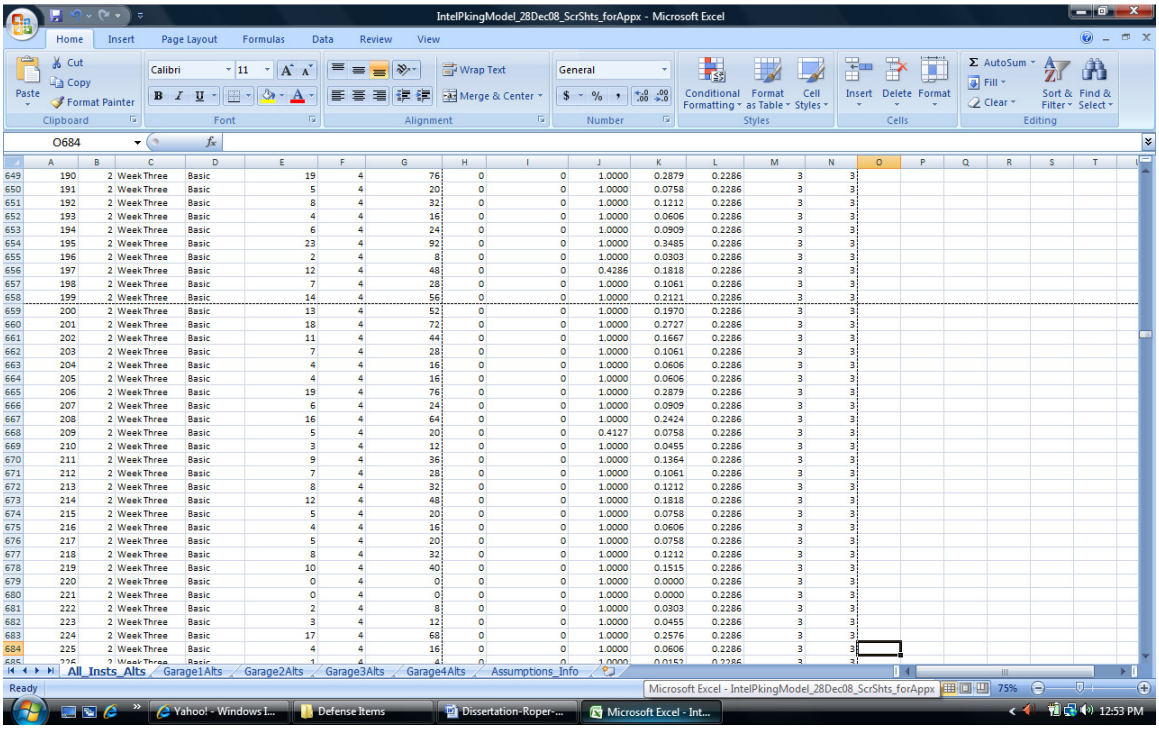
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
575	88	2	WeekTwo	Basic	22	3	66	1	66	0.4921	0.2500	0.2857	1	2
576	89	2	WeekTwo	Basic	4	3	12	0	0	1.0000	0.0455	0.2857	1	2
577	90	2	WeekTwo	Basic	4	3	12	0	0	1.0000	0.0455	0.2857	1	2
578	91	2	WeekTwo	Basic	3	3	9	1	9	1.0000	0.0341	0.2857	1	2
579	92	2	WeekTwo	Basic	21	3	63	1	63	0.4762	0.2386	0.2857	1	2
580	93	2	WeekTwo	Basic	9	3	27	1	27	0.4603	0.1023	0.2857	1	2
581	94	2	WeekTwo	Basic	9	3	27	1	27	1.0000	0.1023	0.2857	1	2
582	95	2	WeekTwo	Basic	3	3	9	0	0	0.6349	0.0341	0.2857	1	2
583	96	2	WeekTwo	Basic	10	3	30	1	30	1.0000	0.1136	0.2857	1	2
584	97	2	WeekTwo	Basic	7	3	21	1	21	0.4444	0.0795	0.2857	1	2
585	98	2	WeekTwo	Basic	2	3	6	1	6	1.0000	0.0227	0.2857	1	2
586	99	2	WeekTwo	Basic	4	3	12	0	0	1.0000	0.0455	0.2857	1	2
587	100	2	WeekTwo	Basic	9	3	27	1	27	1.0000	0.1023	0.2857	1	2
588	101	2	WeekTwo	Basic	9	3	27	1	27	1.0000	0.1023	0.2857	1	2
589	102	2	WeekTwo	Basic	2	3	6	1	6	1.0000	0.0227	0.2857	1	2
590	103	2	WeekTwo	Basic	5	3	15	1	15	1.0000	0.0568	0.2857	1	2
591	104	2	WeekTwo	Basic	4	3	12	1	12	1.0000	0.0455	0.2857	1	2
592	105	2	WeekTwo	Basic	13	3	39	1	39	1.0000	0.1477	0.2857	1	2
593	106	2	WeekTwo	Basic	6	3	18	1	18	1.0000	0.0682	0.2857	1	2
594	107	2	WeekTwo	Basic	1	3	3	0	0	1.0000	0.0114	0.2857	1	2
595	108	2	WeekTwo	Basic	2	3	6	0	0	1.0000	0.0227	0.2857	1	2
596	109	2	WeekTwo	Basic	4	3	12	0	0	1.0000	0.0455	0.2857	1	2
597	110	2	WeekTwo	Basic	20	3	60	1	60	1.0000	0.2273	0.2857	1	2
598	111	2	WeekTwo	Basic	3	3	9	1	9	1.0000	0.0341	0.2857	1	2
599	112	2	WeekTwo	Basic	4	3	12	0	0	1.0000	0.0455	0.2857	1	2
600	113	2	WeekTwo	Basic	2	3	6	1	6	1.0000	0.0227	0.2857	1	2
601	114	2	WeekTwo	Basic	0	3	0	0	0	1.0000	0.0000	0.2857	1	2
602	115	2	WeekTwo	Basic	11	3	33	1	33	1.0000	0.1250	0.2857	1	2
603	144	2	WeekThree	Basic	7	4	28	0	0	1.0000	0.1061	0.2286	3	3
604	145	2	WeekThree	Basic	6	4	24	0	0	1.0000	0.0909	0.2286	3	3
605	146	2	WeekThree	Basic	11	4	44	0	0	1.0000	0.1667	0.2286	3	3
606	147	2	WeekThree	Basic	4	4	16	0	0	1.0000	0.0606	0.2286	3	3
607	148	2	WeekThree	Basic	9	4	36	0	0	1.0000	0.1364	0.2286	3	3
608	149	2	WeekThree	Basic	7	4	28	0	0	1.0000	0.1061	0.2286	3	3
609	150	2	WeekThree	Basic	9	4	36	0	0	1.0000	0.1364	0.2286	3	3
610	151	2	WeekThree	Basic	7	4	28	0	0	1.0000	0.1061	0.2286	3	3

Figure A.18: MS Excel Solver Risk Platform IP Data Set (17)



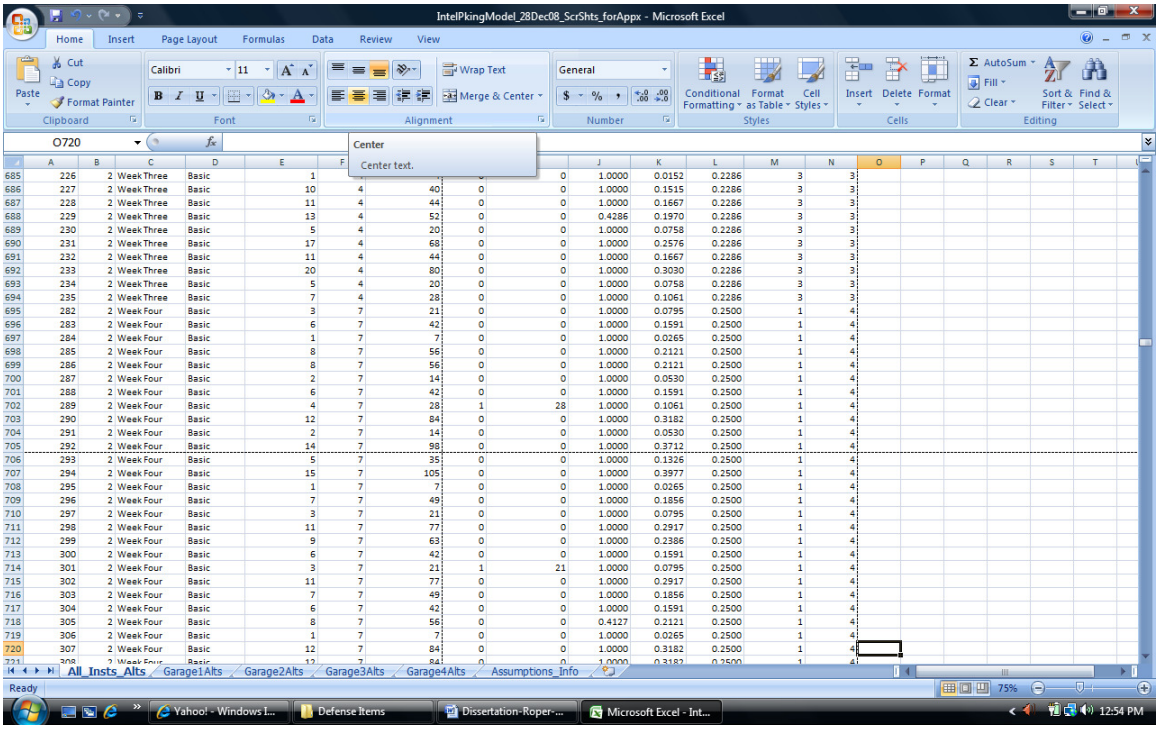
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
612	153	2	WeekThree	Basic	14	4	56	0	0	1.0000	0.2121	0.2286	3	3
613	154	2	WeekThree	Basic	11	4	44	0	0	1.0000	0.1667	0.2286	3	3
614	155	2	WeekThree	Basic	0	4	0	0	0	1.0000	0.0000	0.2286	3	3
615	156	2	WeekThree	Basic	11	4	44	0	0	1.0000	0.1667	0.2286	3	3
616	157	2	WeekThree	Basic	18	4	72	0	0	1.0000	0.2727	0.2286	3	3
617	158	2	WeekThree	Basic	2	4	8	0	0	1.0000	0.0303	0.2286	3	3
618	159	2	WeekThree	Basic	2	4	8	0	0	1.0000	0.0303	0.2286	3	3
619	160	2	WeekThree	Basic	15	4	60	0	0	1.0000	0.2273	0.2286	3	3
620	161	2	WeekThree	Basic	6	4	24	0	0	1.0000	0.0909	0.2286	3	3
621	162	2	WeekThree	Basic	3	4	12	0	0	1.0000	0.0455	0.2286	3	3
622	163	2	WeekThree	Basic	14	4	56	0	0	1.0000	0.2121	0.2286	3	3
623	164	2	WeekThree	Basic	11	4	44	0	0	1.0000	0.1667	0.2286	3	3
624	165	2	WeekThree	Basic	9	4	36	0	0	1.0000	0.1364	0.2286	3	3
625	166	2	WeekThree	Basic	17	4	68	0	0	1.0000	0.2576	0.2286	3	3
626	167	2	WeekThree	Basic	10	4	40	0	0	1.0000	0.1515	0.2286	3	3
627	168	2	WeekThree	Basic	5	4	20	0	0	1.0000	0.0758	0.2286	3	3
628	169	2	WeekThree	Basic	11	4	44	0	0	1.0000	0.1667	0.2286	3	3
629	170	2	WeekThree	Basic	10	4	40	0	0	1.0000	0.1515	0.2286	3	3
630	171	2	WeekThree	Basic	8	4	32	0	0	1.0000	0.1212	0.2286	3	3
631	172	2	WeekThree	Basic	5	4	20	0	0	1.0000	0.0758	0.2286	3	3
632	173	2	WeekThree	Basic	2	4	8	0	0	1.0000	0.0303	0.2286	3	3
633	174	2	WeekThree	Basic	6	4	24	0	0	1.0000	0.0909	0.2286	3	3
634	175	2	WeekThree	Basic	5	4	20	0	0	1.0000	0.0758	0.2286	3	3
635	176	2	WeekThree	Basic	6	4	24	0	0	1.0000	0.0909	0.2286	3	3
636	177	2	WeekThree	Basic	6	4	24	0	0	1.0000	0.0909	0.2286	3	3
637	178	2	WeekThree	Basic	5	4	20	0	0	1.0000	0.0758	0.2286	3	3
638	179	2	WeekThree	Basic	11	4	44	0	0	1.0000	0.1667	0.2286	3	3
639	180	2	WeekThree	Basic	3	4	12	0	0	1.0000	0.0455	0.2286	3	3
640	181	2	WeekThree	Basic	19	4	76	0	0	1.0000	0.2879	0.2286	3	3
641	182	2	WeekThree	Basic	9	4	36	0	0	1.0000	0.1364	0.2286	3	3
642	183	2	WeekThree	Basic	4	4	16	0	0	1.0000	0.0606	0.2286	3	3
643	184	2	WeekThree	Basic	2	4	8	0	0	1.0000	0.0303	0.2286	3	3
644	185	2	WeekThree	Basic	15	4	60	0	0	1.0000	0.2273	0.2286	3	3
645	186	2	WeekThree	Basic	6	4	24	0	0	1.0000	0.0909	0.2286	3	3
646	187	2	WeekThree	Basic	8	4	32	0	0	1.0000	0.1212	0.2286	3	3
647	188	2	WeekThree	Basic	6	4	24	0	0	1.0000	0.0909	0.2286	3	3

Figure A.19: MS Excel Solver Risk Platform IP Data Set (18)



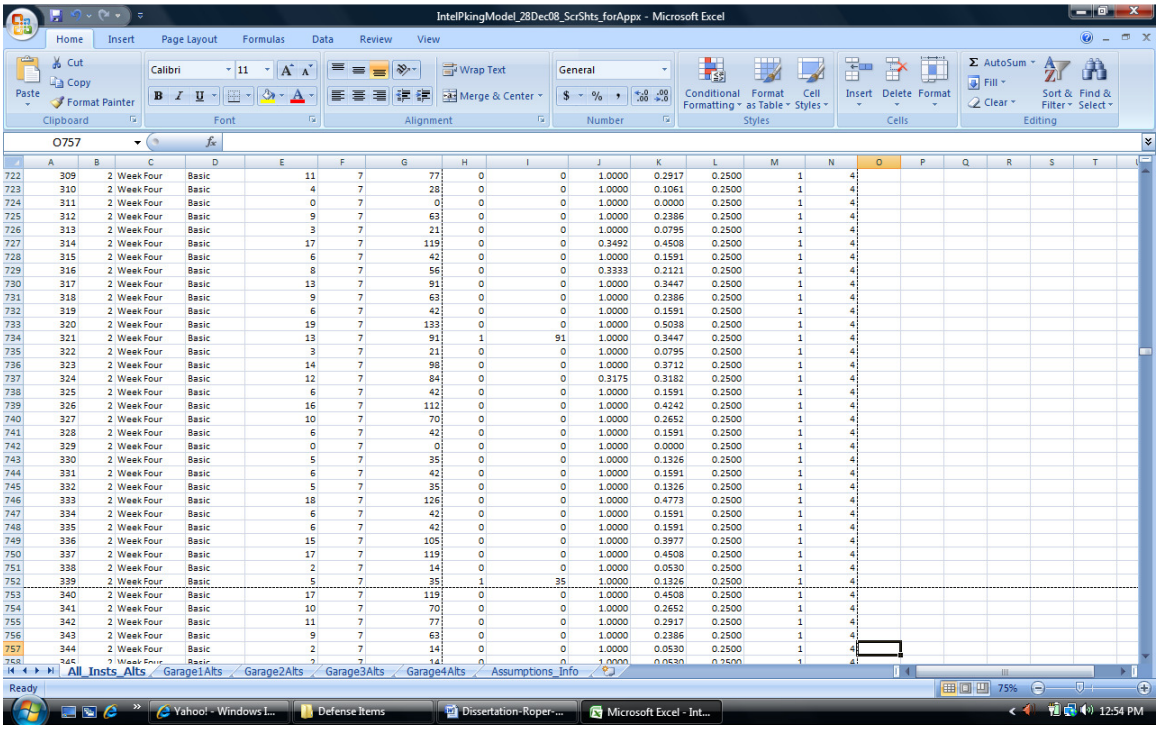
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
649	190	2	Week Three	Basic	19	4	76	0	0	1.0000	0.2879	0.2286	3	3
650	191	2	Week Three	Basic	5	4	20	0	0	1.0000	0.0758	0.2286	3	3
651	192	2	Week Three	Basic	8	4	32	0	0	1.0000	0.1212	0.2286	3	3
652	193	2	Week Three	Basic	4	4	16	0	0	1.0000	0.0606	0.2286	3	3
653	194	2	Week Three	Basic	6	4	24	0	0	1.0000	0.0909	0.2286	3	3
654	195	2	Week Three	Basic	23	4	92	0	0	1.0000	0.3485	0.2286	3	3
655	196	2	Week Three	Basic	2	4	8	0	0	1.0000	0.0303	0.2286	3	3
656	197	2	Week Three	Basic	12	4	48	0	0	0.4286	0.1818	0.2286	3	3
657	198	2	Week Three	Basic	7	4	28	0	0	1.0000	0.1061	0.2286	3	3
658	199	2	Week Three	Basic	14	4	56	0	0	1.0000	0.2121	0.2286	3	3
659	200	2	Week Three	Basic	13	4	52	0	0	1.0000	0.1970	0.2286	3	3
660	201	2	Week Three	Basic	18	4	72	0	0	1.0000	0.2727	0.2286	3	3
661	202	2	Week Three	Basic	11	4	44	0	0	1.0000	0.1667	0.2286	3	3
662	203	2	Week Three	Basic	7	4	28	0	0	1.0000	0.1061	0.2286	3	3
663	204	2	Week Three	Basic	4	4	16	0	0	1.0000	0.0606	0.2286	3	3
664	205	2	Week Three	Basic	4	4	16	0	0	1.0000	0.0606	0.2286	3	3
665	206	2	Week Three	Basic	19	4	76	0	0	1.0000	0.2879	0.2286	3	3
666	207	2	Week Three	Basic	6	4	24	0	0	1.0000	0.0909	0.2286	3	3
667	208	2	Week Three	Basic	16	4	64	0	0	1.0000	0.2424	0.2286	3	3
668	209	2	Week Three	Basic	5	4	20	0	0	0.4127	0.0758	0.2286	3	3
669	210	2	Week Three	Basic	3	4	12	0	0	1.0000	0.0455	0.2286	3	3
670	211	2	Week Three	Basic	9	4	36	0	0	1.0000	0.1364	0.2286	3	3
671	212	2	Week Three	Basic	7	4	28	0	0	1.0000	0.1061	0.2286	3	3
672	213	2	Week Three	Basic	8	4	32	0	0	1.0000	0.1212	0.2286	3	3
673	214	2	Week Three	Basic	12	4	48	0	0	1.0000	0.1818	0.2286	3	3
674	215	2	Week Three	Basic	5	4	20	0	0	1.0000	0.0758	0.2286	3	3
675	216	2	Week Three	Basic	4	4	16	0	0	1.0000	0.0606	0.2286	3	3
676	217	2	Week Three	Basic	5	4	20	0	0	1.0000	0.0758	0.2286	3	3
677	218	2	Week Three	Basic	8	4	32	0	0	1.0000	0.1212	0.2286	3	3
678	219	2	Week Three	Basic	10	4	40	0	0	1.0000	0.1515	0.2286	3	3
679	220	2	Week Three	Basic	0	4	0	0	0	1.0000	0.0000	0.2286	3	3
680	221	2	Week Three	Basic	0	4	0	0	0	1.0000	0.0000	0.2286	3	3
681	222	2	Week Three	Basic	2	4	8	0	0	1.0000	0.0303	0.2286	3	3
682	223	2	Week Three	Basic	3	4	12	0	0	1.0000	0.0455	0.2286	3	3
683	224	2	Week Three	Basic	17	4	68	0	0	1.0000	0.2576	0.2286	3	3
684	225	2	Week Three	Basic	4	4	16	0	0	1.0000	0.0606	0.2286	3	3

Figure A.20: MS Excel Solver Risk Platform IP Data Set (19)



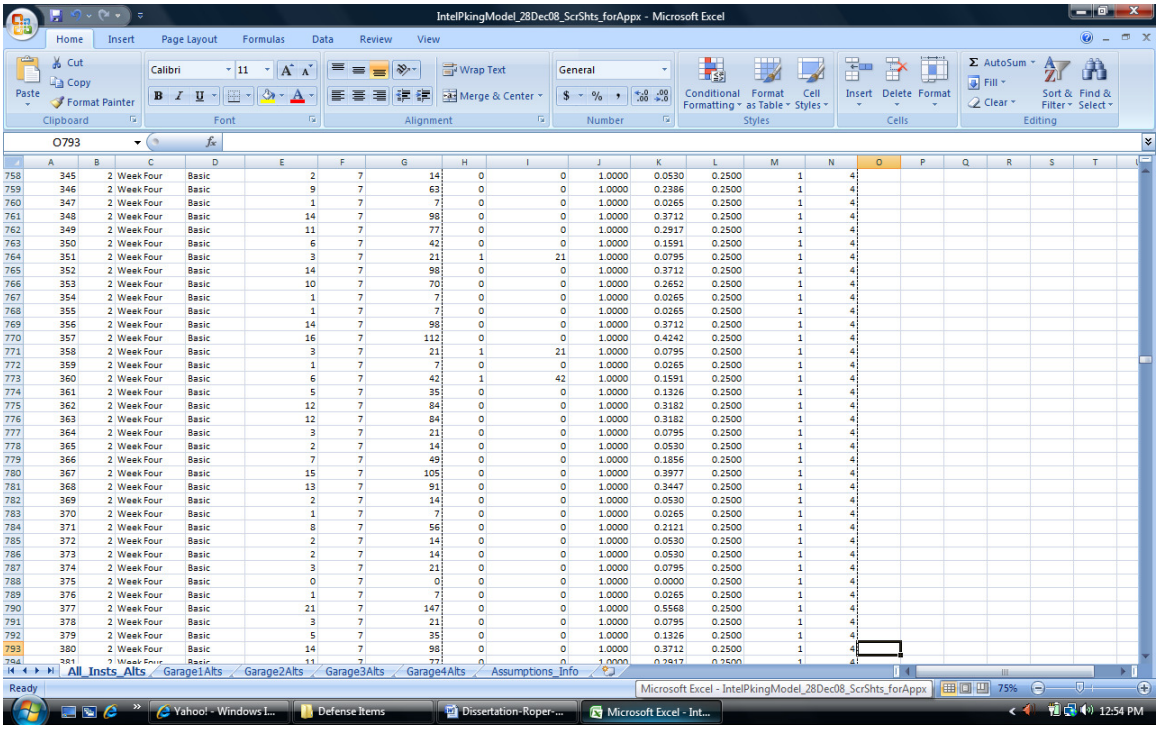
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
685	226	2	Week Three	Basic	1			0		0	1.0000	0.0152	0.2286	3	3
686	227	2	Week Three	Basic	10	4	40	0		0	1.0000	0.1515	0.2286	3	3
687	228	2	Week Three	Basic	11	4	44	0		0	1.0000	0.1667	0.2286	3	3
688	229	2	Week Three	Basic	13	4	52	0		0	0.4286	0.1970	0.2286	3	3
689	230	2	Week Three	Basic	5	4	20	0		0	1.0000	0.0758	0.2286	3	3
690	231	2	Week Three	Basic	17	4	68	0		0	1.0000	0.2576	0.2286	3	3
691	232	2	Week Three	Basic	11	4	44	0		0	1.0000	0.1667	0.2286	3	3
692	233	2	Week Three	Basic	20	4	80	0		0	1.0000	0.3030	0.2286	3	3
693	234	2	Week Three	Basic	5	4	20	0		0	1.0000	0.0758	0.2286	3	3
694	235	2	Week Three	Basic	7	4	28	0		0	1.0000	0.1061	0.2286	3	3
695	282	2	Week Four	Basic	3	7	21	0		0	1.0000	0.0795	0.2500	1	4
696	283	2	Week Four	Basic	6	7	42	0		0	1.0000	0.1591	0.2500	1	4
697	284	2	Week Four	Basic	1	7	7	0		0	1.0000	0.0265	0.2500	1	4
698	285	2	Week Four	Basic	8	7	56	0		0	1.0000	0.2121	0.2500	1	4
699	286	2	Week Four	Basic	8	7	56	0		0	1.0000	0.2121	0.2500	1	4
700	287	2	Week Four	Basic	2	7	14	0		0	1.0000	0.0530	0.2500	1	4
701	288	2	Week Four	Basic	6	7	42	0		0	1.0000	0.1591	0.2500	1	4
702	289	2	Week Four	Basic	4	7	28	1	28	1.0000	0.1061	0.2500	1	4
703	290	2	Week Four	Basic	12	7	84	0		0	1.0000	0.3182	0.2500	1	4
704	291	2	Week Four	Basic	2	7	14	0		0	1.0000	0.0530	0.2500	1	4
705	292	2	Week Four	Basic	14	7	98	0		0	1.0000	0.3712	0.2500	1	4
706	293	2	Week Four	Basic	5	7	35	0		0	1.0000	0.1326	0.2500	1	4
707	294	2	Week Four	Basic	15	7	105	0		0	1.0000	0.3977	0.2500	1	4
708	295	2	Week Four	Basic	1	7	7	0		0	1.0000	0.0265	0.2500	1	4
709	296	2	Week Four	Basic	7	7	49	0		0	1.0000	0.1856	0.2500	1	4
710	297	2	Week Four	Basic	3	7	21	0		0	1.0000	0.0795	0.2500	1	4
711	298	2	Week Four	Basic	11	7	77	0		0	1.0000	0.2917	0.2500	1	4
712	299	2	Week Four	Basic	9	7	63	0		0	1.0000	0.2386	0.2500	1	4
713	300	2	Week Four	Basic	6	7	42	0		0	1.0000	0.1591	0.2500	1	4
714	301	2	Week Four	Basic	3	7	21	1	21	1.0000	0.0795	0.2500	1	4
715	302	2	Week Four	Basic	11	7	77	0		0	1.0000	0.2917	0.2500	1	4
716	303	2	Week Four	Basic	7	7	49	0		0	1.0000	0.1856	0.2500	1	4
717	304	2	Week Four	Basic	6	7	42	0		0	1.0000	0.1591	0.2500	1	4
718	305	2	Week Four	Basic	8	7	56	0		0	0.4127	0.2121	0.2500	1	4
719	306	2	Week Four	Basic	1	7	7	0		0	1.0000	0.0265	0.2500	1	4
720	307	2	Week Four	Basic	12	7	84	0		0	1.0000	0.3182	0.2500	1	4

Figure A.21: MS Excel Solver Risk Platform IP Data Set (20)



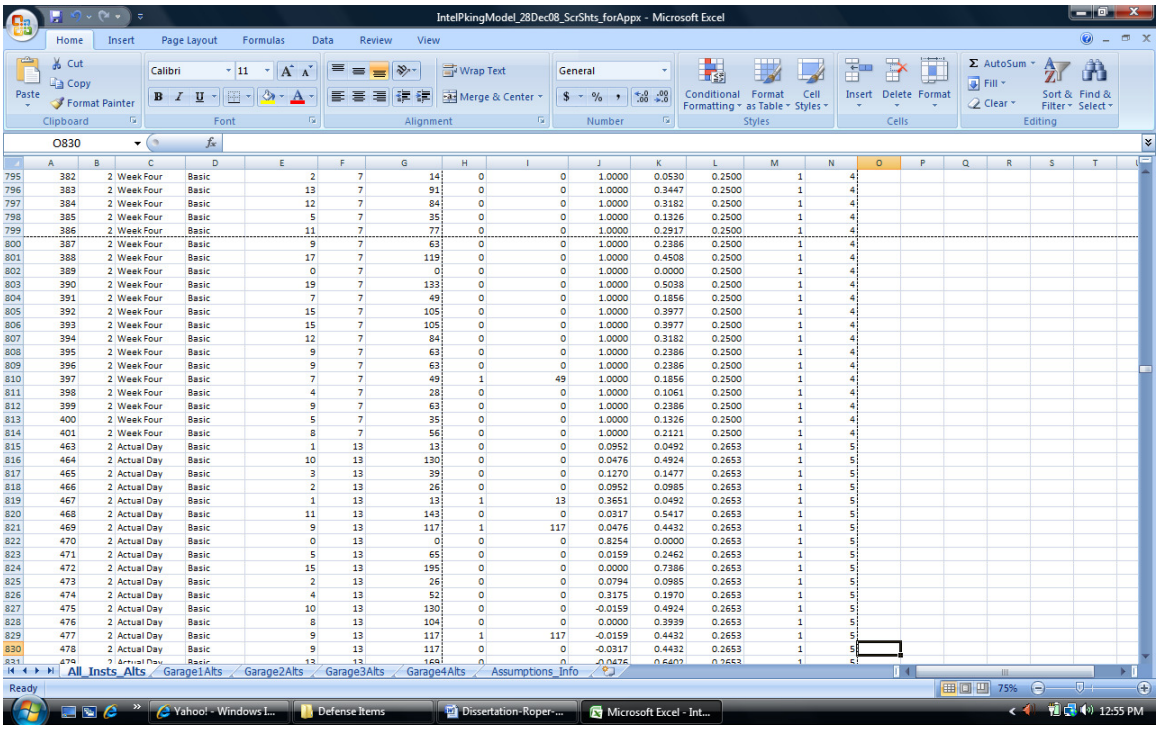
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
722	309	2	Week Four	Basic	11	7	77	0	0	1.0000	0.2917	0.2500	1	4
723	310	2	Week Four	Basic	4	7	28	0	0	1.0000	0.1061	0.2500	1	4
724	311	2	Week Four	Basic	0	7	0	0	0	1.0000	0.0000	0.2500	1	4
725	312	2	Week Four	Basic	9	7	63	0	0	1.0000	0.2386	0.2500	1	4
726	313	2	Week Four	Basic	3	7	21	0	0	1.0000	0.0795	0.2500	1	4
727	314	2	Week Four	Basic	17	7	119	0	0	0.3492	0.4508	0.2500	1	4
728	315	2	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
729	316	2	Week Four	Basic	8	7	56	0	0	0.3333	0.2121	0.2500	1	4
730	317	2	Week Four	Basic	13	7	91	0	0	1.0000	0.3447	0.2500	1	4
731	318	2	Week Four	Basic	9	7	63	0	0	1.0000	0.2386	0.2500	1	4
732	319	2	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
733	320	2	Week Four	Basic	19	7	133	0	0	1.0000	0.5038	0.2500	1	4
734	321	2	Week Four	Basic	13	7	91	1	91	1.0000	0.3447	0.2500	1	4
735	322	2	Week Four	Basic	3	7	21	0	0	1.0000	0.0795	0.2500	1	4
736	323	2	Week Four	Basic	14	7	98	0	0	1.0000	0.3712	0.2500	1	4
737	324	2	Week Four	Basic	12	7	84	0	0	0.3175	0.3182	0.2500	1	4
738	325	2	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
739	326	2	Week Four	Basic	16	7	112	0	0	1.0000	0.4242	0.2500	1	4
740	327	2	Week Four	Basic	10	7	70	0	0	1.0000	0.2652	0.2500	1	4
741	328	2	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
742	329	2	Week Four	Basic	0	7	0	0	0	1.0000	0.0000	0.2500	1	4
743	330	2	Week Four	Basic	5	7	35	0	0	1.0000	0.1326	0.2500	1	4
744	331	2	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
745	332	2	Week Four	Basic	5	7	35	0	0	1.0000	0.1326	0.2500	1	4
746	333	2	Week Four	Basic	18	7	126	0	0	1.0000	0.4773	0.2500	1	4
747	334	2	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
748	335	2	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
749	336	2	Week Four	Basic	15	7	105	0	0	1.0000	0.3977	0.2500	1	4
750	337	2	Week Four	Basic	17	7	119	0	0	1.0000	0.4508	0.2500	1	4
751	338	2	Week Four	Basic	2	7	14	0	0	1.0000	0.0530	0.2500	1	4
752	339	2	Week Four	Basic	5	7	35	1	35	1.0000	0.1326	0.2500	1	4
753	340	2	Week Four	Basic	17	7	119	0	0	1.0000	0.4508	0.2500	1	4
754	341	2	Week Four	Basic	10	7	70	0	0	1.0000	0.2652	0.2500	1	4
755	342	2	Week Four	Basic	11	7	77	0	0	1.0000	0.2917	0.2500	1	4
756	343	2	Week Four	Basic	9	7	63	0	0	1.0000	0.2386	0.2500	1	4
757	344	2	Week Four	Basic	2	7	14	0	0	1.0000	0.0530	0.2500	1	4

Figure A.22: MS Excel Solver Risk Platform IP Data Set (21)



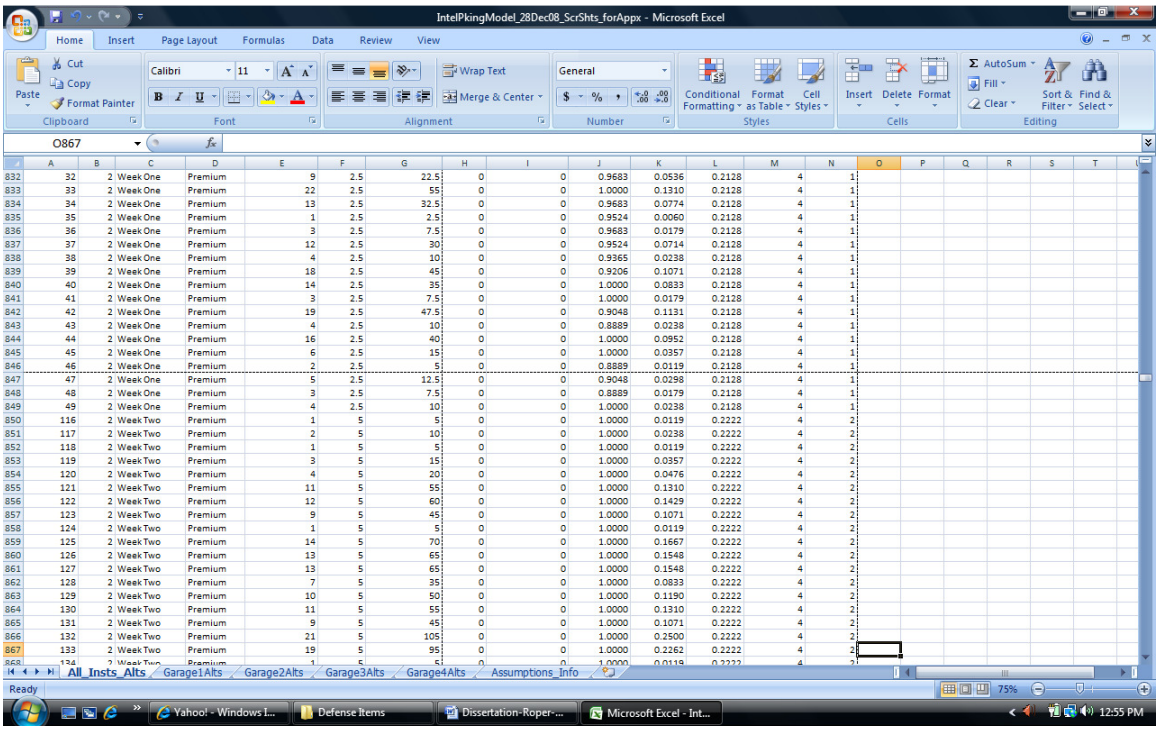
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
758	345	2	Week Four	Basic	2	7	14	0	0	1.0000	0.0530	0.2500	1	4
759	346	2	Week Four	Basic	9	7	63	0	0	1.0000	0.2386	0.2500	1	4
760	347	2	Week Four	Basic	1	7	7	0	0	1.0000	0.0265	0.2500	1	4
761	348	2	Week Four	Basic	14	7	98	0	0	1.0000	0.3712	0.2500	1	4
762	349	2	Week Four	Basic	11	7	77	0	0	1.0000	0.2917	0.2500	1	4
763	350	2	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
764	351	2	Week Four	Basic	3	7	21	1	21	1.0000	0.0795	0.2500	1	4
765	352	2	Week Four	Basic	14	7	98	0	0	1.0000	0.3712	0.2500	1	4
766	353	2	Week Four	Basic	10	7	70	0	0	1.0000	0.2652	0.2500	1	4
767	354	2	Week Four	Basic	1	7	7	0	0	1.0000	0.0265	0.2500	1	4
768	355	2	Week Four	Basic	1	7	7	0	0	1.0000	0.0265	0.2500	1	4
769	356	2	Week Four	Basic	14	7	98	0	0	1.0000	0.3712	0.2500	1	4
770	357	2	Week Four	Basic	16	7	112	0	0	1.0000	0.4242	0.2500	1	4
771	358	2	Week Four	Basic	3	7	21	1	21	1.0000	0.0795	0.2500	1	4
772	359	2	Week Four	Basic	1	7	7	0	0	1.0000	0.0265	0.2500	1	4
773	360	2	Week Four	Basic	6	7	42	1	42	1.0000	0.1591	0.2500	1	4
774	361	2	Week Four	Basic	5	7	35	0	0	1.0000	0.1326	0.2500	1	4
775	362	2	Week Four	Basic	12	7	84	0	0	1.0000	0.3182	0.2500	1	4
776	363	2	Week Four	Basic	12	7	84	0	0	1.0000	0.3182	0.2500	1	4
777	364	2	Week Four	Basic	3	7	21	0	0	1.0000	0.0795	0.2500	1	4
778	365	2	Week Four	Basic	2	7	14	0	0	1.0000	0.0530	0.2500	1	4
779	366	2	Week Four	Basic	7	7	49	0	0	1.0000	0.1856	0.2500	1	4
780	367	2	Week Four	Basic	15	7	105	0	0	1.0000	0.3977	0.2500	1	4
781	368	2	Week Four	Basic	13	7	91	0	0	1.0000	0.3447	0.2500	1	4
782	369	2	Week Four	Basic	2	7	14	0	0	1.0000	0.0530	0.2500	1	4
783	370	2	Week Four	Basic	1	7	7	0	0	1.0000	0.0265	0.2500	1	4
784	371	2	Week Four	Basic	8	7	56	0	0	1.0000	0.2121	0.2500	1	4
785	372	2	Week Four	Basic	2	7	14	0	0	1.0000	0.0530	0.2500	1	4
786	373	2	Week Four	Basic	2	7	14	0	0	1.0000	0.0530	0.2500	1	4
787	374	2	Week Four	Basic	3	7	21	0	0	1.0000	0.0795	0.2500	1	4
788	375	2	Week Four	Basic	0	7	0	0	0	1.0000	0.0000	0.2500	1	4
789	376	2	Week Four	Basic	1	7	7	0	0	1.0000	0.0265	0.2500	1	4
790	377	2	Week Four	Basic	21	7	147	0	0	1.0000	0.5568	0.2500	1	4
791	378	2	Week Four	Basic	3	7	21	0	0	1.0000	0.0795	0.2500	1	4
792	379	2	Week Four	Basic	5	7	35	0	0	1.0000	0.1326	0.2500	1	4
793	380	2	Week Four	Basic	14	7	98	0	0	1.0000	0.3712	0.2500	1	4

