CHAPTER 4

SYSTEM IMPLEMENTATION

"The ability to leverage new science and technology effectively is related not only to the quality of the work performed in the scientific laboratory or to the ability to transfer and develop individual technologies, but also, critically, to the capability of conceptualizing how a multitude of emerging possibilities might be used coherently to define a product that makes business sense." (Iansiti, 1998, p. 5).

The introduction of new technologies often causes a temporary loss of productivity and leads to additional unforeseen costs over a system's life-cycle. One of the reasons for this productivity degradation is traditional systems engineering management fails to plan for the effects of technology implementation. However, planning for technology implementation is not an easy venture. When introducing new technology the decision-maker must decide the optimum system composition, often from a large number of system configuration options, and an equally large number of operational process scenarios. This chapter presents an overview of system implementation followed by case study employing the methodology developed in Chapter 3 to provide new insights into the difficult technology implementation problem.

4.1 System Implementation

In this age of constant influx of new technologies, organizations must continually adopt and exploit those technologies with processes that ensure the systems they develop/procure meet changing organizational performance requirements and long-term cost and performance goals. However, adopting new technologies and processes is difficult due to the complexity and dynamic nature of modern systems. As new technologies evolve, organizations must continually assess the many options for including new components within the system, the interoperability of those components, the production process changes corresponding to the new technology, and the performance that the system will yield after including new components and processes. The organizational goal when implementing new technology should be to reliably, seamlessly, and coherently integrate system components and processes, from a large

number of technological possibilities, to achieve the best operational performance from the system.

Unfortunately, adopting new technologies often brings unexpected consequences for the organization, for the systems it develops/procures and for the provision of the necessary services required for the system's long-term sustainability. Flawed mental models, and the failure to adequately, and accurately, assess the impact of the system's concept of operations often leads to unforeseen losses in productivity, degradations in quality, and unexpected costs for most new technology efforts. These losses usually translate into increased system life-cycle costs. As a consequence many organizations never realize the full performance potential of the new technologies/processes they choose to adopt.

System implementation and system integration are often thought to be synonymous. The system implementation phase is the period between a system's development/procurement and operational phases. The implementation phase considers such aspects as the corrections of discrepancies found during early system assessments, improvements to the operational process, workforce training, joint or parallel operations with an old system, and eventually retirement of the old system (Vaneman, 1997). The activities that take place during this phase are the most disruptive to the operational environment during the system's life-cycle.

In contrast, system integration is typically a bottom up process that combines multiple components of a system together. These components often take the form of hardware or software components. As these components are completed, they are tested to assure that they operate correctly within the system, and interface correctly with other components and/or subsystems (Eisner, 1997 and Buede, 2000). System integration is part of the system's implementation phase.

The systems engineering literature generally fails to recognize the system's implementation phase, instead focusing on system integration. Figure 4-1 shows the system's life-cycle (Blanchard and Fabrycky, 1990) with the system implementation phase included, superimposed on the Defense Acquisition Management Framework (Department of Defense Instruction 5000.2, 2000). The defense Acquisition Management Framework was included with the life-cycle because it succinctly identifies

the major phases within the life-cycle, the major decision points (triangles A-C), as well as when the system reaches initial and full operating capability (IOC and FOC). Decision point D was added because decisions to upgrade the system or processes occur during the system utilization and support phases. That decision point marks the start of a new implementation phase.

The dashed line between system utilization and support phases and the system implementation phase is to support continuous system and process improvements throughout the life-cycle of the system. These continuous system and process improvements can best be described as an improvement spiral. This approach is necessary in most systems because when the system and processes are first developed not all of the system requirements are fully understood, therefore are not addressed in the initial system build (Eisner, 1997). As the system matures, the emerging requirements must be addressed in future iterations. The improvement spiral provides such an avenue.

The improvement spiral (Figure 4-2) is an iterative approach. It defines organizational requirements, evaluates existing technology with other technology (both existing and new innovations), integrates technology with production processes and organizational structures, implements new technology with existing production processes and organizational structures, and finally evaluates the system for the next process improvement. The improvement spiral outlines the steps to be taken to perform a system or process improvement, but fails to specify when that effort should begin.

One of the key hurdles of technology implementation is finding the optimum operating scenario (system configuration and production processes) from a large number of technological possibilities. One solution to overcome this hurdle is to perform a system simulation before committing to the final technology selection, system configuration, or production process adjustment. Simulation models allow the user to test real world scenarios in a virtual world environment.

The system implementation problem contains the characteristics associated with both combinatorial and dynamic complexity. The combinatorial complexity characteristics arise because the project manager or engineer must decide the best technical and operational solution to the problem from a large number of technological and process possibilities. The dynamic complexity arises because decision-makers must
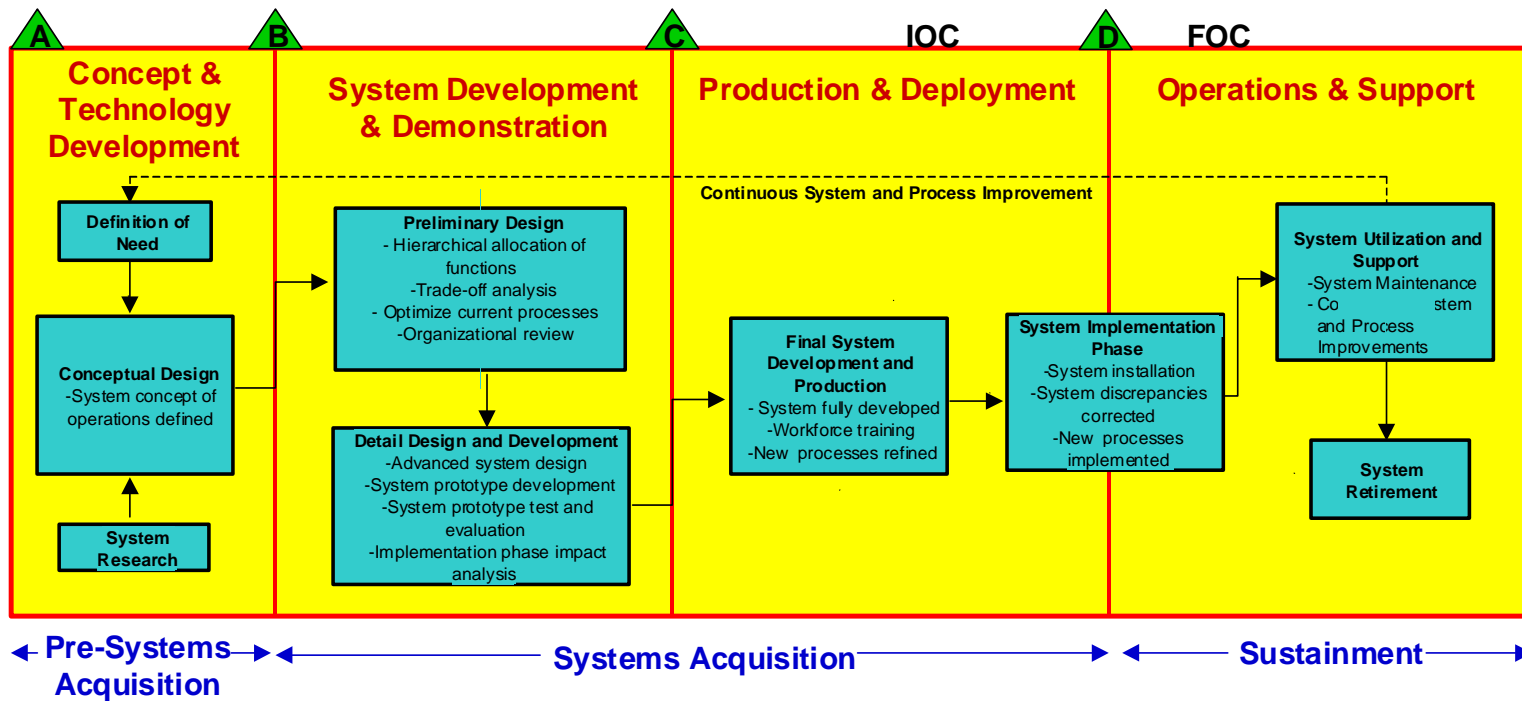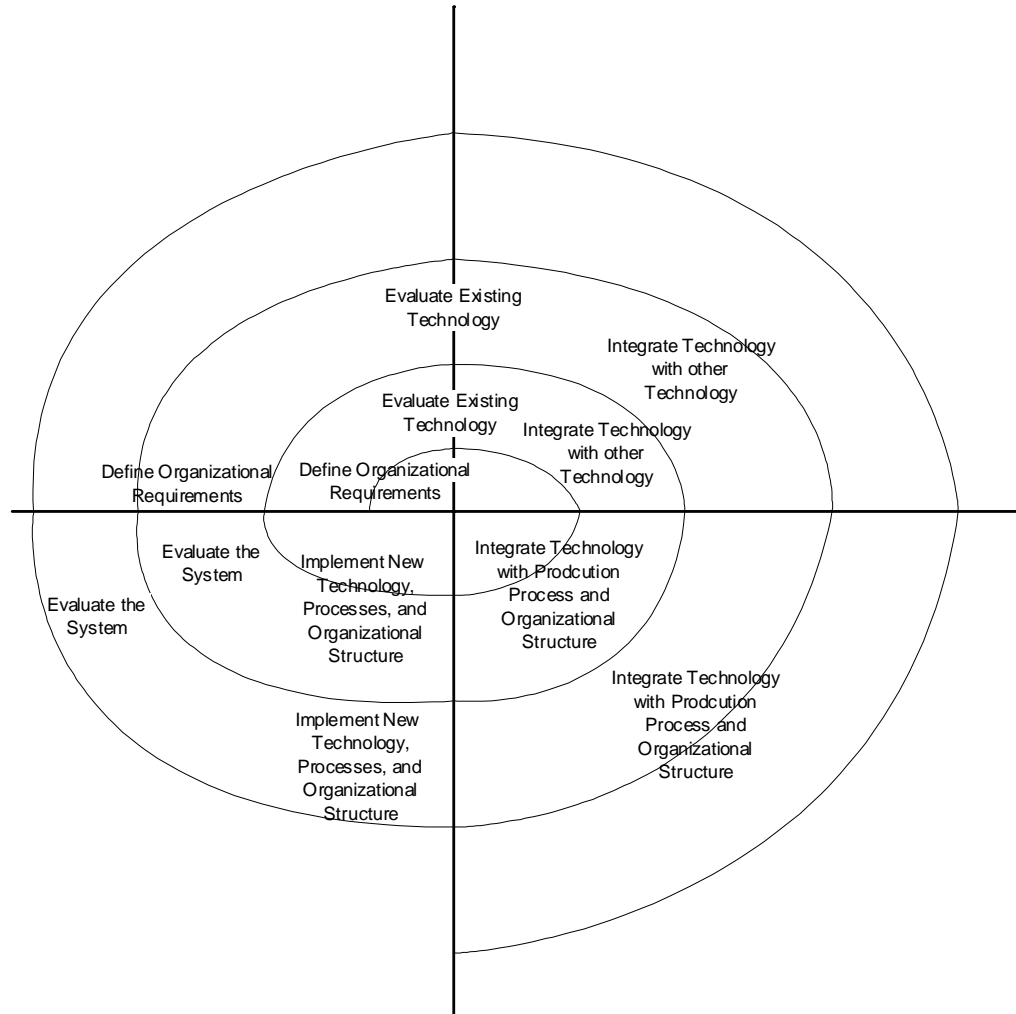
Figure 4-1. The Systems Life-cycle.