Figure A.23: MS Excel Solver Risk Platform IP Data Set (22)



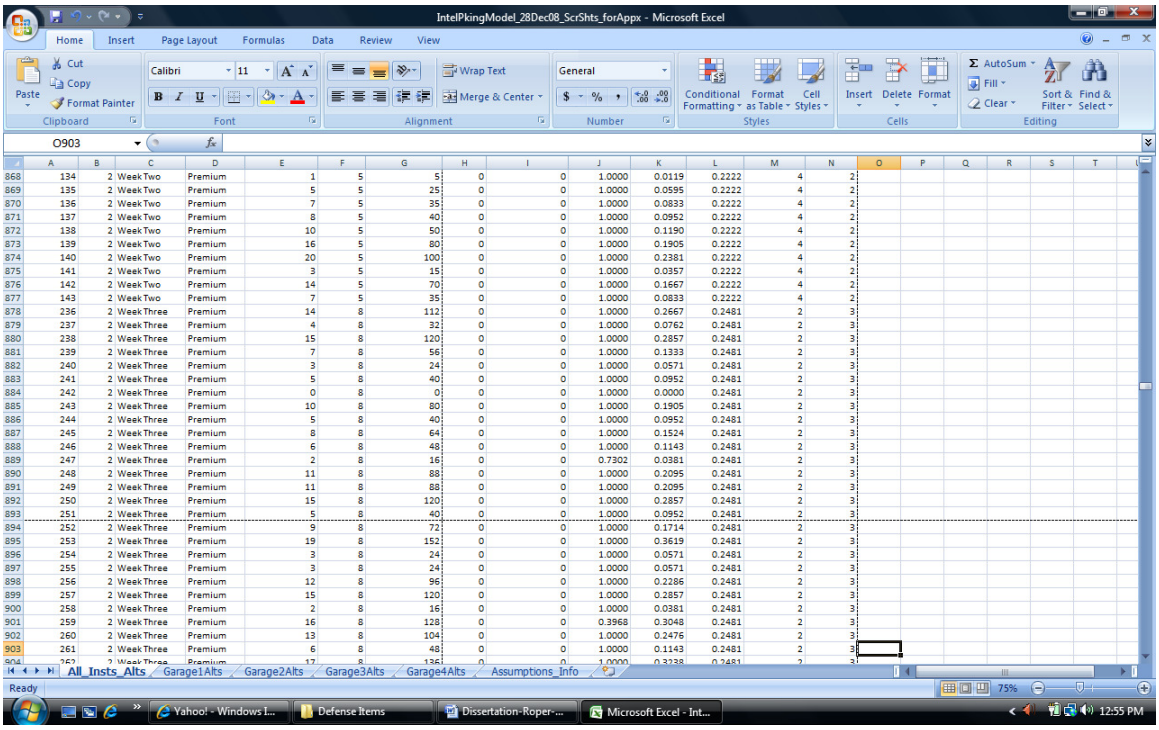
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
795	382	2	Week Four	Basic	2	7	14	0	0	1.0000	0.0530	0.2500	1	4
796	383	2	Week Four	Basic	13	7	91	0	0	1.0000	0.3447	0.2500	1	4
797	384	2	Week Four	Basic	12	7	84	0	0	1.0000	0.3182	0.2500	1	4
798	385	2	Week Four	Basic	5	7	35	0	0	1.0000	0.1326	0.2500	1	4
799	386	2	Week Four	Basic	11	7	77	0	0	1.0000	0.2917	0.2500	1	4
800	387	2	Week Four	Basic	9	7	63	0	0	1.0000	0.2386	0.2500	1	4
801	388	2	Week Four	Basic	17	7	119	0	0	1.0000	0.4508	0.2500	1	4
802	389	2	Week Four	Basic	0	7	0	0	0	1.0000	0.0000	0.2500	1	4
803	390	2	Week Four	Basic	19	7	133	0	0	1.0000	0.5038	0.2500	1	4
804	391	2	Week Four	Basic	7	7	49	0	0	1.0000	0.1856	0.2500	1	4
805	392	2	Week Four	Basic	15	7	105	0	0	1.0000	0.3977	0.2500	1	4
806	393	2	Week Four	Basic	15	7	105	0	0	1.0000	0.3977	0.2500	1	4
807	394	2	Week Four	Basic	12	7	84	0	0	1.0000	0.3182	0.2500	1	4
808	395	2	Week Four	Basic	9	7	63	0	0	1.0000	0.2386	0.2500	1	4
809	396	2	Week Four	Basic	9	7	63	0	0	1.0000	0.2386	0.2500	1	4
810	397	2	Week Four	Basic	7	7	49	1	49	1.0000	0.1856	0.2500	1	4
811	398	2	Week Four	Basic	4	7	28	0	0	1.0000	0.1061	0.2500	1	4
812	399	2	Week Four	Basic	9	7	63	0	0	1.0000	0.2386	0.2500	1	4
813	400	2	Week Four	Basic	5	7	35	0	0	1.0000	0.1326	0.2500	1	4
814	401	2	Week Four	Basic	8	7	56	0	0	1.0000	0.2121	0.2500	1	4
815	463	2	Actual Day	Basic	1	13	13	0	0	0.0952	0.0492	0.2653	1	5
816	464	2	Actual Day	Basic	10	13	130	0	0	0.0476	0.4924	0.2653	1	5
817	465	2	Actual Day	Basic	3	13	39	0	0	0.1270	0.1477	0.2653	1	5
818	466	2	Actual Day	Basic	2	13	26	0	0	0.0952	0.0985	0.2653	1	5
819	467	2	Actual Day	Basic	1	13	13	1	13	0.3651	0.0492	0.2653	1	5
820	468	2	Actual Day	Basic	11	13	143	0	0	0.0317	0.5417	0.2653	1	5
821	469	2	Actual Day	Basic	9	13	117	1	117	0.0476	0.4432	0.2653	1	5
822	470	2	Actual Day	Basic	0	13	0	0	0	0.8254	0.0000	0.2653	1	5
823	471	2	Actual Day	Basic	5	13	65	0	0	0.0159	0.2462	0.2653	1	5
824	472	2	Actual Day	Basic	15	13	195	0	0	0.0000	0.7386	0.2653	1	5
825	473	2	Actual Day	Basic	2	13	26	0	0	0.0794	0.0985	0.2653	1	5
826	474	2	Actual Day	Basic	4	13	52	0	0	0.3175	0.1970	0.2653	1	5
827	475	2	Actual Day	Basic	10	13	130	0	0	-0.0159	0.4924	0.2653	1	5
828	476	2	Actual Day	Basic	8	13	104	0	0	0.0000	0.3939	0.2653	1	5
829	477	2	Actual Day	Basic	9	13	117	1	117	-0.0159	0.4432	0.2653	1	5
830	478	2	Actual Day	Basic	9	13	117	0	0	-0.0317	0.4432	0.2653	1	5

Figure A.24: MS Excel Solver Risk Platform IP Data Set (23)



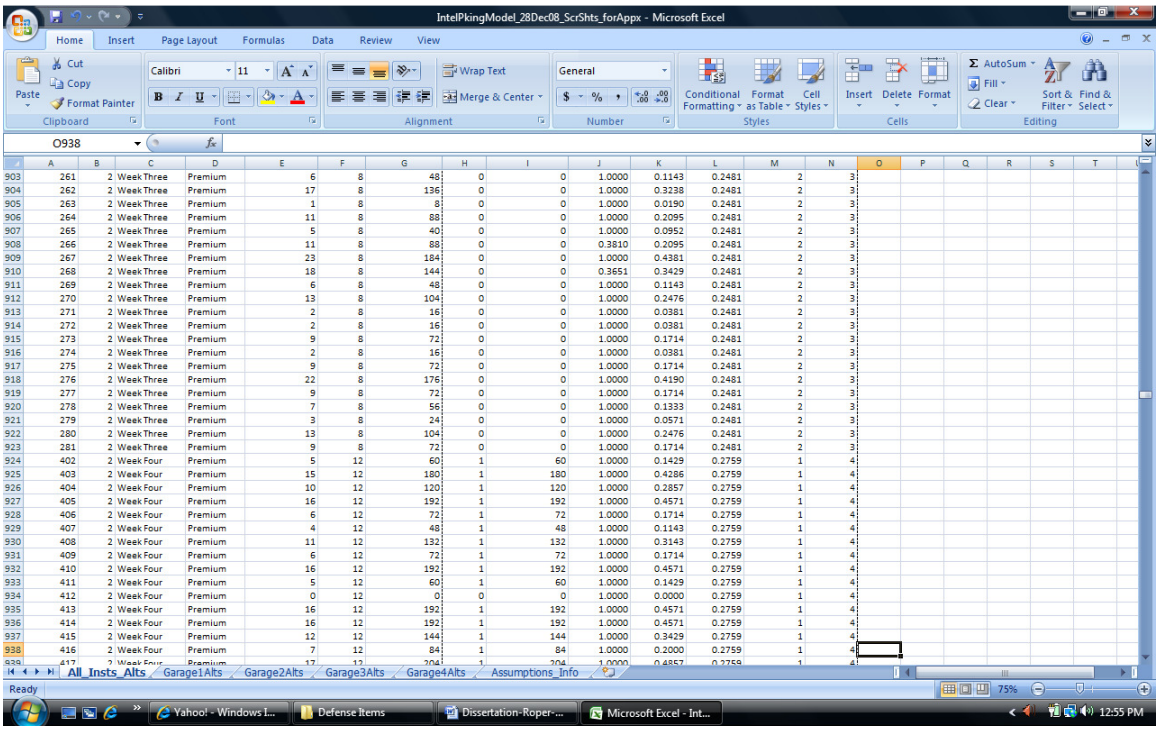
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
832	32	2	Week One	Premium	9	2.5	22.5	0	0	0.9683	0.0536	0.2128	4	1
833	33	2	Week One	Premium	22	2.5	55	0	0	1.0000	0.1310	0.2128	4	1
834	34	2	Week One	Premium	13	2.5	32.5	0	0	0.9683	0.0774	0.2128	4	1
835	35	2	Week One	Premium	1	2.5	2.5	0	0	0.9524	0.0060	0.2128	4	1
836	36	2	Week One	Premium	3	2.5	7.5	0	0	0.9683	0.0179	0.2128	4	1
837	37	2	Week One	Premium	12	2.5	30	0	0	0.9524	0.0714	0.2128	4	1
838	38	2	Week One	Premium	4	2.5	10	0	0	0.9365	0.0238	0.2128	4	1
839	39	2	Week One	Premium	18	2.5	45	0	0	0.9206	0.1071	0.2128	4	1
840	40	2	Week One	Premium	14	2.5	35	0	0	1.0000	0.0833	0.2128	4	1
841	41	2	Week One	Premium	3	2.5	7.5	0	0	1.0000	0.0179	0.2128	4	1
842	42	2	Week One	Premium	19	2.5	47.5	0	0	0.9048	0.1131	0.2128	4	1
843	43	2	Week One	Premium	4	2.5	10	0	0	0.8889	0.0238	0.2128	4	1
844	44	2	Week One	Premium	16	2.5	40	0	0	1.0000	0.0952	0.2128	4	1
845	45	2	Week One	Premium	6	2.5	15	0	0	1.0000	0.0357	0.2128	4	1
846	46	2	Week One	Premium	2	2.5	5	0	0	0.8889	0.0119	0.2128	4	1
847	47	2	Week One	Premium	5	2.5	12.5	0	0	0.9048	0.0298	0.2128	4	1
848	48	2	Week One	Premium	3	2.5	7.5	0	0	0.8889	0.0179	0.2128	4	1
849	49	2	Week One	Premium	4	2.5	10	0	0	1.0000	0.0238	0.2128	4	1
850	116	2	Week Two	Premium	1	5	5	0	0	1.0000	0.0119	0.2222	4	2
851	117	2	Week Two	Premium	2	5	10	0	0	1.0000	0.0238	0.2222	4	2
852	118	2	Week Two	Premium	1	5	5	0	0	1.0000	0.0119	0.2222	4	2
853	119	2	Week Two	Premium	3	5	15	0	0	1.0000	0.0357	0.2222	4	2
854	120	2	Week Two	Premium	4	5	20	0	0	1.0000	0.0476	0.2222	4	2
855	121	2	Week Two	Premium	11	5	55	0	0	1.0000	0.1310	0.2222	4	2
856	122	2	Week Two	Premium	12	5	60	0	0	1.0000	0.1429	0.2222	4	2
857	123	2	Week Two	Premium	9	5	45	0	0	1.0000	0.1071	0.2222	4	2
858	124	2	Week Two	Premium	1	5	5	0	0	1.0000	0.0119	0.2222	4	2
859	125	2	Week Two	Premium	14	5	70	0	0	1.0000	0.1667	0.2222	4	2
860	126	2	Week Two	Premium	13	5	65	0	0	1.0000	0.1548	0.2222	4	2
861	127	2	Week Two	Premium	13	5	65	0	0	1.0000	0.1548	0.2222	4	2
862	128	2	Week Two	Premium	7	5	35	0	0	1.0000	0.0833	0.2222	4	2
863	129	2	Week Two	Premium	10	5	50	0	0	1.0000	0.1190	0.2222	4	2
864	130	2	Week Two	Premium	11	5	55	0	0	1.0000	0.1310	0.2222	4	2
865	131	2	Week Two	Premium	9	5	45	0	0	1.0000	0.1071	0.2222	4	2
866	132	2	Week Two	Premium	21	5	105	0	0	1.0000	0.2500	0.2222	4	2
867	133	2	Week Two	Premium	19	5	95	0	0	1.0000	0.2262	0.2222	4	2

Figure A.25: MS Excel Solver Risk Platform IP Data Set (24)



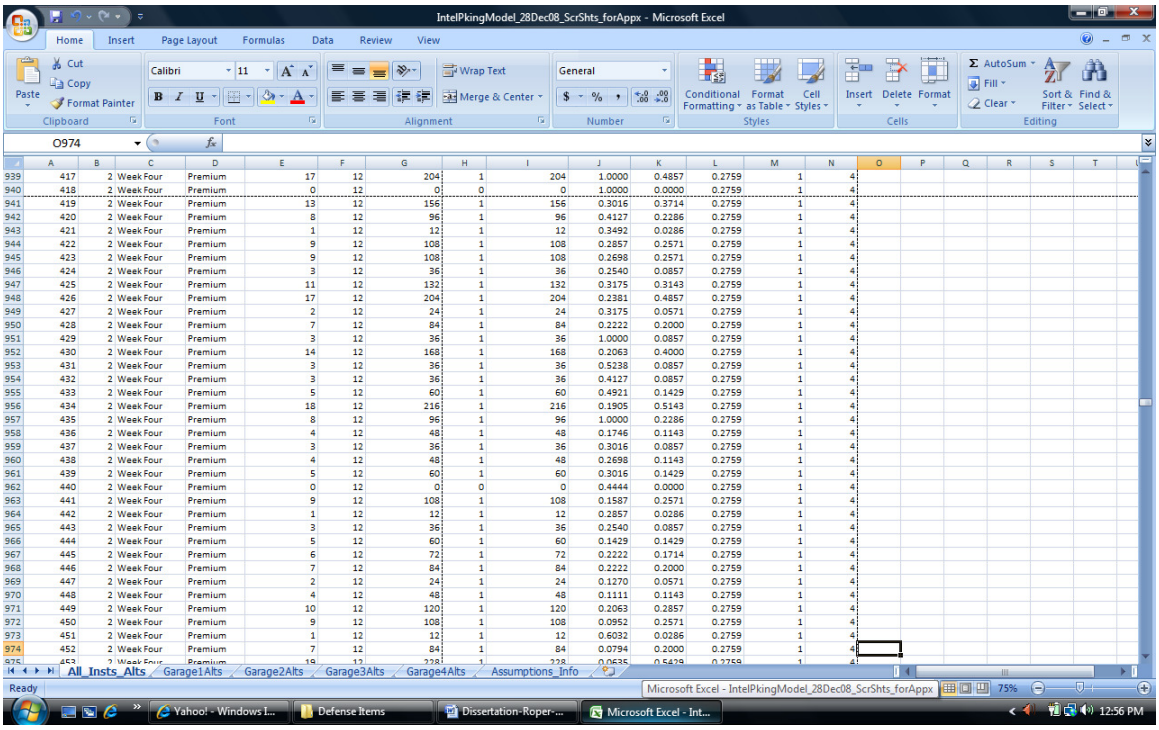
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
868	134	2	Week Two	Premium	1	5	5	0	0	1.0000	0.0119	0.2222	4	2
869	135	2	Week Two	Premium	5	5	25	0	0	1.0000	0.0595	0.2222	4	2
870	136	2	Week Two	Premium	7	5	35	0	0	1.0000	0.0833	0.2222	4	2
871	137	2	Week Two	Premium	8	5	40	0	0	1.0000	0.0952	0.2222	4	2
872	138	2	Week Two	Premium	10	5	50	0	0	1.0000	0.1190	0.2222	4	2
873	139	2	Week Two	Premium	16	5	80	0	0	1.0000	0.1905	0.2222	4	2
874	140	2	Week Two	Premium	20	5	100	0	0	1.0000	0.2381	0.2222	4	2
875	141	2	Week Two	Premium	3	5	15	0	0	1.0000	0.0357	0.2222	4	2
876	142	2	Week Two	Premium	14	5	70	0	0	1.0000	0.1667	0.2222	4	2
877	143	2	Week Two	Premium	7	5	35	0	0	1.0000	0.0833	0.2222	4	2
878	236	2	Week Three	Premium	14	8	112	0	0	1.0000	0.2667	0.2481	2	3
879	237	2	Week Three	Premium	4	8	32	0	0	1.0000	0.0762	0.2481	2	3
880	238	2	Week Three	Premium	15	8	120	0	0	1.0000	0.2857	0.2481	2	3
881	239	2	Week Three	Premium	7	8	56	0	0	1.0000	0.1333	0.2481	2	3
882	240	2	Week Three	Premium	3	8	24	0	0	1.0000	0.0571	0.2481	2	3
883	241	2	Week Three	Premium	5	8	40	0	0	1.0000	0.0952	0.2481	2	3
884	242	2	Week Three	Premium	0	8	0	0	0	1.0000	0.0000	0.2481	2	3
885	243	2	Week Three	Premium	10	8	80	0	0	1.0000	0.1905	0.2481	2	3
886	244	2	Week Three	Premium	5	8	40	0	0	1.0000	0.0952	0.2481	2	3
887	245	2	Week Three	Premium	8	8	64	0	0	1.0000	0.1524	0.2481	2	3
888	246	2	Week Three	Premium	6	8	48	0	0	1.0000	0.1143	0.2481	2	3
889	247	2	Week Three	Premium	2	8	16	0	0	0.7302	0.0381	0.2481	2	3
890	248	2	Week Three	Premium	11	8	88	0	0	1.0000	0.2095	0.2481	2	3
891	249	2	Week Three	Premium	11	8	88	0	0	1.0000	0.2095	0.2481	2	3
892	250	2	Week Three	Premium	15	8	120	0	0	1.0000	0.2857	0.2481	2	3
893	251	2	Week Three	Premium	5	8	40	0	0	1.0000	0.0952	0.2481	2	3
894	252	2	Week Three	Premium	9	8	72	0	0	1.0000	0.1714	0.2481	2	3
895	253	2	Week Three	Premium	19	8	152	0	0	1.0000	0.3619	0.2481	2	3
896	254	2	Week Three	Premium	3	8	24	0	0	1.0000	0.0571	0.2481	2	3
897	255	2	Week Three	Premium	3	8	24	0	0	1.0000	0.0571	0.2481	2	3
898	256	2	Week Three	Premium	12	8	96	0	0	1.0000	0.2286	0.2481	2	3
899	257	2	Week Three	Premium	15	8	120	0	0	1.0000	0.2857	0.2481	2	3
900	258	2	Week Three	Premium	2	8	16	0	0	1.0000	0.0381	0.2481	2	3
901	259	2	Week Three	Premium	16	8	128	0	0	0.3968	0.3048	0.2481	2	3
902	260	2	Week Three	Premium	13	8	104	0	0	1.0000	0.2476	0.2481	2	3
903	261	2	Week Three	Premium	6	8	48	0	0	1.0000	0.1143	0.2481	2	3

Figure A.26: MS Excel Solver Risk Platform IP Data Set (25)



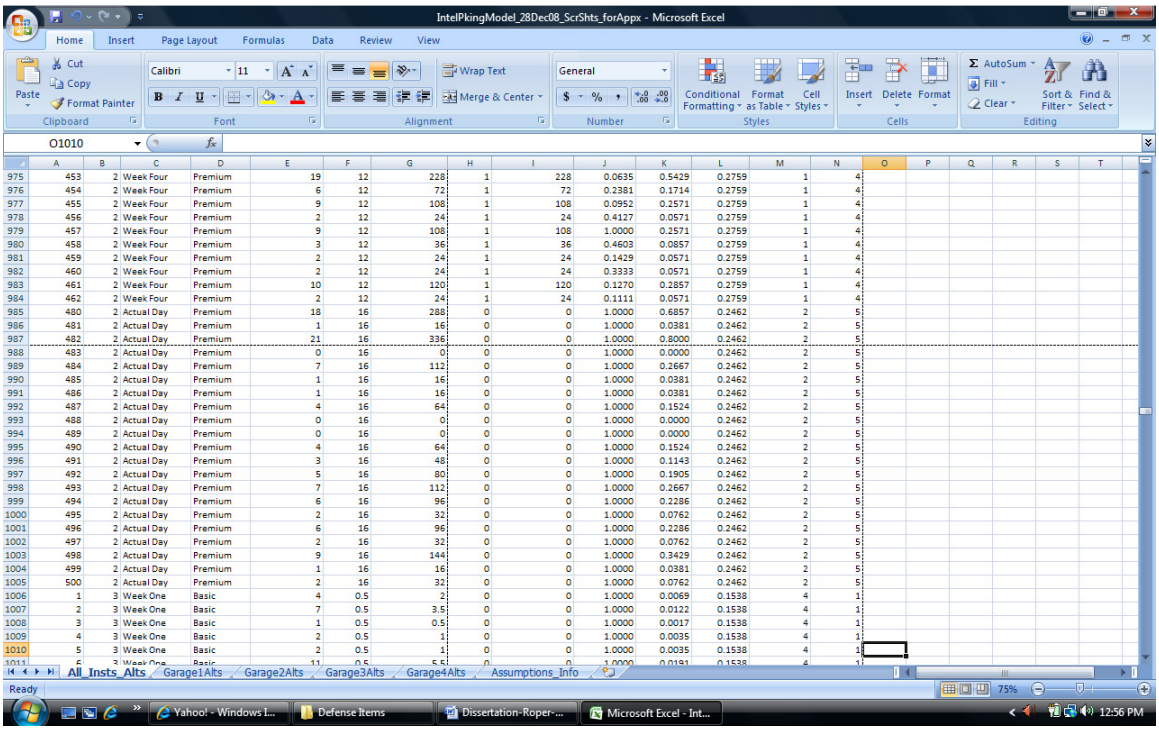
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
903	261	2	Week Three	Premium	6	8	48	0	0	1.0000	0.1143	0.2481	2	3
904	262	2	Week Three	Premium	17	8	136	0	0	1.0000	0.3238	0.2481	2	3
905	263	2	Week Three	Premium	1	8	8	0	0	1.0000	0.0190	0.2481	2	3
906	264	2	Week Three	Premium	11	8	88	0	0	1.0000	0.2095	0.2481	2	3
907	265	2	Week Three	Premium	5	8	40	0	0	1.0000	0.0952	0.2481	2	3
908	266	2	Week Three	Premium	11	8	88	0	0	0.3810	0.2095	0.2481	2	3
909	267	2	Week Three	Premium	23	8	184	0	0	1.0000	0.4381	0.2481	2	3
910	268	2	Week Three	Premium	18	8	144	0	0	0.3651	0.3429	0.2481	2	3
911	269	2	Week Three	Premium	6	8	48	0	0	1.0000	0.1143	0.2481	2	3
912	270	2	Week Three	Premium	13	8	104	0	0	1.0000	0.2476	0.2481	2	3
913	271	2	Week Three	Premium	2	8	16	0	0	1.0000	0.0381	0.2481	2	3
914	272	2	Week Three	Premium	2	8	16	0	0	1.0000	0.0381	0.2481	2	3
915	273	2	Week Three	Premium	9	8	72	0	0	1.0000	0.1714	0.2481	2	3
916	274	2	Week Three	Premium	2	8	16	0	0	1.0000	0.0381	0.2481	2	3
917	275	2	Week Three	Premium	9	8	72	0	0	1.0000	0.1714	0.2481	2	3
918	276	2	Week Three	Premium	22	8	176	0	0	1.0000	0.4190	0.2481	2	3
919	277	2	Week Three	Premium	9	8	72	0	0	1.0000	0.1714	0.2481	2	3
920	278	2	Week Three	Premium	7	8	56	0	0	1.0000	0.1333	0.2481	2	3
921	279	2	Week Three	Premium	3	8	24	0	0	1.0000	0.0571	0.2481	2	3
922	280	2	Week Three	Premium	13	8	104	0	0	1.0000	0.2476	0.2481	2	3
923	281	2	Week Three	Premium	9	8	72	0	0	1.0000	0.1714	0.2481	2	3
924	402	2	Week Four	Premium	5	12	60	1	60	1.0000	0.1429	0.2759	1	4
925	403	2	Week Four	Premium	15	12	180	1	180	1.0000	0.4286	0.2759	1	4
926	404	2	Week Four	Premium	10	12	120	1	120	1.0000	0.2857	0.2759	1	4
927	405	2	Week Four	Premium	16	12	192	1	192	1.0000	0.4571	0.2759	1	4
928	406	2	Week Four	Premium	6	12	72	1	72	1.0000	0.1714	0.2759	1	4
929	407	2	Week Four	Premium	4	12	48	1	48	1.0000	0.1143	0.2759	1	4
930	408	2	Week Four	Premium	11	12	132	1	132	1.0000	0.3143	0.2759	1	4
931	409	2	Week Four	Premium	6	12	72	1	72	1.0000	0.1714	0.2759	1	4
932	410	2	Week Four	Premium	16	12	192	1	192	1.0000	0.4571	0.2759	1	4
933	411	2	Week Four	Premium	5	12	60	1	60	1.0000	0.1429	0.2759	1	4
934	412	2	Week Four	Premium	0	12	0	0	0	1.0000	0.0000	0.2759	1	4
935	413	2	Week Four	Premium	16	12	192	1	192	1.0000	0.4571	0.2759	1	4
936	414	2	Week Four	Premium	16	12	192	1	192	1.0000	0.4571	0.2759	1	4
937	415	2	Week Four	Premium	12	12	144	1	144	1.0000	0.3429	0.2759	1	4
938	416	2	Week Four	Premium	7	12	84	1	84	1.0000	0.2000	0.2759	1	4

Figure A.27: MS Excel Solver Risk Platform IP Data Set (26)



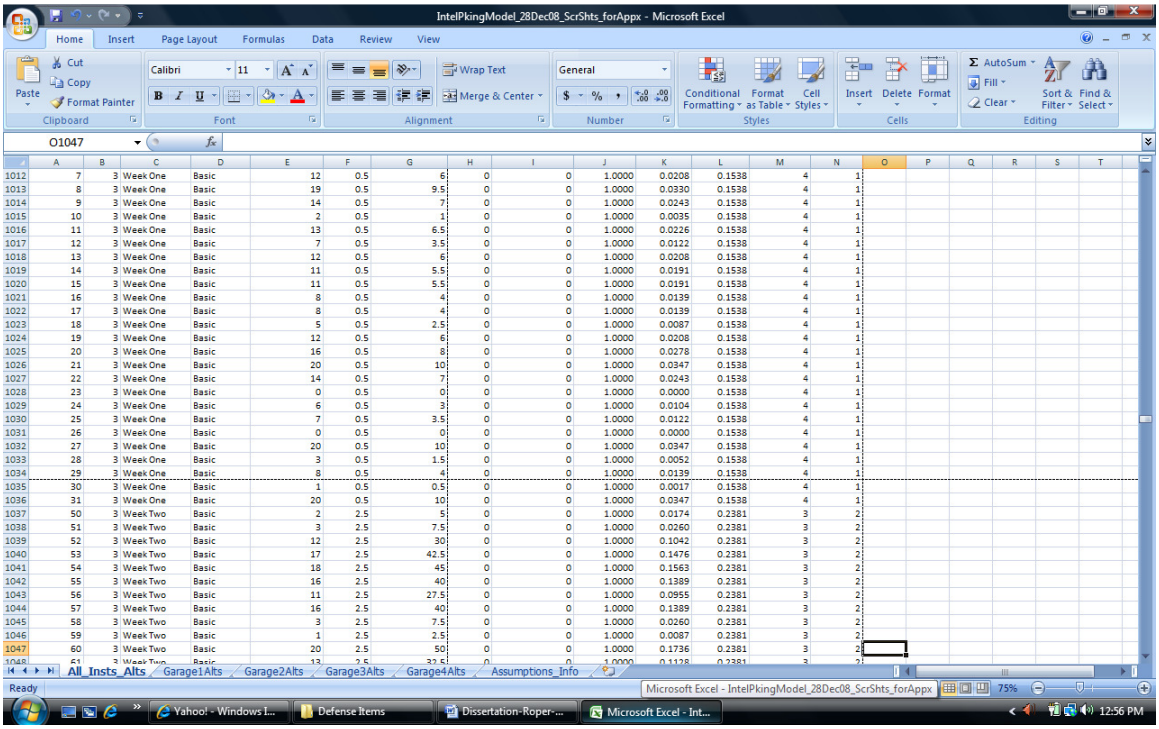
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
939	417	2	Week Four	Premium	17	12	204	1	204	1.0000	0.4857	0.2759	1	4
940	418	2	Week Four	Premium	0	12	0	0	0	1.0000	0.0000	0.2759	1	4
941	419	2	Week Four	Premium	13	12	156	1	156	0.3016	0.3714	0.2759	1	4
942	420	2	Week Four	Premium	8	12	96	1	96	0.4127	0.2286	0.2759	1	4
943	421	2	Week Four	Premium	1	12	12	1	12	0.3492	0.0286	0.2759	1	4
944	422	2	Week Four	Premium	9	12	108	1	108	0.2857	0.2571	0.2759	1	4
945	423	2	Week Four	Premium	9	12	108	1	108	0.2698	0.2571	0.2759	1	4
946	424	2	Week Four	Premium	3	12	36	1	36	0.2540	0.0857	0.2759	1	4
947	425	2	Week Four	Premium	11	12	132	1	132	0.3175	0.3143	0.2759	1	4
948	426	2	Week Four	Premium	17	12	204	1	204	0.2381	0.4857	0.2759	1	4
949	427	2	Week Four	Premium	2	12	24	1	24	0.3175	0.0571	0.2759	1	4
950	428	2	Week Four	Premium	7	12	84	1	84	0.2222	0.2000	0.2759	1	4
951	429	2	Week Four	Premium	3	12	36	1	36	1.0000	0.0857	0.2759	1	4
952	430	2	Week Four	Premium	14	12	168	1	168	0.2063	0.4000	0.2759	1	4
953	431	2	Week Four	Premium	3	12	36	1	36	0.5238	0.0857	0.2759	1	4
954	432	2	Week Four	Premium	3	12	36	1	36	0.4127	0.0857	0.2759	1	4
955	433	2	Week Four	Premium	5	12	60	1	60	0.4921	0.1429	0.2759	1	4
956	434	2	Week Four	Premium	18	12	216	1	216	0.1905	0.5143	0.2759	1	4
957	435	2	Week Four	Premium	8	12	96	1	96	1.0000	0.2286	0.2759	1	4
958	436	2	Week Four	Premium	4	12	48	1	48	0.1746	0.1143	0.2759	1	4
959	437	2	Week Four	Premium	3	12	36	1	36	0.3016	0.0857	0.2759	1	4
960	438	2	Week Four	Premium	4	12	48	1	48	0.2698	0.1143	0.2759	1	4
961	439	2	Week Four	Premium	5	12	60	1	60	0.3016	0.1429	0.2759	1	4
962	440	2	Week Four	Premium	0	12	0	0	0	0.4444	0.0000	0.2759	1	4
963	441	2	Week Four	Premium	9	12	108	1	108	0.1587	0.2571	0.2759	1	4
964	442	2	Week Four	Premium	1	12	12	1	12	0.2857	0.0286	0.2759	1	4
965	443	2	Week Four	Premium	3	12	36	1	36	0.2540	0.0857	0.2759	1	4
966	444	2	Week Four	Premium	5	12	60	1	60	0.1429	0.1429	0.2759	1	4
967	445	2	Week Four	Premium	6	12	72	1	72	0.2222	0.1714	0.2759	1	4
968	446	2	Week Four	Premium	7	12	84	1	84	0.2222	0.2000	0.2759	1	4
969	447	2	Week Four	Premium	2	12	24	1	24	0.1270	0.0571	0.2759	1	4
970	448	2	Week Four	Premium	4	12	48	1	48	0.1111	0.1143	0.2759	1	4
971	449	2	Week Four	Premium	10	12	120	1	120	0.2063	0.2857	0.2759	1	4
972	450	2	Week Four	Premium	9	12	108	1	108	0.0952	0.2571	0.2759	1	4
973	451	2	Week Four	Premium	1	12	12	1	12	0.6032	0.0286	0.2759	1	4
974	452	2	Week Four	Premium	7	12	84	1	84	0.0794	0.2000	0.2759	1	4

Figure A.28: MS Excel Solver Risk Platform IP Data Set (27)



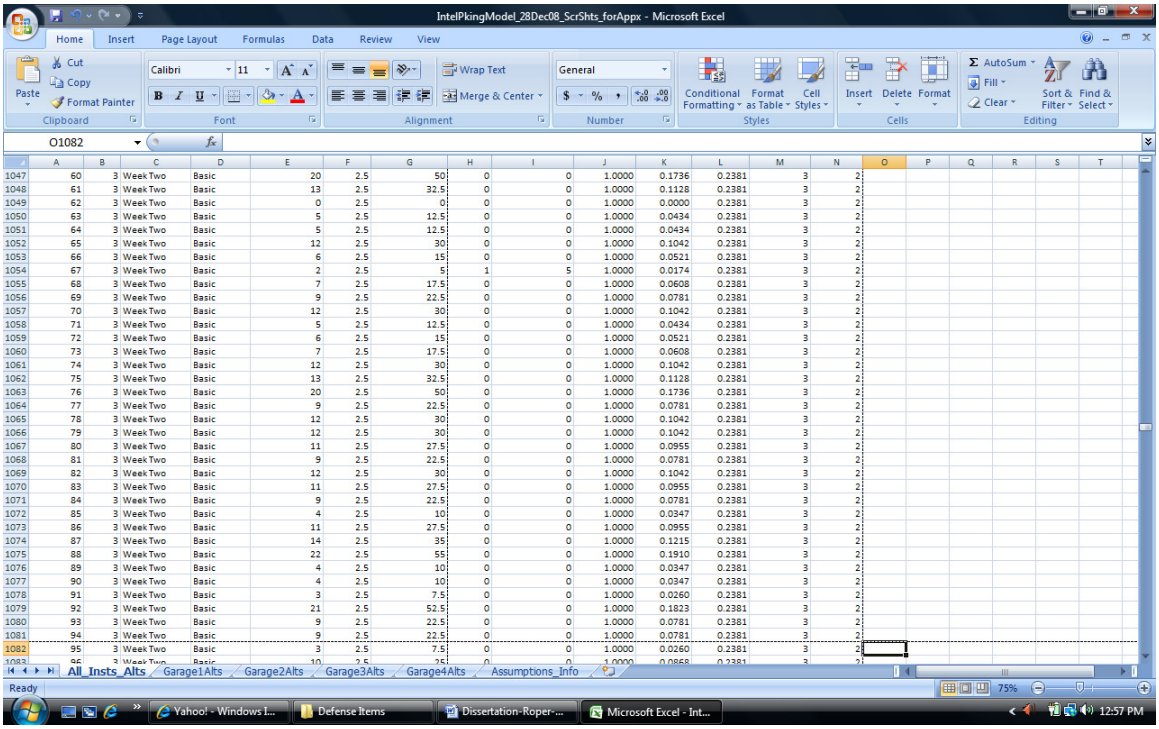
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
975	453	2	Week Four	Premium	19	12	228	1	228	0.0635	0.5429	0.2759	1	4
976	454	2	Week Four	Premium	6	12	72	1	72	0.2381	0.1714	0.2759	1	4
977	455	2	Week Four	Premium	9	12	108	1	108	0.0952	0.2571	0.2759	1	4
978	456	2	Week Four	Premium	2	12	24	1	24	0.4127	0.0571	0.2759	1	4
979	457	2	Week Four	Premium	9	12	108	1	108	1.0000	0.2571	0.2759	1	4
980	458	2	Week Four	Premium	3	12	36	1	36	0.4603	0.0857	0.2759	1	4
981	459	2	Week Four	Premium	2	12	24	1	24	0.1429	0.0571	0.2759	1	4
982	460	2	Week Four	Premium	2	12	24	1	24	0.3333	0.0571	0.2759	1	4
983	461	2	Week Four	Premium	10	12	120	1	120	0.1270	0.2857	0.2759	1	4
984	462	2	Week Four	Premium	2	12	24	1	24	0.1111	0.0571	0.2759	1	4
985	480	2	Actual Day	Premium	18	16	288	0	0	1.0000	0.6857	0.2462	2	5
986	481	2	Actual Day	Premium	1	16	16	0	0	1.0000	0.0381	0.2462	2	5
987	482	2	Actual Day	Premium	21	16	336	0	0	1.0000	0.8000	0.2462	2	5
988	483	2	Actual Day	Premium	0	16	0	0	0	1.0000	0.0000	0.2462	2	5
989	484	2	Actual Day	Premium	7	16	112	0	0	1.0000	0.2667	0.2462	2	5
990	485	2	Actual Day	Premium	1	16	16	0	0	1.0000	0.0381	0.2462	2	5
991	486	2	Actual Day	Premium	1	16	16	0	0	1.0000	0.0381	0.2462	2	5
992	487	2	Actual Day	Premium	4	16	64	0	0	1.0000	0.1524	0.2462	2	5
993	488	2	Actual Day	Premium	0	16	0	0	0	1.0000	0.0000	0.2462	2	5
994	489	2	Actual Day	Premium	0	16	0	0	0	1.0000	0.0000	0.2462	2	5
995	490	2	Actual Day	Premium	4	16	64	0	0	1.0000	0.1524	0.2462	2	5
996	491	2	Actual Day	Premium	3	16	48	0	0	1.0000	0.1143	0.2462	2	5
997	492	2	Actual Day	Premium	5	16	80	0	0	1.0000	0.1905	0.2462	2	5
998	493	2	Actual Day	Premium	7	16	112	0	0	1.0000	0.2667	0.2462	2	5
999	494	2	Actual Day	Premium	6	16	96	0	0	1.0000	0.2286	0.2462	2	5
1000	495	2	Actual Day	Premium	2	16	32	0	0	1.0000	0.0762	0.2462	2	5
1001	496	2	Actual Day	Premium	6	16	96	0	0	1.0000	0.2286	0.2462	2	5
1002	497	2	Actual Day	Premium	2	16	32	0	0	1.0000	0.0762	0.2462	2	5
1003	498	2	Actual Day	Premium	9	16	144	0	0	1.0000	0.3429	0.2462	2	5
1004	499	2	Actual Day	Premium	1	16	16	0	0	1.0000	0.0381	0.2462	2	5
1005	500	2	Actual Day	Premium	2	16	32	0	0	1.0000	0.0762	0.2462	2	5
1006	1	3	Week One	Basic	4	0.5	2	0	0	1.0000	0.0069	0.1538	4	1
1007	2	3	Week One	Basic	7	0.5	3.5	0	0	1.0000	0.0122	0.1538	4	1
1008	3	3	Week One	Basic	1	0.5	0.5	0	0	1.0000	0.0017	0.1538	4	1
1009	4	3	Week One	Basic	2	0.5	1	0	0	1.0000	0.0035	0.1538	4	1
1010	5	3	Week One	Basic	2	0.5	1	0	0	1.0000	0.0035	0.1538	4	1

Figure A.29: MS Excel Solver Risk Platform IP Data Set (28)



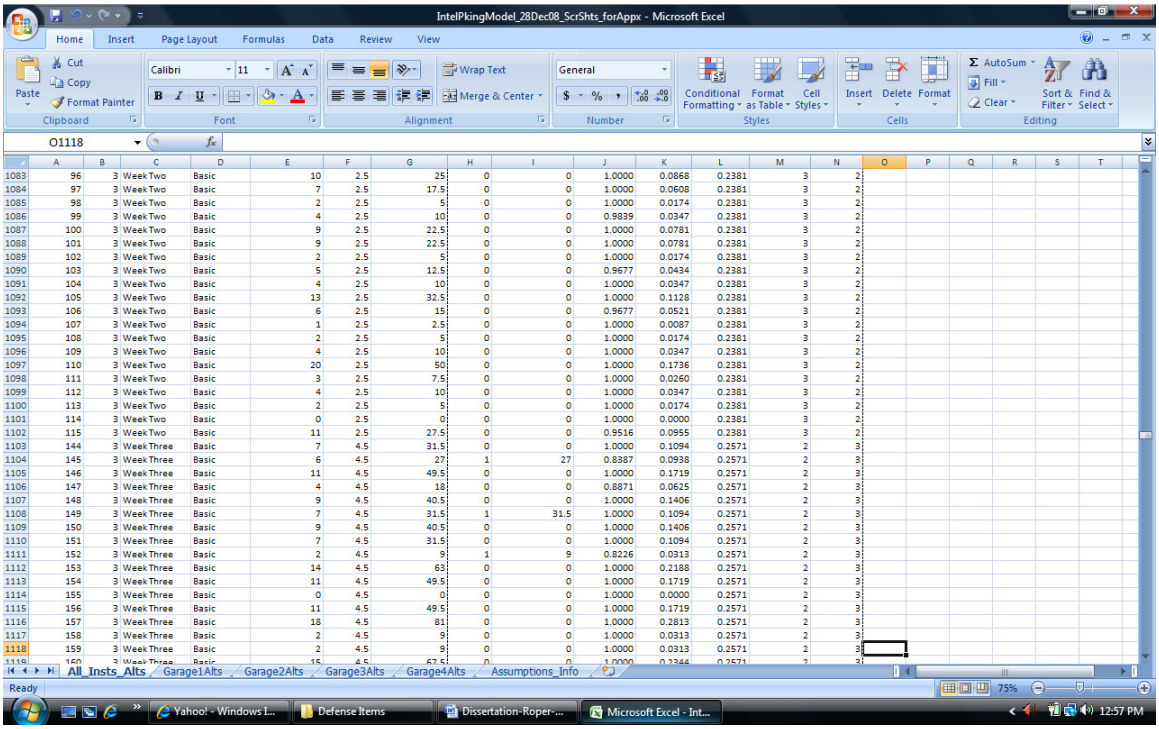
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1012	7	3	Week One	Basic	12	0.5	6	0	0	1.0000	0.0208	0.1538	4	1
1013	8	3	Week One	Basic	19	0.5	9.5	0	0	1.0000	0.0330	0.1538	4	1
1014	9	3	Week One	Basic	14	0.5	7	0	0	1.0000	0.0243	0.1538	4	1
1015	10	3	Week One	Basic	2	0.5	1	0	0	1.0000	0.0035	0.1538	4	1
1016	11	3	Week One	Basic	13	0.5	6.5	0	0	1.0000	0.0226	0.1538	4	1
1017	12	3	Week One	Basic	7	0.5	3.5	0	0	1.0000	0.0122	0.1538	4	1
1018	13	3	Week One	Basic	12	0.5	6	0	0	1.0000	0.0208	0.1538	4	1
1019	14	3	Week One	Basic	11	0.5	5.5	0	0	1.0000	0.0191	0.1538	4	1
1020	15	3	Week One	Basic	11	0.5	5.5	0	0	1.0000	0.0191	0.1538	4	1
1021	16	3	Week One	Basic	8	0.5	4	0	0	1.0000	0.0139	0.1538	4	1
1022	17	3	Week One	Basic	8	0.5	4	0	0	1.0000	0.0139	0.1538	4	1
1023	18	3	Week One	Basic	5	0.5	2.5	0	0	1.0000	0.0087	0.1538	4	1
1024	19	3	Week One	Basic	12	0.5	6	0	0	1.0000	0.0208	0.1538	4	1
1025	20	3	Week One	Basic	16	0.5	8	0	0	1.0000	0.0278	0.1538	4	1
1026	21	3	Week One	Basic	20	0.5	10	0	0	1.0000	0.0347	0.1538	4	1
1027	22	3	Week One	Basic	14	0.5	7	0	0	1.0000	0.0243	0.1538	4	1
1028	23	3	Week One	Basic	0	0.5	0	0	0	1.0000	0.0000	0.1538	4	1
1029	24	3	Week One	Basic	6	0.5	3	0	0	1.0000	0.0104	0.1538	4	1
1030	25	3	Week One	Basic	7	0.5	3.5	0	0	1.0000	0.0122	0.1538	4	1
1031	26	3	Week One	Basic	0	0.5	0	0	0	1.0000	0.0000	0.1538	4	1
1032	27	3	Week One	Basic	20	0.5	10	0	0	1.0000	0.0347	0.1538	4	1
1033	28	3	Week One	Basic	3	0.5	1.5	0	0	1.0000	0.0052	0.1538	4	1
1034	29	3	Week One	Basic	8	0.5	4	0	0	1.0000	0.0139	0.1538	4	1
1035	30	3	Week One	Basic	1	0.5	0.5	0	0	1.0000	0.0017	0.1538	4	1
1036	31	3	Week One	Basic	20	0.5	10	0	0	1.0000	0.0347	0.1538	4	1
1037	50	3	Week Two	Basic	2	2.5	5	0	0	1.0000	0.0174	0.2381	3	2
1038	51	3	Week Two	Basic	3	2.5	7.5	0	0	1.0000	0.0260	0.2381	3	2
1039	52	3	Week Two	Basic	12	2.5	30	0	0	1.0000	0.1042	0.2381	3	2
1040	53	3	Week Two	Basic	17	2.5	42.5	0	0	1.0000	0.1476	0.2381	3	2
1041	54	3	Week Two	Basic	18	2.5	45	0	0	1.0000	0.1563	0.2381	3	2
1042	55	3	Week Two	Basic	16	2.5	40	0	0	1.0000	0.1389	0.2381	3	2
1043	56	3	Week Two	Basic	11	2.5	27.5	0	0	1.0000	0.0955	0.2381	3	2
1044	57	3	Week Two	Basic	16	2.5	40	0	0	1.0000	0.1389	0.2381	3	2
1045	58	3	Week Two	Basic	3	2.5	7.5	0	0	1.0000	0.0260	0.2381	3	2
1046	59	3	Week Two	Basic	1	2.5	2.5	0	0	1.0000	0.0087	0.2381	3	2
1047	60	3	Week Two	Basic	20	2.5	50	0	0	1.0000	0.1736	0.2381	3	2

Figure A.30: MS Excel Solver Risk Platform IP Data Set (29)



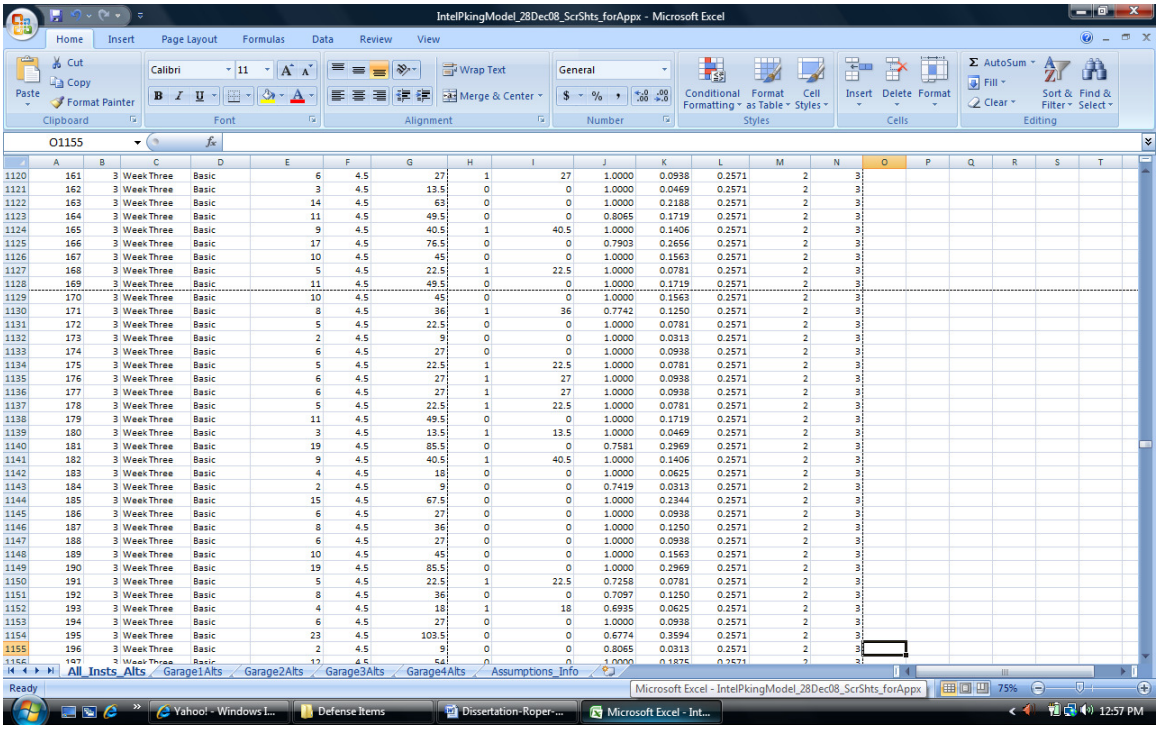
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1047	60	3	Week Two	Basic	20	2.5	50	0	0	1.0000	0.1736	0.2381	3	2
1048	61	3	Week Two	Basic	13	2.5	32.5	0	0	1.0000	0.1128	0.2381	3	2
1049	62	3	Week Two	Basic	0	2.5	0	0	0	1.0000	0.0000	0.2381	3	2
1050	63	3	Week Two	Basic	5	2.5	12.5	0	0	1.0000	0.0434	0.2381	3	2
1051	64	3	Week Two	Basic	5	2.5	12.5	0	0	1.0000	0.0434	0.2381	3	2
1052	65	3	Week Two	Basic	12	2.5	30	0	0	1.0000	0.1042	0.2381	3	2
1053	66	3	Week Two	Basic	6	2.5	15	0	0	1.0000	0.0521	0.2381	3	2
1054	67	3	Week Two	Basic	2	2.5	5	1	5	1.0000	0.0174	0.2381	3	2
1055	68	3	Week Two	Basic	7	2.5	17.5	0	0	1.0000	0.0608	0.2381	3	2
1056	69	3	Week Two	Basic	9	2.5	22.5	0	0	1.0000	0.0781	0.2381	3	2
1057	70	3	Week Two	Basic	12	2.5	30	0	0	1.0000	0.1042	0.2381	3	2
1058	71	3	Week Two	Basic	5	2.5	12.5	0	0	1.0000	0.0434	0.2381	3	2
1059	72	3	Week Two	Basic	6	2.5	15	0	0	1.0000	0.0521	0.2381	3	2
1060	73	3	Week Two	Basic	7	2.5	17.5	0	0	1.0000	0.0608	0.2381	3	2
1061	74	3	Week Two	Basic	12	2.5	30	0	0	1.0000	0.1042	0.2381	3	2
1062	75	3	Week Two	Basic	13	2.5	32.5	0	0	1.0000	0.1128	0.2381	3	2
1063	76	3	Week Two	Basic	20	2.5	50	0	0	1.0000	0.1736	0.2381	3	2
1064	77	3	Week Two	Basic	9	2.5	22.5	0	0	1.0000	0.0781	0.2381	3	2
1065	78	3	Week Two	Basic	12	2.5	30	0	0	1.0000	0.1042	0.2381	3	2
1066	79	3	Week Two	Basic	12	2.5	30	0	0	1.0000	0.1042	0.2381	3	2
1067	80	3	Week Two	Basic	11	2.5	27.5	0	0	1.0000	0.0955	0.2381	3	2
1068	81	3	Week Two	Basic	9	2.5	22.5	0	0	1.0000	0.0781	0.2381	3	2
1069	82	3	Week Two	Basic	12	2.5	30	0	0	1.0000	0.1042	0.2381	3	2
1070	83	3	Week Two	Basic	11	2.5	27.5	0	0	1.0000	0.0955	0.2381	3	2
1071	84	3	Week Two	Basic	9	2.5	22.5	0	0	1.0000	0.0781	0.2381	3	2
1072	85	3	Week Two	Basic	4	2.5	10	0	0	1.0000	0.0347	0.2381	3	2
1073	86	3	Week Two	Basic	11	2.5	27.5	0	0	1.0000	0.0955	0.2381	3	2
1074	87	3	Week Two	Basic	14	2.5	35	0	0	1.0000	0.1215	0.2381	3	2
1075	88	3	Week Two	Basic	22	2.5	55	0	0	1.0000	0.1910	0.2381	3	2
1076	89	3	Week Two	Basic	4	2.5	10	0	0	1.0000	0.0347	0.2381	3	2
1077	90	3	Week Two	Basic	4	2.5	10	0	0	1.0000	0.0347	0.2381	3	2
1078	91	3	Week Two	Basic	3	2.5	7.5	0	0	1.0000	0.0260	0.2381	3	2
1079	92	3	Week Two	Basic	21	2.5	52.5	0	0	1.0000	0.1823	0.2381	3	2
1080	93	3	Week Two	Basic	9	2.5	22.5	0	0	1.0000	0.0781	0.2381	3	2
1081	94	3	Week Two	Basic	9	2.5	22.5	0	0	1.0000	0.0781	0.2381	3	2
1082	95	3	Week Two	Basic	3	2.5	7.5	0	0	1.0000	0.0260	0.2381	3	2

Figure A.31: MS Excel Solver Risk Platform IP Data Set (30)



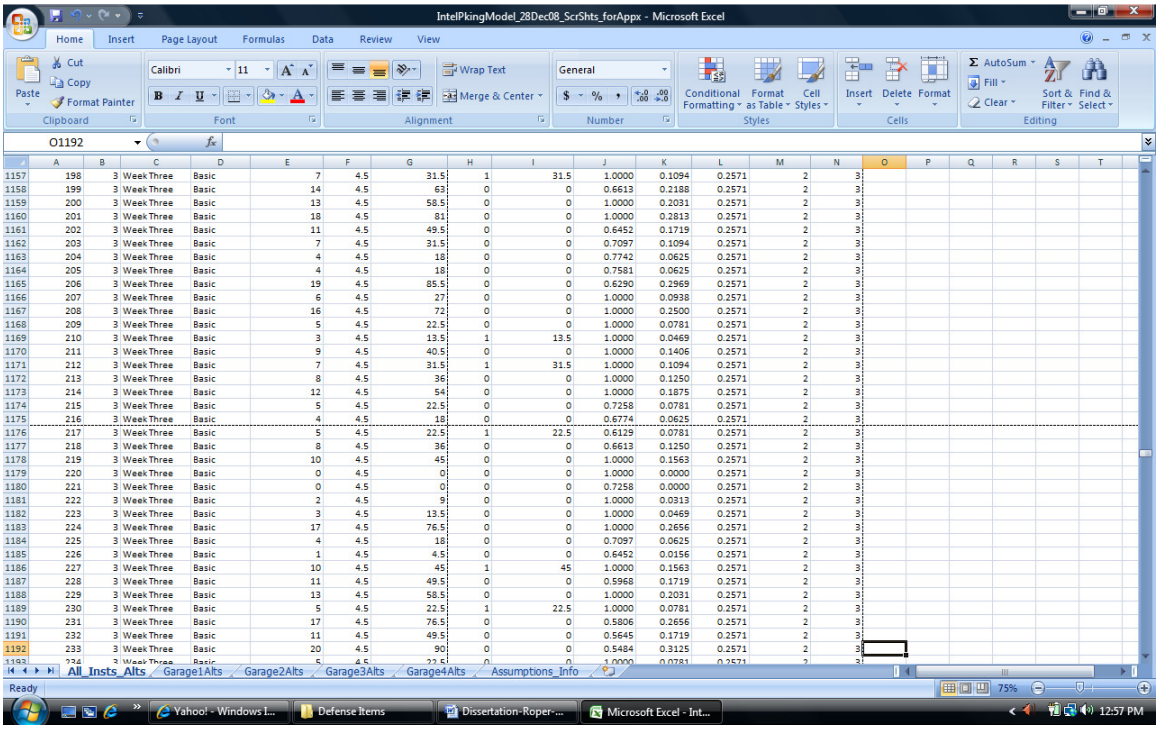
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1083	96	3	Week Two	Basic	10	2.5	25	0	0	1.0000	0.0868	0.2381	3	2
1084	97	3	Week Two	Basic	7	2.5	17.5	0	0	1.0000	0.0608	0.2381	3	2
1085	98	3	Week Two	Basic	2	2.5	5	0	0	1.0000	0.0174	0.2381	3	2
1086	99	3	Week Two	Basic	4	2.5	10	0	0	0.9839	0.0347	0.2381	3	2
1087	100	3	Week Two	Basic	9	2.5	22.5	0	0	1.0000	0.0781	0.2381	3	2
1088	101	3	Week Two	Basic	9	2.5	22.5	0	0	1.0000	0.0781	0.2381	3	2
1089	102	3	Week Two	Basic	2	2.5	5	0	0	1.0000	0.0174	0.2381	3	2
1090	103	3	Week Two	Basic	5	2.5	12.5	0	0	0.9677	0.0434	0.2381	3	2
1091	104	3	Week Two	Basic	4	2.5	10	0	0	1.0000	0.0347	0.2381	3	2
1092	105	3	Week Two	Basic	13	2.5	32.5	0	0	1.0000	0.1128	0.2381	3	2
1093	106	3	Week Two	Basic	6	2.5	15	0	0	0.9677	0.0521	0.2381	3	2
1094	107	3	Week Two	Basic	1	2.5	2.5	0	0	1.0000	0.0087	0.2381	3	2
1095	108	3	Week Two	Basic	2	2.5	5	0	0	1.0000	0.0174	0.2381	3	2
1096	109	3	Week Two	Basic	4	2.5	10	0	0	1.0000	0.0347	0.2381	3	2
1097	110	3	Week Two	Basic	20	2.5	50	0	0	1.0000	0.1736	0.2381	3	2
1098	111	3	Week Two	Basic	3	2.5	7.5	0	0	1.0000	0.0260	0.2381	3	2
1099	112	3	Week Two	Basic	4	2.5	10	0	0	1.0000	0.0347	0.2381	3	2
1100	113	3	Week Two	Basic	2	2.5	5	0	0	1.0000	0.0174	0.2381	3	2
1101	114	3	Week Two	Basic	0	2.5	0	0	0	1.0000	0.0000	0.2381	3	2
1102	115	3	Week Two	Basic	11	2.5	27.5	0	0	0.9516	0.0955	0.2381	3	2
1103	144	3	Week Three	Basic	7	4.5	31.5	0	0	1.0000	0.1094	0.2571	2	3
1104	145	3	Week Three	Basic	6	4.5	27	1	27	0.8387	0.0938	0.2571	2	3
1105	146	3	Week Three	Basic	11	4.5	49.5	0	0	1.0000	0.1719	0.2571	2	3
1106	147	3	Week Three	Basic	4	4.5	18	0	0	0.8871	0.0625	0.2571	2	3
1107	148	3	Week Three	Basic	9	4.5	40.5	0	0	1.0000	0.1406	0.2571	2	3
1108	149	3	Week Three	Basic	7	4.5	31.5	1	31.5	1.0000	0.1094	0.2571	2	3
1109	150	3	Week Three	Basic	9	4.5	40.5	0	0	1.0000	0.1406	0.2571	2	3
1110	151	3	Week Three	Basic	7	4.5	31.5	0	0	1.0000	0.1094	0.2571	2	3
1111	152	3	Week Three	Basic	2	4.5	9	1	9	0.8226	0.0313	0.2571	2	3
1112	153	3	Week Three	Basic	14	4.5	63	0	0	1.0000	0.2188	0.2571	2	3
1113	154	3	Week Three	Basic	11	4.5	49.5	0	0	1.0000	0.1719	0.2571	2	3
1114	155	3	Week Three	Basic	0	4.5	0	0	0	1.0000	0.0000	0.2571	2	3
1115	156	3	Week Three	Basic	11	4.5	49.5	0	0	1.0000	0.1719	0.2571	2	3
1116	157	3	Week Three	Basic	18	4.5	81	0	0	1.0000	0.2813	0.2571	2	3
1117	158	3	Week Three	Basic	2	4.5	9	0	0	1.0000	0.0313	0.2571	2	3
1118	159	3	Week Three	Basic	2	4.5	9	0	0	1.0000	0.0313	0.2571	2	3

Figure A.32: MS Excel Solver Risk Platform IP Data Set (31)



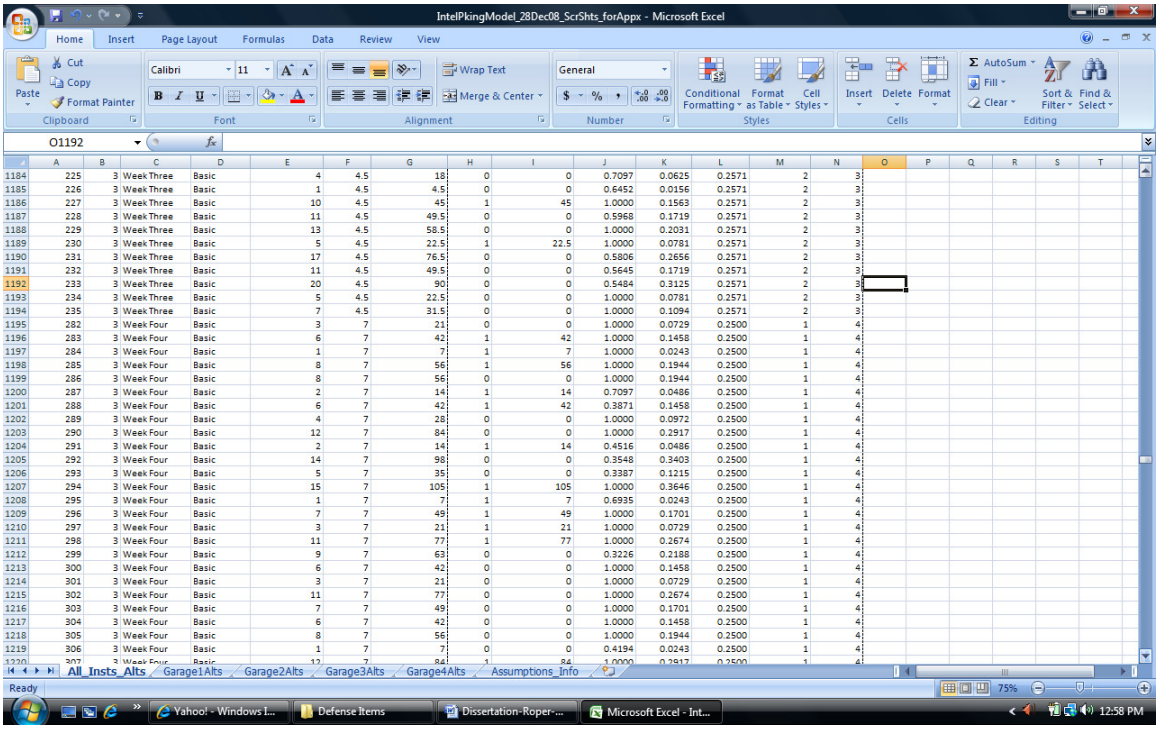
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1120	161	3	Week Three	Basic	6	4.5	27	1	27	1.0000	0.0938	0.2571	2	3
1121	162	3	Week Three	Basic	3	4.5	13.5	0	0	1.0000	0.0469	0.2571	2	3
1122	163	3	Week Three	Basic	14	4.5	63	0	0	1.0000	0.2188	0.2571	2	3
1123	164	3	Week Three	Basic	11	4.5	49.5	0	0	0.8065	0.1719	0.2571	2	3
1124	165	3	Week Three	Basic	9	4.5	40.5	1	40.5	1.0000	0.1406	0.2571	2	3
1125	166	3	Week Three	Basic	17	4.5	76.5	0	0	0.7903	0.2656	0.2571	2	3
1126	167	3	Week Three	Basic	10	4.5	45	0	0	1.0000	0.1563	0.2571	2	3
1127	168	3	Week Three	Basic	5	4.5	22.5	1	22.5	1.0000	0.0781	0.2571	2	3
1128	169	3	Week Three	Basic	11	4.5	49.5	0	0	1.0000	0.1719	0.2571	2	3
1129	170	3	Week Three	Basic	10	4.5	45	0	0	1.0000	0.1563	0.2571	2	3
1130	171	3	Week Three	Basic	8	4.5	36	1	36	0.7742	0.1250	0.2571	2	3
1131	172	3	Week Three	Basic	5	4.5	22.5	0	0	1.0000	0.0781	0.2571	2	3
1132	173	3	Week Three	Basic	2	4.5	9	0	0	1.0000	0.0313	0.2571	2	3
1133	174	3	Week Three	Basic	6	4.5	27	0	0	1.0000	0.0938	0.2571	2	3
1134	175	3	Week Three	Basic	5	4.5	22.5	1	22.5	1.0000	0.0781	0.2571	2	3
1135	176	3	Week Three	Basic	6	4.5	27	1	27	1.0000	0.0938	0.2571	2	3
1136	177	3	Week Three	Basic	6	4.5	27	1	27	1.0000	0.0938	0.2571	2	3
1137	178	3	Week Three	Basic	5	4.5	22.5	1	22.5	1.0000	0.0781	0.2571	2	3
1138	179	3	Week Three	Basic	11	4.5	49.5	0	0	1.0000	0.1719	0.2571	2	3
1139	180	3	Week Three	Basic	3	4.5	13.5	1	13.5	1.0000	0.0469	0.2571	2	3
1140	181	3	Week Three	Basic	19	4.5	85.5	0	0	0.7581	0.2969	0.2571	2	3
1141	182	3	Week Three	Basic	9	4.5	40.5	1	40.5	1.0000	0.1406	0.2571	2	3
1142	183	3	Week Three	Basic	4	4.5	18	0	0	1.0000	0.0625	0.2571	2	3
1143	184	3	Week Three	Basic	2	4.5	9	0	0	0.7419	0.0313	0.2571	2	3
1144	185	3	Week Three	Basic	15	4.5	67.5	0	0	1.0000	0.2344	0.2571	2	3
1145	186	3	Week Three	Basic	6	4.5	27	0	0	1.0000	0.0938	0.2571	2	3
1146	187	3	Week Three	Basic	8	4.5	36	0	0	1.0000	0.1250	0.2571	2	3
1147	188	3	Week Three	Basic	6	4.5	27	0	0	1.0000	0.0938	0.2571	2	3
1148	189	3	Week Three	Basic	10	4.5	45	0	0	1.0000	0.1563	0.2571	2	3
1149	190	3	Week Three	Basic	19	4.5	85.5	0	0	1.0000	0.2969	0.2571	2	3
1150	191	3	Week Three	Basic	5	4.5	22.5	1	22.5	0.7258	0.0781	0.2571	2	3
1151	192	3	Week Three	Basic	8	4.5	36	0	0	0.7097	0.1250	0.2571	2	3
1152	193	3	Week Three	Basic	4	4.5	18	1	18	0.6935	0.0625	0.2571	2	3
1153	194	3	Week Three	Basic	6	4.5	27	0	0	1.0000	0.0938	0.2571	2	3
1154	195	3	Week Three	Basic	23	4.5	103.5	0	0	0.6774	0.3594	0.2571	2	3
1155	196	3	Week Three	Basic	2	4.5	9	0	0	0.8065	0.0313	0.2571	2	3

Figure A.33: MS Excel Solver Risk Platform IP Data Set (32)



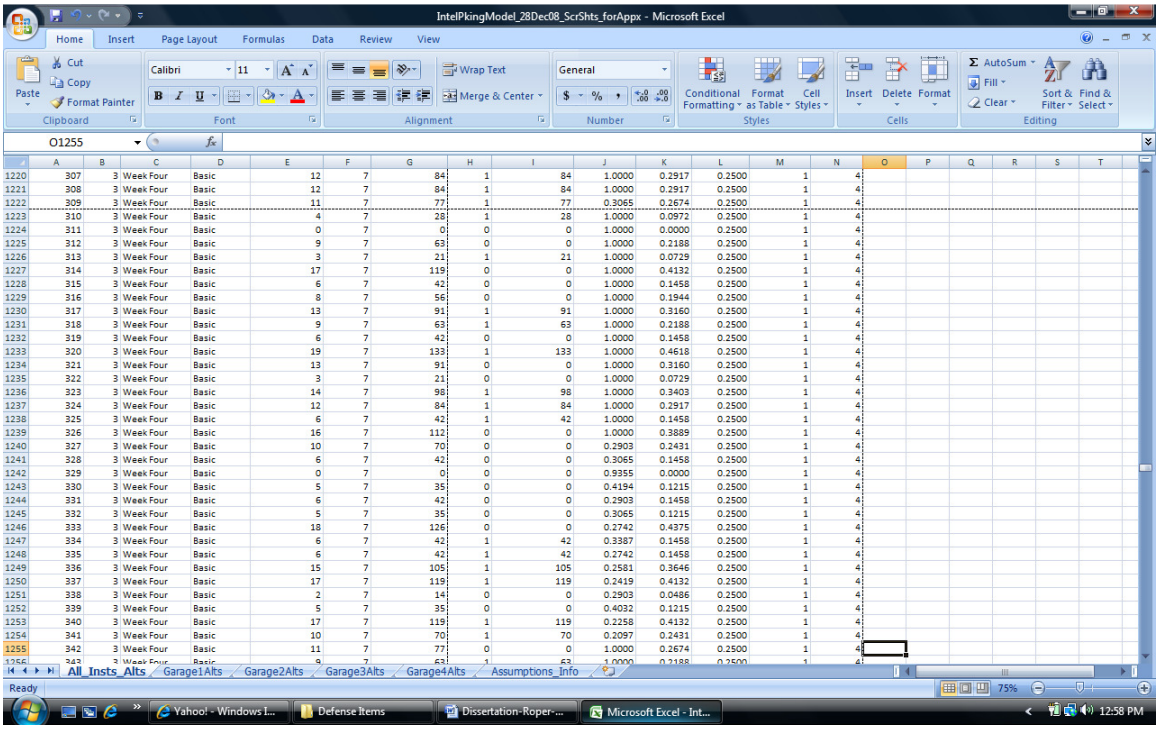
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1157	198	3	Week Three	Basic	7	4.5	31.5	1	31.5	1.0000	0.1094	0.2571	2	3
1158	199	3	Week Three	Basic	14	4.5	63	0	0	0.6613	0.2188	0.2571	2	3
1159	200	3	Week Three	Basic	13	4.5	58.5	0	0	1.0000	0.2031	0.2571	2	3
1160	201	3	Week Three	Basic	18	4.5	81	0	0	1.0000	0.2813	0.2571	2	3
1161	202	3	Week Three	Basic	11	4.5	49.5	0	0	0.6452	0.1719	0.2571	2	3
1162	203	3	Week Three	Basic	7	4.5	31.5	0	0	0.7097	0.1094	0.2571	2	3
1163	204	3	Week Three	Basic	4	4.5	18	0	0	0.7742	0.0625	0.2571	2	3
1164	205	3	Week Three	Basic	4	4.5	18	0	0	0.7581	0.0625	0.2571	2	3
1165	206	3	Week Three	Basic	19	4.5	85.5	0	0	0.6290	0.2969	0.2571	2	3
1166	207	3	Week Three	Basic	6	4.5	27	0	0	1.0000	0.0938	0.2571	2	3
1167	208	3	Week Three	Basic	16	4.5	72	0	0	1.0000	0.2500	0.2571	2	3
1168	209	3	Week Three	Basic	5	4.5	22.5	0	0	1.0000	0.0781	0.2571	2	3
1169	210	3	Week Three	Basic	3	4.5	13.5	1	13.5	1.0000	0.0469	0.2571	2	3
1170	211	3	Week Three	Basic	9	4.5	40.5	0	0	1.0000	0.1406	0.2571	2	3
1171	212	3	Week Three	Basic	7	4.5	31.5	1	31.5	1.0000	0.1094	0.2571	2	3
1172	213	3	Week Three	Basic	8	4.5	36	0	0	1.0000	0.1250	0.2571	2	3
1173	214	3	Week Three	Basic	12	4.5	54	0	0	1.0000	0.1875	0.2571	2	3
1174	215	3	Week Three	Basic	5	4.5	22.5	0	0	0.7258	0.0781	0.2571	2	3
1175	216	3	Week Three	Basic	4	4.5	18	0	0	0.6774	0.0625	0.2571	2	3
1176	217	3	Week Three	Basic	5	4.5	22.5	1	22.5	0.6129	0.0781	0.2571	2	3
1177	218	3	Week Three	Basic	8	4.5	36	0	0	0.6613	0.1250	0.2571	2	3
1178	219	3	Week Three	Basic	10	4.5	45	0	0	1.0000	0.1563	0.2571	2	3
1179	220	3	Week Three	Basic	0	4.5	0	0	0	1.0000	0.0000	0.2571	2	3
1180	221	3	Week Three	Basic	0	4.5	0	0	0	0.7258	0.0000	0.2571	2	3
1181	222	3	Week Three	Basic	2	4.5	9	0	0	1.0000	0.0313	0.2571	2	3
1182	223	3	Week Three	Basic	3	4.5	13.5	0	0	1.0000	0.0469	0.2571	2	3
1183	224	3	Week Three	Basic	17	4.5	76.5	0	0	1.0000	0.2656	0.2571	2	3
1184	225	3	Week Three	Basic	4	4.5	18	0	0	0.7097	0.0625	0.2571	2	3
1185	226	3	Week Three	Basic	1	4.5	4.5	0	0	0.6452	0.0156	0.2571	2	3
1186	227	3	Week Three	Basic	10	4.5	45	1	45	1.0000	0.1563	0.2571	2	3
1187	228	3	Week Three	Basic	11	4.5	49.5	0	0	0.5968	0.1719	0.2571	2	3
1188	229	3	Week Three	Basic	13	4.5	58.5	0	0	1.0000	0.2031	0.2571	2	3
1189	230	3	Week Three	Basic	5	4.5	22.5	1	22.5	1.0000	0.0781	0.2571	2	3
1190	231	3	Week Three	Basic	17	4.5	76.5	0	0	0.5806	0.2656	0.2571	2	3
1191	232	3	Week Three	Basic	11	4.5	49.5	0	0	0.5645	0.1719	0.2571	2	3
1192	233	3	Week Three	Basic	20	4.5	90	0	0	0.5484	0.3125	0.2571	2	3