Figure 4-2. The Improvement Spiral.

decide the best time to introduce those new technologies and the speed at which that implementation needs to occur to meet the requirements imposed upon the system.

The remainder of this chapter is devoted to demonstrating how the concepts developed in Chapter 3 can be applied to solve the system implementation problem.

4.2 System Implementation – A Case Study

As briefly discussed in Section 3.3.3, this research studies the productive efficiency of an organization that compiles information and disseminates it via an Internet-like media. The organization has recently entered into the business of providing

information. Data population is planned to occur over a ten-year period. This case study evaluates the organization's plans to implement a system that will produce the desired amount of information, and explore production issues that were not considered in the original plan, and will seek to define more efficient and effective implementation procedures through alternative system policies.

The organization in this case study is real but will remain nameless in this document. System structures and data have been altered in many cases to further protect the identity of the organization. While system structures and data have been altered to discreetly protect the organization, the alterations were made in proportion so that the system behavior is preserved. Additionally, the current basic policies of the organization are being modeled, along with policies suggested by this study.

In short, this case study seeks to examine organizational production and related system implementation policies, and not analyze the specific hardware and software components, or detailed production processes of specific systems. Section 4.2.1 discusses the system and its associated problems. This section will also discuss the production policies that will be considered. Section 4.2.2 discusses the dynamic hypothesis (i.e. believed drivers of system performance), and the production assumptions which are believed to be applicable to this system. Section 4.2.3 discusses the system conceptualization and model development. Section 4.2.4 will discuss model validation. Section 4.2.5 provides the results of the model and policy analysis.

4.2.1   System and Problem Definition

The organization's charter is to produce four primary types of data. The goal is to produce 12,000 cells of each type of data within a ten-year time horizon. A cell of data is defined as data that populates a certain grid. The grid is a defined spatial size, limited by physical boundaries. However, while each grid has an equal spatial size, the content of the data within each grid varies in density. Thus the file size for each cell is not consistent, nor is the amount of production time (time required to populate the data in each cell) even within the same data type.

Three of the four data types also provide special (i.e. tailored) data sets. These data sets are subsets of the original data, which when some value is added, provides data

unique for a specific customer. These data sets neither contribute nor detract from the data totals, but do use the labor and workstations that are used for other production activities. Special data production has priority over all other data production activities.

The organization's current concept of operations establishes a production goal of 100 cells per month, for 120 months, to satisfy the requirement for each data type. Once the cells of data are populated, the current concept of operations assumes the data to be timeless. That is, data decomposition, and the maintenance of the decomposed data, is not considered to be part of future production requirements, or are used for future resource planning. However, a small faction of managers within the organization recognize that data will deteriorate over time, and have developed "straw man" estimates of the decomposition rates for each data type. An even smaller faction of those managers recognizes the need to maintain the decomposed data. Maintaining decomposed data will take less production time than repopulating the cell.

Another concept that has been widely explored is the issue of using in-house employees and supporting workstations, versus out-sourcing work to contractors who are assigned to populate cells of data. Three of the four data types currently out-source production to contractors. The role of contractor support is considered for data maintenance and production activities. Contractor support is not considered for special data production.

The role of technology is widely discussed when considering future production. Technology innovations such as automated information extraction and automated change detection are assumed capabilities for some data types. Bringing this new technology to fruition is a difficult task at best. However, the impact of technology insertion will be examined for some of the data types in this study. Other data types will assume no new technological advances during this time horizon.

The following are questions that this case study seeks to answer for the corresponding data types:

1. What is the impact of data decomposition on the system? (All data types)

2a. What are the associated costs of a system performing maintenance? (All data types)

2b. Is the system optimized for performance? (All data types)

3. What is the optimal in-house employee/contractor ratio when contractors are only supporting new

   production? (Data type 1)

4. What is the optimal in-house employee/contractor ratio when contractors are supporting new production and maintenance functions? (Data type 2)

5. What is the impact of advanced technology (i.e. automated change detection and automated information extraction) on the production process? (Data type 3)

6. What is the optimal in-house employee/contractor ratio when contractors are supporting both new production and data maintenance, and advanced technology has been inserted into the organization for in-house production? (Data type 4)

7. Identify the best times to add additional capacity to the system. (All data types)

The goal of this study is to evaluate alternative system structures and policies. The dynamic productive efficiency model will be used to answer these questions. The organization's current concept of operations will be simulated using a base structure. The excursion structures will evaluate and seek to optimize alternative system structures and policies.

4.2.2   Dynamic Hypotheses and Applicable Production Assumptions

Now that the problem is identified, theories about the cause(s) of the problem are developed. These theories, also known as the dynamic hypotheses, are believed to account for the problematic behavior demonstrated by the system (Sterman, 2000) and generally lead to the key system performance drivers. The dynamic theories can be adjusted as more is learned about the system and the problem from both the modeling and data collection efforts.

A litmus test when defining the dynamic hypotheses is, "Does the dynamic hypotheses identify endogenous or exogenous elements of the system?" All elements identified within the dynamic hypotheses should be endogenous to the system. This is an important point because the only elements that should be evaluated in a system dynamics model are those that can be changed and controlled (i.e. the endogenous variables). If exogenous elements are identified in the dynamic hypotheses, the system boundaries

must either be expanded to include those elements, or the analyst must exclude those elements from further consideration.

In this case study, the source of the problem appears to be data decomposing as a function of time. The data decomposition rates directly effects how much good data is in the system, the number of production resources required to produce new data sets and maintain existing aged data sets, the cost per data set, and when additional resources should be added to the system to best facilitate maintaining new data. While the data decomposition rates cannot be controlled, as it is a phenomenon natural to the data, the rate at which data is produced and maintained can be controlled. This control comes from adjusting the production resources associated with the production activities. These production resources include in-house employees, workstations, and contractor support. Since these variables are believed to be the key drivers of meeting the production goals, these are the variables that will be optimized with the hill-climbing optimization structures in each of the sub-systems.

The system outputs are four distinct types of information. As the outputs are placed onto the organization's servers (represented by the data *Du* and base data *BDu* variables in the model), the production process is considered complete. Customers download the information from the servers at undetermined periodicity (an exogenous event not modeled). The information placed onto the server is time-sensitive. That is as time passes, information deteriorates at a certain rate and is a function of the data type. When the information deteriorates beyond a certain point, either data maintenance is required, or the data production process has to begin anew.

Two types of behavior appear to be predominant in this production system. Each of the information types (represented in the model as sub-systems) exhibits S-shaped growth and exponential decay behaviors. One may argue that such a system usually exhibits exponential growth as opposed to S-shaped growth due to the system adjustments that take place. This is true because during the new data production phases we observe the positive feedback loop to be dominant. However, over time the system exhibits S-shaped growth as the system's future the production capacity of the organization and the requirements from the customers equalize, and the system achieves

a state of dynamic equilibrium. The exponential decay behavior comes from the data deteriorating as a function of time.

Discovering two dominant dynamic behaviors within the system is significant because each behavior type corresponds to a different set of production axioms. The significance of this finding is that the decision-maker must work with two distinct sets of assumptions when making improvements within the system. Since the production process is governed by the S-shaped growth behavior, and the data resident on the servers are dominated by exponential decay behavior, the behaviors are treated as separate structures when considering the production assumptions.

First consider the production process assumptions and S-shaped growth behavior. Since there are inputs into the system and the system has activity, DA.1(a and b) do not apply. The system uses various source materials (treated as exogenous variables) employees, workstations, and contractors as inputs. Since some of those inputs may be more heavily weighted than others (e.g. workstations are more heavily weighted than employees in scenarios 3 and 4), the inputs can be increased at a disproportionate rate (by including additional source materials that contribute more to the production process) without negatively effecting output. Since this is true, the strong input disposability (DA.3(b)) is believed to apply. Since a disproportionate increase in certain inputs is possible, then a proportionate increase in inputs will not negatively affect outputs, thus DA.2(a) applies. The S-shaped growth behavior has an upper limit that represents the maximum production capacity. Thus outputs are finite and bounded, so the scarcity axiom (DA.4) applies. The system also is a closed and convex combinations of inputs and outputs are part of the production possibility set, therefore DA.5 and DA.6 apply.

Next consider the data resident between the organization's data servers and the data maintenance queue or the aged base data level. It is in this portion of the system where the exponential decay behavior is dominant. The data decomposition as a function of time is analogous to a system producing a desirable output (useful information) and an undesirable output (data that deteriorates over time). Since activity takes place within the system, DA.1(b) does not apply. The strong output disposability axioms state that outputs can be costlessly disposed of. If the system's output is an exogenous variable (i.e., no feedback mechanism from the output to the system), then as data deteriorates it is

disposed of without cost as is the case for the base case (i.e. current system structures and policies), then the strong output disposability axiom applies. As shown in Section 3.2, if DA.3(b) applies than DA.3(a) also applies. However, in the excursion case, the data maintenance queue has feedback to the production process through maintenance, therefore DA.3(b) would not apply. DA.3(a) also does not apply to the excursion run because the excursion cases is not producing any undesirable outputs. As in the S-shaped growth behavior, the system is bounded, closed and convex combinations of inputs and outputs are part of the production possibility set, therefore DA.4, DA.5, and DA.6 apply.

Currently the organization allows the information on the server to degrade until it is no longer of any value to their customers.   One of the policies that is being explored by this research is the concept of creating a data maintenance environment.   In this environment data would be recompiled using the existing information base as long as there was a demand for the information. Implementing this policy/process improvement creates a feedback mechanism that triggers the recompilation process from the deteriorating data via the data maintenance queue.   This change in the structure eliminates the exponential decay behavior, thus changes the production assumptions. The new system structure combines the once decoupled production process and data deterioration structures into an S-shaped growth with overshoot structure (the oscillatory behavior is caused by the deterioration delay that occurs before information is recompiled). Therefore the dynamic axioms that apply to this structure (DA. 2(a and b), DA.4, DA.4, and DA.6) now apply to the entire system.