Figure A.34: MS Excel Solver Risk Platform IP Data Set (33)



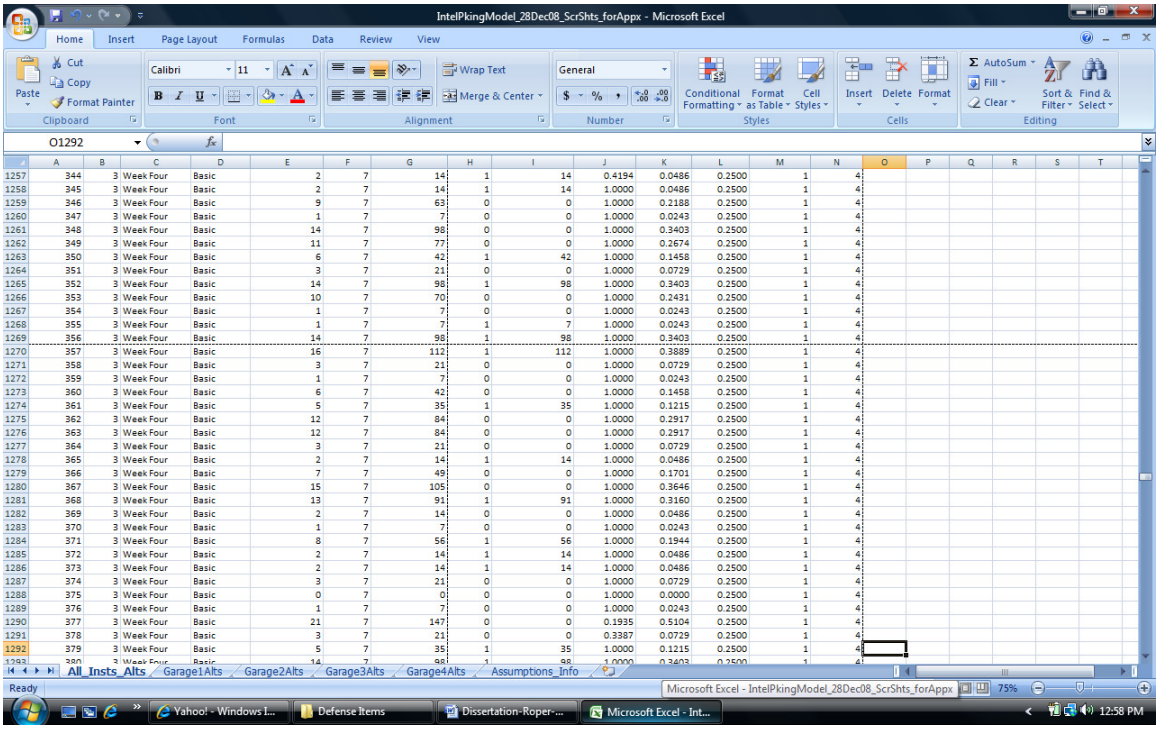
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1184	225	3	Week Three	Basic	4	4.5	18	0	0	0.7097	0.0625	0.2571	2	3
1185	226	3	Week Three	Basic	1	4.5	4.5	0	0	0.6452	0.0156	0.2571	2	3
1186	227	3	Week Three	Basic	10	4.5	45	1	45	1.0000	0.1563	0.2571	2	3
1187	228	3	Week Three	Basic	11	4.5	49.5	0	0	0.5968	0.1719	0.2571	2	3
1188	229	3	Week Three	Basic	13	4.5	58.5	0	0	1.0000	0.2031	0.2571	2	3
1189	230	3	Week Three	Basic	5	4.5	22.5	1	22.5	1.0000	0.0781	0.2571	2	3
1190	231	3	Week Three	Basic	17	4.5	76.5	0	0	0.5806	0.2656	0.2571	2	3
1191	232	3	Week Three	Basic	11	4.5	49.5	0	0	0.5645	0.1719	0.2571	2	3
1192	233	3	Week Three	Basic	20	4.5	90	0	0	0.5484	0.3125	0.2571	2	3
1193	234	3	Week Three	Basic	5	4.5	22.5	0	0	1.0000	0.0781	0.2571	2	3
1194	235	3	Week Three	Basic	7	4.5	31.5	0	0	1.0000	0.1094	0.2571	2	3
1195	282	3	Week Four	Basic	3	7	21	0	0	1.0000	0.0729	0.2500	1	4
1196	283	3	Week Four	Basic	6	7	42	1	42	1.0000	0.1458	0.2500	1	4
1197	284	3	Week Four	Basic	1	7	7	1	7	1.0000	0.0243	0.2500	1	4
1198	285	3	Week Four	Basic	8	7	56	1	56	1.0000	0.1944	0.2500	1	4
1199	286	3	Week Four	Basic	8	7	56	0	0	1.0000	0.1944	0.2500	1	4
1200	287	3	Week Four	Basic	2	7	14	1	14	0.7097	0.0486	0.2500	1	4
1201	288	3	Week Four	Basic	6	7	42	1	42	0.3871	0.1458	0.2500	1	4
1202	289	3	Week Four	Basic	4	7	28	0	0	1.0000	0.0972	0.2500	1	4
1203	290	3	Week Four	Basic	12	7	84	0	0	1.0000	0.2917	0.2500	1	4
1204	291	3	Week Four	Basic	2	7	14	1	14	0.4516	0.0486	0.2500	1	4
1205	292	3	Week Four	Basic	14	7	98	0	0	0.3548	0.3403	0.2500	1	4
1206	293	3	Week Four	Basic	5	7	35	0	0	0.3387	0.1215	0.2500	1	4
1207	294	3	Week Four	Basic	15	7	105	1	105	1.0000	0.3646	0.2500	1	4
1208	295	3	Week Four	Basic	1	7	7	1	7	0.6935	0.0243	0.2500	1	4
1209	296	3	Week Four	Basic	7	7	49	1	49	1.0000	0.1701	0.2500	1	4
1210	297	3	Week Four	Basic	3	7	21	1	21	1.0000	0.0729	0.2500	1	4
1211	298	3	Week Four	Basic	11	7	77	1	77	1.0000	0.2674	0.2500	1	4
1212	299	3	Week Four	Basic	9	7	63	0	0	0.3226	0.2188	0.2500	1	4
1213	300	3	Week Four	Basic	6	7	42	0	0	1.0000	0.1458	0.2500	1	4
1214	301	3	Week Four	Basic	3	7	21	0	0	1.0000	0.0729	0.2500	1	4
1215	302	3	Week Four	Basic	11	7	77	0	0	1.0000	0.2674	0.2500	1	4
1216	303	3	Week Four	Basic	7	7	49	0	0	1.0000	0.1701	0.2500	1	4
1217	304	3	Week Four	Basic	6	7	42	0	0	1.0000	0.1458	0.2500	1	4
1218	305	3	Week Four	Basic	8	7	56	0	0	1.0000	0.1944	0.2500	1	4
1219	306	3	Week Four	Basic	1	7	7	0	0	0.4194	0.0243	0.2500	1	4

Figure A.35: MS Excel Solver Risk Platform IP Data Set (34)



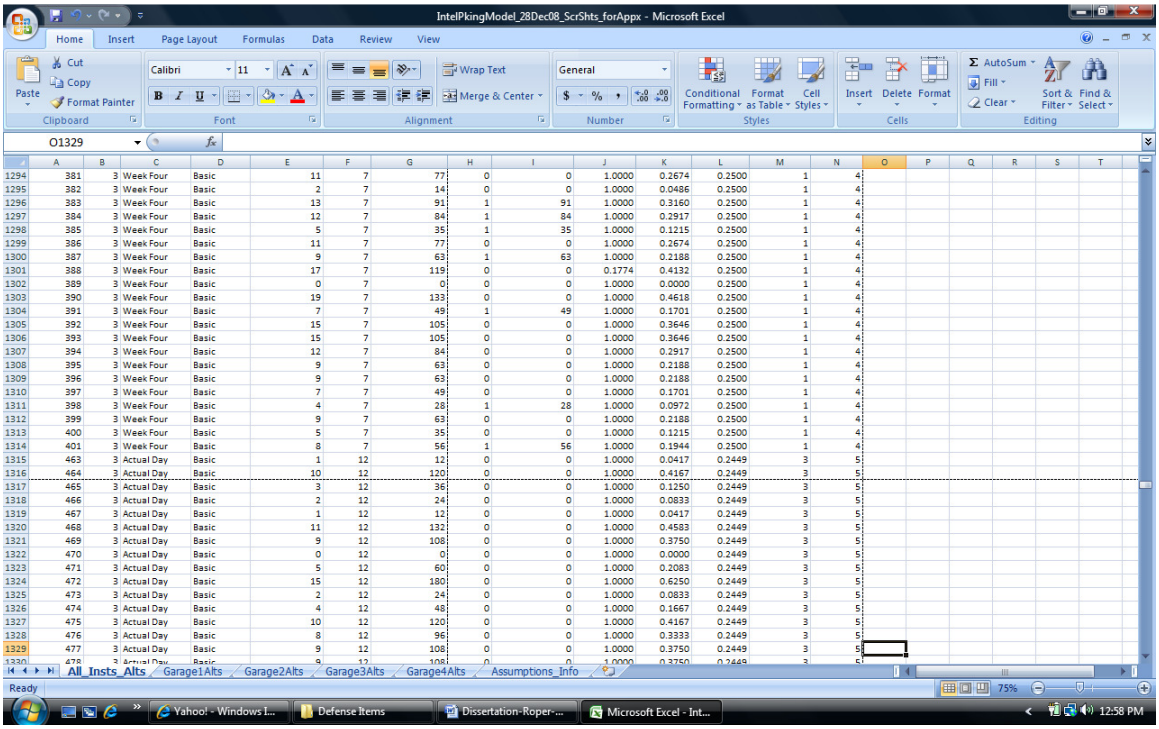
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1220	307	3	Week Four	Basic	12	7	84	1	84	1.0000	0.2917	0.2500	1	4
1221	308	3	Week Four	Basic	12	7	84	1	84	1.0000	0.2917	0.2500	1	4
1222	309	3	Week Four	Basic	11	7	77	1	77	0.3065	0.2674	0.2500	1	4
1223	310	3	Week Four	Basic	4	7	28	1	28	1.0000	0.0972	0.2500	1	4
1224	311	3	Week Four	Basic	0	7	0	0	0	1.0000	0.0000	0.2500	1	4
1225	312	3	Week Four	Basic	9	7	63	0	0	1.0000	0.2188	0.2500	1	4
1226	313	3	Week Four	Basic	3	7	21	1	21	1.0000	0.0729	0.2500	1	4
1227	314	3	Week Four	Basic	17	7	119	0	0	1.0000	0.4132	0.2500	1	4
1228	315	3	Week Four	Basic	6	7	42	0	0	1.0000	0.1458	0.2500	1	4
1229	316	3	Week Four	Basic	8	7	56	0	0	1.0000	0.1944	0.2500	1	4
1230	317	3	Week Four	Basic	13	7	91	1	91	1.0000	0.3160	0.2500	1	4
1231	318	3	Week Four	Basic	9	7	63	1	63	1.0000	0.2188	0.2500	1	4
1232	319	3	Week Four	Basic	6	7	42	0	0	1.0000	0.1458	0.2500	1	4
1233	320	3	Week Four	Basic	19	7	133	1	133	1.0000	0.4618	0.2500	1	4
1234	321	3	Week Four	Basic	13	7	91	0	0	1.0000	0.3160	0.2500	1	4
1235	322	3	Week Four	Basic	3	7	21	0	0	1.0000	0.0729	0.2500	1	4
1236	323	3	Week Four	Basic	14	7	98	1	98	1.0000	0.3403	0.2500	1	4
1237	324	3	Week Four	Basic	12	7	84	1	84	1.0000	0.2917	0.2500	1	4
1238	325	3	Week Four	Basic	6	7	42	1	42	1.0000	0.1458	0.2500	1	4
1239	326	3	Week Four	Basic	16	7	112	0	0	1.0000	0.3889	0.2500	1	4
1240	327	3	Week Four	Basic	10	7	70	0	0	0.2903	0.2431	0.2500	1	4
1241	328	3	Week Four	Basic	6	7	42	0	0	0.3065	0.1458	0.2500	1	4
1242	329	3	Week Four	Basic	0	7	0	0	0	0.9355	0.0000	0.2500	1	4
1243	330	3	Week Four	Basic	5	7	35	0	0	0.4194	0.1215	0.2500	1	4
1244	331	3	Week Four	Basic	6	7	42	0	0	0.2903	0.1458	0.2500	1	4
1245	332	3	Week Four	Basic	5	7	35	0	0	0.3065	0.1215	0.2500	1	4
1246	333	3	Week Four	Basic	18	7	126	0	0	0.2742	0.4375	0.2500	1	4
1247	334	3	Week Four	Basic	6	7	42	1	42	0.3387	0.1458	0.2500	1	4
1248	335	3	Week Four	Basic	6	7	42	1	42	0.2742	0.1458	0.2500	1	4
1249	336	3	Week Four	Basic	15	7	105	1	105	0.2581	0.3646	0.2500	1	4
1250	337	3	Week Four	Basic	17	7	119	1	119	0.2419	0.4132	0.2500	1	4
1251	338	3	Week Four	Basic	2	7	14	0	0	0.2903	0.0486	0.2500	1	4
1252	339	3	Week Four	Basic	5	7	35	0	0	0.4032	0.1215	0.2500	1	4
1253	340	3	Week Four	Basic	17	7	119	1	119	0.2258	0.4132	0.2500	1	4
1254	341	3	Week Four	Basic	10	7	70	1	70	0.2097	0.2431	0.2500	1	4
1255	342	3	Week Four	Basic	11	7	77	0	0	1.0000	0.2674	0.2500	1	4

Figure A.36: MS Excel Solver Risk Platform IP Data Set (35)



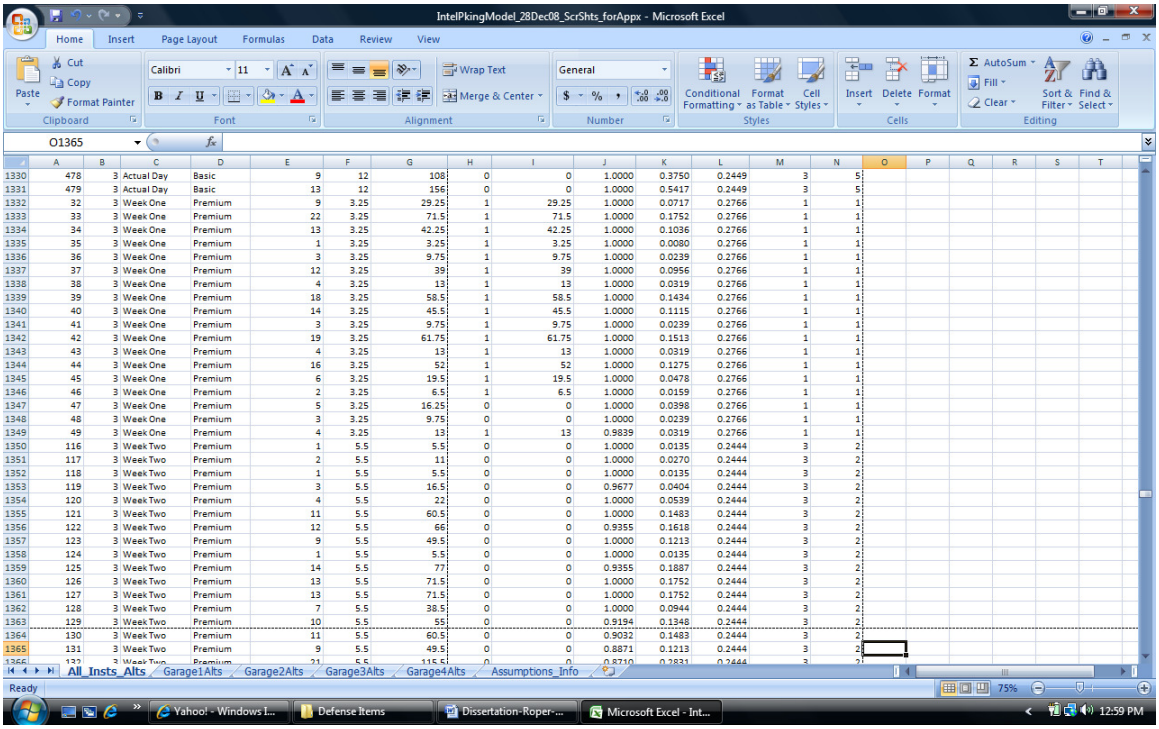
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1257	344	3	Week Four	Basic	2	7	14	1	14	0.4194	0.0486	0.2500	1	4
1258	345	3	Week Four	Basic	2	7	14	1	14	1.0000	0.0486	0.2500	1	4
1259	346	3	Week Four	Basic	9	7	63	0	0	1.0000	0.2188	0.2500	1	4
1260	347	3	Week Four	Basic	1	7	7	0	0	1.0000	0.0243	0.2500	1	4
1261	348	3	Week Four	Basic	14	7	98	0	0	1.0000	0.3403	0.2500	1	4
1262	349	3	Week Four	Basic	11	7	77	0	0	1.0000	0.2674	0.2500	1	4
1263	350	3	Week Four	Basic	6	7	42	1	42	1.0000	0.1458	0.2500	1	4
1264	351	3	Week Four	Basic	3	7	21	0	0	1.0000	0.0729	0.2500	1	4
1265	352	3	Week Four	Basic	14	7	98	1	98	1.0000	0.3403	0.2500	1	4
1266	353	3	Week Four	Basic	10	7	70	0	0	1.0000	0.2431	0.2500	1	4
1267	354	3	Week Four	Basic	1	7	7	0	0	1.0000	0.0243	0.2500	1	4
1268	355	3	Week Four	Basic	1	7	7	1	7	1.0000	0.0243	0.2500	1	4
1269	356	3	Week Four	Basic	14	7	98	1	98	1.0000	0.3403	0.2500	1	4
1270	357	3	Week Four	Basic	16	7	112	1	112	1.0000	0.3889	0.2500	1	4
1271	358	3	Week Four	Basic	3	7	21	0	0	1.0000	0.0729	0.2500	1	4
1272	359	3	Week Four	Basic	1	7	7	0	0	1.0000	0.0243	0.2500	1	4
1273	360	3	Week Four	Basic	6	7	42	0	0	1.0000	0.1458	0.2500	1	4
1274	361	3	Week Four	Basic	5	7	35	1	35	1.0000	0.1215	0.2500	1	4
1275	362	3	Week Four	Basic	12	7	84	0	0	1.0000	0.2917	0.2500	1	4
1276	363	3	Week Four	Basic	12	7	84	0	0	1.0000	0.2917	0.2500	1	4
1277	364	3	Week Four	Basic	3	7	21	0	0	1.0000	0.0729	0.2500	1	4
1278	365	3	Week Four	Basic	2	7	14	1	14	1.0000	0.0486	0.2500	1	4
1279	366	3	Week Four	Basic	7	7	49	0	0	1.0000	0.1701	0.2500	1	4
1280	367	3	Week Four	Basic	15	7	105	0	0	1.0000	0.3646	0.2500	1	4
1281	368	3	Week Four	Basic	13	7	91	1	91	1.0000	0.3160	0.2500	1	4
1282	369	3	Week Four	Basic	2	7	14	0	0	1.0000	0.0486	0.2500	1	4
1283	370	3	Week Four	Basic	1	7	7	0	0	1.0000	0.0243	0.2500	1	4
1284	371	3	Week Four	Basic	8	7	56	1	56	1.0000	0.1944	0.2500	1	4
1285	372	3	Week Four	Basic	2	7	14	1	14	1.0000	0.0486	0.2500	1	4
1286	373	3	Week Four	Basic	2	7	14	1	14	1.0000	0.0486	0.2500	1	4
1287	374	3	Week Four	Basic	3	7	21	0	0	1.0000	0.0729	0.2500	1	4
1288	375	3	Week Four	Basic	0	7	0	0	0	1.0000	0.0000	0.2500	1	4
1289	376	3	Week Four	Basic	1	7	7	0	0	1.0000	0.0243	0.2500	1	4
1290	377	3	Week Four	Basic	21	7	147	0	0	0.1935	0.5104	0.2500	1	4
1291	378	3	Week Four	Basic	3	7	21	0	0	0.3387	0.0729	0.2500	1	4
1292	379	3	Week Four	Basic	5	7	35	1	35	1.0000	0.1215	0.2500	1	4

Figure A.37: MS Excel Solver Risk Platform IP Data Set (36)



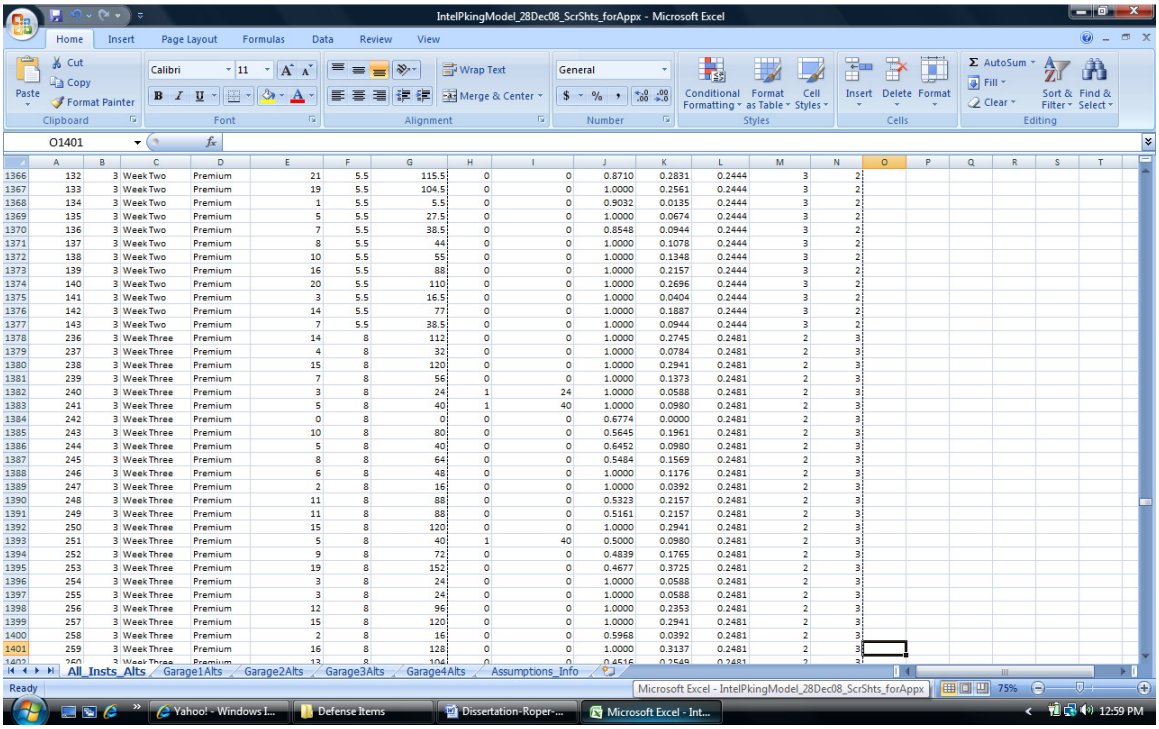
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1294	381	3	Week Four	Basic	11	7	77	0	0	1.0000	0.2674	0.2500	1	4
1295	382	3	Week Four	Basic	2	7	14	0	0	1.0000	0.0486	0.2500	1	4
1296	383	3	Week Four	Basic	13	7	91	1	91	1.0000	0.3160	0.2500	1	4
1297	384	3	Week Four	Basic	12	7	84	1	84	1.0000	0.2917	0.2500	1	4
1298	385	3	Week Four	Basic	5	7	35	1	35	1.0000	0.1215	0.2500	1	4
1299	386	3	Week Four	Basic	11	7	77	0	0	1.0000	0.2674	0.2500	1	4
1300	387	3	Week Four	Basic	9	7	63	1	63	1.0000	0.2188	0.2500	1	4
1301	388	3	Week Four	Basic	17	7	119	0	0	0.1774	0.4132	0.2500	1	4
1302	389	3	Week Four	Basic	0	7	0	0	0	1.0000	0.0000	0.2500	1	4
1303	390	3	Week Four	Basic	19	7	133	0	0	1.0000	0.4618	0.2500	1	4
1304	391	3	Week Four	Basic	7	7	49	1	49	1.0000	0.1701	0.2500	1	4
1305	392	3	Week Four	Basic	15	7	105	0	0	1.0000	0.3646	0.2500	1	4
1306	393	3	Week Four	Basic	15	7	105	0	0	1.0000	0.3646	0.2500	1	4
1307	394	3	Week Four	Basic	12	7	84	0	0	1.0000	0.2917	0.2500	1	4
1308	395	3	Week Four	Basic	9	7	63	0	0	1.0000	0.2188	0.2500	1	4
1309	396	3	Week Four	Basic	9	7	63	0	0	1.0000	0.2188	0.2500	1	4
1310	397	3	Week Four	Basic	7	7	49	0	0	1.0000	0.1701	0.2500	1	4
1311	398	3	Week Four	Basic	4	7	28	1	28	1.0000	0.0972	0.2500	1	4
1312	399	3	Week Four	Basic	9	7	63	0	0	1.0000	0.2188	0.2500	1	4
1313	400	3	Week Four	Basic	5	7	35	0	0	1.0000	0.1215	0.2500	1	4
1314	401	3	Week Four	Basic	8	7	56	1	56	1.0000	0.1944	0.2500	1	4
1315	463	3	Actual Day	Basic	1	12	12	0	0	1.0000	0.0417	0.2449	3	5
1316	464	3	Actual Day	Basic	10	12	120	0	0	1.0000	0.4167	0.2449	3	5
1317	465	3	Actual Day	Basic	3	12	36	0	0	1.0000	0.1250	0.2449	3	5
1318	466	3	Actual Day	Basic	2	12	24	0	0	1.0000	0.0833	0.2449	3	5
1319	467	3	Actual Day	Basic	1	12	12	0	0	1.0000	0.0417	0.2449	3	5
1320	468	3	Actual Day	Basic	11	12	132	0	0	1.0000	0.4583	0.2449	3	5
1321	469	3	Actual Day	Basic	9	12	108	0	0	1.0000	0.3750	0.2449	3	5
1322	470	3	Actual Day	Basic	0	12	0	0	0	1.0000	0.0000	0.2449	3	5
1323	471	3	Actual Day	Basic	5	12	60	0	0	1.0000	0.2083	0.2449	3	5
1324	472	3	Actual Day	Basic	15	12	180	0	0	1.0000	0.6250	0.2449	3	5
1325	473	3	Actual Day	Basic	2	12	24	0	0	1.0000	0.0833	0.2449	3	5
1326	474	3	Actual Day	Basic	4	12	48	0	0	1.0000	0.1667	0.2449	3	5
1327	475	3	Actual Day	Basic	10	12	120	0	0	1.0000	0.4167	0.2449	3	5
1328	476	3	Actual Day	Basic	8	12	96	0	0	1.0000	0.3333	0.2449	3	5
1329	477	3	Actual Day	Basic	9	12	108	0	0	1.0000	0.3750	0.2449	3	5

Figure A.38: MS Excel Solver Risk Platform IP Data Set (37)



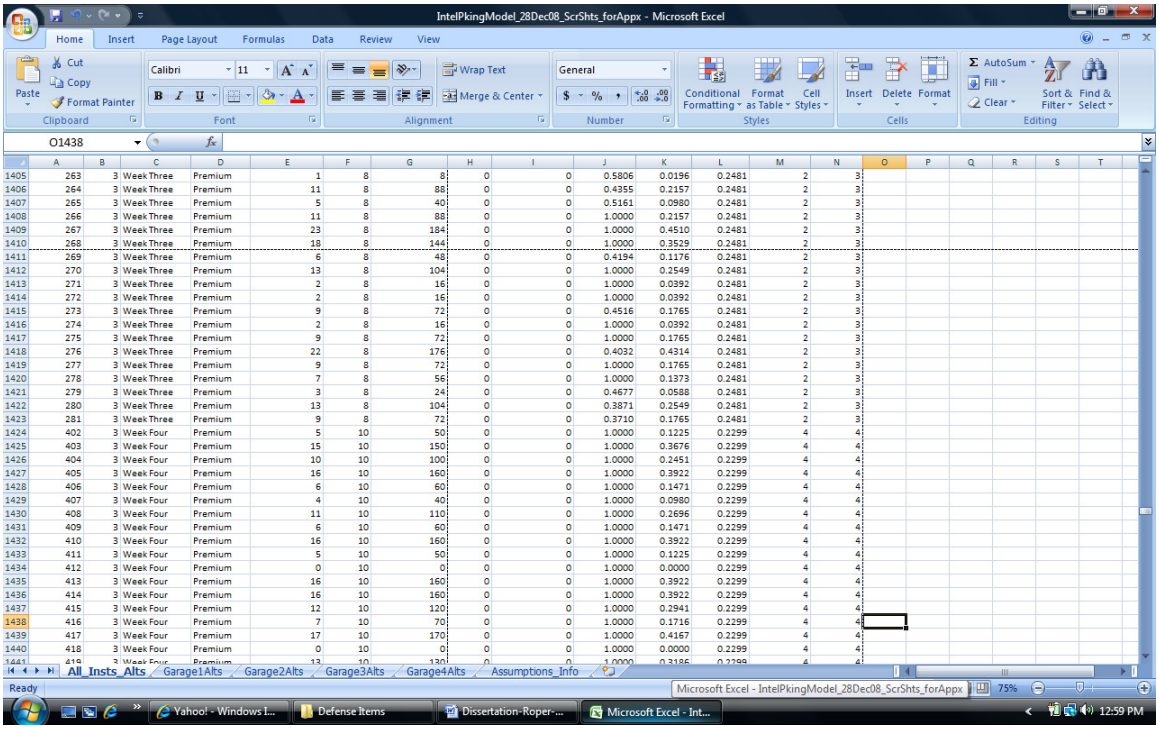
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1330	478	3	Actual Day	Basic	9	12	108	0	0	1.0000	0.3750	0.2449	3	5
1331	479	3	Actual Day	Basic	13	12	156	0	0	1.0000	0.5417	0.2449	3	5
1332	32	3	Week One	Premium	9	3.25	29.25	1	29.25	1.0000	0.0717	0.2766	1	1
1333	33	3	Week One	Premium	22	3.25	71.5	1	71.5	1.0000	0.1752	0.2766	1	1
1334	34	3	Week One	Premium	13	3.25	42.25	1	42.25	1.0000	0.1036	0.2766	1	1
1335	35	3	Week One	Premium	1	3.25	3.25	1	3.25	1.0000	0.0080	0.2766	1	1
1336	36	3	Week One	Premium	3	3.25	9.75	1	9.75	1.0000	0.0239	0.2766	1	1
1337	37	3	Week One	Premium	12	3.25	39	1	39	1.0000	0.0956	0.2766	1	1
1338	38	3	Week One	Premium	4	3.25	13	1	13	1.0000	0.0319	0.2766	1	1
1339	39	3	Week One	Premium	18	3.25	58.5	1	58.5	1.0000	0.1434	0.2766	1	1
1340	40	3	Week One	Premium	14	3.25	45.5	1	45.5	1.0000	0.1115	0.2766	1	1
1341	41	3	Week One	Premium	3	3.25	9.75	1	9.75	1.0000	0.0239	0.2766	1	1
1342	42	3	Week One	Premium	19	3.25	61.75	1	61.75	1.0000	0.1513	0.2766	1	1
1343	43	3	Week One	Premium	4	3.25	13	1	13	1.0000	0.0319	0.2766	1	1
1344	44	3	Week One	Premium	16	3.25	52	1	52	1.0000	0.1275	0.2766	1	1
1345	45	3	Week One	Premium	6	3.25	19.5	1	19.5	1.0000	0.0478	0.2766	1	1
1346	46	3	Week One	Premium	2	3.25	6.5	1	6.5	1.0000	0.0159	0.2766	1	1
1347	47	3	Week One	Premium	5	3.25	16.25	0	0	1.0000	0.0398	0.2766	1	1
1348	48	3	Week One	Premium	3	3.25	9.75	0	0	1.0000	0.0239	0.2766	1	1
1349	49	3	Week One	Premium	4	3.25	13	1	13	0.9839	0.0319	0.2766	1	1
1350	116	3	Week Two	Premium	1	5.5	5.5	0	0	1.0000	0.0135	0.2444	3	2
1351	117	3	Week Two	Premium	2	5.5	11	0	0	1.0000	0.0270	0.2444	3	2
1352	118	3	Week Two	Premium	1	5.5	5.5	0	0	1.0000	0.0135	0.2444	3	2
1353	119	3	Week Two	Premium	3	5.5	16.5	0	0	0.9677	0.0404	0.2444	3	2
1354	120	3	Week Two	Premium	4	5.5	22	0	0	1.0000	0.0539	0.2444	3	2
1355	121	3	Week Two	Premium	11	5.5	60.5	0	0	1.0000	0.1483	0.2444	3	2
1356	122	3	Week Two	Premium	12	5.5	66	0	0	0.9355	0.1618	0.2444	3	2
1357	123	3	Week Two	Premium	9	5.5	49.5	0	0	1.0000	0.1213	0.2444	3	2
1358	124	3	Week Two	Premium	1	5.5	5.5	0	0	1.0000	0.0135	0.2444	3	2
1359	125	3	Week Two	Premium	14	5.5	77	0	0	0.9355	0.1887	0.2444	3	2
1360	126	3	Week Two	Premium	13	5.5	71.5	0	0	1.0000	0.1752	0.2444	3	2
1361	127	3	Week Two	Premium	13	5.5	71.5	0	0	1.0000	0.1752	0.2444	3	2
1362	128	3	Week Two	Premium	7	5.5	38.5	0	0	1.0000	0.0944	0.2444	3	2
1363	129	3	Week Two	Premium	10	5.5	55	0	0	0.9194	0.1348	0.2444	3	2
1364	130	3	Week Two	Premium	11	5.5	60.5	0	0	0.9032	0.1483	0.2444	3	2
1365	131	3	Week Two	Premium	9	5.5	49.5	0	0	0.8871	0.1213	0.2444	3	2

Figure A.39: MS Excel Solver Risk Platform IP Data Set (38)



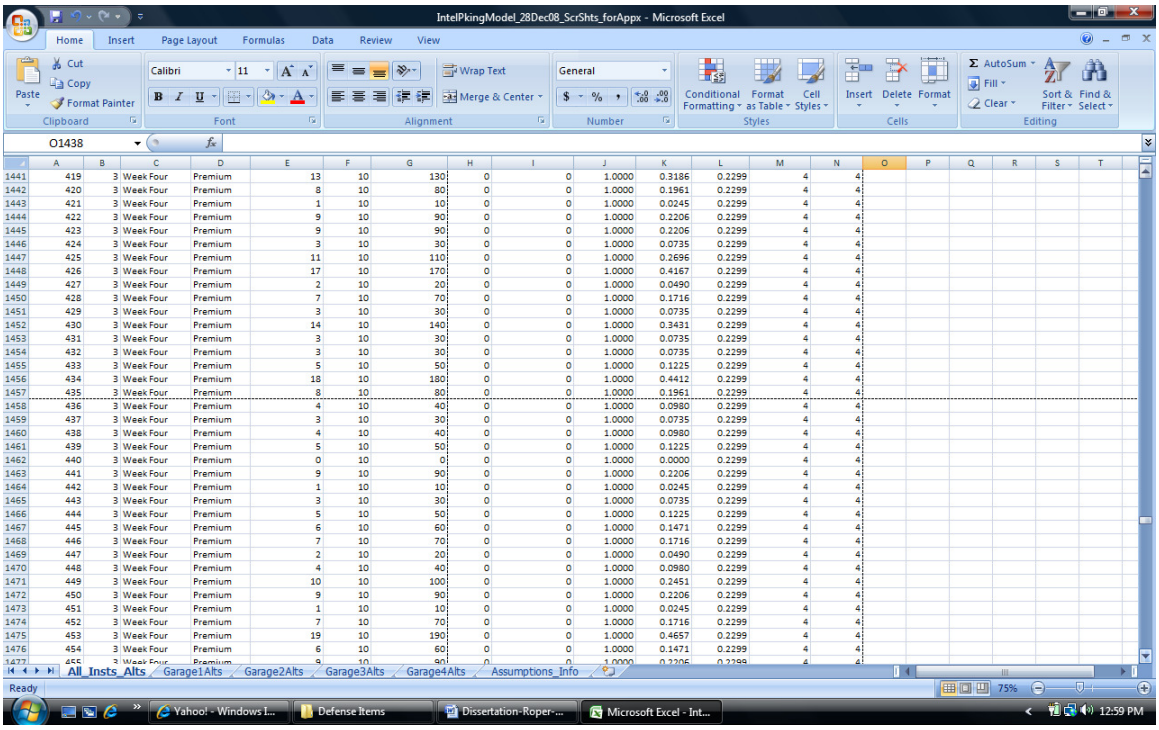
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1366	132	3	Week Two	Premium	21	5.5	115.5	0	0	0.8710	0.2831	0.2444	3	2
1367	133	3	Week Two	Premium	19	5.5	104.5	0	0	1.0000	0.2561	0.2444	3	2
1368	134	3	Week Two	Premium	1	5.5	5.5	0	0	0.9032	0.0135	0.2444	3	2
1369	135	3	Week Two	Premium	5	5.5	27.5	0	0	1.0000	0.0674	0.2444	3	2
1370	136	3	Week Two	Premium	7	5.5	38.5	0	0	0.8548	0.0944	0.2444	3	2
1371	137	3	Week Two	Premium	8	5.5	44	0	0	1.0000	0.1078	0.2444	3	2
1372	138	3	Week Two	Premium	10	5.5	55	0	0	1.0000	0.1348	0.2444	3	2
1373	139	3	Week Two	Premium	16	5.5	88	0	0	1.0000	0.2157	0.2444	3	2
1374	140	3	Week Two	Premium	20	5.5	110	0	0	1.0000	0.2696	0.2444	3	2
1375	141	3	Week Two	Premium	3	5.5	16.5	0	0	1.0000	0.0404	0.2444	3	2
1376	142	3	Week Two	Premium	14	5.5	77	0	0	1.0000	0.1887	0.2444	3	2
1377	143	3	Week Two	Premium	7	5.5	38.5	0	0	1.0000	0.0944	0.2444	3	2
1378	236	3	Week Three	Premium	14	8	112	0	0	1.0000	0.2745	0.2481	2	3
1379	237	3	Week Three	Premium	4	8	32	0	0	1.0000	0.0784	0.2481	2	3
1380	238	3	Week Three	Premium	15	8	120	0	0	1.0000	0.2941	0.2481	2	3
1381	239	3	Week Three	Premium	7	8	56	0	0	1.0000	0.1373	0.2481	2	3
1382	240	3	Week Three	Premium	3	8	24	1	24	1.0000	0.0588	0.2481	2	3
1383	241	3	Week Three	Premium	5	8	40	1	40	1.0000	0.0980	0.2481	2	3
1384	242	3	Week Three	Premium	0	8	0	0	0	0.6774	0.0000	0.2481	2	3
1385	243	3	Week Three	Premium	10	8	80	0	0	0.5645	0.1961	0.2481	2	3
1386	244	3	Week Three	Premium	5	8	40	0	0	0.6452	0.0980	0.2481	2	3
1387	245	3	Week Three	Premium	8	8	64	0	0	0.5484	0.1569	0.2481	2	3
1388	246	3	Week Three	Premium	6	8	48	0	0	1.0000	0.1176	0.2481	2	3
1389	247	3	Week Three	Premium	2	8	16	0	0	1.0000	0.0392	0.2481	2	3
1390	248	3	Week Three	Premium	11	8	88	0	0	0.5323	0.2157	0.2481	2	3
1391	249	3	Week Three	Premium	11	8	88	0	0	0.5161	0.2157	0.2481	2	3
1392	250	3	Week Three	Premium	15	8	120	0	0	1.0000	0.2941	0.2481	2	3
1393	251	3	Week Three	Premium	5	8	40	1	40	0.5000	0.0980	0.2481	2	3
1394	252	3	Week Three	Premium	9	8	72	0	0	0.4839	0.1765	0.2481	2	3
1395	253	3	Week Three	Premium	19	8	152	0	0	0.4677	0.3725	0.2481	2	3
1396	254	3	Week Three	Premium	3	8	24	0	0	1.0000	0.0588	0.2481	2	3
1397	255	3	Week Three	Premium	3	8	24	0	0	1.0000	0.0588	0.2481	2	3
1398	256	3	Week Three	Premium	12	8	96	0	0	1.0000	0.2353	0.2481	2	3
1399	257	3	Week Three	Premium	15	8	120	0	0	1.0000	0.2941	0.2481	2	3
1400	258	3	Week Three	Premium	2	8	16	0	0	0.5968	0.0392	0.2481	2	3
1401	259	3	Week Three	Premium	16	8	128	0	0	1.0000	0.3137	0.2481	2	3

Figure A.40: MS Excel Solver Risk Platform IP Data Set (39)



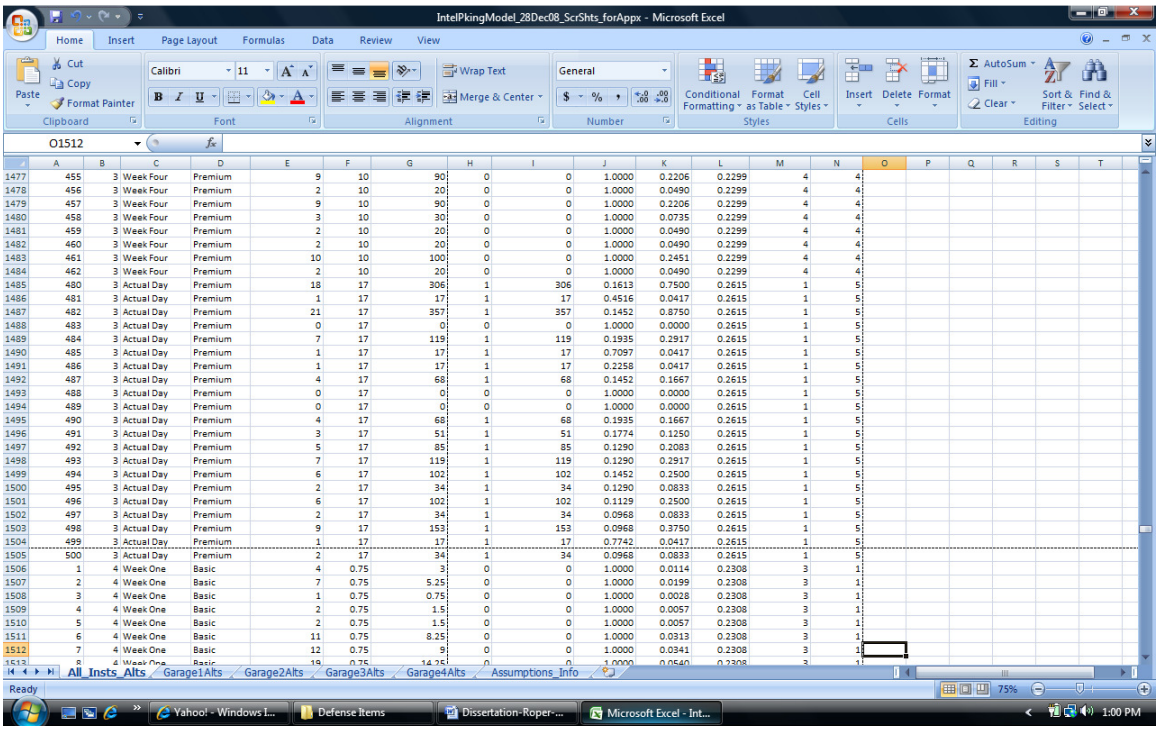
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1405	263	3	Week Three	Premium	1	8	8	0	0	0.5806	0.0196	0.2481	2	3
1406	264	3	Week Three	Premium	11	8	88	0	0	0.4355	0.2157	0.2481	2	3
1407	265	3	Week Three	Premium	5	8	40	0	0	0.5161	0.0980	0.2481	2	3
1408	266	3	Week Three	Premium	11	8	88	0	0	1.0000	0.2157	0.2481	2	3
1409	267	3	Week Three	Premium	23	8	184	0	0	1.0000	0.4510	0.2481	2	3
1410	268	3	Week Three	Premium	18	8	144	0	0	1.0000	0.3529	0.2481	2	3
1411	269	3	Week Three	Premium	6	8	48	0	0	0.4194	0.1176	0.2481	2	3
1412	270	3	Week Three	Premium	13	8	104	0	0	1.0000	0.2549	0.2481	2	3
1413	271	3	Week Three	Premium	2	8	16	0	0	1.0000	0.0392	0.2481	2	3
1414	272	3	Week Three	Premium	2	8	16	0	0	1.0000	0.0392	0.2481	2	3
1415	273	3	Week Three	Premium	9	8	72	0	0	0.4516	0.1765	0.2481	2	3
1416	274	3	Week Three	Premium	2	8	16	0	0	1.0000	0.0392	0.2481	2	3
1417	275	3	Week Three	Premium	9	8	72	0	0	1.0000	0.1765	0.2481	2	3
1418	276	3	Week Three	Premium	22	8	176	0	0	0.4032	0.4314	0.2481	2	3
1419	277	3	Week Three	Premium	9	8	72	0	0	1.0000	0.1765	0.2481	2	3
1420	278	3	Week Three	Premium	7	8	56	0	0	1.0000	0.1373	0.2481	2	3
1421	279	3	Week Three	Premium	3	8	24	0	0	0.4677	0.0588	0.2481	2	3
1422	280	3	Week Three	Premium	13	8	104	0	0	0.3871	0.2549	0.2481	2	3
1423	281	3	Week Three	Premium	9	8	72	0	0	0.3710	0.1765	0.2481	2	3
1424	402	3	Week Four	Premium	5	10	50	0	0	1.0000	0.1225	0.2299	4	4
1425	403	3	Week Four	Premium	15	10	150	0	0	1.0000	0.3676	0.2299	4	4
1426	404	3	Week Four	Premium	10	10	100	0	0	1.0000	0.2451	0.2299	4	4
1427	405	3	Week Four	Premium	16	10	160	0	0	1.0000	0.3922	0.2299	4	4
1428	406	3	Week Four	Premium	6	10	60	0	0	1.0000	0.1471	0.2299	4	4
1429	407	3	Week Four	Premium	4	10	40	0	0	1.0000	0.0980	0.2299	4	4
1430	408	3	Week Four	Premium	11	10	110	0	0	1.0000	0.2696	0.2299	4	4
1431	409	3	Week Four	Premium	6	10	60	0	0	1.0000	0.1471	0.2299	4	4
1432	410	3	Week Four	Premium	16	10	160	0	0	1.0000	0.3922	0.2299	4	4
1433	411	3	Week Four	Premium	5	10	50	0	0	1.0000	0.1225	0.2299	4	4
1434	412	3	Week Four	Premium	0	10	0	0	0	1.0000	0.0000	0.2299	4	4
1435	413	3	Week Four	Premium	16	10	160	0	0	1.0000	0.3922	0.2299	4	4
1436	414	3	Week Four	Premium	16	10	160	0	0	1.0000	0.3922	0.2299	4	4
1437	415	3	Week Four	Premium	12	10	120	0	0	1.0000	0.2941	0.2299	4	4
1438	416	3	Week Four	Premium	7	10	70	0	0	1.0000	0.1716	0.2299	4	4
1439	417	3	Week Four	Premium	17	10	170	0	0	1.0000	0.4167	0.2299	4	4
1440	418	3	Week Four	Premium	0	10	0	0	0	1.0000	0.0000	0.2299	4	4

Figure A.41: MS Excel Solver Risk Platform IP Data Set (40)



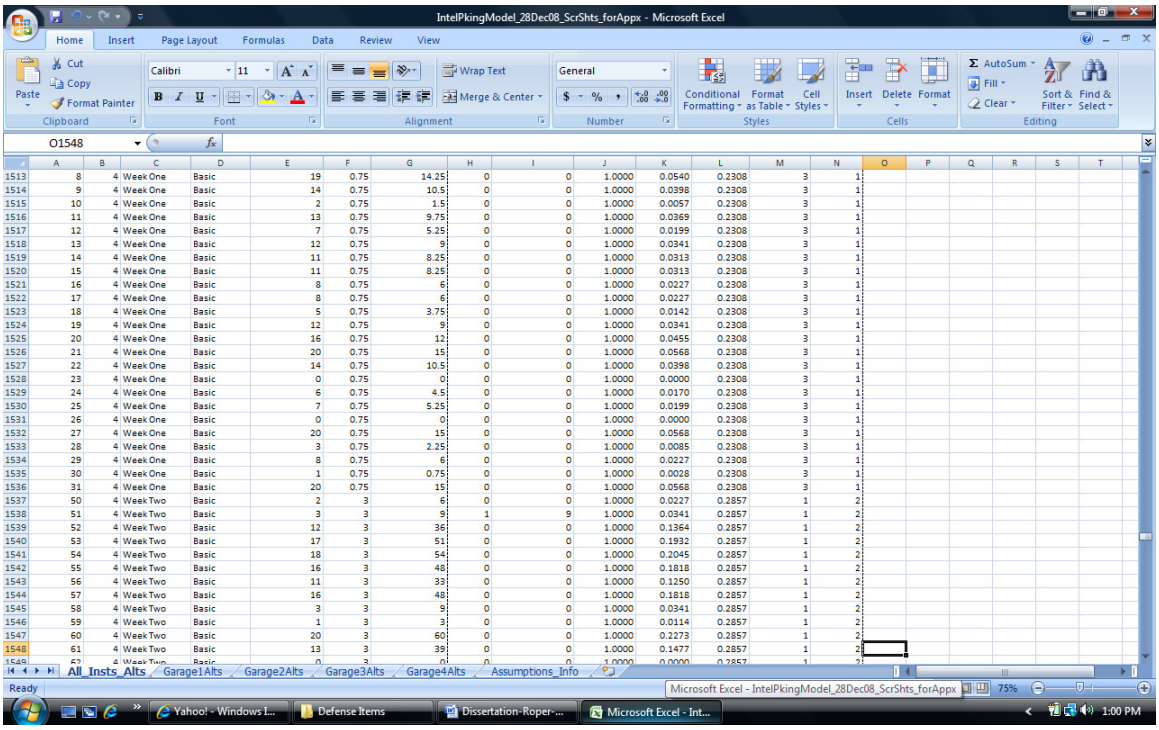
1441	419	3	Week Four	Premium	13	10	130	0	0	1.0000	0.3186	0.2299	4	4
1442	420	3	Week Four	Premium	8	10	80	0	0	1.0000	0.1961	0.2299	4	4
1443	421	3	Week Four	Premium	1	10	10	0	0	1.0000	0.0245	0.2299	4	4
1444	422	3	Week Four	Premium	9	10	90	0	0	1.0000	0.2206	0.2299	4	4
1445	423	3	Week Four	Premium	9	10	90	0	0	1.0000	0.2206	0.2299	4	4
1446	424	3	Week Four	Premium	3	10	30	0	0	1.0000	0.0735	0.2299	4	4
1447	425	3	Week Four	Premium	11	10	110	0	0	1.0000	0.2696	0.2299	4	4
1448	426	3	Week Four	Premium	17	10	170	0	0	1.0000	0.4167	0.2299	4	4
1449	427	3	Week Four	Premium	2	10	20	0	0	1.0000	0.0490	0.2299	4	4
1450	428	3	Week Four	Premium	7	10	70	0	0	1.0000	0.1716	0.2299	4	4
1451	429	3	Week Four	Premium	3	10	30	0	0	1.0000	0.0735	0.2299	4	4
1452	430	3	Week Four	Premium	14	10	140	0	0	1.0000	0.3431	0.2299	4	4
1453	431	3	Week Four	Premium	3	10	30	0	0	1.0000	0.0735	0.2299	4	4
1454	432	3	Week Four	Premium	3	10	30	0	0	1.0000	0.0735	0.2299	4	4
1455	433	3	Week Four	Premium	5	10	50	0	0	1.0000	0.1225	0.2299	4	4
1456	434	3	Week Four	Premium	18	10	180	0	0	1.0000	0.4412	0.2299	4	4
1457	435	3	Week Four	Premium	8	10	80	0	0	1.0000	0.1961	0.2299	4	4
1458	436	3	Week Four	Premium	4	10	40	0	0	1.0000	0.0980	0.2299	4	4
1459	437	3	Week Four	Premium	3	10	30	0	0	1.0000	0.0735	0.2299	4	4
1460	438	3	Week Four	Premium	4	10	40	0	0	1.0000	0.0980	0.2299	4	4
1461	439	3	Week Four	Premium	5	10	50	0	0	1.0000	0.1225	0.2299	4	4
1462	440	3	Week Four	Premium	0	10	0	0	0	1.0000	0.0000	0.2299	4	4
1463	441	3	Week Four	Premium	9	10	90	0	0	1.0000	0.2206	0.2299	4	4
1464	442	3	Week Four	Premium	1	10	10	0	0	1.0000	0.0245	0.2299	4	4
1465	443	3	Week Four	Premium	3	10	30	0	0	1.0000	0.0735	0.2299	4	4
1466	444	3	Week Four	Premium	5	10	50	0	0	1.0000	0.1225	0.2299	4	4
1467	445	3	Week Four	Premium	6	10	60	0	0	1.0000	0.1471	0.2299	4	4
1468	446	3	Week Four	Premium	7	10	70	0	0	1.0000	0.1716	0.2299	4	4
1469	447	3	Week Four	Premium	2	10	20	0	0	1.0000	0.0490	0.2299	4	4
1470	448	3	Week Four	Premium	4	10	40	0	0	1.0000	0.0980	0.2299	4	4
1471	449	3	Week Four	Premium	10	10	100	0	0	1.0000	0.2451	0.2299	4	4
1472	450	3	Week Four	Premium	9	10	90	0	0	1.0000	0.2206	0.2299	4	4
1473	451	3	Week Four	Premium	1	10	10	0	0	1.0000	0.0245	0.2299	4	4
1474	452	3	Week Four	Premium	7	10	70	0	0	1.0000	0.1716	0.2299	4	4
1475	453	3	Week Four	Premium	19	10	190	0	0	1.0000	0.4657	0.2299	4	4
1476	454	3	Week Four	Premium	6	10	60	0	0	1.0000	0.1471	0.2299	4	4

Figure A.42: MS Excel Solver Risk Platform IP Data Set (41)



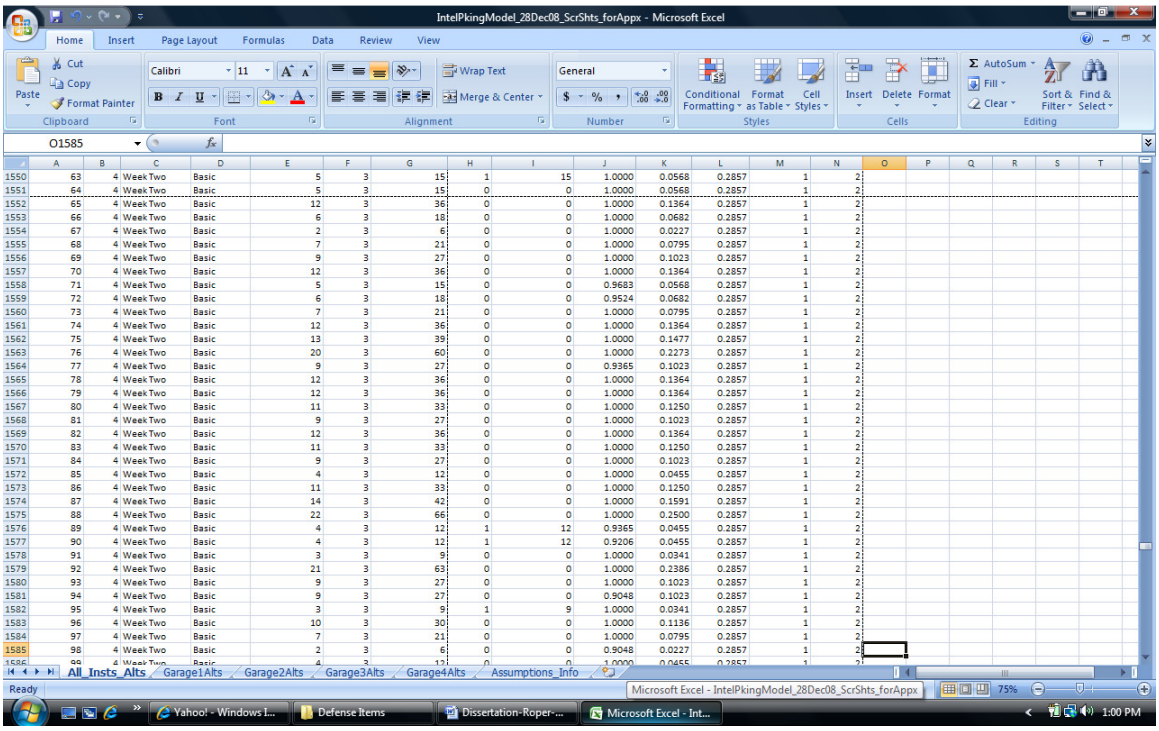
1477	455	3	Week Four	Premium	9	10	90	0	0	1.0000	0.2206	0.2299	4	4
1478	456	3	Week Four	Premium	2	10	20	0	0	1.0000	0.0490	0.2299	4	4
1479	457	3	Week Four	Premium	9	10	90	0	0	1.0000	0.2206	0.2299	4	4
1480	458	3	Week Four	Premium	3	10	30	0	0	1.0000	0.0735	0.2299	4	4
1481	459	3	Week Four	Premium	2	10	20	0	0	1.0000	0.0490	0.2299	4	4
1482	460	3	Week Four	Premium	2	10	20	0	0	1.0000	0.0490	0.2299	4	4
1483	461	3	Week Four	Premium	10	10	100	0	0	1.0000	0.2451	0.2299	4	4
1484	462	3	Week Four	Premium	2	10	20	0	0	1.0000	0.0490	0.2299	4	4
1485	480	3	Actual Day	Premium	18	17	306	1	306	0.1613	0.7500	0.2615	1	5
1486	481	3	Actual Day	Premium	1	17	17	1	17	0.4516	0.0417	0.2615	1	5
1487	482	3	Actual Day	Premium	21	17	357	1	357	0.1452	0.8750	0.2615	1	5
1488	483	3	Actual Day	Premium	0	17	0	0	0	1.0000	0.0000	0.2615	1	5
1489	484	3	Actual Day	Premium	7	17	119	1	119	0.1935	0.2917	0.2615	1	5
1490	485	3	Actual Day	Premium	1	17	17	1	17	0.7097	0.0417	0.2615	1	5
1491	486	3	Actual Day	Premium	1	17	17	1	17	0.2258	0.0417	0.2615	1	5
1492	487	3	Actual Day	Premium	4	17	68	1	68	0.1452	0.1667	0.2615	1	5
1493	488	3	Actual Day	Premium	0	17	0	0	0	1.0000	0.0000	0.2615	1	5
1494	489	3	Actual Day	Premium	0	17	0	0	0	1.0000	0.0000	0.2615	1	5
1495	490	3	Actual Day	Premium	4	17	68	1	68	0.1935	0.1667	0.2615	1	5
1496	491	3	Actual Day	Premium	3	17	51	1	51	0.1774	0.1250	0.2615	1	5
1497	492	3	Actual Day	Premium	5	17	85	1	85	0.1290	0.2083	0.2615	1	5
1498	493	3	Actual Day	Premium	7	17	119	1	119	0.1290	0.2917	0.2615	1	5
1499	494	3	Actual Day	Premium	6	17	102	1	102	0.1452	0.2500	0.2615	1	5
1500	495	3	Actual Day	Premium	2	17	34	1	34	0.1290	0.0833	0.2615	1	5
1501	496	3	Actual Day	Premium	6	17	102	1	102	0.1129	0.2500	0.2615	1	5
1502	497	3	Actual Day	Premium	2	17	34	1	34	0.0968	0.0833	0.2615	1	5
1503	498	3	Actual Day	Premium	9	17	153	1	153	0.0968	0.3750	0.2615	1	5
1504	499	3	Actual Day	Premium	1	17	17	1	17	0.7742	0.0417	0.2615	1	5
1505	500	3	Actual Day	Premium	2	17	34	1	34	0.0968	0.0833	0.2615	1	5
1506	1	4	Week One	Basic	4	0.75	3	0	0	1.0000	0.0114	0.2308	3	1
1507	2	4	Week One	Basic	7	0.75	5.25	0	0	1.0000	0.0199	0.2308	3	1
1508	3	4	Week One	Basic	1	0.75	0.75	0	0	1.0000	0.0028	0.2308	3	1
1509	4	4	Week One	Basic	2	0.75	1.5	0	0	1.0000	0.0057	0.2308	3	1
1510	5	4	Week One	Basic	2	0.75	1.5	0	0	1.0000	0.0057	0.2308	3	1
1511	6	4	Week One	Basic	11	0.75	8.25	0	0	1.0000	0.0313	0.2308	3	1
1512	7	4	Week One	Basic	12	0.75	9	0	0	1.0000	0.0341	0.2308	3	1

Figure A.43: MS Excel Solver Risk Platform IP Data Set (42)



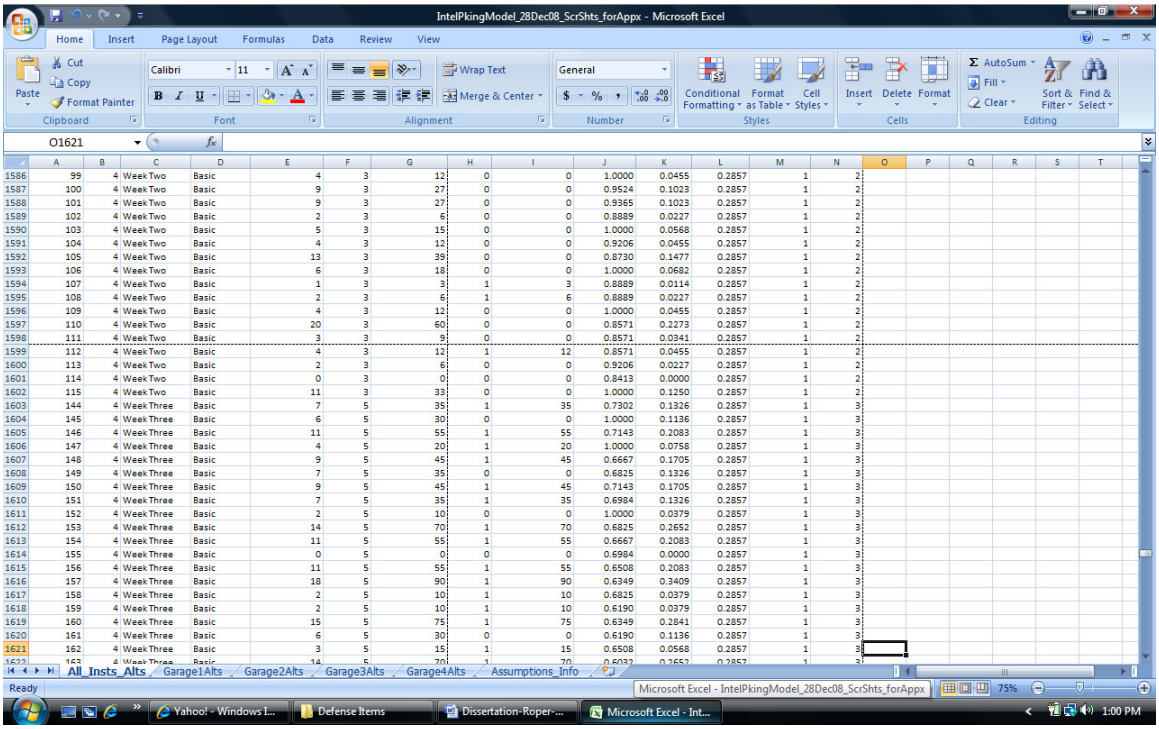
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1513	8	4	Week One	Basic	19	0.75	14.25	0	0	1.0000	0.0540	0.2308	3	1
1514	9	4	Week One	Basic	14	0.75	10.5	0	0	1.0000	0.0398	0.2308	3	1
1515	10	4	Week One	Basic	2	0.75	1.5	0	0	1.0000	0.0057	0.2308	3	1
1516	11	4	Week One	Basic	13	0.75	9.75	0	0	1.0000	0.0369	0.2308	3	1
1517	12	4	Week One	Basic	7	0.75	5.25	0	0	1.0000	0.0199	0.2308	3	1
1518	13	4	Week One	Basic	12	0.75	9	0	0	1.0000	0.0341	0.2308	3	1
1519	14	4	Week One	Basic	11	0.75	8.25	0	0	1.0000	0.0313	0.2308	3	1
1520	15	4	Week One	Basic	11	0.75	8.25	0	0	1.0000	0.0313	0.2308	3	1
1521	16	4	Week One	Basic	8	0.75	6	0	0	1.0000	0.0227	0.2308	3	1
1522	17	4	Week One	Basic	8	0.75	6	0	0	1.0000	0.0227	0.2308	3	1
1523	18	4	Week One	Basic	5	0.75	3.75	0	0	1.0000	0.0142	0.2308	3	1
1524	19	4	Week One	Basic	12	0.75	9	0	0	1.0000	0.0341	0.2308	3	1
1525	20	4	Week One	Basic	16	0.75	12	0	0	1.0000	0.0455	0.2308	3	1
1526	21	4	Week One	Basic	20	0.75	15	0	0	1.0000	0.0568	0.2308	3	1
1527	22	4	Week One	Basic	14	0.75	10.5	0	0	1.0000	0.0398	0.2308	3	1
1528	23	4	Week One	Basic	0	0.75	0	0	0	1.0000	0.0000	0.2308	3	1
1529	24	4	Week One	Basic	6	0.75	4.5	0	0	1.0000	0.0170	0.2308	3	1
1530	25	4	Week One	Basic	7	0.75	5.25	0	0	1.0000	0.0199	0.2308	3	1
1531	26	4	Week One	Basic	0	0.75	0	0	0	1.0000	0.0000	0.2308	3	1
1532	27	4	Week One	Basic	20	0.75	15	0	0	1.0000	0.0568	0.2308	3	1
1533	28	4	Week One	Basic	3	0.75	2.25	0	0	1.0000	0.0085	0.2308	3	1
1534	29	4	Week One	Basic	8	0.75	6	0	0	1.0000	0.0227	0.2308	3	1
1535	30	4	Week One	Basic	1	0.75	0.75	0	0	1.0000	0.0028	0.2308	3	1
1536	31	4	Week One	Basic	20	0.75	15	0	0	1.0000	0.0568	0.2308	3	1
1537	50	4	Week Two	Basic	2	3	6	0	0	1.0000	0.0227	0.2857	1	2
1538	51	4	Week Two	Basic	3	3	9	1	9	1.0000	0.0341	0.2857	1	2
1539	52	4	Week Two	Basic	12	3	36	0	0	1.0000	0.1364	0.2857	1	2
1540	53	4	Week Two	Basic	17	3	51	0	0	1.0000	0.1932	0.2857	1	2
1541	54	4	Week Two	Basic	18	3	54	0	0	1.0000	0.2045	0.2857	1	2
1542	55	4	Week Two	Basic	16	3	48	0	0	1.0000	0.1818	0.2857	1	2
1543	56	4	Week Two	Basic	11	3	33	0	0	1.0000	0.1250	0.2857	1	2
1544	57	4	Week Two	Basic	16	3	48	0	0	1.0000	0.1818	0.2857	1	2
1545	58	4	Week Two	Basic	3	3	9	0	0	1.0000	0.0341	0.2857	1	2
1546	59	4	Week Two	Basic	1	3	3	0	0	1.0000	0.0114	0.2857	1	2
1547	60	4	Week Two	Basic	20	3	60	0	0	1.0000	0.2273	0.2857	1	2
1548	61	4	Week Two	Basic	13	3	39	0	0	1.0000	0.1477	0.2857	1	2

Figure A.44: MS Excel Solver Risk Platform IP Data Set (43)



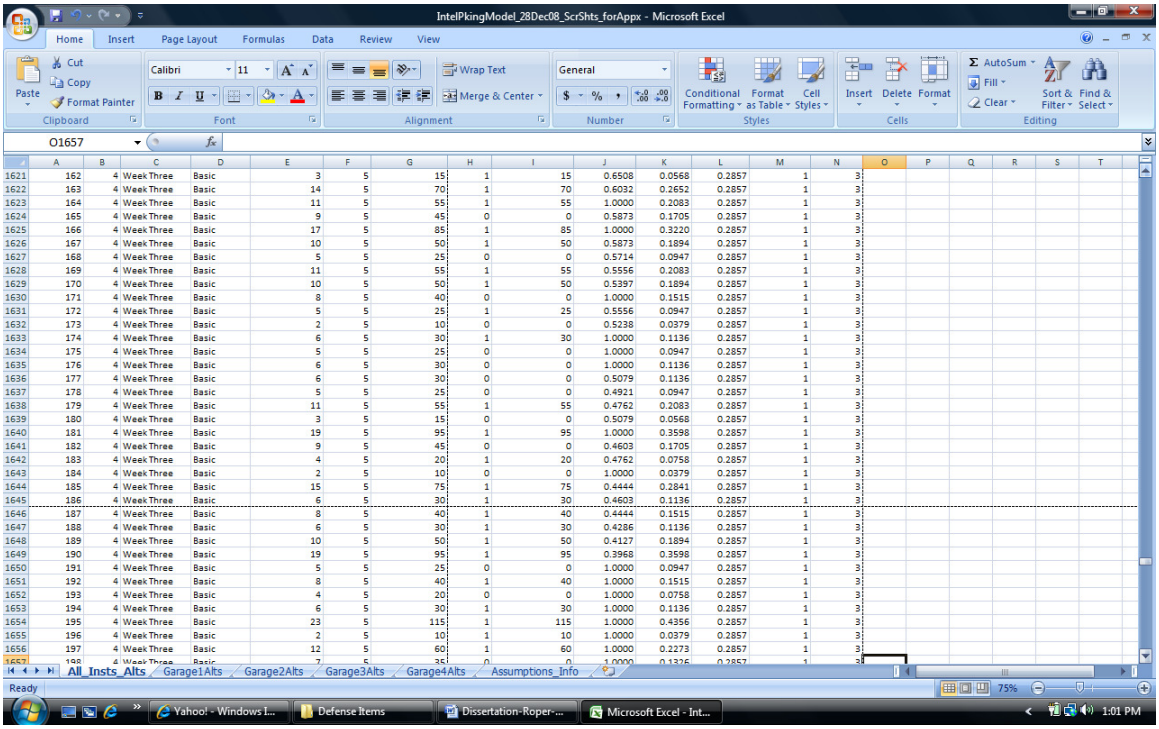
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1550	63	4	Week Two	Basic	5	3	15	1	15	1.0000	0.0568	0.2857	1	2
1551	64	4	Week Two	Basic	5	3	15	0	0	1.0000	0.0568	0.2857	1	2
1552	65	4	Week Two	Basic	12	3	36	0	0	1.0000	0.1364	0.2857	1	2
1553	66	4	Week Two	Basic	6	3	18	0	0	1.0000	0.0682	0.2857	1	2
1554	67	4	Week Two	Basic	2	3	6	0	0	1.0000	0.0227	0.2857	1	2
1555	68	4	Week Two	Basic	7	3	21	0	0	1.0000	0.0795	0.2857	1	2
1556	69	4	Week Two	Basic	9	3	27	0	0	1.0000	0.1023	0.2857	1	2
1557	70	4	Week Two	Basic	12	3	36	0	0	1.0000	0.1364	0.2857	1	2
1558	71	4	Week Two	Basic	5	3	15	0	0	0.9683	0.0568	0.2857	1	2
1559	72	4	Week Two	Basic	6	3	18	0	0	0.9524	0.0682	0.2857	1	2
1560	73	4	Week Two	Basic	7	3	21	0	0	1.0000	0.0795	0.2857	1	2
1561	74	4	Week Two	Basic	12	3	36	0	0	1.0000	0.1364	0.2857	1	2
1562	75	4	Week Two	Basic	13	3	39	0	0	1.0000	0.1477	0.2857	1	2
1563	76	4	Week Two	Basic	20	3	60	0	0	1.0000	0.2273	0.2857	1	2
1564	77	4	Week Two	Basic	9	3	27	0	0	0.9365	0.1023	0.2857	1	2
1565	78	4	Week Two	Basic	12	3	36	0	0	1.0000	0.1364	0.2857	1	2
1566	79	4	Week Two	Basic	12	3	36	0	0	1.0000	0.1364	0.2857	1	2
1567	80	4	Week Two	Basic	11	3	33	0	0	1.0000	0.1250	0.2857	1	2
1568	81	4	Week Two	Basic	9	3	27	0	0	1.0000	0.1023	0.2857	1	2
1569	82	4	Week Two	Basic	12	3	36	0	0	1.0000	0.1364	0.2857	1	2
1570	83	4	Week Two	Basic	11	3	33	0	0	1.0000	0.1250	0.2857	1	2
1571	84	4	Week Two	Basic	9	3	27	0	0	1.0000	0.1023	0.2857	1	2
1572	85	4	Week Two	Basic	4	3	12	0	0	1.0000	0.0455	0.2857	1	2
1573	86	4	Week Two	Basic	11	3	33	0	0	1.0000	0.1250	0.2857	1	2
1574	87	4	Week Two	Basic	14	3	42	0	0	1.0000	0.1591	0.2857	1	2
1575	88	4	Week Two	Basic	22	3	66	0	0	1.0000	0.2500	0.2857	1	2
1576	89	4	Week Two	Basic	4	3	12	1	12	0.9365	0.0455	0.2857	1	2
1577	90	4	Week Two	Basic	4	3	12	1	12	0.9206	0.0455	0.2857	1	2
1578	91	4	Week Two	Basic	3	3	9	0	0	1.0000	0.0341	0.2857	1	2
1579	92	4	Week Two	Basic	21	3	63	0	0	1.0000	0.2386	0.2857	1	2
1580	93	4	Week Two	Basic	9	3	27	0	0	1.0000	0.1023	0.2857	1	2
1581	94	4	Week Two	Basic	9	3	27	0	0	0.9048	0.1023	0.2857	1	2
1582	95	4	Week Two	Basic	3	3	9	1	9	1.0000	0.0341	0.2857	1	2
1583	96	4	Week Two	Basic	10	3	30	0	0	1.0000	0.1136	0.2857	1	2
1584	97	4	Week Two	Basic	7	3	21	0	0	1.0000	0.0795	0.2857	1	2
1585	98	4	Week Two	Basic	2	3	6	0	0	0.9048	0.0227	0.2857	1	2