4.2.3   Data Collection, System Conceptualization, and Model Formulation
4.2.3.1 Data Collection

The data collected for this case study was collected over a 30-month period at four geographically disperse offices of the organization. During this data collection period, system stakeholders who understand the system, its input and output elements, processes, and critical structural links were interviewed and requested to provide data. The interviews (which assumed the form of informal discussions and e-mail exchanges) had the purpose of collecting system goals, actual and projected metrics, and to gain an insight and understanding into organizational policies, cultures, and interrelationships

among system components.   In SD modeling, understanding the structure of the system is essential if problems are to be interrelated and interpreted.   Without a sound understanding of the system structures, all information gleaned from that system would simply be fragments of information that are incapable of being interrelated (Forrester, 1968).

Data collection was focused in four fundamental areas:

1. Identifying the system boundaries;

2. Understanding the system structure;

3. Defining interacting variables;

4. Finding the values of parameters.

The selection of system boundaries cannot be tested by a definite theory. Boundaries must be established so that all of the elements or components are enclosed within the system, essentially forming a closed system. The closed system concept is essential because the internal structure of the system must be isolated to study the behavior that one is seeking to control, without the interaction with the environment (Forrester, 1968). Thus for the problems presented in this case study, only the production systems and related elements are considered.   The model drivers (employees, workstations, and contractors) are considered endogenous to the model, while the raw source material for the system is exogenous to the model.   In all scenarios being considered, the collection of raw source material is the responsibility of different entities within the organization, and is assumed to be readily available when the production organizations require that material for transformation into data. If the scope of these problems were broadened to include aspects of the raw material collection, the system boundaries would have to be expanded.   It is important to note that often the boundaries of the system(s) may not be clear. Model boundaries that contain elements that cannot be controlled by the system, or do not contain critical elements within the system will yield incomplete results.

The system structure consists of the physical, organizational, and decision-making structures. The physical structure consists of the levels, rates, time delays, and interfaces with the external environment.   The decision-making structure includes formal and informal organizational policies, directives and standard operating procedures, the

decision-maker's mental models of the system, organizational culture and tradition, incentives, rewards, and habits. The organizational structure consists of organizational lines of authority, organization of the decision-making units, information availability and quality, including possible delay, distortion and bias.

The third concept in data collection is to determine if the identified variables within the system are properly interconnected. These relationships among the variables are often the most difficult portion of the model to develop, but are among the most important when developing the SD model. The difficulty lies in the fact that many relationships between variables are informal and have not been related quantitatively. Therefore, the model is developed using descriptive information only. Developing the relationships has proven to be the most difficult task and time consuming in data collection, as different mental models exists for each stakeholder. These differences were deconflicted by additional discussions and requests for additional information, and by considering the anticipated system behavior. Careful attention was given to this effort as failure to include proper system elements and relationships in the model can cause devastating results by forecasting the wrong outcome (Forrester, 1961).

The fourth concept in the data collection effort is to determine the data that supports the definitions of the variables and constants. The data sources available for the variables used in the study are many and varied. Various stakeholders provided the data supporting specific variables. However, this approach was problematic because: (i) the production concepts of the organization were fluid, thus data that was perfectly valid yesterday, is outdated and irrelevant today; (ii) since in virtually all cases the information provided were projections of resources the system used, and data the system output, the data was subject to each individuals understanding of the concept of operations and the technology being employed; and (iii) in some cases, data supporting various political agendas was introduced. The data was deconflicted by comparing the multiple sources of data against each other and against the concept of operations (which in most cases was informal due to the fluidness of the production system processes), and against the expected system behavior. Unusual observations that would have severely skewed the model results with respect to system behavior and magnitude of the performance estimates were discounted.

Despite the fluidness of the production concept of operations, the related system behaviors (and consequently the assumptions discussed in section 4.2.2) remained consistent throughout the data collection phase.   The result of collecting data on the model parameters is summarized in Table 4-1. This data represents the model inputs and initial conditions after being adjusted to protect the identity of the organization.

4.2.3.2 System Conceptualization and Model Development

The four production systems being evaluated have many common elements and structures. However, each has its own nuances, which makes it unique. Each of the scenarios has a 160-month time horizon. This time horizon was selected to observe the behavior of the system after it achieved a steady state (steady state for all scenarios occurred at approximately period 123). This discussion will begin with a description of elements that are common to each production system, and then will address the differences. The model code is presented in Appendix D.

Each of the production scenarios begins with a base case that resembles the current production concept of operations and a similar production excursion structure designed to test the concept being posed in the scenario.   Raw information (exogenous to the system) enters into the system and is transformed into base data through the data production rate *(DPRu)* where *u* represents the data type (1, 2, 3, or 4).   The transformation is governed by a Cobb-Douglas Function that combines employees *(Eu)*, workstations *(Wu)*, and the data production standard *(PSu)* into data *(Du)* via a data production rate *(DPRu)* as shown the relationship:

$$DPRu = (PSu)(Eu^{eepu}Wu^{ewpu})$$ (4-1)

Where *eepu* is the elasticity exponent that represents the contribution of the production employees, and *ewpu* is the elasticity exponent which represents the contribution of the production workstations. The production exponents and *PSu* are equivalent for the base cases and production excursion structures.

Table 4-1. Model Inputs and Initial Conditions.

VARIABLE	DATA 1	DATA 2	DATA3	DATA 4
Base Contractors *(BC)*	519 contractors	202 contractors	N/A	259 contractors
Base Employees *(BE)*	778 employees	202 employees	105 employees	270 employees
Base Workstations *(BW)*	778 workstations	202 workstations	304 workstations	518 workstations
Contractors *(C)*	20 contractors	50 contractors	N/A	50 contractors
Contractor Adjustment Time *(Cat)*	2 months	2 months	N/A	2 months
Contractor Maintenance Standard *(CMS)*	N/A	500 hours/cell	N/A	650 hours/cell
Contractor Production Standard *(CPS)*	2,200 hours/cell	750 hours/cell	N/A	1,300 hours/cell
Cost per Contractor *(cpC)*	$14,000/month	$14,000/month	N/A	$14,000/month
Cost per Employee *(cpE)*	$8,000/month	$8,000/month	$8,000/month	$8,000/month
Cost per Workstation *(cpW)*	$2,000/month	$2,000/month	$3,500/month	$3,500/month
Data [1] Decomposition Rates a *(DDRa)*	25% of D1 will decompose at 12 month intervals	50% of D2 will decompose at 12 month intervals	30% of D3 decomposes at 60 month intervals	30% of D4 will decompose at 36 month intervals
Data Decomposition Rates b *(DDRb)*	50% of D1 will decompose at 24 month intervals	50% of D2 will decompose at 24 month intervals	N/A	40% of D4 will decompose at 72 month intervals
Data Decomposition Rates c *(DDRc)*	25% of D1 will decompose at a 48 month rate	N/A	N/A	30% of D4 will decompose at 108 month rates
Data Maintenance Standard *(MS)*[2] (Normal distribution assumed)	Min = 1,200 hours/cell Max = 700 hours/cell Mean = 1,000 hours/cell $\sigma = 100$ hours/cell	Min = 500 hours/cell Max = 200 hours/cell Mean = 400 hours/cell $\sigma = 45$ hours/cell	Min = 225 hours/cell Max = 100 hours/cell Mean = 200 hours/cell $\sigma = 60$ hours/cell	Min = 550 hours/cell Max = 200 hours/cell Mean = 400 hours/cell $\sigma = 50$ hours/cell
Data Population Requirement *(DN)*	12,000 cells	12,000 cells	12,000 cells	12,000 cells
Data Production Standard *(PS)*	Min = 2,400 hours/cell	Min = 750 hours/cell	Min = 450 hours/cell	Min = 1,200 hours/cell

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[1] Data decomposition rates are the same for the base and excursion cases.
[2] Data Maintenance Standard minimum reflects the minimum number of cells produced and is associated with the longest time. Conversely, the maximum reflects the maximum number of cells produced and is associated with the shortest time.

(Normal distribution assumed)	Max = 1,800 hours/cell Mean = 2,000 hours/cell σ = 200 hours/cell	Max = 370 hours/cell Mean = 560 hours/cell σ = 75 hours/cell	Max = 300 hours/cell Mean = 400 hours/cell σ = 60 hours/cell	Max = 750 hours/cell Mean = 1,000 hours/cell σ = 100 hours/cell
Employees *(E)*	30 employees	50 employees	10 employees	40
Employee Adjustment Time *(Eat)*[3]	6 months	6 months	6 months	12 months
Employee Maintenance Exponent *(eem)*	.5	.5	.1	.2
Employee Production Exponent *(eep)*	.5	.5	.2	.3
Employee Special Exponent *(ees)*	N/A	.5	.3	.3
Maintenance Workstation Exponent *(ewm)*	.5	.5	.9	.8
Special Data Production Standard *(SPS)*	N/A	50 hours/cell	25 hours/cell	25 hours/cell
Special Data Requirement *(SN)*	N/A	6 cells/month	10 cells/month	14 cells/month
Workstations *(W)*	30 workstations	50 workstations	30 workstations	120 workstations
Workstation Adjustment Rate *(Wat)*	6 months	6 months	6 months	12 months
Workstation Production Exponent *(ewp)*	.5	.5	.8	.7
Workstation Special Exponent *(ews)*	N/A	.5	.7	.7

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[3] Employee adjustment time was modified to equal the workstation adjustment time due to interdependencies between the variables. See discussion in section 4.2.6.

Before the production and maintenance standards, *PSu* and *MSu,* can be used in the model directly, the values in Table 4-1 must be converted to a monthly standard that can be used in equation 4-1. The units for the *DPRu*, and subsequently for the data maintenance rate *DMRu*, must be cells/month. Table 4-1 shows the production and maintenance standards as hours/cell. To make this conversion, the number of employee and workstation hours per month must be divided by the standards shown in Table 4-1. For example, the mean data production standard for scenario 1 is 2,000 hours/cell. Each employee works 160 hours/month, using a workstation. Thus (160 hours/month*employee*workstation)/(2,000 hours/cell) yields .08 cells/month*employee*workstation. This conversion from the hours/cell, in Table 4-1, to cells/month*employee*workstation is implied in the model for the *PSu* and *MSu* variables. The converted values are shown the comments portion of the textual model in Appendix D. Since the units of *PSu* are cells/month*employee*workstation, the units that result from equation 4-1 is cells/month. A similar relationship exists for contractor production standards *CPSu.*

The use Cobb-Douglas Production Function (Cobb & Douglas, 1928) is used in this case study because it allows for the contribution of the key drivers to be considered in the same equation. This is an important concept as the organization generally multiplies the production standard with the number of employees to obtain the projected output. This approach works well if one assumes that a workstation is available for use whenever the employee requires it for production. However, this assumption is not appropriate for instances where advanced technology is inserted and the employee presents a smaller contribution to output than the workstations.