Figure A.45: MS Excel Solver Risk Platform IP Data Set (44)



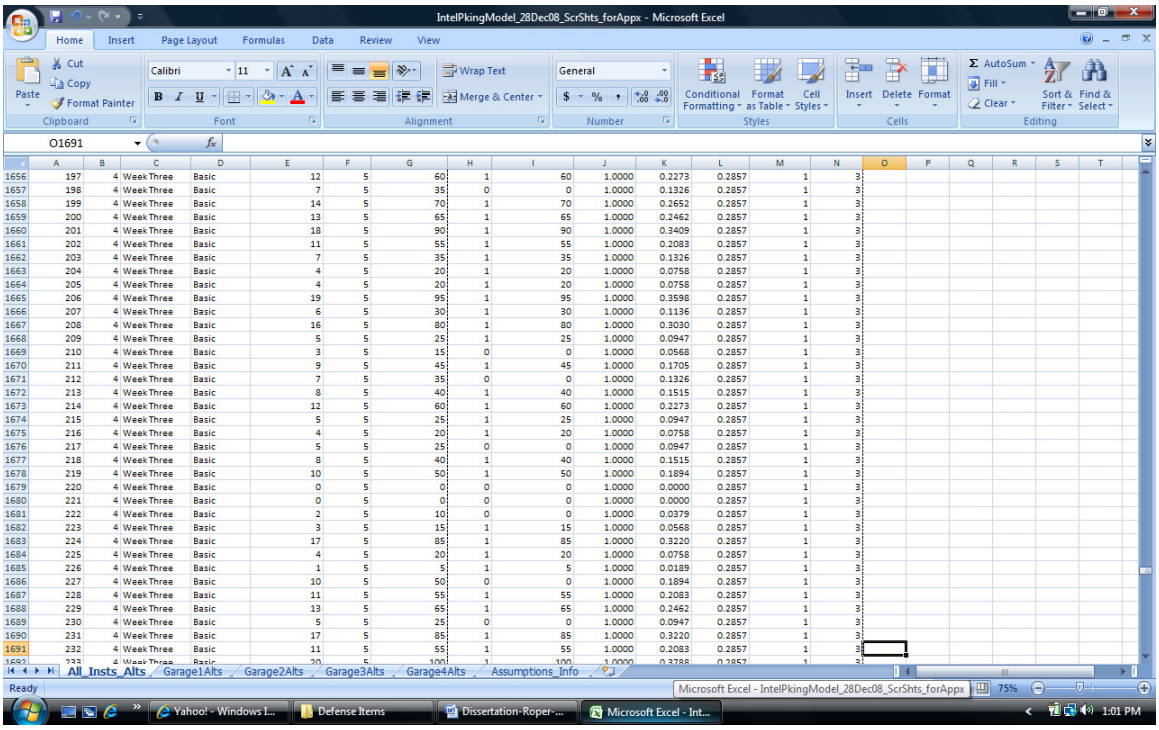
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1586	99	4	Week Two	Basic	4	3	12	0	0	1.0000	0.0455	0.2857	1	2
1587	100	4	Week Two	Basic	9	3	27	0	0	0.9524	0.1023	0.2857	1	2
1588	101	4	Week Two	Basic	9	3	27	0	0	0.9365	0.1023	0.2857	1	2
1589	102	4	Week Two	Basic	2	3	6	0	0	0.8889	0.0227	0.2857	1	2
1590	103	4	Week Two	Basic	5	3	15	0	0	1.0000	0.0568	0.2857	1	2
1591	104	4	Week Two	Basic	4	3	12	0	0	0.9206	0.0455	0.2857	1	2
1592	105	4	Week Two	Basic	13	3	39	0	0	0.8730	0.1477	0.2857	1	2
1593	106	4	Week Two	Basic	6	3	18	0	0	1.0000	0.0682	0.2857	1	2
1594	107	4	Week Two	Basic	1	3	3	1	3	0.8889	0.0114	0.2857	1	2
1595	108	4	Week Two	Basic	2	3	6	1	6	0.8889	0.0227	0.2857	1	2
1596	109	4	Week Two	Basic	4	3	12	0	0	1.0000	0.0455	0.2857	1	2
1597	110	4	Week Two	Basic	20	3	60	0	0	0.8571	0.2273	0.2857	1	2
1598	111	4	Week Two	Basic	3	3	9	0	0	0.8571	0.0341	0.2857	1	2
1599	112	4	Week Two	Basic	4	3	12	1	12	0.8571	0.0455	0.2857	1	2
1600	113	4	Week Two	Basic	2	3	6	0	0	0.9206	0.0227	0.2857	1	2
1601	114	4	Week Two	Basic	0	3	0	0	0	0.8413	0.0000	0.2857	1	2
1602	115	4	Week Two	Basic	11	3	33	0	0	1.0000	0.1250	0.2857	1	2
1603	144	4	Week Three	Basic	7	5	35	1	35	0.7302	0.1326	0.2857	1	3
1604	145	4	Week Three	Basic	6	5	30	0	0	1.0000	0.1136	0.2857	1	3
1605	146	4	Week Three	Basic	11	5	55	1	55	0.7143	0.2083	0.2857	1	3
1606	147	4	Week Three	Basic	4	5	20	1	20	1.0000	0.0758	0.2857	1	3
1607	148	4	Week Three	Basic	9	5	45	1	45	0.6667	0.1705	0.2857	1	3
1608	149	4	Week Three	Basic	7	5	35	0	0	0.6825	0.1326	0.2857	1	3
1609	150	4	Week Three	Basic	9	5	45	1	45	0.7143	0.1705	0.2857	1	3
1610	151	4	Week Three	Basic	7	5	35	1	35	0.6984	0.1326	0.2857	1	3
1611	152	4	Week Three	Basic	2	5	10	0	0	1.0000	0.0379	0.2857	1	3
1612	153	4	Week Three	Basic	14	5	70	1	70	0.6825	0.2652	0.2857	1	3
1613	154	4	Week Three	Basic	11	5	55	1	55	0.6667	0.2083	0.2857	1	3
1614	155	4	Week Three	Basic	0	5	0	0	0	0.6984	0.0000	0.2857	1	3
1615	156	4	Week Three	Basic	11	5	55	1	55	0.6508	0.2083	0.2857	1	3
1616	157	4	Week Three	Basic	18	5	90	1	90	0.6349	0.3409	0.2857	1	3
1617	158	4	Week Three	Basic	2	5	10	1	10	0.6825	0.0379	0.2857	1	3
1618	159	4	Week Three	Basic	2	5	10	1	10	0.6190	0.0379	0.2857	1	3
1619	160	4	Week Three	Basic	15	5	75	1	75	0.6349	0.2841	0.2857	1	3
1620	161	4	Week Three	Basic	6	5	30	0	0	0.6190	0.1136	0.2857	1	3
1621	162	4	Week Three	Basic	3	5	15	1	15	0.6508	0.0568	0.2857	1	3

Figure A.46: MS Excel Solver Risk Platform IP Data Set (45)



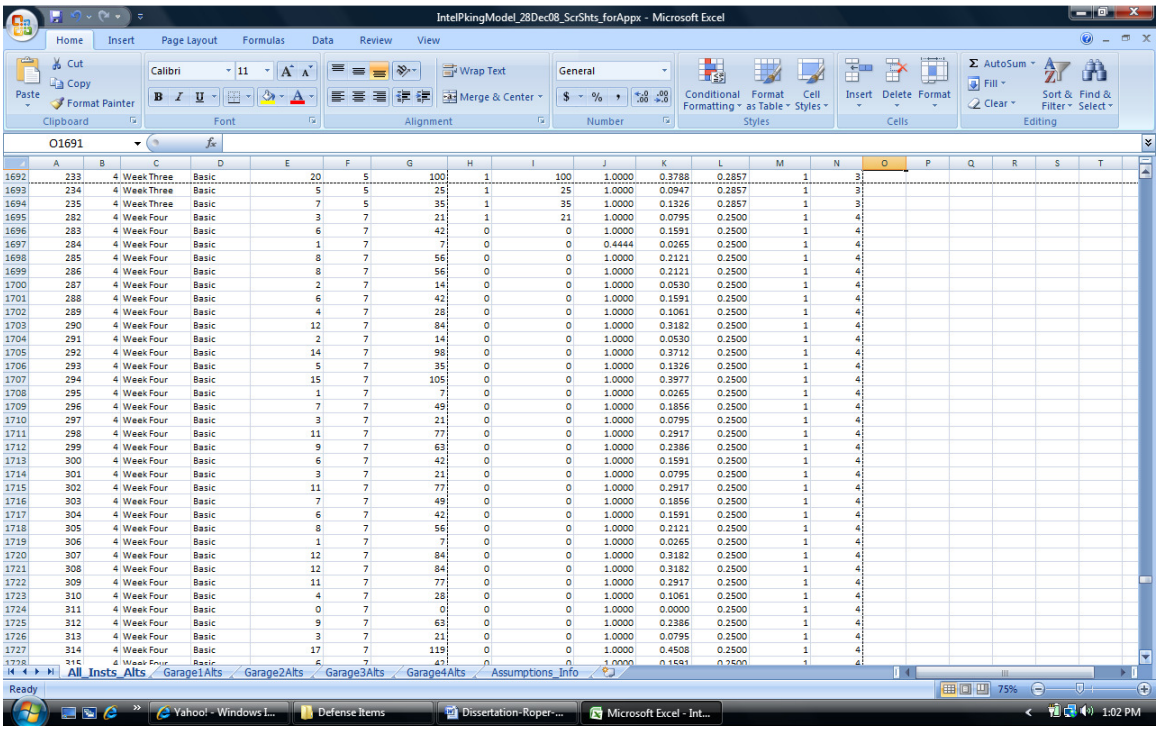
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1621	162	4	Week Three	Basic	3	5	15	1	15	0.6508	0.0568	0.2857	1	3
1622	163	4	Week Three	Basic	14	5	70	1	70	0.6032	0.2652	0.2857	1	3
1623	164	4	Week Three	Basic	11	5	55	1	55	1.0000	0.2083	0.2857	1	3
1624	165	4	Week Three	Basic	9	5	45	0	0	0.5873	0.1705	0.2857	1	3
1625	166	4	Week Three	Basic	17	5	85	1	85	1.0000	0.3220	0.2857	1	3
1626	167	4	Week Three	Basic	10	5	50	1	50	0.5873	0.1894	0.2857	1	3
1627	168	4	Week Three	Basic	5	5	25	0	0	0.5714	0.0947	0.2857	1	3
1628	169	4	Week Three	Basic	11	5	55	1	55	0.5556	0.2083	0.2857	1	3
1629	170	4	Week Three	Basic	10	5	50	1	50	0.5397	0.1894	0.2857	1	3
1630	171	4	Week Three	Basic	8	5	40	0	0	1.0000	0.1515	0.2857	1	3
1631	172	4	Week Three	Basic	5	5	25	1	25	0.5556	0.0947	0.2857	1	3
1632	173	4	Week Three	Basic	2	5	10	0	0	0.5238	0.0379	0.2857	1	3
1633	174	4	Week Three	Basic	6	5	30	1	30	1.0000	0.1136	0.2857	1	3
1634	175	4	Week Three	Basic	5	5	25	0	0	1.0000	0.0947	0.2857	1	3
1635	176	4	Week Three	Basic	6	5	30	0	0	1.0000	0.1136	0.2857	1	3
1636	177	4	Week Three	Basic	6	5	30	0	0	0.5079	0.1136	0.2857	1	3
1637	178	4	Week Three	Basic	5	5	25	0	0	0.4921	0.0947	0.2857	1	3
1638	179	4	Week Three	Basic	11	5	55	1	55	0.4762	0.2083	0.2857	1	3
1639	180	4	Week Three	Basic	3	5	15	0	0	0.5079	0.0568	0.2857	1	3
1640	181	4	Week Three	Basic	19	5	95	1	95	1.0000	0.3598	0.2857	1	3
1641	182	4	Week Three	Basic	9	5	45	0	0	0.4603	0.1705	0.2857	1	3
1642	183	4	Week Three	Basic	4	5	20	1	20	0.4762	0.0758	0.2857	1	3
1643	184	4	Week Three	Basic	2	5	10	0	0	1.0000	0.0379	0.2857	1	3
1644	185	4	Week Three	Basic	15	5	75	1	75	0.4444	0.2841	0.2857	1	3
1645	186	4	Week Three	Basic	6	5	30	1	30	0.4603	0.1136	0.2857	1	3
1646	187	4	Week Three	Basic	8	5	40	1	40	0.4444	0.1515	0.2857	1	3
1647	188	4	Week Three	Basic	6	5	30	1	30	0.4286	0.1136	0.2857	1	3
1648	189	4	Week Three	Basic	10	5	50	1	50	0.4127	0.1894	0.2857	1	3
1649	190	4	Week Three	Basic	19	5	95	1	95	0.3968	0.3598	0.2857	1	3
1650	191	4	Week Three	Basic	5	5	25	0	0	1.0000	0.0947	0.2857	1	3
1651	192	4	Week Three	Basic	8	5	40	1	40	1.0000	0.1515	0.2857	1	3
1652	193	4	Week Three	Basic	4	5	20	0	0	1.0000	0.0758	0.2857	1	3
1653	194	4	Week Three	Basic	6	5	30	1	30	1.0000	0.1136	0.2857	1	3
1654	195	4	Week Three	Basic	23	5	115	1	115	1.0000	0.4356	0.2857	1	3
1655	196	4	Week Three	Basic	2	5	10	1	10	1.0000	0.0379	0.2857	1	3
1656	197	4	Week Three	Basic	12	5	60	1	60	1.0000	0.2273	0.2857	1	3

Figure A.47: MS Excel Solver Risk Platform IP Data Set (46)



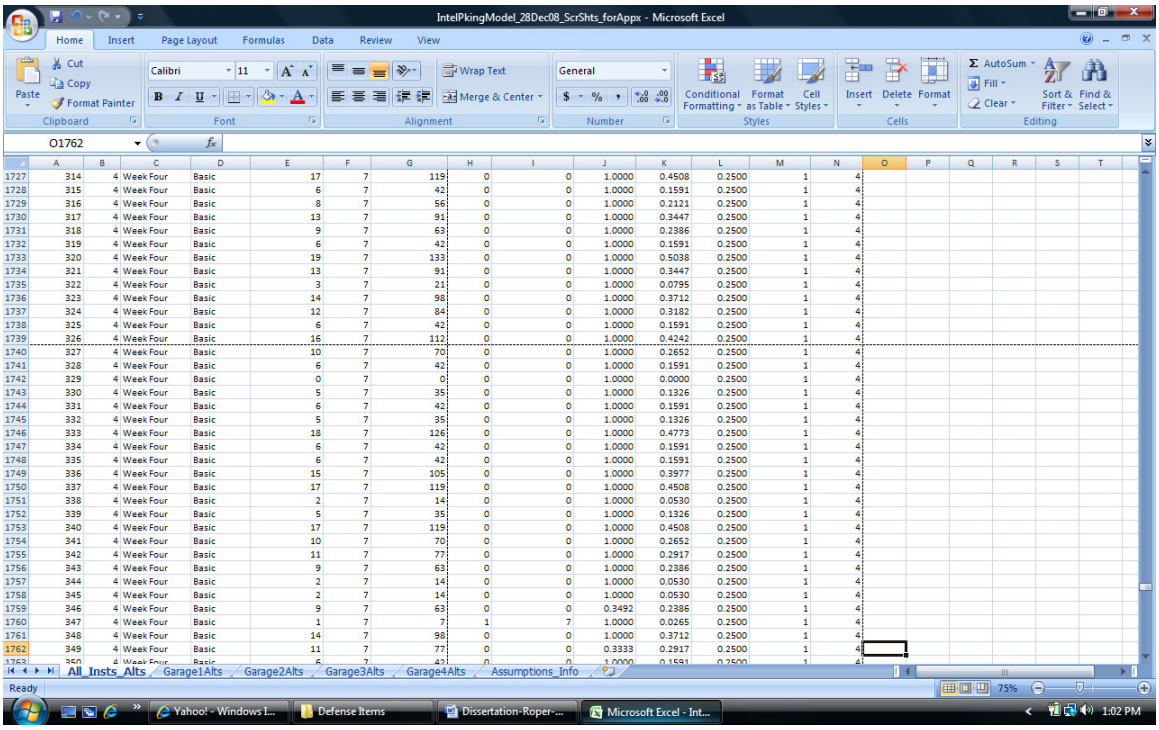
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1656	197	4	Week Three	Basic	12	5	60	1	60	1.0000	0.2273	0.2857	1	3
1657	198	4	Week Three	Basic	7	5	35	0	0	1.0000	0.1326	0.2857	1	3
1658	199	4	Week Three	Basic	14	5	70	1	70	1.0000	0.2652	0.2857	1	3
1659	200	4	Week Three	Basic	13	5	65	1	65	1.0000	0.2462	0.2857	1	3
1660	201	4	Week Three	Basic	18	5	90	1	90	1.0000	0.3409	0.2857	1	3
1661	202	4	Week Three	Basic	11	5	55	1	55	1.0000	0.2083	0.2857	1	3
1662	203	4	Week Three	Basic	7	5	35	1	35	1.0000	0.1326	0.2857	1	3
1663	204	4	Week Three	Basic	4	5	20	1	20	1.0000	0.0758	0.2857	1	3
1664	205	4	Week Three	Basic	4	5	20	1	20	1.0000	0.0758	0.2857	1	3
1665	206	4	Week Three	Basic	19	5	95	1	95	1.0000	0.3598	0.2857	1	3
1666	207	4	Week Three	Basic	6	5	30	1	30	1.0000	0.1136	0.2857	1	3
1667	208	4	Week Three	Basic	16	5	80	1	80	1.0000	0.3030	0.2857	1	3
1668	209	4	Week Three	Basic	5	5	25	1	25	1.0000	0.0947	0.2857	1	3
1669	210	4	Week Three	Basic	3	5	15	0	0	1.0000	0.0568	0.2857	1	3
1670	211	4	Week Three	Basic	9	5	45	1	45	1.0000	0.1705	0.2857	1	3
1671	212	4	Week Three	Basic	7	5	35	0	0	1.0000	0.1326	0.2857	1	3
1672	213	4	Week Three	Basic	8	5	40	1	40	1.0000	0.1515	0.2857	1	3
1673	214	4	Week Three	Basic	12	5	60	1	60	1.0000	0.2273	0.2857	1	3
1674	215	4	Week Three	Basic	5	5	25	1	25	1.0000	0.0947	0.2857	1	3
1675	216	4	Week Three	Basic	4	5	20	1	20	1.0000	0.0758	0.2857	1	3
1676	217	4	Week Three	Basic	5	5	25	0	0	1.0000	0.0947	0.2857	1	3
1677	218	4	Week Three	Basic	8	5	40	1	40	1.0000	0.1515	0.2857	1	3
1678	219	4	Week Three	Basic	10	5	50	1	50	1.0000	0.1894	0.2857	1	3
1679	220	4	Week Three	Basic	0	5	0	0	0	1.0000	0.0000	0.2857	1	3
1680	221	4	Week Three	Basic	0	5	0	0	0	1.0000	0.0000	0.2857	1	3
1681	222	4	Week Three	Basic	2	5	10	0	0	1.0000	0.0379	0.2857	1	3
1682	223	4	Week Three	Basic	3	5	15	1	15	1.0000	0.0568	0.2857	1	3
1683	224	4	Week Three	Basic	17	5	85	1	85	1.0000	0.3220	0.2857	1	3
1684	225	4	Week Three	Basic	4	5	20	1	20	1.0000	0.0758	0.2857	1	3
1685	226	4	Week Three	Basic	1	5	5	1	5	1.0000	0.0189	0.2857	1	3
1686	227	4	Week Three	Basic	10	5	50	0	0	1.0000	0.1894	0.2857	1	3
1687	228	4	Week Three	Basic	11	5	55	1	55	1.0000	0.2083	0.2857	1	3
1688	229	4	Week Three	Basic	13	5	65	1	65	1.0000	0.2462	0.2857	1	3
1689	230	4	Week Three	Basic	5	5	25	0	0	1.0000	0.0947	0.2857	1	3
1690	231	4	Week Three	Basic	17	5	85	1	85	1.0000	0.3220	0.2857	1	3
1691	232	4	Week Three	Basic	11	5	55	1	55	1.0000	0.2083	0.2857	1	3

Figure A.48: MS Excel Solver Risk Platform IP Data Set (47)



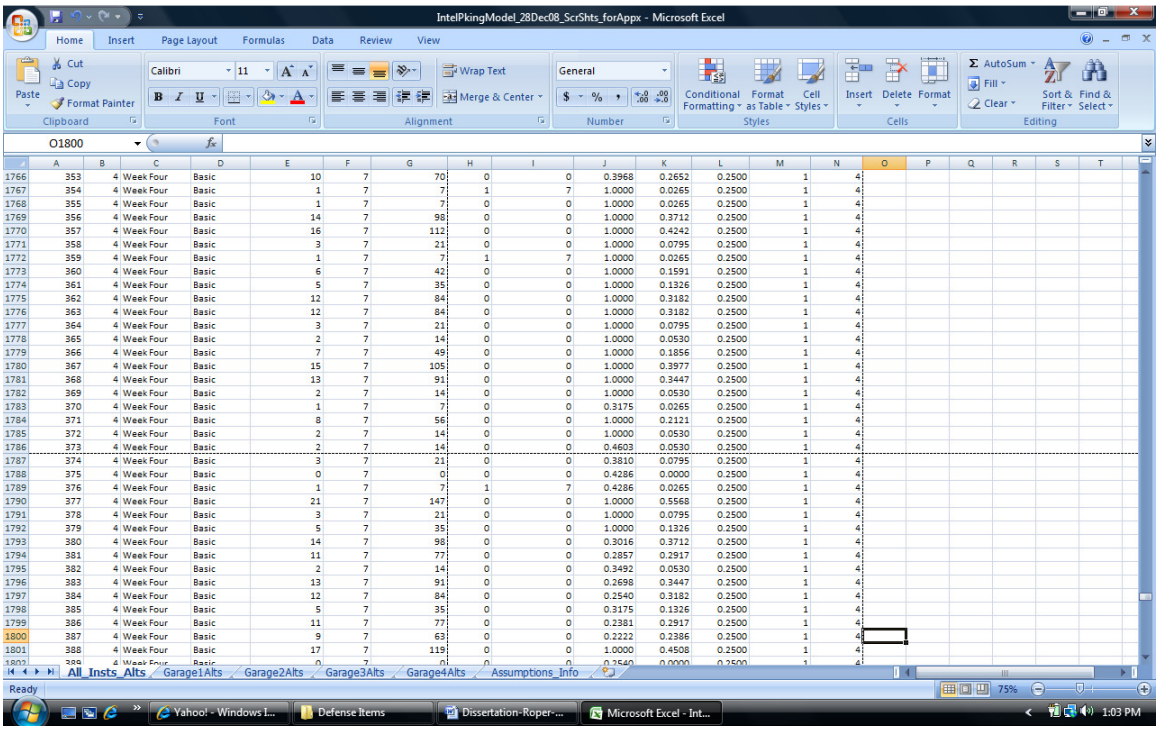
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1692	233	4	Week Three	Basic	20	5	100	1	100	1.0000	0.3788	0.2857	1	3
1693	234	4	Week Three	Basic	5	5	25	1	25	1.0000	0.0947	0.2857	1	3
1694	235	4	Week Three	Basic	7	5	35	1	35	1.0000	0.1326	0.2857	1	3
1695	282	4	Week Four	Basic	3	7	21	1	21	1.0000	0.0795	0.2500	1	4
1696	283	4	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
1697	284	4	Week Four	Basic	1	7	7	0	0	0.4444	0.0265	0.2500	1	4
1698	285	4	Week Four	Basic	8	7	56	0	0	1.0000	0.2121	0.2500	1	4
1699	286	4	Week Four	Basic	8	7	56	0	0	1.0000	0.2121	0.2500	1	4
1700	287	4	Week Four	Basic	2	7	14	0	0	1.0000	0.0530	0.2500	1	4
1701	288	4	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
1702	289	4	Week Four	Basic	4	7	28	0	0	1.0000	0.1061	0.2500	1	4
1703	290	4	Week Four	Basic	12	7	84	0	0	1.0000	0.3182	0.2500	1	4
1704	291	4	Week Four	Basic	2	7	14	0	0	1.0000	0.0530	0.2500	1	4
1705	292	4	Week Four	Basic	14	7	98	0	0	1.0000	0.3712	0.2500	1	4
1706	293	4	Week Four	Basic	5	7	35	0	0	1.0000	0.1326	0.2500	1	4
1707	294	4	Week Four	Basic	15	7	105	0	0	1.0000	0.3977	0.2500	1	4
1708	295	4	Week Four	Basic	1	7	7	0	0	1.0000	0.0265	0.2500	1	4
1709	296	4	Week Four	Basic	7	7	49	0	0	1.0000	0.1856	0.2500	1	4
1710	297	4	Week Four	Basic	3	7	21	0	0	1.0000	0.0795	0.2500	1	4
1711	298	4	Week Four	Basic	11	7	77	0	0	1.0000	0.2917	0.2500	1	4
1712	299	4	Week Four	Basic	9	7	63	0	0	1.0000	0.2386	0.2500	1	4
1713	300	4	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
1714	301	4	Week Four	Basic	3	7	21	0	0	1.0000	0.0795	0.2500	1	4
1715	302	4	Week Four	Basic	11	7	77	0	0	1.0000	0.2917	0.2500	1	4
1716	303	4	Week Four	Basic	7	7	49	0	0	1.0000	0.1856	0.2500	1	4
1717	304	4	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
1718	305	4	Week Four	Basic	8	7	56	0	0	1.0000	0.2121	0.2500	1	4
1719	306	4	Week Four	Basic	1	7	7	0	0	1.0000	0.0265	0.2500	1	4
1720	307	4	Week Four	Basic	12	7	84	0	0	1.0000	0.3182	0.2500	1	4
1721	308	4	Week Four	Basic	12	7	84	0	0	1.0000	0.3182	0.2500	1	4
1722	309	4	Week Four	Basic	11	7	77	0	0	1.0000	0.2917	0.2500	1	4
1723	310	4	Week Four	Basic	4	7	28	0	0	1.0000	0.1061	0.2500	1	4
1724	311	4	Week Four	Basic	0	7	0	0	0	1.0000	0.0000	0.2500	1	4
1725	312	4	Week Four	Basic	9	7	63	0	0	1.0000	0.2386	0.2500	1	4
1726	313	4	Week Four	Basic	3	7	21	0	0	1.0000	0.0795	0.2500	1	4
1727	314	4	Week Four	Basic	17	7	119	0	0	1.0000	0.4508	0.2500	1	4

Figure A.49: MS Excel Solver Risk Platform IP Data Set (48)



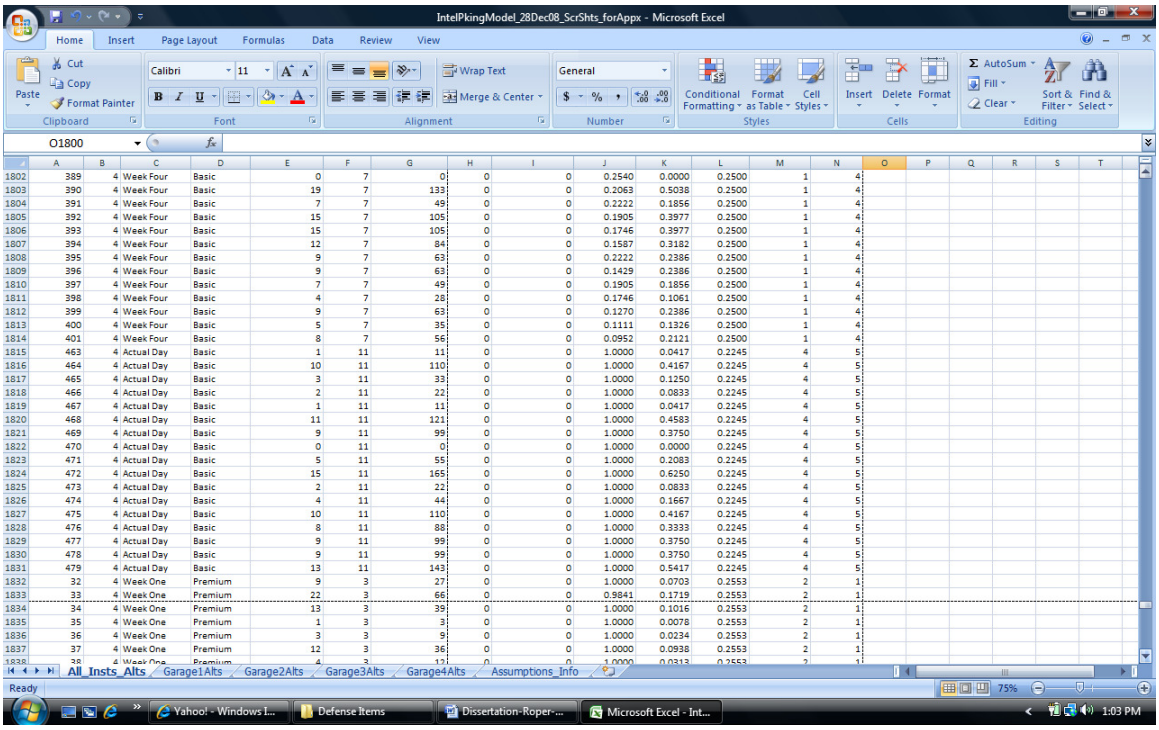
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1727	314	4	Week Four	Basic	17	7	119	0	0	1.0000	0.4508	0.2500	1	4
1728	315	4	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
1729	316	4	Week Four	Basic	8	7	56	0	0	1.0000	0.2121	0.2500	1	4
1730	317	4	Week Four	Basic	13	7	91	0	0	1.0000	0.3447	0.2500	1	4
1731	318	4	Week Four	Basic	9	7	63	0	0	1.0000	0.2386	0.2500	1	4
1732	319	4	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
1733	320	4	Week Four	Basic	19	7	133	0	0	1.0000	0.5038	0.2500	1	4
1734	321	4	Week Four	Basic	13	7	91	0	0	1.0000	0.3447	0.2500	1	4
1735	322	4	Week Four	Basic	3	7	21	0	0	1.0000	0.0795	0.2500	1	4
1736	323	4	Week Four	Basic	14	7	98	0	0	1.0000	0.3712	0.2500	1	4
1737	324	4	Week Four	Basic	12	7	84	0	0	1.0000	0.3182	0.2500	1	4
1738	325	4	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
1739	326	4	Week Four	Basic	16	7	112	0	0	1.0000	0.4242	0.2500	1	4
1740	327	4	Week Four	Basic	10	7	70	0	0	1.0000	0.2652	0.2500	1	4
1741	328	4	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
1742	329	4	Week Four	Basic	0	7	0	0	0	1.0000	0.0000	0.2500	1	4
1743	330	4	Week Four	Basic	5	7	35	0	0	1.0000	0.1326	0.2500	1	4
1744	331	4	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
1745	332	4	Week Four	Basic	5	7	35	0	0	1.0000	0.1326	0.2500	1	4
1746	333	4	Week Four	Basic	18	7	126	0	0	1.0000	0.4773	0.2500	1	4
1747	334	4	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
1748	335	4	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
1749	336	4	Week Four	Basic	15	7	105	0	0	1.0000	0.3977	0.2500	1	4
1750	337	4	Week Four	Basic	17	7	119	0	0	1.0000	0.4508	0.2500	1	4
1751	338	4	Week Four	Basic	2	7	14	0	0	1.0000	0.0530	0.2500	1	4
1752	339	4	Week Four	Basic	5	7	35	0	0	1.0000	0.1326	0.2500	1	4
1753	340	4	Week Four	Basic	17	7	119	0	0	1.0000	0.4508	0.2500	1	4
1754	341	4	Week Four	Basic	10	7	70	0	0	1.0000	0.2652	0.2500	1	4
1755	342	4	Week Four	Basic	11	7	77	0	0	1.0000	0.2917	0.2500	1	4
1756	343	4	Week Four	Basic	9	7	63	0	0	1.0000	0.2386	0.2500	1	4
1757	344	4	Week Four	Basic	2	7	14	0	0	1.0000	0.0530	0.2500	1	4
1758	345	4	Week Four	Basic	2	7	14	0	0	1.0000	0.0530	0.2500	1	4
1759	346	4	Week Four	Basic	9	7	63	0	0	0.3492	0.2386	0.2500	1	4
1760	347	4	Week Four	Basic	1	7	7	1	7	1.0000	0.0265	0.2500	1	4
1761	348	4	Week Four	Basic	14	7	98	0	0	1.0000	0.3712	0.2500	1	4
1762	349	4	Week Four	Basic	11	7	77	0	0	0.3333	0.2917	0.2500	1	4

Figure A.50: MS Excel Solver Risk Platform IP Data Set (49)



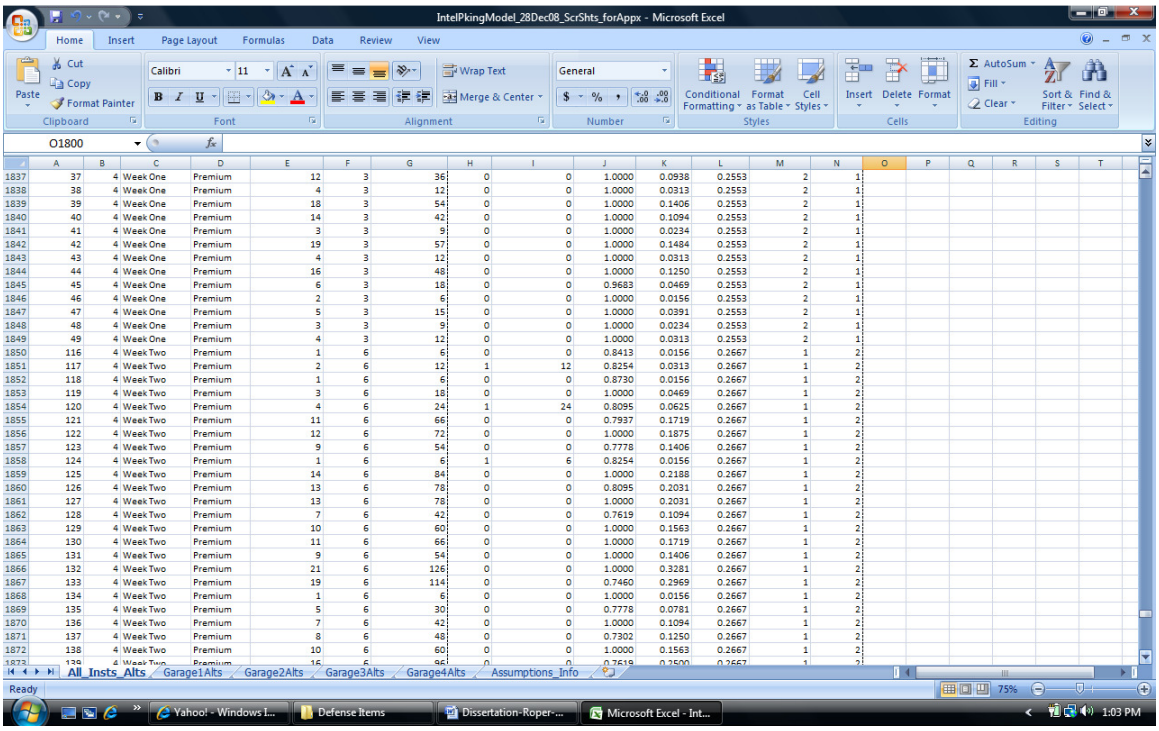
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1766	353	4	Week Four	Basic	10	7	70	0	0	0.3968	0.2652	0.2500	1	4
1767	354	4	Week Four	Basic	1	7	7	1	7	1.0000	0.0265	0.2500	1	4
1768	355	4	Week Four	Basic	1	7	7	0	0	1.0000	0.0265	0.2500	1	4
1769	356	4	Week Four	Basic	14	7	98	0	0	1.0000	0.3712	0.2500	1	4
1770	357	4	Week Four	Basic	16	7	112	0	0	1.0000	0.4242	0.2500	1	4
1771	358	4	Week Four	Basic	3	7	21	0	0	1.0000	0.0795	0.2500	1	4
1772	359	4	Week Four	Basic	1	7	7	1	7	1.0000	0.0265	0.2500	1	4
1773	360	4	Week Four	Basic	6	7	42	0	0	1.0000	0.1591	0.2500	1	4
1774	361	4	Week Four	Basic	5	7	35	0	0	1.0000	0.1326	0.2500	1	4
1775	362	4	Week Four	Basic	12	7	84	0	0	1.0000	0.3182	0.2500	1	4
1776	363	4	Week Four	Basic	12	7	84	0	0	1.0000	0.3182	0.2500	1	4
1777	364	4	Week Four	Basic	3	7	21	0	0	1.0000	0.0795	0.2500	1	4
1778	365	4	Week Four	Basic	2	7	14	0	0	1.0000	0.0530	0.2500	1	4
1779	366	4	Week Four	Basic	7	7	49	0	0	1.0000	0.1856	0.2500	1	4
1780	367	4	Week Four	Basic	15	7	105	0	0	1.0000	0.3977	0.2500	1	4
1781	368	4	Week Four	Basic	13	7	91	0	0	1.0000	0.3447	0.2500	1	4
1782	369	4	Week Four	Basic	2	7	14	0	0	1.0000	0.0530	0.2500	1	4
1783	370	4	Week Four	Basic	1	7	7	0	0	0.3175	0.0265	0.2500	1	4
1784	371	4	Week Four	Basic	8	7	56	0	0	1.0000	0.2121	0.2500	1	4
1785	372	4	Week Four	Basic	2	7	14	0	0	1.0000	0.0530	0.2500	1	4
1786	373	4	Week Four	Basic	2	7	14	0	0	0.4603	0.0530	0.2500	1	4
1787	374	4	Week Four	Basic	3	7	21	0	0	0.3810	0.0795	0.2500	1	4
1788	375	4	Week Four	Basic	0	7	0	0	0	0.4286	0.0000	0.2500	1	4
1789	376	4	Week Four	Basic	1	7	7	1	7	0.4286	0.0265	0.2500	1	4
1790	377	4	Week Four	Basic	21	7	147	0	0	1.0000	0.5568	0.2500	1	4
1791	378	4	Week Four	Basic	3	7	21	0	0	1.0000	0.0795	0.2500	1	4
1792	379	4	Week Four	Basic	5	7	35	0	0	1.0000	0.1326	0.2500	1	4
1793	380	4	Week Four	Basic	14	7	98	0	0	0.3016	0.3712	0.2500	1	4
1794	381	4	Week Four	Basic	11	7	77	0	0	0.2857	0.2917	0.2500	1	4
1795	382	4	Week Four	Basic	2	7	14	0	0	0.3492	0.0530	0.2500	1	4
1796	383	4	Week Four	Basic	13	7	91	0	0	0.2698	0.3447	0.2500	1	4
1797	384	4	Week Four	Basic	12	7	84	0	0	0.2540	0.3182	0.2500	1	4
1798	385	4	Week Four	Basic	5	7	35	0	0	0.3175	0.1326	0.2500	1	4
1799	386	4	Week Four	Basic	11	7	77	0	0	0.2381	0.2917	0.2500	1	4
1800	387	4	Week Four	Basic	9	7	63	0	0	0.2222	0.2386	0.2500	1	4
1801	388	4	Week Four	Basic	17	7	119	0	0	1.0000	0.4508	0.2500	1	4