Two important assumptions accompany Cobb-Douglas Production Functions. First, all in-house production is generated as a result of the production function (Cobb and Douglas, 1928). Thus, the production function does not account for managerial overhead. Nor does the basic Cobb-Douglas Production Function include the addition of contractor production included in scenarios 1, 2 and 4. Contractor production is not a function of the Cobb-Douglas Production Function in this system because the contribution of the contractors to the system in not dependent on in-house employees. The second assumption is that any change to the elasticity exponents will result in a

proportional change to the input variables (Cobb and Douglas, 1928), and if the sum of the elasticities changes the output will also change.

The elasticity exponents are gleaned from the projected marginal productivity of the variables with respect to production. Thus the projected marginal productivity of employees, $\partial Du / \partial Eu$, is equal to the elasticity, and describes the contribution, of employees to the production of data. The projected marginal productivity of workstations, $\partial Du / \partial Wu$, is equal to the elasticity, and describes the contribution, of workstations. This means, if *ewpu* = .75, and *eepu* = .25, then a small change in *Eu* will have the same effect as three times an equal change in *Wu*. When *ewpu* = *eepu*, then any equivalent change in one of the variables will have the same effect on the system (Cobb and Douglas, 1928). Thus if *eepu* = *eewu*, both employees and workstations contribute equally to the production process. For scenarios that investigated the role of advanced technology insertion *ewpu* > *eepu*, as the workstations were assumed to contribute more to the production process than the employees do. Since this case study is projecting the future, the exponents used are estimates. As the system is implemented, and real data can be collected, these exponents can be refined.

In each of the scenarios, constant returns to scale are assumed, thus *eepu* + *ewpu* = 1. Constant returns to scale are assumed because due to funding constraints the organization cannot realistically increase their production output to the extent where additional capacity will result in decreasing returns to scale. For the system to achieve decreasing returns to scale, additional capacity will have to yield an output of smaller proportion than the input. Increasing returns to scale is not applicable to this system either because proportional increases in production capacity will not lead to a disproportional increase in production. By assuming constant returns to scale, it is assumed that there is a balance between employees and workstations.

Scenarios 1, 2, and 4 include additional capacity from contractor support. When contractor support is used, equation 4-1 becomes:

$$DPRu = (PSu)(Eu^{eepu})(Wu^{ewpu}) + (CPSu)(Cu) \tag{4-2}$$

Where *CPSu* is the contractors production standard, and *Cu* is the number of contractors. The number of contractors, and the associated production standard, is not included in the Cobb-Douglas portion of the equation because contractor production is not dependent upon the number of in-house employees or workstations. Thus, if the number of in-house employees was equal to zero, production will continue if $Cu \neq 0$. Since contractor support is aggregated to the number of contractors and does not considers the supporting infrastructure (the support infrastructure is considered to be exogenous the system), any associated exponent would equal one, and therefore is not included.

The base case and production excursion cases continue with the data decomposition concept. As previously stated only a small faction of the organizations management subscribes to the concept of data decomposition. However, the organization does have some rudimentary data supporting this concept, and because a common-sense approach dictates that the data is not timeless, it is modeled in each scenario. The data decomposition allows for a one-to-one comparison between the base and production excursion cases during this analysis. As the data production rate adds to the data level variable *Du*, the decomposition rate removes aged data from the total, and adds it to the aged base data *(ADu)* in the base structure, and to the data maintenance queue *(DMu)* in the production excursion structure. The total amount of good data in the system is defined as:

$$Du = Du_{t-1} + \int_0^t (DPRu - \sum DDRuv)dt \qquad (4\text{-}3)$$

Where *DDRuv* is the decomposition rate *v* of data *u,* and Du_{t-1} is the total amount of good data during the previous time period.

The decomposition rates are assumed to be equal for the base and production excursion cases. Since the current concept of operations does not consider maintenance, the base structure ends with the aged base data level. The base structure for scenario 1 is shown as a representative example in Figure 4-3(a).

The production excursion structure continues with data maintenance. Similar to the production rate *(DPRu)*, the maintenance rate *(DMRu)* is governed by a Cobb-Douglas Function. The *DMRu* removes aged data from the maintenance queue, adds

value to the data to make it current, and then redeposit the completed data into the data *(Du)* level. Maintenance is assumed to take priority over in-house new production, thus employees workstations are assigned to maintenance activities prior to being assigned to new production. This is a logical assumption, as the data maintenance standard *(MSu)* is a fraction of the time required by *PSu.* Thus the concept is to maintain the data that has already been produced before adding new data to the system.

Since maintenance data takes priority over production data, equation 4-1 becomes:

$$DPRu = (PSu)(Eu - EMu)^{eepu}(Wu - WMu)^{ewpu} \qquad (4\text{-}4)$$

Where *EMu* is the number of employees, and *WMu* is the number of workstations, dedicated to maintenance of aged data. Like the data production rate *(DRPu)* the data maintenance rate *(DMRu)* assumes the form of a Cobb-Douglas Production Function as:

$$DMRu = (MSu)(EMu^{eemu})(WMu^{ewmu}) \qquad (4\text{-}5)$$

Where *MSu* is the maintenance standard, *EMu* is the number of employees, and *WMu* is the number of workstations dedicated to data maintenance. If current technology and process are being simulated, *eepu = eemu* and *ewpu = ewmu.* Constant returns to scale are assumed.

Incorporating the maintenance function into the total accumulation of good data, equation 4-3 becomes:

$$Du = Du_{t-1} + \int_0^t (DRURu + DMRu - \sum DDRuv)dt \qquad (4\text{-}6)$$

Figure 4-3(b) illustrates the typical structure for the excursion.

The structures for scenarios 2, 3, and 4 include elements for special data production. Special data does not contribute to the data totals in the data level *Du* or the totals in the base data level *BDu.* Special data is included in the model only because it takes away resources from both the data productions and the date maintenance functions, because the special data requirement has priority the number highest production
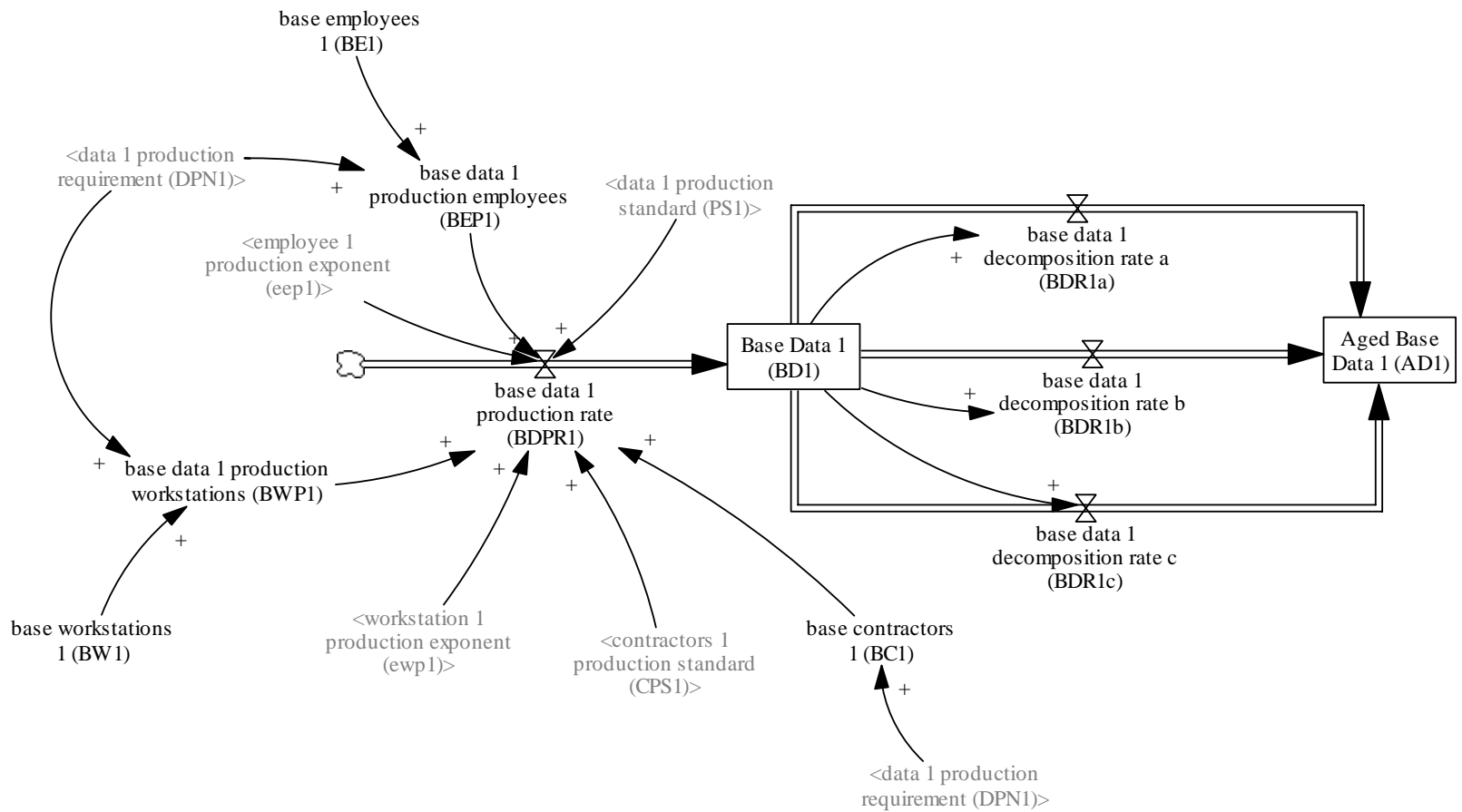
Figure 4-3(a). Scenario 1 Base Case.

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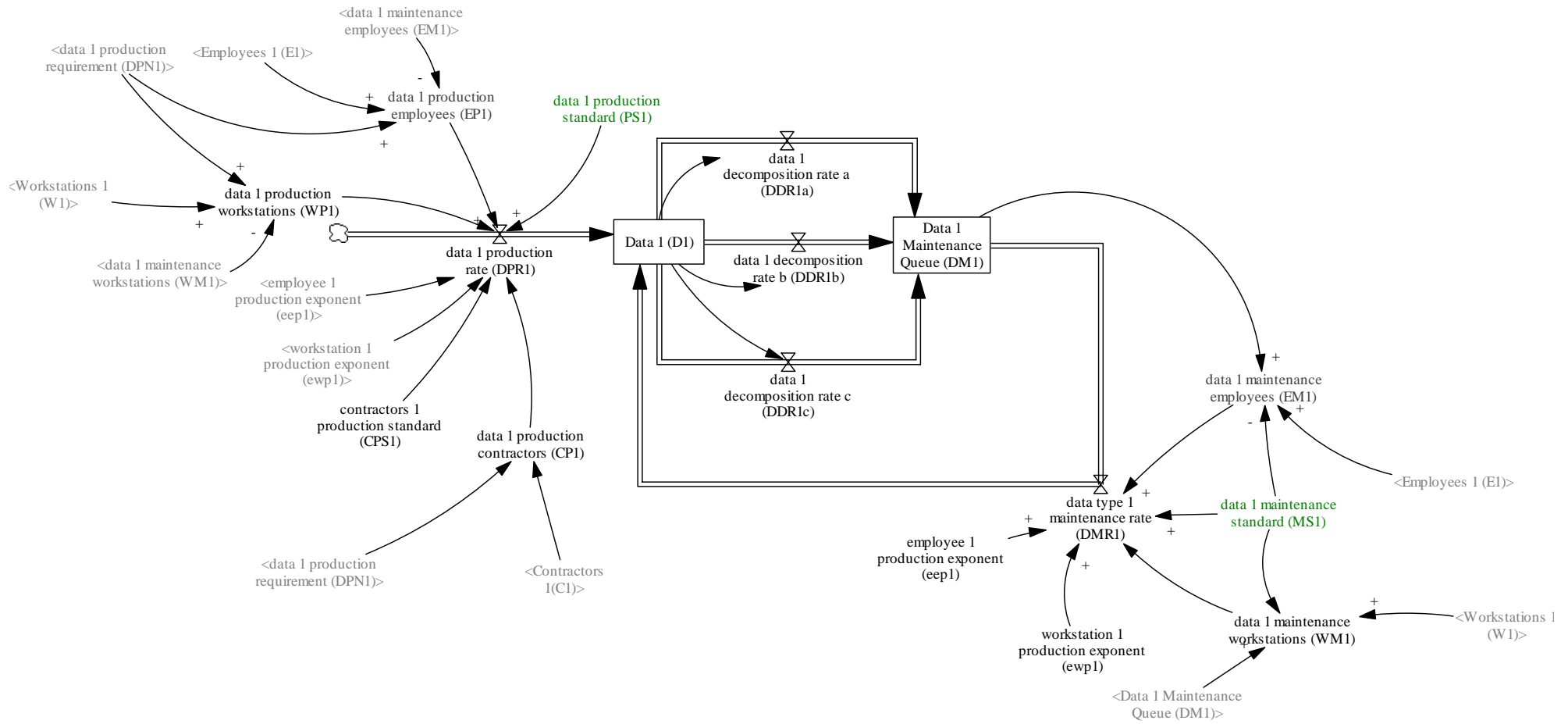
Figure 4-3(b). Scenario 1 Excursion Case.

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requirement. The special data requirement arrives in the system via the special data requirement rate ($SNRu$). The amount of in-house resources applied to producing special data sets is determine by dividing the special data requirement *(SNu)* by the special data production standard ($SPSu$). Thus when the special data production requirement *(SNu)* is greater than zero, equation 4-4 becomes:

$$DPRu = (PSu)(Eu - EMu - SEu)^{eepu}(Wu - WMu - SWu)^{ewpu}$$

(4-7)

Where *SEu* is the number of employees and *SWu* is the number of workstations dedicated to special production. When *DPNu=0*, equation 4-5 becomes:

$$DMRu = (MSu)(EMu - SEu)^{eemu}(WMu - SWu)^{ewmu}$$

(4-8)

The system's key drivers are the variables optimized in the model. As identified in Section 4.2.2, the systems key drivers are employees, workstations, and contractors (scenarios 1,2 and 4). The optimization structures take the form of the hill-climbing optimization structure discussed in Section 3.5. The most significant difference between the generic structure presented in Chapter 3, and the hill-climbing optimization structure is that the production function defined here is based on the causal relationships defined by the organization. Like, the electric power example in Chapter 3, the relative production is defined by comparing the production goals to the production function. Recall from the electric power production example, that the production function was the amount of electricity that could be theoretically produced. In this case study, the production function *(Dpu)* is the amount of output that can be theoretically produced by the data production rate *(DPRu)*, the data maintenance rate *(DMRu)*, and where applicable the special data production rate *(SPRu)*.

The variables shown with the employee hill-climbing optimization labeled as be "theoretical" were added to the model for simulation convenience. During the verification of scenarios 2 and 4, it was discovered that after all new production was completed that the contractors went through a ramping down period as they were moving to the data maintenance task. While the ramping down period generally lasted less than

ten iterations, additional new production continued to be generated. This had dramatic, and erroneous, effects on the calculations for employees, workstations, and contractors. This behavior did not mimic real world production as the real world system has a finite goal of 12,000 cells. The introduction of the artificial data theoretical maintenance *DTMu* forces all resources to be shifted to data maintenance once data production was completed. For consistency purposes across all subsystems, the theoretical values were included. In most instances, the theoretical values are mirror images of their predecessor values. However, this artificial variable does correct the simulation anomaly when needed[4].

The employee and workstation variables use the same relative production relationship *(Dpu*/Dpu)* which compares the data production function *(Dpu)* to the data production goal *(Dpu*)*. In contrast, in scenarios that explore the contractor influence, the relative production variable only considers aspects of production in which the contractors support. For example, in scenario 1 contract support is used only for production. Thus the production goal in the numerator only reflects the system's new production goal, and the production function in the denominator only reflects the production contributed to new production. The data maintenance requirement of resources needed to perform such activities is not included in scenario 2.

The contractor hill-climbing optimization structures for scenario 2 and 4 are also noteworthy. In these scenarios, contractors perform new production first, and then when new production is completed, perform data maintenance. Therefore when the data production requirement is *DPNu* > 0, then the ratio of *DPNu/DTPu* is the relative contractor production *RCPu* value that influences the structure, where *DTPu* is the theoretical production rate. When *DPNu* = 0, *RCPu* = *DMNu/DTMu* where *DMNu* is the data maintenance requirement and *DTMu* is the theoretical maintenance rate.

The hill-climbing optimization structures for employees, workstations, and contractors for scenario 1 are illustrated in Figures 4-3(c-e).

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[4] I have spent a considerable amount of time trying to understand the dynamics of this problem. I have attempted to model this problem with the Stella software, but was unable to replicate the behavior.

The total cost and technical efficiency are similar across the scenarios. The only departure from the structure of scenario 1 (Figure 4-3(f)), is in scenario 3 where contractors are not considered.

Scenario 2 is the first scenario to contain the special data requirement (Figure 4-4(a)). When this requirement is present it takes priority over maintenance and normal production requirement. The special requirement is generated outside of the system boundaries. The requirement enters into the system and is recorded as a monthly rate. The requirement is stored in a level variable until it is completed, and is then disseminated to the customer who is exogenous to the system. The special data produced during this production process does no contribute to the total good data levels *(Du* and *BDu)*, but the resources used to create the special data sets are detracted from normal data production and maintenance. The number of employees and workstations required is dependent on the special data requirement, the production standard and the elasticity exponents. A Cobb-Douglas Production Function also governs this production process.

The production excursion structures for scenarios 2 and 4 allow for contractors to perform maintenance functions. As in scenario 1, the in-house employees are required to perform maintenance functions before producing new cells of data. The contractor's first priority in scenarios 2 and 4 is to produce new data, and when all new data is completed, to proceed with data maintenance activities.

The structure for scenario 2 assumes present day technology, therefore all structure exponents are equal to 0.5.

The relative production calculation in the employee optimization considers two additional variables. The theoretical special data rate is added to the numerator *Dpu,* and the special data requirement *(SNu)* is added to the numerator. The relative contractor production *(RCPu)* also changes as the theoretical maintenance rate is added to the numerator, and the data maintenance required *(DMNu)* is added to the numerator. The structures for scenarios 2 are illustrated in Figures 4-4(a-g)

The structures for scenario 3 (Figures 4-5(a-f)) offer the departure from the structures which represent the other scenarios. The purpose of scenario 3 is to test the impact of advanced technology insertion on the system. To isolate the variables in the structure to best answer the questions, contractor support was eliminated. The data type

which would benefit the most from advanced technology contains the least stressing maintenance requirement as determined by only one data decomposition rate.

To test the advanced technology insertion, the workstation production exponent is changed to *ewp3* = 0.8, the workstation maintenance exponent is changed to *ewm3=0.9*, and the workstation special exponent is changed to *ews3=0.7*. Therefore the organization anticipates the advanced technology to contribute to new production the most, and special data production the least. Constant returns to scale are assumed, thus the employee exponents for production, maintenance, and special production are 0.2, 0.1, and 0.3 respectively.

Scenario 4 (Figures 4-6(a-g)) is designed to test many of the concepts tested in the previous scenarios together. The decomposition rate of the data is designed to stress the system, much like that of scenario 1. Special data requirements are imposed on the system like in scenarios 2 and 3. Contractors perform both production and maintenance function like in scenario 2. And, advanced technology is inserted into the system, much like it is in scenario 3.