Figure A.51: MS Excel Solver Risk Platform IP Data Set (50)



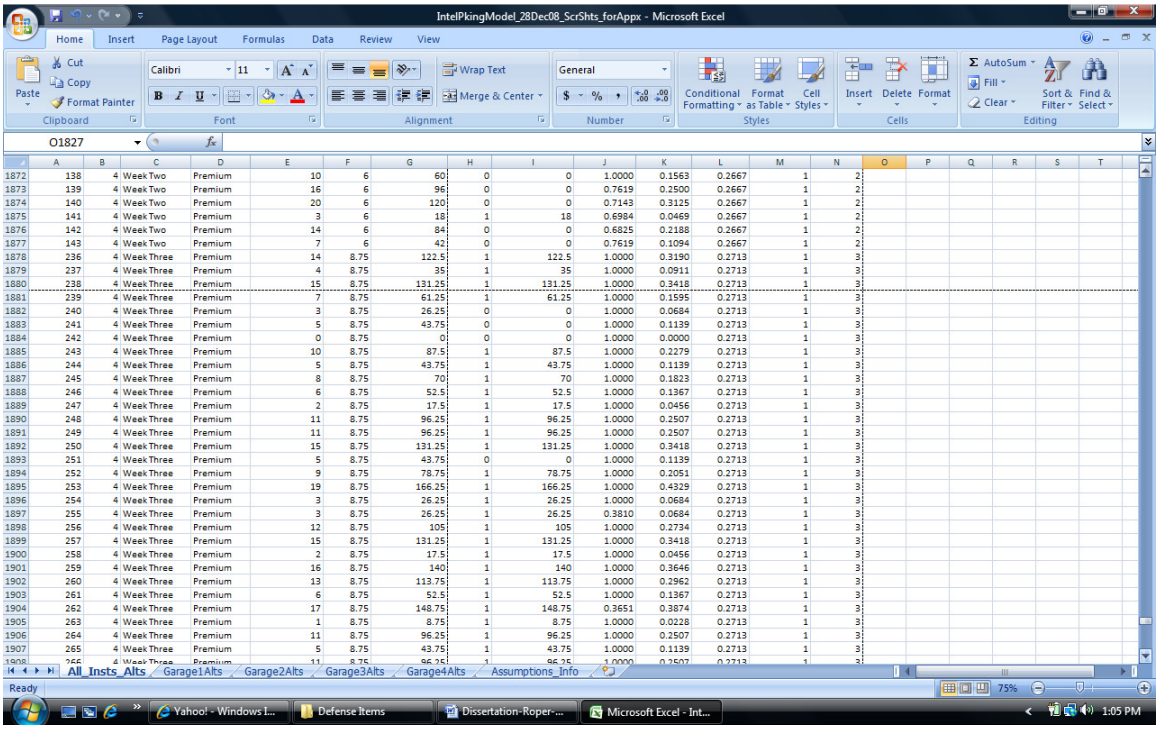
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1802	389	4	Week Four	Basic	0	7	0	0	0	0.2540	0.0000	0.2500	1	4
1803	390	4	Week Four	Basic	19	7	133	0	0	0.2063	0.5038	0.2500	1	4
1804	391	4	Week Four	Basic	7	7	49	0	0	0.2222	0.1856	0.2500	1	4
1805	392	4	Week Four	Basic	15	7	105	0	0	0.1905	0.3977	0.2500	1	4
1806	393	4	Week Four	Basic	15	7	105	0	0	0.1746	0.3977	0.2500	1	4
1807	394	4	Week Four	Basic	12	7	84	0	0	0.1587	0.3182	0.2500	1	4
1808	395	4	Week Four	Basic	9	7	63	0	0	0.2222	0.2386	0.2500	1	4
1809	396	4	Week Four	Basic	9	7	63	0	0	0.1429	0.2386	0.2500	1	4
1810	397	4	Week Four	Basic	7	7	49	0	0	0.1905	0.1856	0.2500	1	4
1811	398	4	Week Four	Basic	4	7	28	0	0	0.1746	0.1061	0.2500	1	4
1812	399	4	Week Four	Basic	9	7	63	0	0	0.1270	0.2386	0.2500	1	4
1813	400	4	Week Four	Basic	5	7	35	0	0	0.1111	0.1326	0.2500	1	4
1814	401	4	Week Four	Basic	8	7	56	0	0	0.0952	0.2121	0.2500	1	4
1815	463	4	Actual Day	Basic	1	11	11	0	0	1.0000	0.0417	0.2245	4	5
1816	464	4	Actual Day	Basic	10	11	110	0	0	1.0000	0.4167	0.2245	4	5
1817	465	4	Actual Day	Basic	3	11	33	0	0	1.0000	0.1250	0.2245	4	5
1818	466	4	Actual Day	Basic	2	11	22	0	0	1.0000	0.0833	0.2245	4	5
1819	467	4	Actual Day	Basic	1	11	11	0	0	1.0000	0.0417	0.2245	4	5
1820	468	4	Actual Day	Basic	11	11	121	0	0	1.0000	0.4583	0.2245	4	5
1821	469	4	Actual Day	Basic	9	11	99	0	0	1.0000	0.3750	0.2245	4	5
1822	470	4	Actual Day	Basic	0	11	0	0	0	1.0000	0.0000	0.2245	4	5
1823	471	4	Actual Day	Basic	5	11	55	0	0	1.0000	0.2083	0.2245	4	5
1824	472	4	Actual Day	Basic	15	11	165	0	0	1.0000	0.6250	0.2245	4	5
1825	473	4	Actual Day	Basic	2	11	22	0	0	1.0000	0.0833	0.2245	4	5
1826	474	4	Actual Day	Basic	4	11	44	0	0	1.0000	0.1667	0.2245	4	5
1827	475	4	Actual Day	Basic	10	11	110	0	0	1.0000	0.4167	0.2245	4	5
1828	476	4	Actual Day	Basic	8	11	88	0	0	1.0000	0.3333	0.2245	4	5
1829	477	4	Actual Day	Basic	9	11	99	0	0	1.0000	0.3750	0.2245	4	5
1830	478	4	Actual Day	Basic	9	11	99	0	0	1.0000	0.3750	0.2245	4	5
1831	479	4	Actual Day	Basic	13	11	143	0	0	1.0000	0.5417	0.2245	4	5
1832	32	4	Week One	Premium	9	3	27	0	0	1.0000	0.0703	0.2553	2	1
1833	33	4	Week One	Premium	22	3	66	0	0	0.9841	0.1719	0.2553	2	1
1834	34	4	Week One	Premium	13	3	39	0	0	1.0000	0.1016	0.2553	2	1
1835	35	4	Week One	Premium	1	3	3	0	0	1.0000	0.0078	0.2553	2	1
1836	36	4	Week One	Premium	3	3	9	0	0	1.0000	0.0234	0.2553	2	1
1837	37	4	Week One	Premium	12	3	36	0	0	1.0000	0.0938	0.2553	2	1

Figure A.52: MS Excel Solver Risk Platform IP Data Set (51)



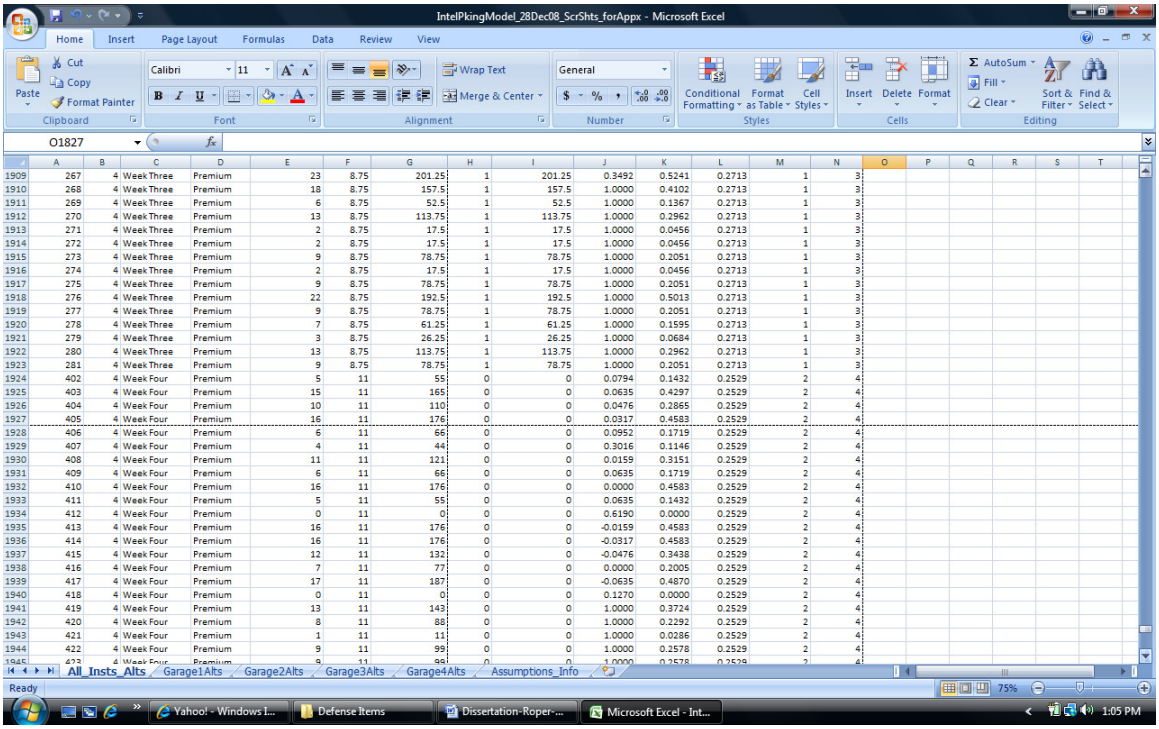
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1837	37	4	Week One	Premium	12	3	36	0	0	1.0000	0.0938	0.2553	2	1
1838	38	4	Week One	Premium	4	3	12	0	0	1.0000	0.0313	0.2553	2	1
1839	39	4	Week One	Premium	18	3	54	0	0	1.0000	0.1406	0.2553	2	1
1840	40	4	Week One	Premium	14	3	42	0	0	1.0000	0.1094	0.2553	2	1
1841	41	4	Week One	Premium	3	3	9	0	0	1.0000	0.0234	0.2553	2	1
1842	42	4	Week One	Premium	19	3	57	0	0	1.0000	0.1484	0.2553	2	1
1843	43	4	Week One	Premium	4	3	12	0	0	1.0000	0.0313	0.2553	2	1
1844	44	4	Week One	Premium	16	3	48	0	0	1.0000	0.1250	0.2553	2	1
1845	45	4	Week One	Premium	6	3	18	0	0	0.9683	0.0469	0.2553	2	1
1846	46	4	Week One	Premium	2	3	6	0	0	1.0000	0.0156	0.2553	2	1
1847	47	4	Week One	Premium	5	3	15	0	0	1.0000	0.0391	0.2553	2	1
1848	48	4	Week One	Premium	3	3	9	0	0	1.0000	0.0234	0.2553	2	1
1849	49	4	Week One	Premium	4	3	12	0	0	1.0000	0.0313	0.2553	2	1
1850	116	4	Week Two	Premium	1	6	6	0	0	0.8413	0.0156	0.2667	1	2
1851	117	4	Week Two	Premium	2	6	12	1	12	0.8254	0.0313	0.2667	1	2
1852	118	4	Week Two	Premium	1	6	6	0	0	0.8730	0.0156	0.2667	1	2
1853	119	4	Week Two	Premium	3	6	18	0	0	1.0000	0.0469	0.2667	1	2
1854	120	4	Week Two	Premium	4	6	24	1	24	0.8095	0.0625	0.2667	1	2
1855	121	4	Week Two	Premium	11	6	66	0	0	0.7937	0.1719	0.2667	1	2
1856	122	4	Week Two	Premium	12	6	72	0	0	1.0000	0.1875	0.2667	1	2
1857	123	4	Week Two	Premium	9	6	54	0	0	0.7778	0.1406	0.2667	1	2
1858	124	4	Week Two	Premium	1	6	6	1	6	0.8254	0.0156	0.2667	1	2
1859	125	4	Week Two	Premium	14	6	84	0	0	1.0000	0.2188	0.2667	1	2
1860	126	4	Week Two	Premium	13	6	78	0	0	0.8095	0.2031	0.2667	1	2
1861	127	4	Week Two	Premium	13	6	78	0	0	1.0000	0.2031	0.2667	1	2
1862	128	4	Week Two	Premium	7	6	42	0	0	0.7619	0.1094	0.2667	1	2
1863	129	4	Week Two	Premium	10	6	60	0	0	1.0000	0.1563	0.2667	1	2
1864	130	4	Week Two	Premium	11	6	66	0	0	1.0000	0.1719	0.2667	1	2
1865	131	4	Week Two	Premium	9	6	54	0	0	1.0000	0.1406	0.2667	1	2
1866	132	4	Week Two	Premium	21	6	126	0	0	1.0000	0.3281	0.2667	1	2
1867	133	4	Week Two	Premium	19	6	114	0	0	0.7460	0.2969	0.2667	1	2
1868	134	4	Week Two	Premium	1	6	6	0	0	1.0000	0.0156	0.2667	1	2
1869	135	4	Week Two	Premium	5	6	30	0	0	0.7778	0.0781	0.2667	1	2
1870	136	4	Week Two	Premium	7	6	42	0	0	1.0000	0.1094	0.2667	1	2
1871	137	4	Week Two	Premium	8	6	48	0	0	0.7302	0.1250	0.2667	1	2
1872	138	4	Week Two	Premium	10	6	60	0	0	1.0000	0.1563	0.2667	1	2

Figure A.53: MS Excel Solver Risk Platform IP Data Set (52)



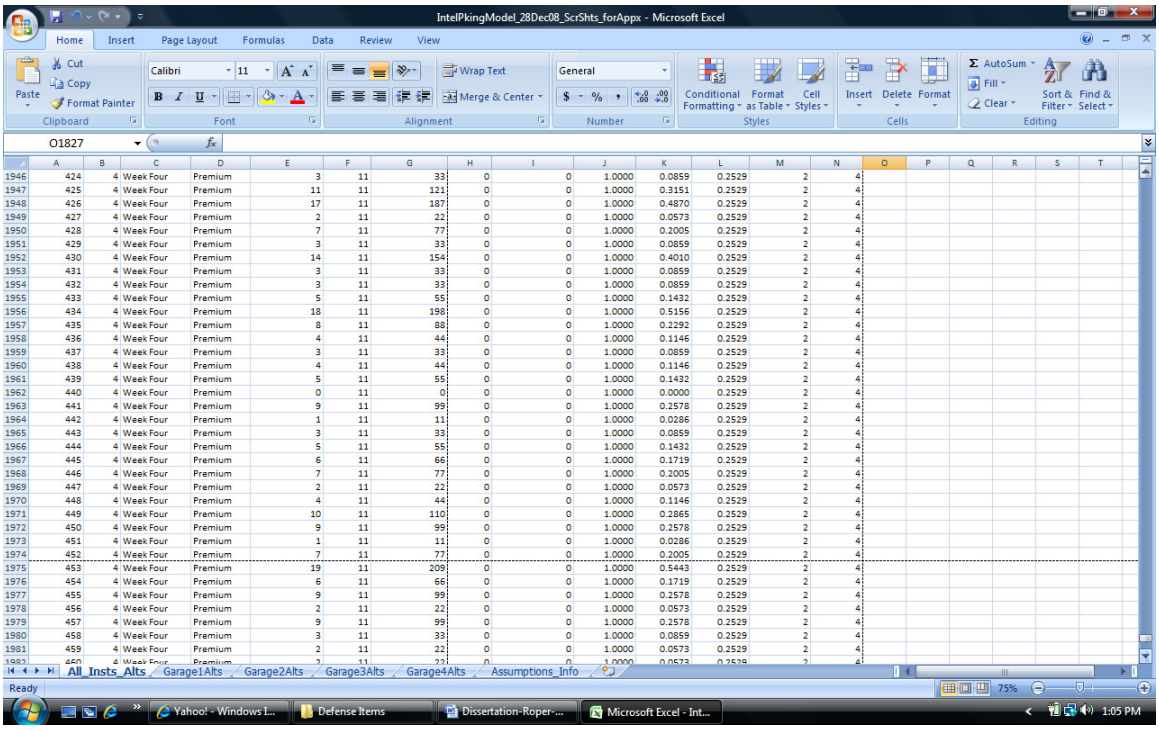
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1872	138	4	Week Two	Premium	10	6	60	0	0	1.0000	0.1563	0.2667	1	2
1873	139	4	Week Two	Premium	16	6	96	0	0	0.7619	0.2500	0.2667	1	2
1874	140	4	Week Two	Premium	20	6	120	0	0	0.7143	0.3125	0.2667	1	2
1875	141	4	Week Two	Premium	3	6	18	1	18	0.6984	0.0469	0.2667	1	2
1876	142	4	Week Two	Premium	14	6	84	0	0	0.6825	0.2188	0.2667	1	2
1877	143	4	Week Two	Premium	7	6	42	0	0	0.7619	0.1094	0.2667	1	2
1878	236	4	Week Three	Premium	14	8.75	122.5	1	122.5	1.0000	0.3190	0.2713	1	3
1879	237	4	Week Three	Premium	4	8.75	35	1	35	1.0000	0.0911	0.2713	1	3
1880	238	4	Week Three	Premium	15	8.75	131.25	1	131.25	1.0000	0.3418	0.2713	1	3
1881	239	4	Week Three	Premium	7	8.75	61.25	1	61.25	1.0000	0.1595	0.2713	1	3
1882	240	4	Week Three	Premium	3	8.75	26.25	0	0	1.0000	0.0684	0.2713	1	3
1883	241	4	Week Three	Premium	5	8.75	43.75	0	0	1.0000	0.1139	0.2713	1	3
1884	242	4	Week Three	Premium	0	8.75	0	0	0	1.0000	0.0000	0.2713	1	3
1885	243	4	Week Three	Premium	10	8.75	87.5	1	87.5	1.0000	0.2279	0.2713	1	3
1886	244	4	Week Three	Premium	5	8.75	43.75	1	43.75	1.0000	0.1139	0.2713	1	3
1887	245	4	Week Three	Premium	8	8.75	70	1	70	1.0000	0.1823	0.2713	1	3
1888	246	4	Week Three	Premium	6	8.75	52.5	1	52.5	1.0000	0.1367	0.2713	1	3
1889	247	4	Week Three	Premium	2	8.75	17.5	1	17.5	1.0000	0.0456	0.2713	1	3
1890	248	4	Week Three	Premium	11	8.75	96.25	1	96.25	1.0000	0.2507	0.2713	1	3
1891	249	4	Week Three	Premium	11	8.75	96.25	1	96.25	1.0000	0.2507	0.2713	1	3
1892	250	4	Week Three	Premium	15	8.75	131.25	1	131.25	1.0000	0.3418	0.2713	1	3
1893	251	4	Week Three	Premium	5	8.75	43.75	0	0	1.0000	0.1139	0.2713	1	3
1894	252	4	Week Three	Premium	9	8.75	78.75	1	78.75	1.0000	0.2051	0.2713	1	3
1895	253	4	Week Three	Premium	19	8.75	166.25	1	166.25	1.0000	0.4329	0.2713	1	3
1896	254	4	Week Three	Premium	3	8.75	26.25	1	26.25	1.0000	0.0684	0.2713	1	3
1897	255	4	Week Three	Premium	3	8.75	26.25	1	26.25	0.3810	0.0684	0.2713	1	3
1898	256	4	Week Three	Premium	12	8.75	105	1	105	1.0000	0.2734	0.2713	1	3
1899	257	4	Week Three	Premium	15	8.75	131.25	1	131.25	1.0000	0.3418	0.2713	1	3
1900	258	4	Week Three	Premium	2	8.75	17.5	1	17.5	1.0000	0.0456	0.2713	1	3
1901	259	4	Week Three	Premium	16	8.75	140	1	140	1.0000	0.3646	0.2713	1	3
1902	260	4	Week Three	Premium	13	8.75	113.75	1	113.75	1.0000	0.2962	0.2713	1	3
1903	261	4	Week Three	Premium	6	8.75	52.5	1	52.5	1.0000	0.1367	0.2713	1	3
1904	262	4	Week Three	Premium	17	8.75	148.75	1	148.75	0.3651	0.3874	0.2713	1	3
1905	263	4	Week Three	Premium	1	8.75	8.75	1	8.75	1.0000	0.0228	0.2713	1	3
1906	264	4	Week Three	Premium	11	8.75	96.25	1	96.25	1.0000	0.2507	0.2713	1	3
1907	265	4	Week Three	Premium	5	8.75	43.75	1	43.75	1.0000	0.1139	0.2713	1	3

Figure A.54: MS Excel Solver Risk Platform IP Data Set (53)



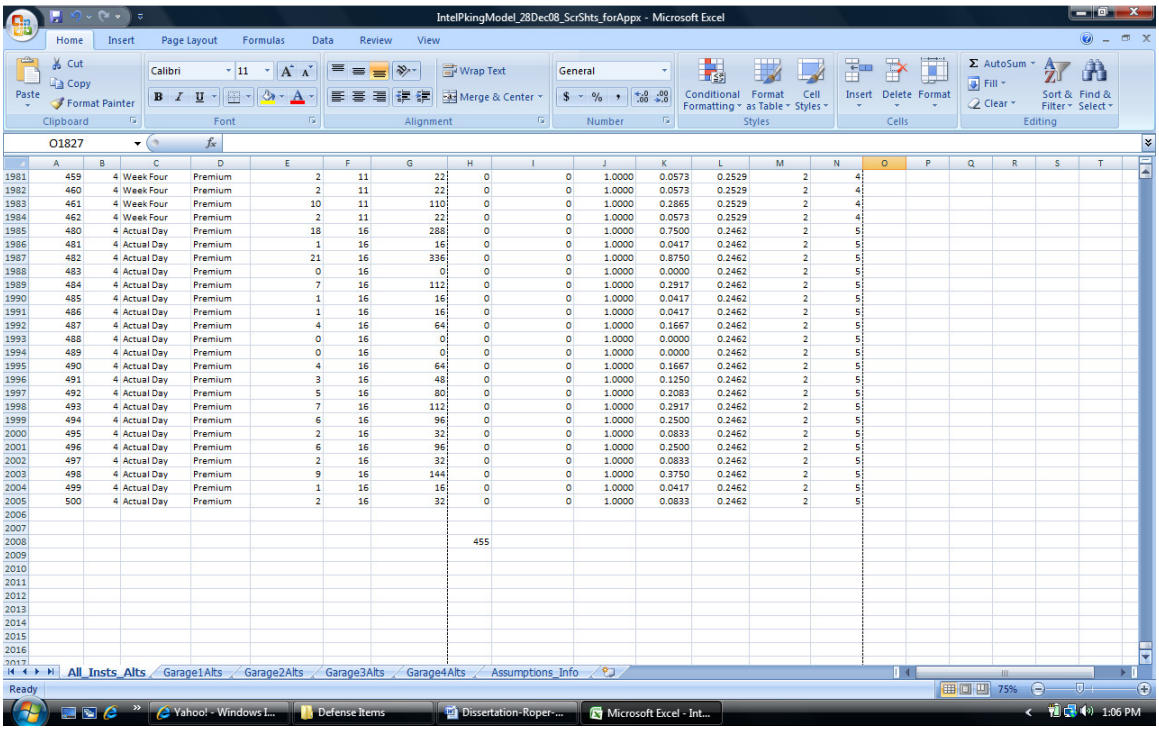
	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1909	267	4	Week Three	Premium	23	8.75	201.25	1	201.25	0.3492	0.5241	0.2713	1	3
1910	268	4	Week Three	Premium	18	8.75	157.5	1	157.5	1.0000	0.4102	0.2713	1	3
1911	269	4	Week Three	Premium	6	8.75	52.5	1	52.5	1.0000	0.1367	0.2713	1	3
1912	270	4	Week Three	Premium	13	8.75	113.75	1	113.75	1.0000	0.2962	0.2713	1	3
1913	271	4	Week Three	Premium	2	8.75	17.5	1	17.5	1.0000	0.0456	0.2713	1	3
1914	272	4	Week Three	Premium	2	8.75	17.5	1	17.5	1.0000	0.0456	0.2713	1	3
1915	273	4	Week Three	Premium	9	8.75	78.75	1	78.75	1.0000	0.2051	0.2713	1	3
1916	274	4	Week Three	Premium	2	8.75	17.5	1	17.5	1.0000	0.0456	0.2713	1	3
1917	275	4	Week Three	Premium	9	8.75	78.75	1	78.75	1.0000	0.2051	0.2713	1	3
1918	276	4	Week Three	Premium	22	8.75	192.5	1	192.5	1.0000	0.5013	0.2713	1	3
1919	277	4	Week Three	Premium	9	8.75	78.75	1	78.75	1.0000	0.2051	0.2713	1	3
1920	278	4	Week Three	Premium	7	8.75	61.25	1	61.25	1.0000	0.1595	0.2713	1	3
1921	279	4	Week Three	Premium	3	8.75	26.25	1	26.25	1.0000	0.0684	0.2713	1	3
1922	280	4	Week Three	Premium	13	8.75	113.75	1	113.75	1.0000	0.2962	0.2713	1	3
1923	281	4	Week Three	Premium	9	8.75	78.75	1	78.75	1.0000	0.2051	0.2713	1	3
1924	402	4	Week Four	Premium	5	11	55	0	0	0.0794	0.1432	0.2529	2	4
1925	403	4	Week Four	Premium	15	11	165	0	0	0.0635	0.4297	0.2529	2	4
1926	404	4	Week Four	Premium	10	11	110	0	0	0.0476	0.2865	0.2529	2	4
1927	405	4	Week Four	Premium	16	11	176	0	0	0.0317	0.4583	0.2529	2	4
1928	406	4	Week Four	Premium	6	11	66	0	0	0.0952	0.1719	0.2529	2	4
1929	407	4	Week Four	Premium	4	11	44	0	0	0.3016	0.1146	0.2529	2	4
1930	408	4	Week Four	Premium	11	11	121	0	0	0.0159	0.3151	0.2529	2	4
1931	409	4	Week Four	Premium	6	11	66	0	0	0.0635	0.1719	0.2529	2	4
1932	410	4	Week Four	Premium	16	11	176	0	0	0.0000	0.4583	0.2529	2	4
1933	411	4	Week Four	Premium	5	11	55	0	0	0.0635	0.1432	0.2529	2	4
1934	412	4	Week Four	Premium	0	11	0	0	0	0.6190	0.0000	0.2529	2	4
1935	413	4	Week Four	Premium	16	11	176	0	0	-0.0159	0.4583	0.2529	2	4
1936	414	4	Week Four	Premium	16	11	176	0	0	-0.0317	0.4583	0.2529	2	4
1937	415	4	Week Four	Premium	12	11	132	0	0	-0.0476	0.3438	0.2529	2	4
1938	416	4	Week Four	Premium	7	11	77	0	0	0.0000	0.2005	0.2529	2	4
1939	417	4	Week Four	Premium	17	11	187	0	0	-0.0635	0.4870	0.2529	2	4
1940	418	4	Week Four	Premium	0	11	0	0	0	0.1270	0.0000	0.2529	2	4
1941	419	4	Week Four	Premium	13	11	143	0	0	1.0000	0.3724	0.2529	2	4
1942	420	4	Week Four	Premium	8	11	88	0	0	1.0000	0.2292	0.2529	2	4
1943	421	4	Week Four	Premium	1	11	11	0	0	1.0000	0.0286	0.2529	2	4
1944	422	4	Week Four	Premium	9	11	99	0	0	1.0000	0.2578	0.2529	2	4

Figure A.55: MS Excel Solver Risk Platform IP Data Set (54)



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1946	424	4	Week Four	Premium	3	11	33	0	0	1.0000	0.0859	0.2529	2	4
1947	425	4	Week Four	Premium	11	11	121	0	0	1.0000	0.3151	0.2529	2	4
1948	426	4	Week Four	Premium	17	11	187	0	0	1.0000	0.4870	0.2529	2	4
1949	427	4	Week Four	Premium	2	11	22	0	0	1.0000	0.0573	0.2529	2	4
1950	428	4	Week Four	Premium	7	11	77	0	0	1.0000	0.2005	0.2529	2	4
1951	429	4	Week Four	Premium	3	11	33	0	0	1.0000	0.0859	0.2529	2	4
1952	430	4	Week Four	Premium	14	11	154	0	0	1.0000	0.4010	0.2529	2	4
1953	431	4	Week Four	Premium	3	11	33	0	0	1.0000	0.0859	0.2529	2	4
1954	432	4	Week Four	Premium	3	11	33	0	0	1.0000	0.0859	0.2529	2	4
1955	433	4	Week Four	Premium	5	11	55	0	0	1.0000	0.1432	0.2529	2	4
1956	434	4	Week Four	Premium	18	11	198	0	0	1.0000	0.5156	0.2529	2	4
1957	435	4	Week Four	Premium	8	11	88	0	0	1.0000	0.2292	0.2529	2	4
1958	436	4	Week Four	Premium	4	11	44	0	0	1.0000	0.1146	0.2529	2	4
1959	437	4	Week Four	Premium	3	11	33	0	0	1.0000	0.0859	0.2529	2	4
1960	438	4	Week Four	Premium	4	11	44	0	0	1.0000	0.1146	0.2529	2	4
1961	439	4	Week Four	Premium	5	11	55	0	0	1.0000	0.1432	0.2529	2	4
1962	440	4	Week Four	Premium	0	11	0	0	0	1.0000	0.0000	0.2529	2	4
1963	441	4	Week Four	Premium	9	11	99	0	0	1.0000	0.2578	0.2529	2	4
1964	442	4	Week Four	Premium	1	11	11	0	0	1.0000	0.0286	0.2529	2	4
1965	443	4	Week Four	Premium	3	11	33	0	0	1.0000	0.0859	0.2529	2	4
1966	444	4	Week Four	Premium	5	11	55	0	0	1.0000	0.1432	0.2529	2	4
1967	445	4	Week Four	Premium	6	11	66	0	0	1.0000	0.1719	0.2529	2	4
1968	446	4	Week Four	Premium	7	11	77	0	0	1.0000	0.2005	0.2529	2	4
1969	447	4	Week Four	Premium	2	11	22	0	0	1.0000	0.0573	0.2529	2	4
1970	448	4	Week Four	Premium	4	11	44	0	0	1.0000	0.1146	0.2529	2	4
1971	449	4	Week Four	Premium	10	11	110	0	0	1.0000	0.2865	0.2529	2	4
1972	450	4	Week Four	Premium	9	11	99	0	0	1.0000	0.2578	0.2529	2	4
1973	451	4	Week Four	Premium	1	11	11	0	0	1.0000	0.0286	0.2529	2	4
1974	452	4	Week Four	Premium	7	11	77	0	0	1.0000	0.2005	0.2529	2	4
1975	453	4	Week Four	Premium	19	11	209	0	0	1.0000	0.5443	0.2529	2	4
1976	454	4	Week Four	Premium	6	11	66	0	0	1.0000	0.1719	0.2529	2	4
1977	455	4	Week Four	Premium	9	11	99	0	0	1.0000	0.2578	0.2529	2	4
1978	456	4	Week Four	Premium	2	11	22	0	0	1.0000	0.0573	0.2529	2	4
1979	457	4	Week Four	Premium	9	11	99	0	0	1.0000	0.2578	0.2529	2	4
1980	458	4	Week Four	Premium	3	11	33	0	0	1.0000	0.0859	0.2529	2	4
1981	459	4	Week Four	Premium	2	11	22	0	0	1.0000	0.0573	0.2529	2	4

Figure A.56: MS Excel Solver Risk Platform IP Data Set (55)



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1981	459	4	Week Four	Premium	2	11	22	0	0	1.0000	0.0573	0.2529	2	4
1982	460	4	Week Four	Premium	2	11	22	0	0	1.0000	0.0573	0.2529	2	4
1983	461	4	Week Four	Premium	10	11	110	0	0	1.0000	0.2865	0.2529	2	4
1984	462	4	Week Four	Premium	2	11	22	0	0	1.0000	0.0573	0.2529	2	4
1985	480	4	Actual Day	Premium	18	16	288	0	0	1.0000	0.7500	0.2462	2	5
1986	481	4	Actual Day	Premium	1	16	16	0	0	1.0000	0.0417	0.2462	2	5
1987	482	4	Actual Day	Premium	21	16	336	0	0	1.0000	0.8750	0.2462	2	5
1988	483	4	Actual Day	Premium	0	16	0	0	0	1.0000	0.0000	0.2462	2	5
1989	484	4	Actual Day	Premium	7	16	112	0	0	1.0000	0.2917	0.2462	2	5
1990	485	4	Actual Day	Premium	1	16	16	0	0	1.0000	0.0417	0.2462	2	5
1991	486	4	Actual Day	Premium	1	16	16	0	0	1.0000	0.0417	0.2462	2	5
1992	487	4	Actual Day	Premium	4	16	64	0	0	1.0000	0.1667	0.2462	2	5
1993	488	4	Actual Day	Premium	0	16	0	0	0	1.0000	0.0000	0.2462	2	5
1994	489	4	Actual Day	Premium	0	16	0	0	0	1.0000	0.0000	0.2462	2	5
1995	490	4	Actual Day	Premium	4	16	64	0	0	1.0000	0.1667	0.2462	2	5
1996	491	4	Actual Day	Premium	3	16	48	0	0	1.0000	0.1250	0.2462	2	5
1997	492	4	Actual Day	Premium	5	16	80	0	0	1.0000	0.2083	0.2462	2	5
1998	493	4	Actual Day	Premium	7	16	112	0	0	1.0000	0.2917	0.2462	2	5
1999	494	4	Actual Day	Premium	6	16	96	0	0	1.0000	0.2500	0.2462	2	5
2000	495	4	Actual Day	Premium	2	16	32	0	0	1.0000	0.0833	0.2462	2	5
2001	496	4	Actual Day	Premium	6	16	96	0	0	1.0000	0.2500	0.2462	2	5
2002	497	4	Actual Day	Premium	2	16	32	0	0	1.0000	0.0833	0.2462	2	5
2003	498	4	Actual Day	Premium	9	16	144	0	0	1.0000	0.3750	0.2462	2	5
2004	499	4	Actual Day	Premium	1	16	16	0	0	1.0000	0.0417	0.2462	2	5
2005	500	4	Actual Day	Premium	2	16	32	0	0	1.0000	0.0833	0.2462	2	5
2006														
2007														
2008								455						
2009														
2010														
2011														
2012														
2013														
2014														
2015														
2016														

Figure A.57: MS Excel Solver Risk Platform IP Data Set (56)

Also in **Chapter 3**, an approach to use the IP solutions to train and test an artificial neural network in order to make online parking reservation decisions was proposed and results demonstrated. The neural network approach to make real-time decisions was found to be reasonable, even within the more complex multiple-garage environment. The Basic class breadboard (within the software package NeuroSolutions) is shown in *Figure A.2*.