4.2.4   Model Results and Policy Analysis

In addition the common question of the impact of data decomposition, the associated cost of system maintenance, and identifying the most opportune time to insert additional capacity, scenario 1 was designed to assess the impact of contractor support for the new production. Current technology is assumed thus the elasticity exponents for employees and workstations are equal at 0.5. Initial conditions for production resources (excursion structure) are: *E1*= 30 employees, *W1*= 30 workstations, and *C1*= 20 contractors. These are the variables that will be adjusted during the transient phase as the data maintenance function begins. Initial conditions for production resources for the base structure are: *BE1* = 778 employees, *BW1* = 778 workstations, and *BC1* = 519 contractors. Initial conditions for the base case in each scenario were established by conducting an optimization run based on the mean production and maintenance times, and with all adjustment times equal to one. This approach allows the model to predict how many resources would be required without any constraints imposed by the optimization
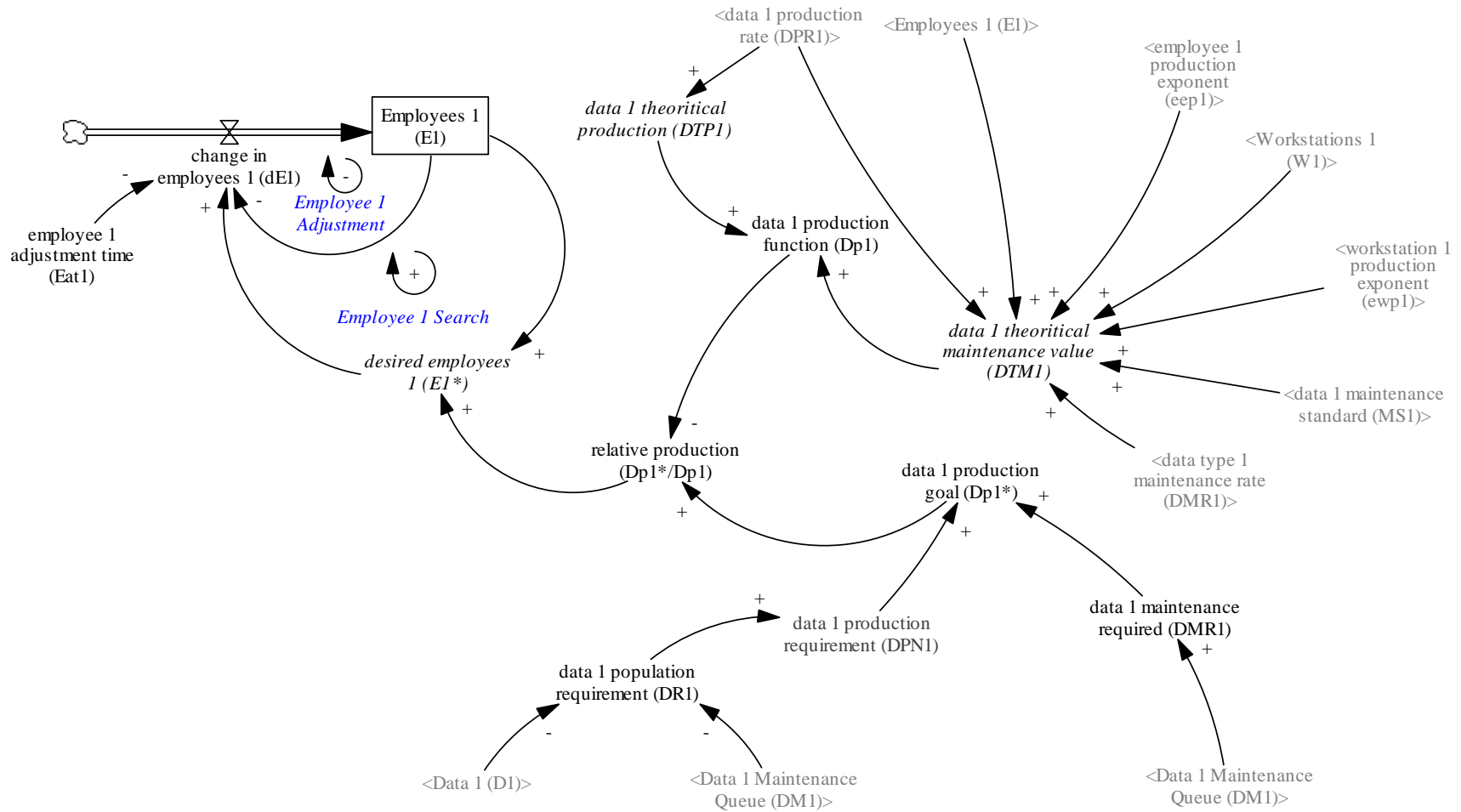