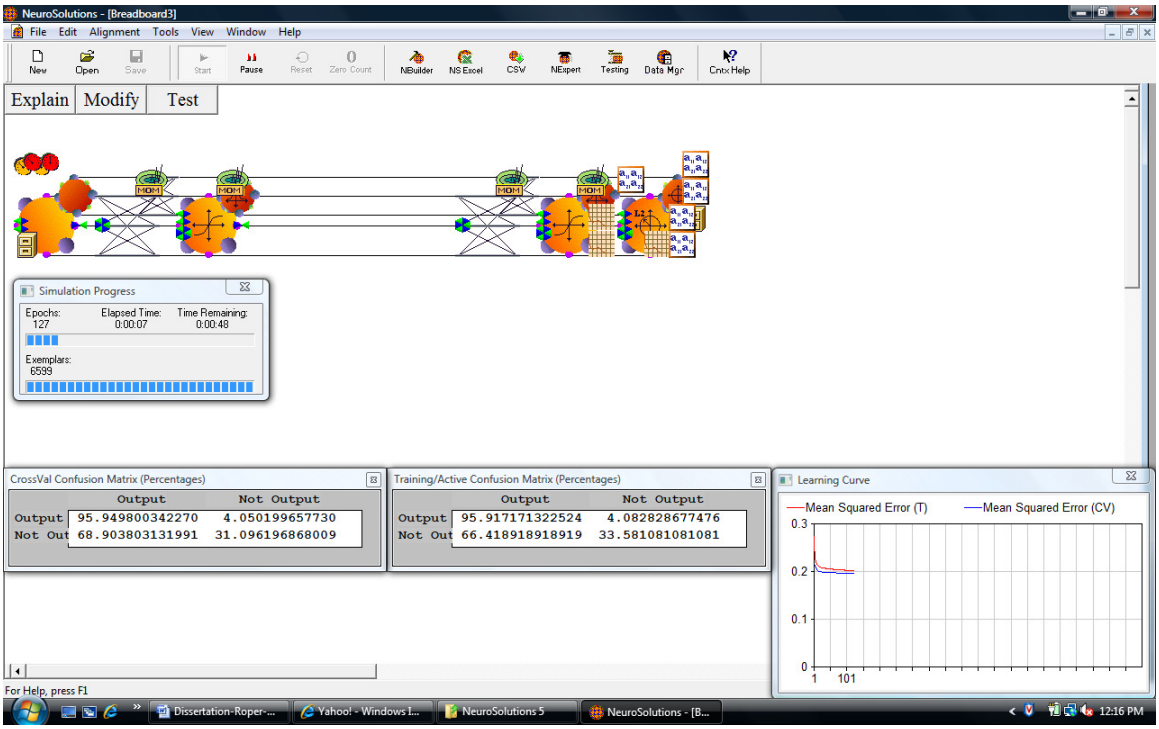


Figure A.2: Basic Parking Class Neural Network Breadboard Sample

The model above receives inputs (in the case of this research, those defined in **Section 3.3.4** of this thesis), and uses the back-propagation structure to generate an output. In this case, the output is the decision of whether to accept or reject a request for parking. In order to generate quality output, an artificial neural network must go through an initial learning period, generally described in terms of two phases: training and testing. The training phase pairs input data with its corresponding output. The network then processes the inputs and compares its resulting outputs against the desired outputs. Errors are then propagated back through the system, causing the system to adjust the weights which control the network. This process occurs over and over as the weights are continually tweaked. The set of data which enables the training is

called the "training set." During the training of a network the same set of data is processed many times as the connection weights are ever refined. *Figure A.2* shows a breadboard undergoing the training process.

In **Chapter 4** of this thesis, we discuss the general structure of the VISSIM models and their viability for use in scientific hypothesis testing. Details regarding the coding and network-building process are given below.

One might start by editing vehicle type definitions and characteristics. Included in this are vehicle speed, acceleration, weight, power, desired speed, color, vehicle model, and dwell time distributions and profiles. For the purposes of this work, default parameters were adopted. A screen shot of the vehicle type dialogue is provided in *Figure A.3*.

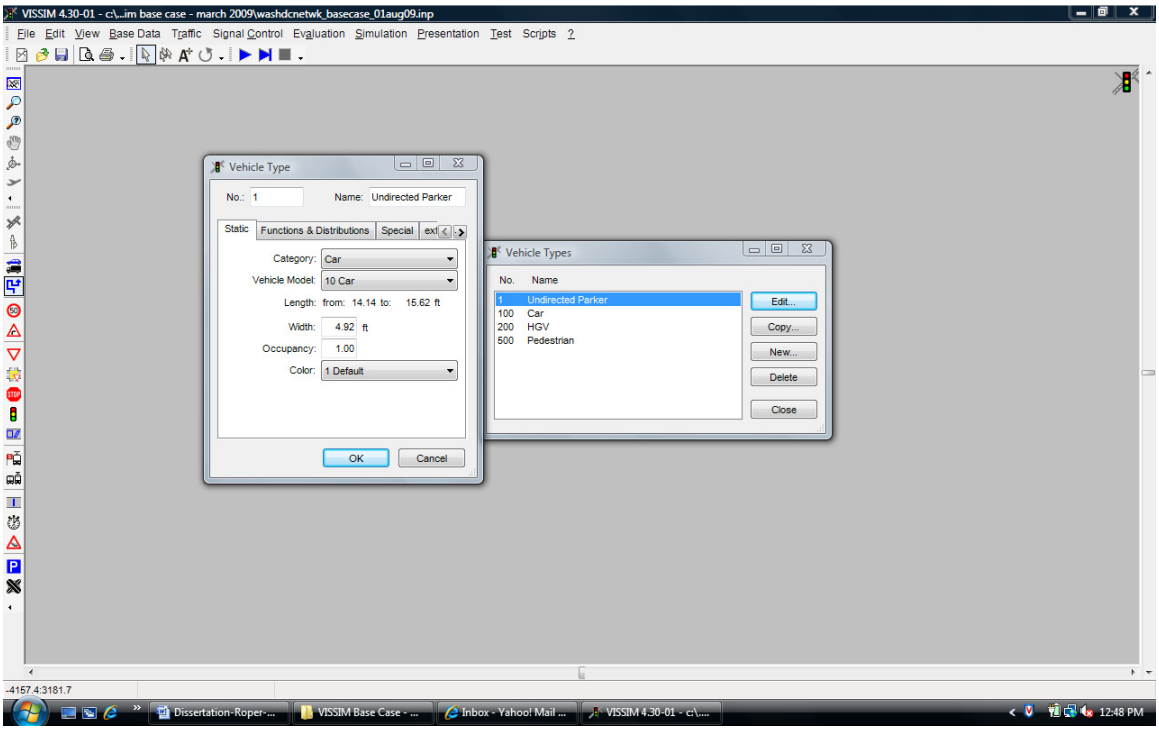


Figure A.3: Vehicle Type Dialogue within VISSIM

A logical next step is to define traffic compositions as relative quantities of various vehicle types. Alternatively, the modeler could define his or her own vehicle types with specific desired vehicle characteristics. Traffic compositions were used in this modeling work (traffic compositions for both the Base and Alternative Case models are provided in *Figures A.4 and A.5*) to ensure that the correct proportion of vehicles simply navigating the network versus vehicles performing some parking function was achieved. For example, a traffic composition for the Base Network might be composed of 14 undirected parkers, 5 heavy vehicles, and 77 cars. For the Alternative Case network, traffic compositions are defined for every hour, so that individual reservations and individual parker behaviors are captured. For instance, a traffic composition for a particular hour at a particular entry point might consist of 3 undirected parkers, Reserved Vehicle ID 1, Reserved Vehicle ID 2, Reserved Vehicle ID 3, Reserved Vehicle ID 4, 5 heavy vehicles, and 77 cars. It is important to note that the entire "through-travel" population, as well as the entire parking populations, is kept constant across the two models.

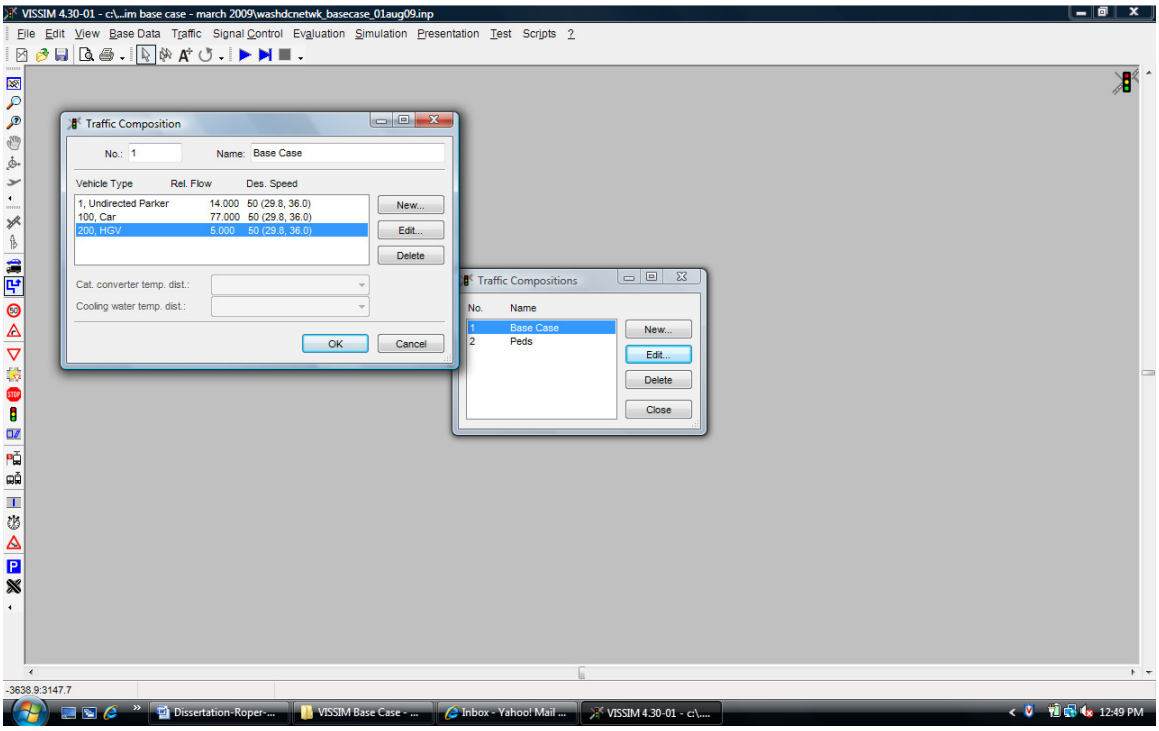


Figure A.4: Traffic Composition Dialogue within VISSIM (Base Case Model)

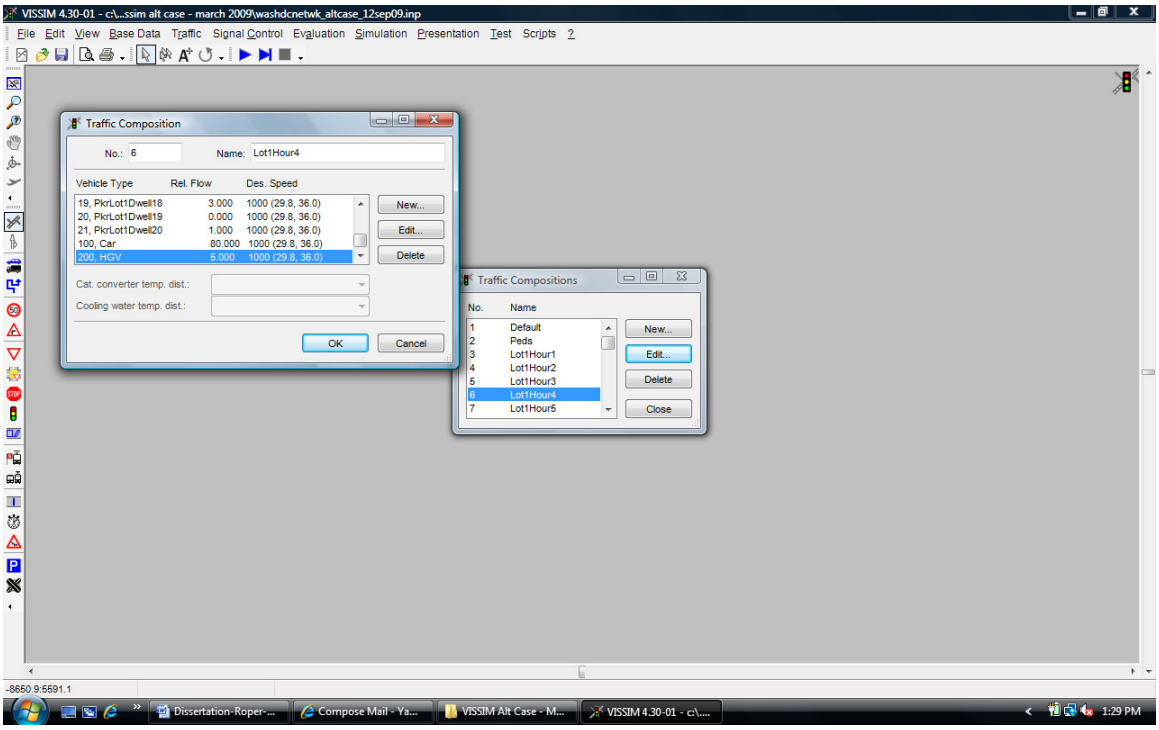


Figure A.5: Traffic Composition Dialogue within VISSIM (Alternative Case Model)

The modeler may now use the traffic compositions defined earlier to define network vehicle inputs, as shown in *Figure A.6*. Vehicles can be inserted on any link of the network, but edge links are most commonly used, since this is most often the case in reality. In addition, most urban networks require pedestrian volume inputs as well. These are defined on individual pedestrian crosswalk links. A nominal, assumed pedestrian traffic of 100 persons per hour is defined for each intersection to accurately model urban traffic conditions.

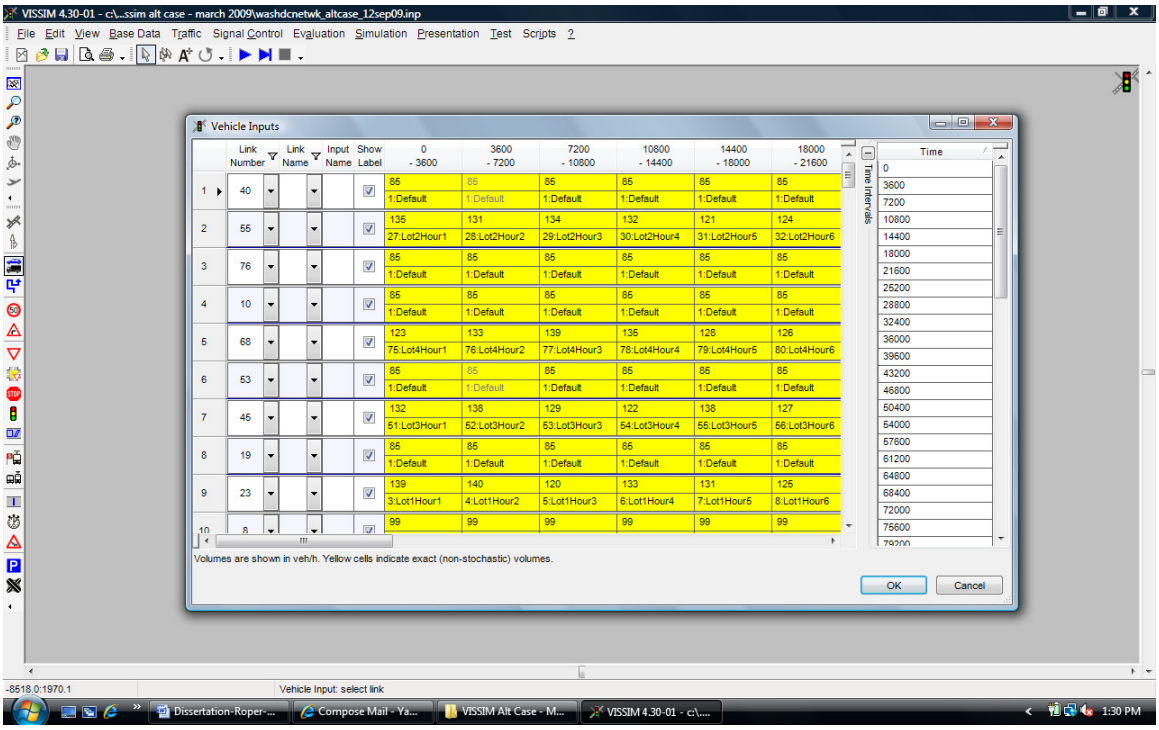


Figure A.6: Vehicle Inputs Dialogue within VISSIM

A next logical step is to code the actual links and connectors within the network (network views available within **Chapter 4** content). Any segment on which a vehicle can travel must be defined with links and anywhere a vehicle (or pedestrian) can transition from one link to another must be defined with a connector. Oftentimes, networks are either exact replicas of existing networks or loosely based on a real network. Other times, the network is completely hypothetical. In cases, where the network is based on a real network, background images of the network (such as that shown in *Figure A.7)* can be used to accurately scale and model the network. For these models, we use an actual approximately 3 square mile area of the Washington, D.C. downtown area, and it is scaled using an actual map image.

Figure A.7: Washington DC Background Map

A next rational step in the VISSIM coding process is to define routing decision points and routes. Routing decisions are decision points where vehicles are directed in one of several defined routes. To establish a routing decision, the modeler selects the point on the network where they wish cars to choose a future path. For example, a network routing decision might be ahead of an intersection where the vehicle must choose to continue straight, take a right turn, or take a left turn. Modelers define what fraction of vehicles will make which choice when defining the routing decision. A routing decision dialogue from the VISSIM model is shown in *Figure A.8*.

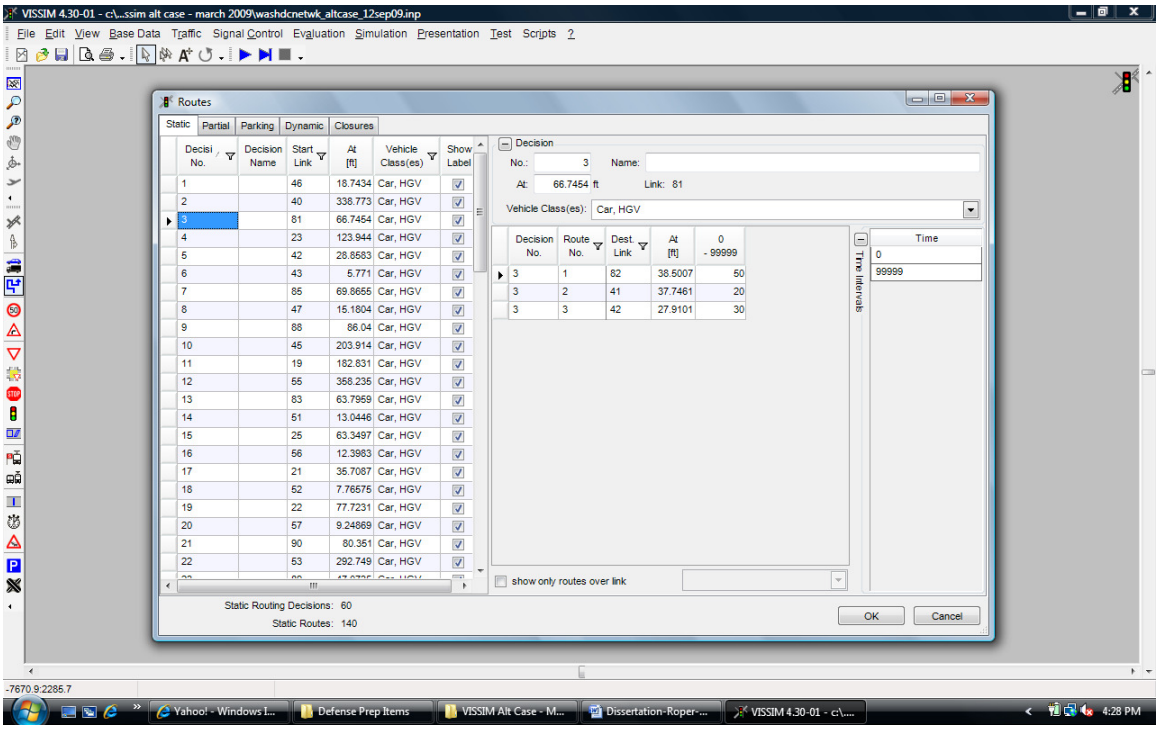


Figure A.8: VISSIM Model Routing Decision Dialogue

Also, for all turns, the modeler must include reduced speed areas in order to model turning behaviors realistically. For the purposes of these two models, routing decisions are defined by traffic compositions vehicle types. For example, there are routing decisions that route "through-traffic" from intersection to intersection with defined probabilities determining what kind of turn the vehicle makes. Additionally, there are routing decisions that route parkers into their reserved parking lot and area, and in the Alternative Case model, routing decisions route specific cars holding a reservation to a particular lot for their particular dwell time.

Especially in the case of urban central business districts, the modeler must next define traffic signal controls and signal groups. VISSIM permits both fixed time controllers and other signal control schemes, including vehicle actuated signals. For this research, we assumed a standard signal cycle for each of the network intersections, and one of the signal head dialogues is shown in *Figure A.9* below.

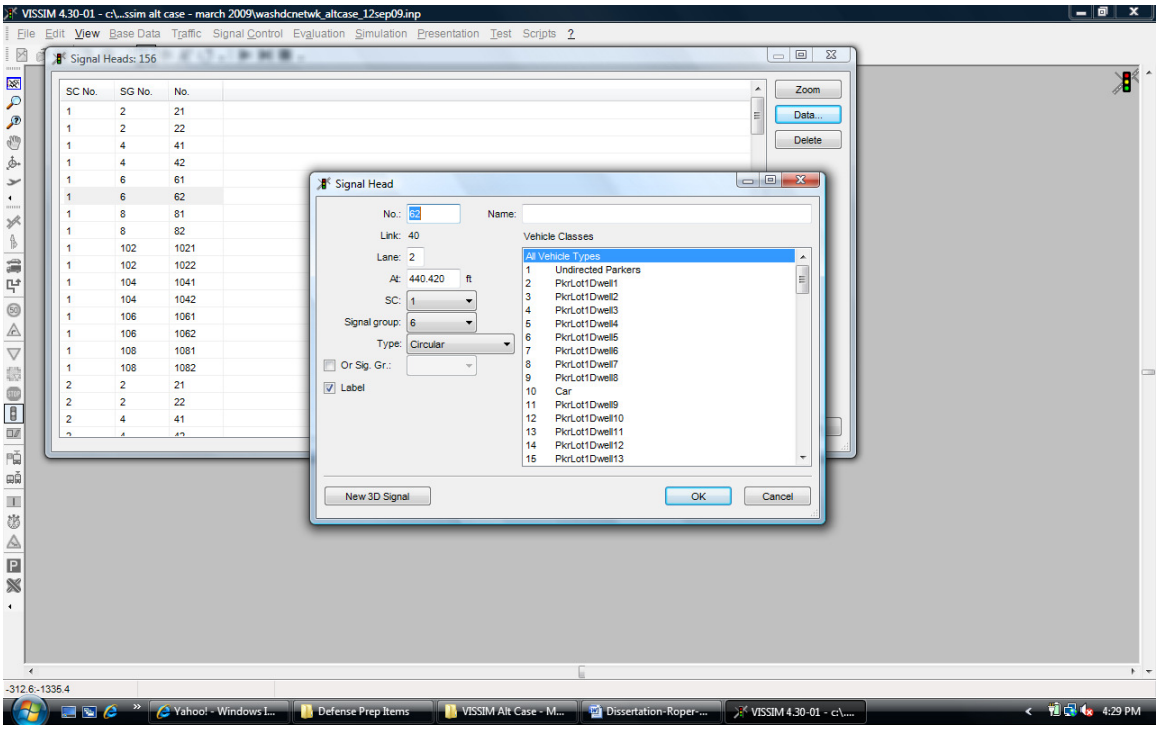


Figure A.9: VISSIM Model Signal Head Definition Dialogue

Finally, for networks that require it, one must code transit lines, signal heads, priority rules for non-signalized intersections, parking lots, street-side parking, and permissive and non-permissive movement stop signs. Clearly, parking elements are required for this particular line of research. Parking lots or garages can be defined to contain actual parking spaces, and they must have a parking routing decision to direct vehicles in parking behaviors. Four parking lots are defined within these two networks, one of which is shown in *Figure A.10*. Each parking lot is located approximately in its location within the actual network, and contains 300 parking spaces. These are "real" parking spots within VISSIM, as opposed to virtual parking spaces.

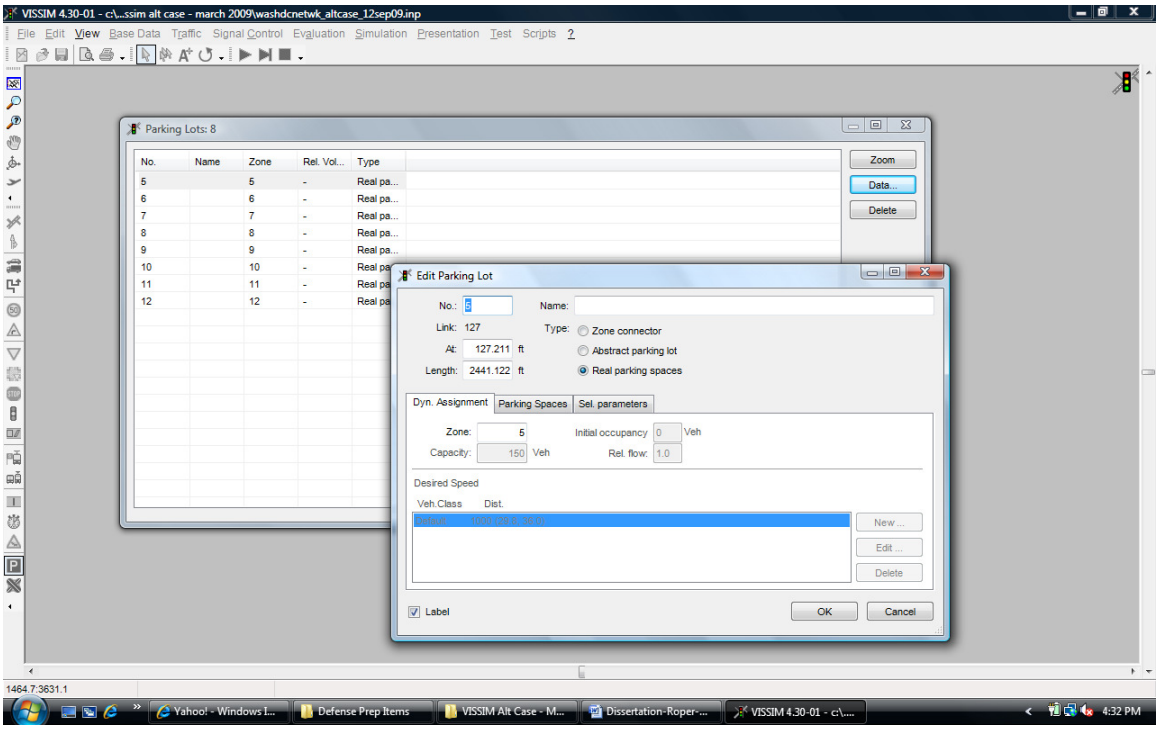


Figure A.10: VISSIM Model Parking Lot Definition Dialogue

Typically, when coding a VISSIM network, the final steps are to define types of simulation outputs. The VISSIM package offers many different types of performance measure outputs. Data collection points can be defined to collect point data such as car counts and volume. Travel time segments are defined to collect data on delay, average, and/or raw travel time data. Furthermore, network nodes can be defined to collect data like queue counts, average vehicle density, and many other indicators. The dialogue box for defining overall network performance metrics for collection is shown in *Figure A.11*.

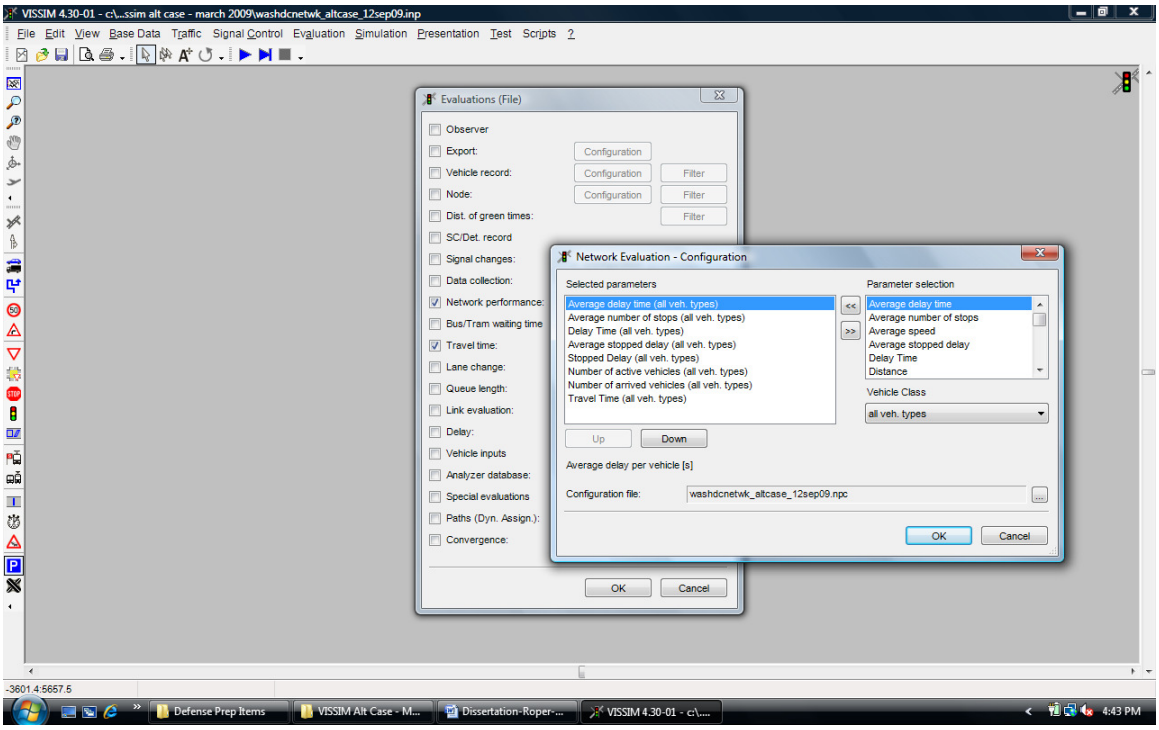


Figure A.11: VISSIM Model Network Performance Metric Definition Dialogue

For the purposes of measuring the performance of these networks, we use outputs including total network delay, total network stop delay, average delay per vehicle, average travel time, and average stop delay per vehicle. These outputs are used to measure differences between the two models as detailed in **Section 4.6.**

The primary purpose of **Chapter 5** was to evaluate the performance of the urban parking system from the perspective of the set of relevant stakeholders using the hyperbolic DEA model within the context of the matrix DEA construct. The stakeholder models, including that of the parking provider, the parking district user, and the surrounding community, had defined inputs and outputs to the hyperbolic DEA model, which allowed for the inclusion of undesirable outputs such as network delay and incidence of extreme congestion.

The hyperbolic DEA model itself was coded in Microsoft Excel Solver, and code from both the parking provider model (*Figure A.12)* and the community/societal model (*Figure A.13)* are provided below.

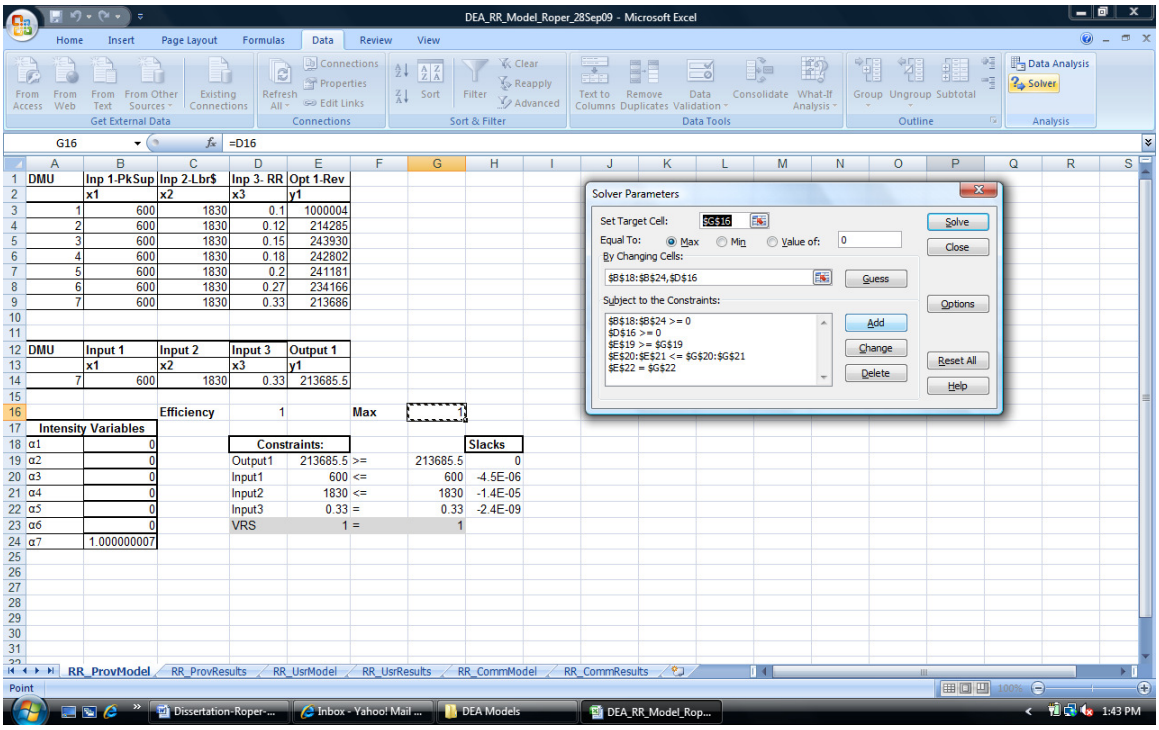


Figure A.12: DEA Model Code within MS Excel Solver (Parking Provider Stakeholder Model)

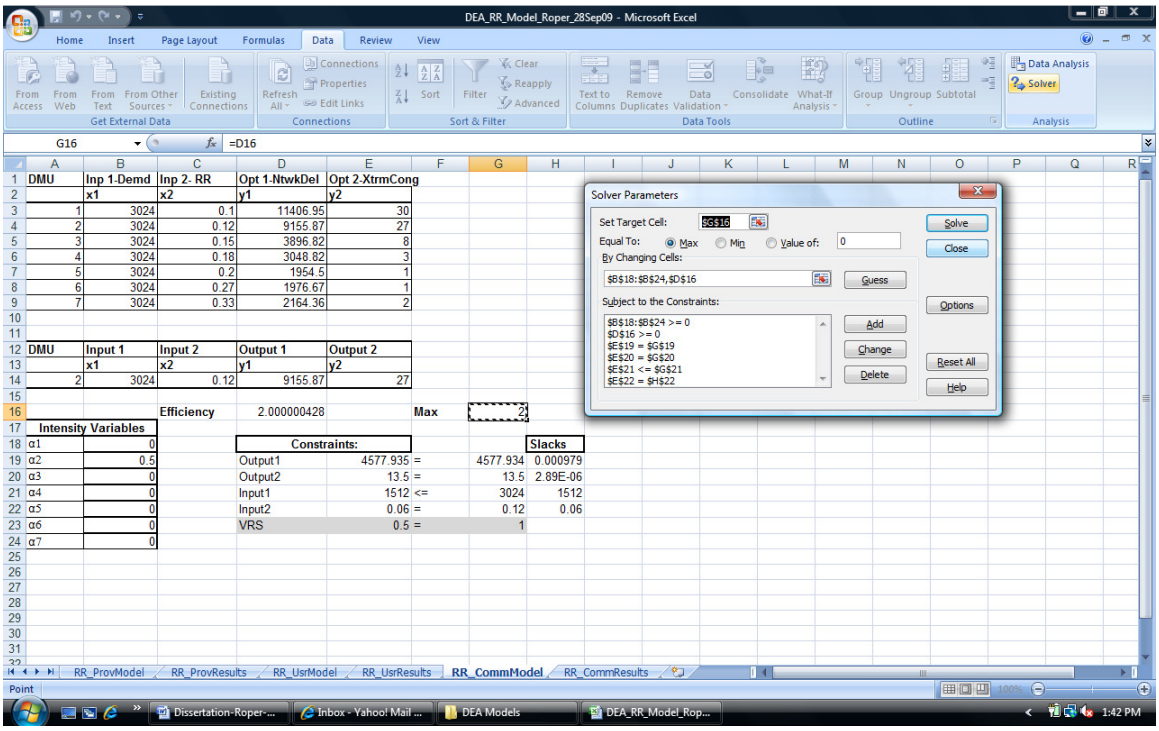


Figure A.13: DEA Model Code within MS Excel Solver (Community Stakeholder Model)