Figure 4-3(c). Scenario 1 Employees Hill-Climbing Optimization Structure.
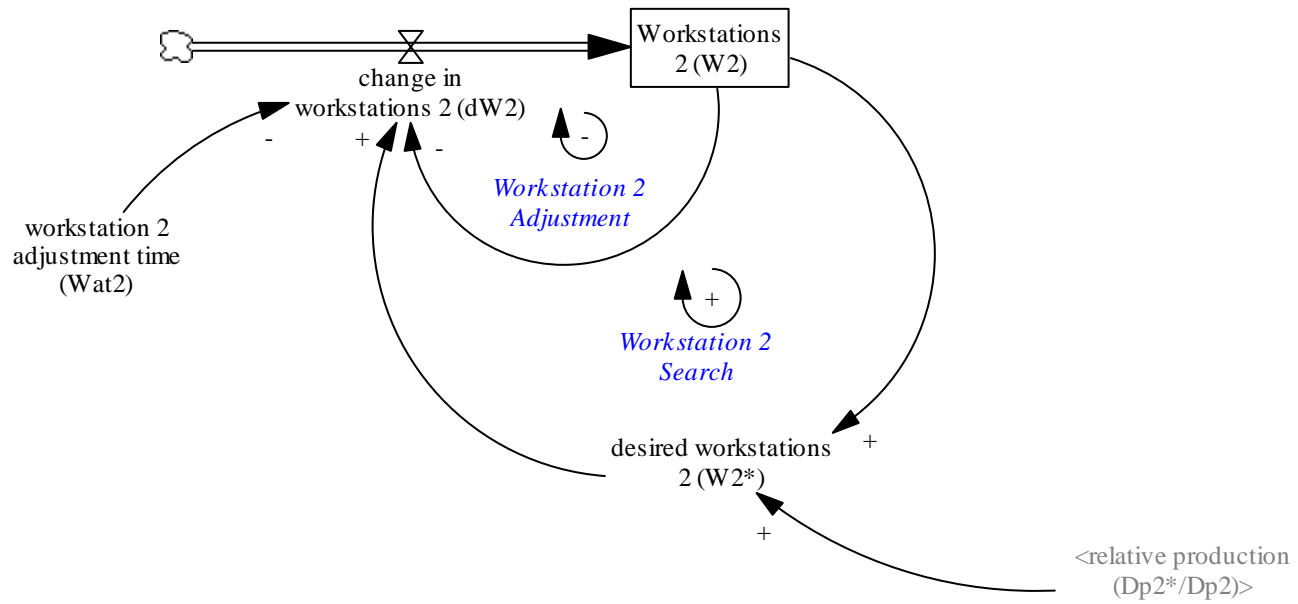
133
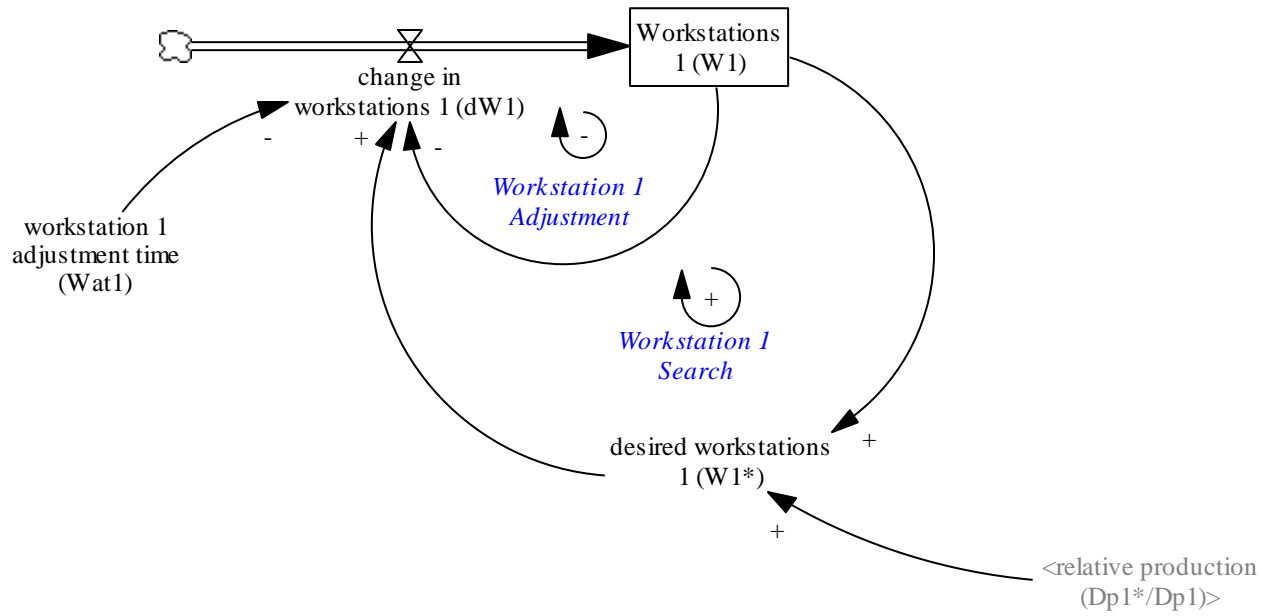
Figure 4-3(d). Scenario 1 Workstations Hill-Climbing Optimization Structure.
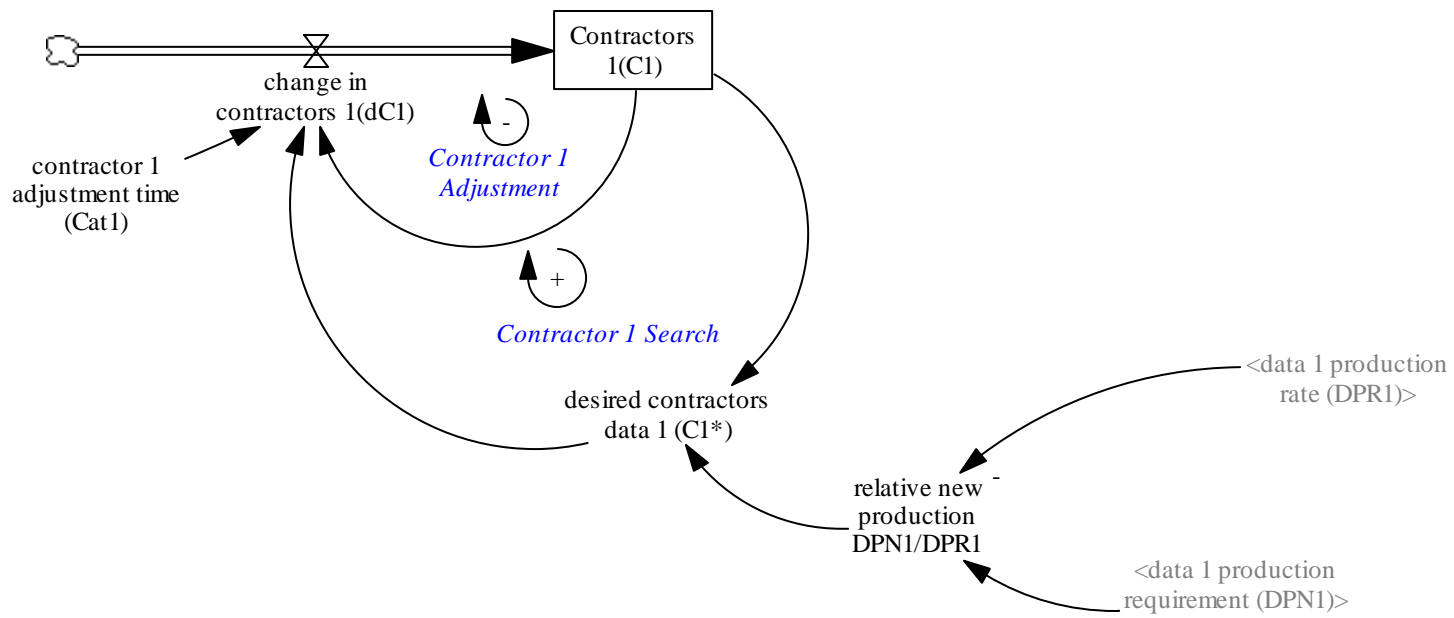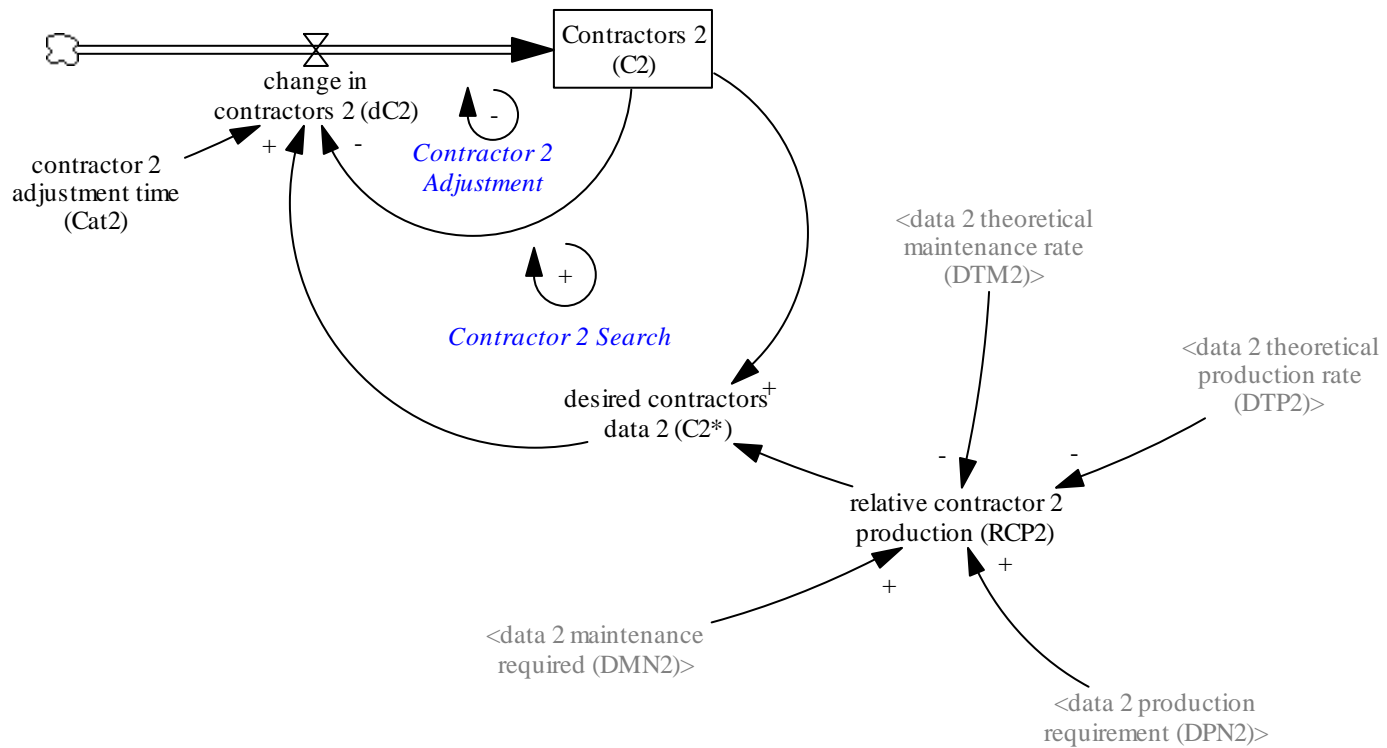
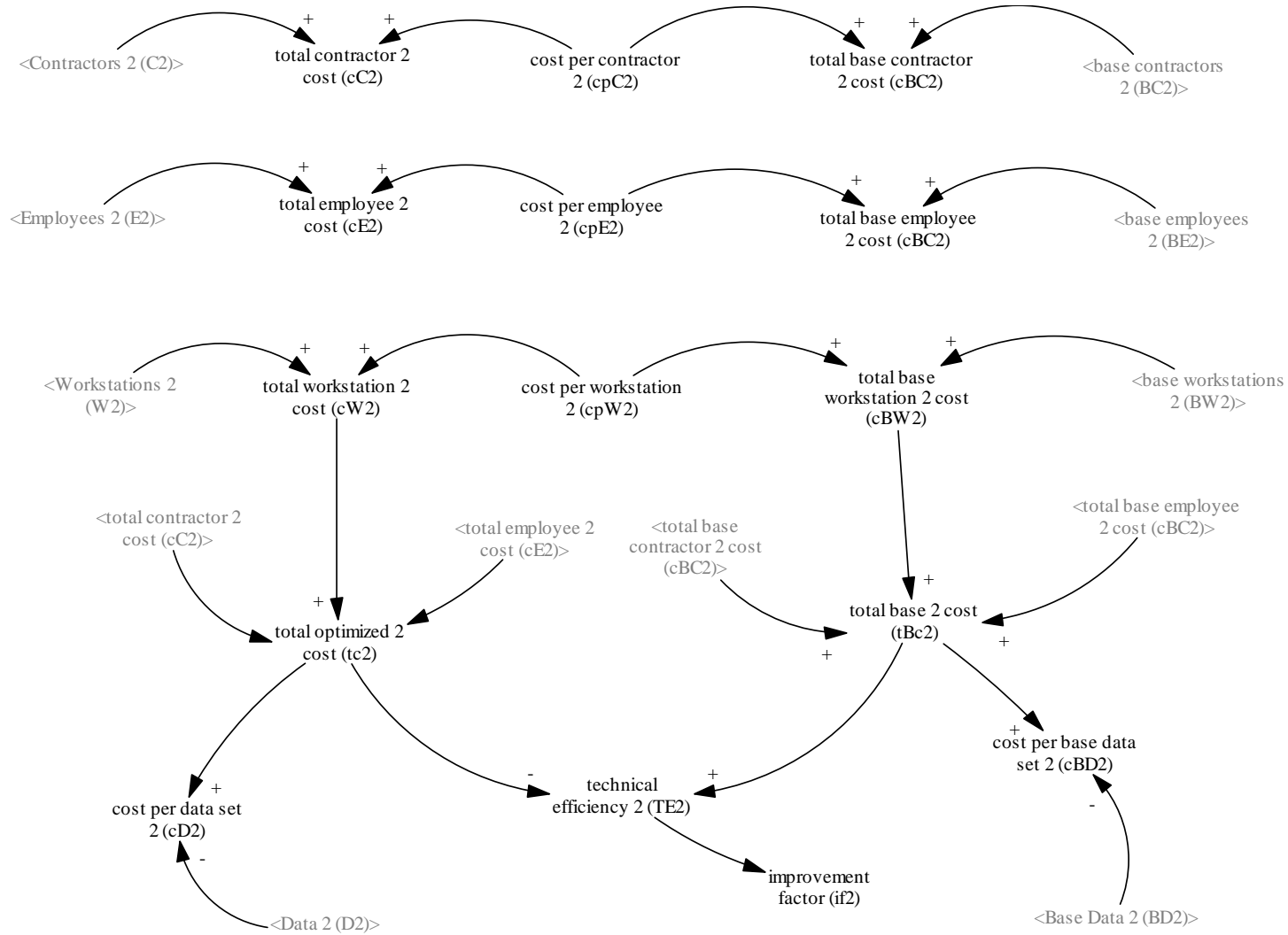**Figure 4-3(e).** Scenario 1 Contractors Hill-Climbing Optimization Structure.
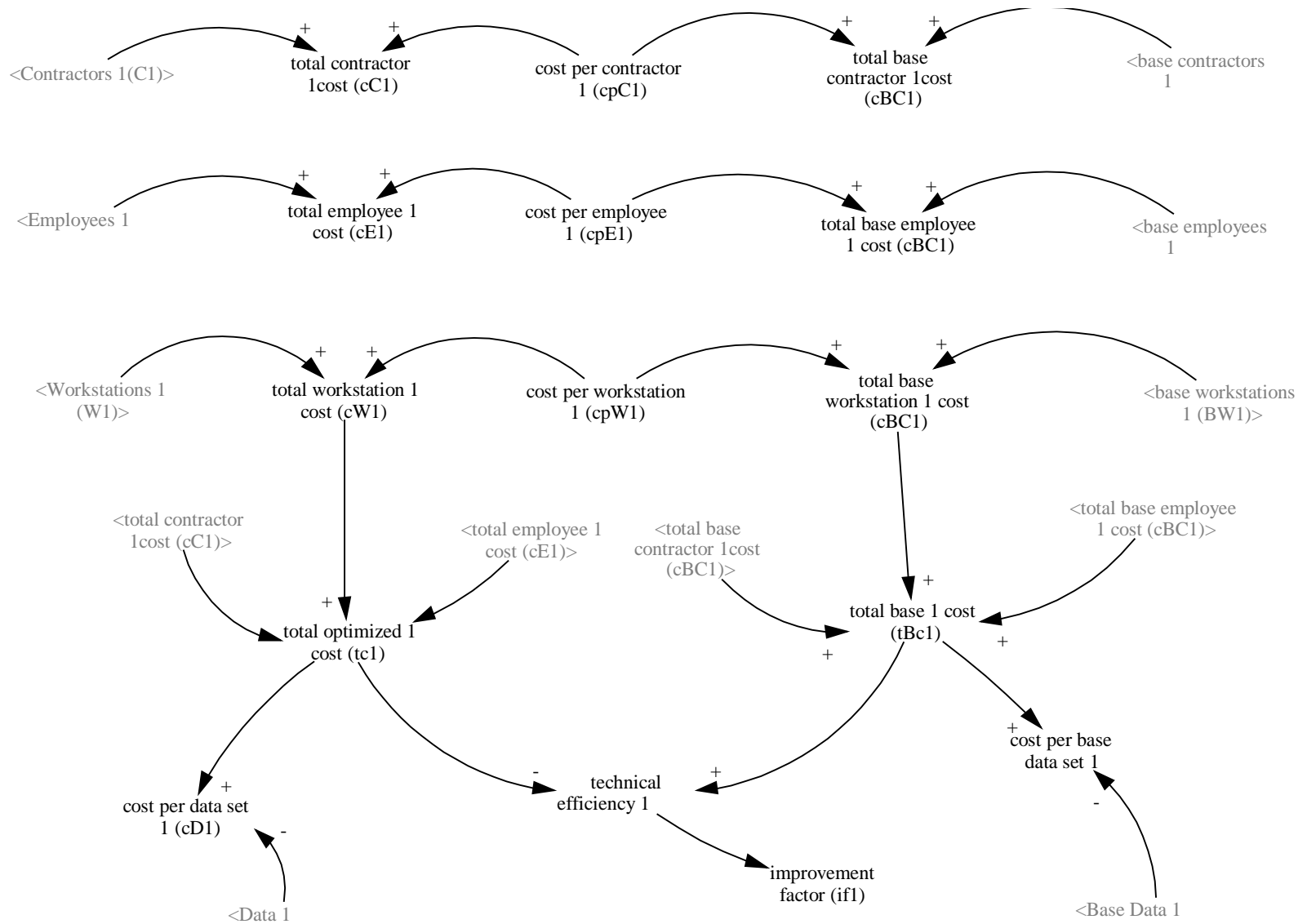
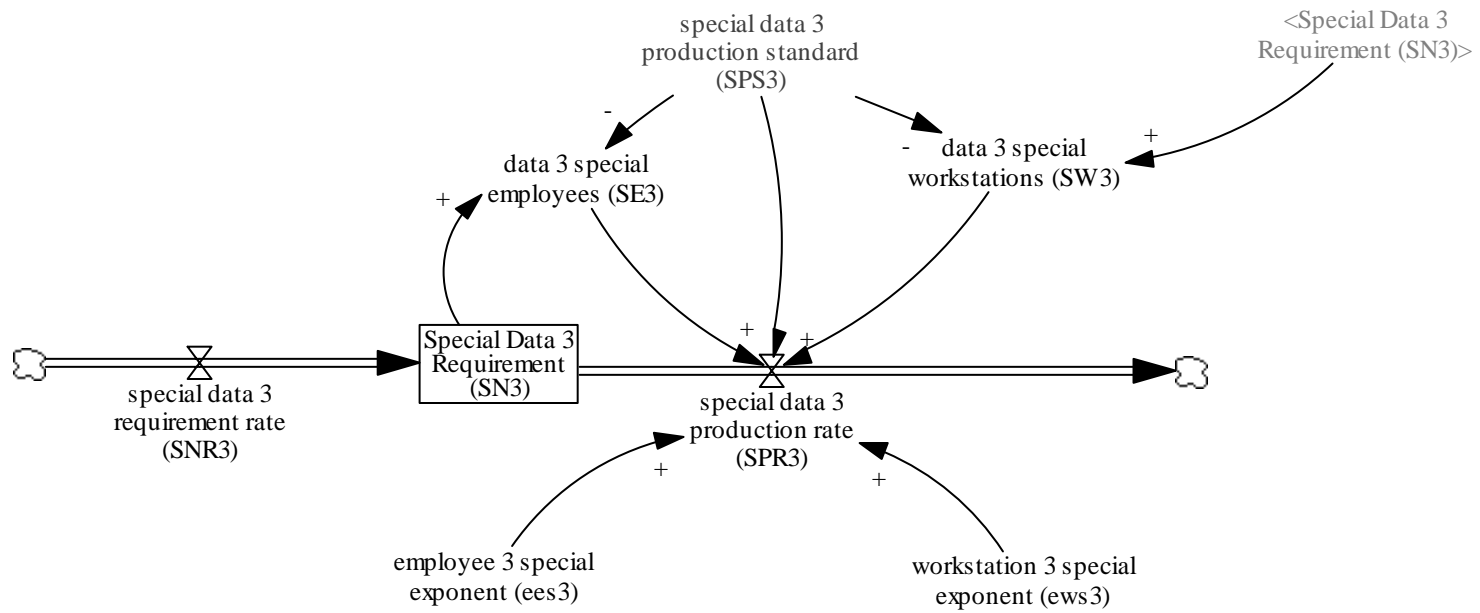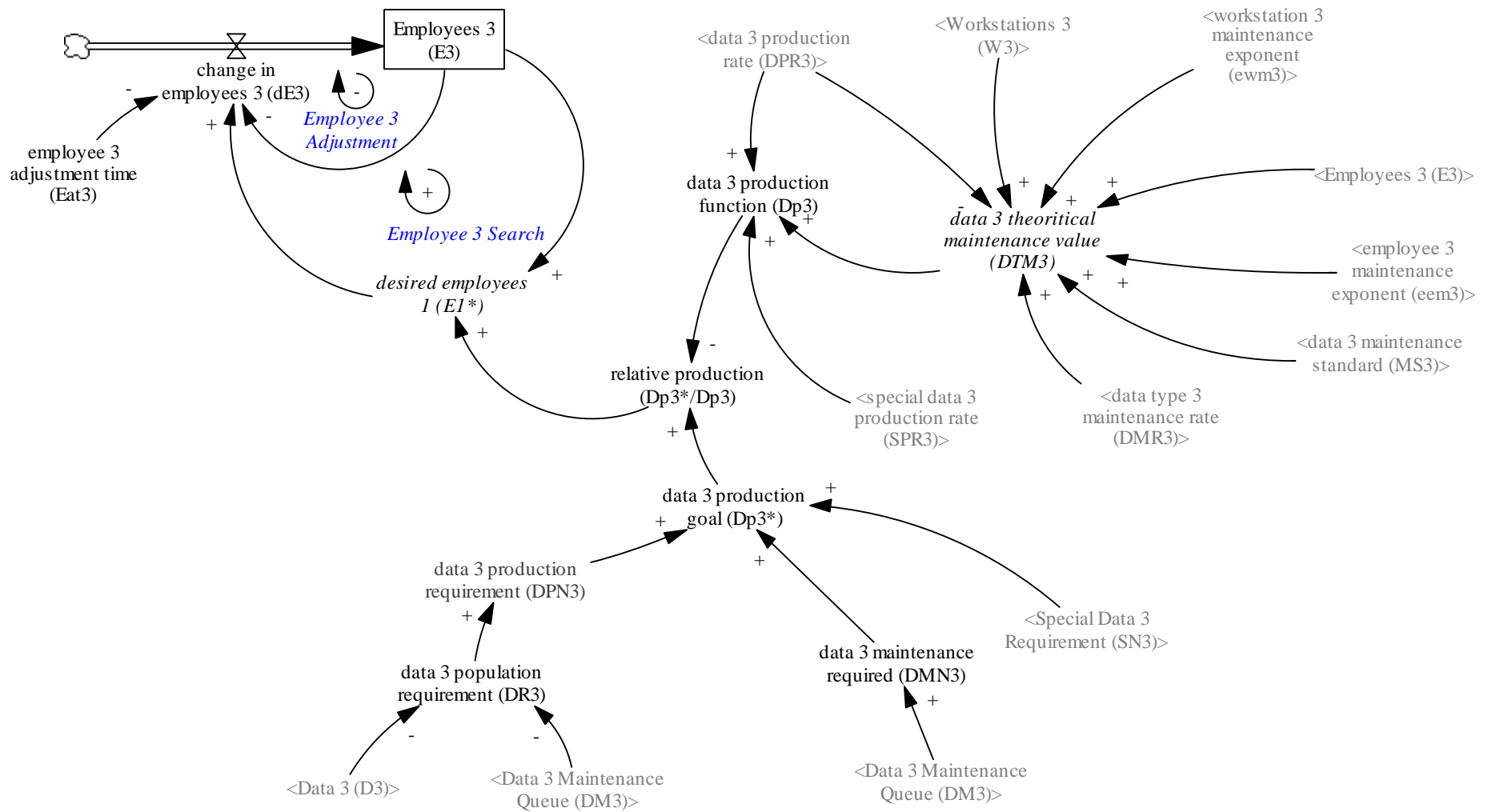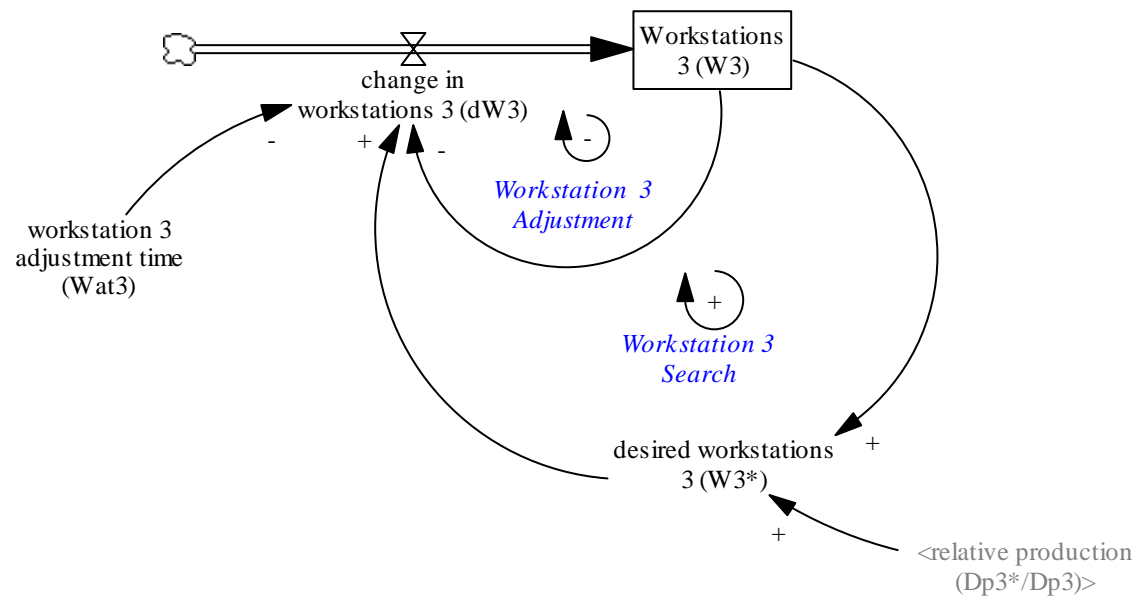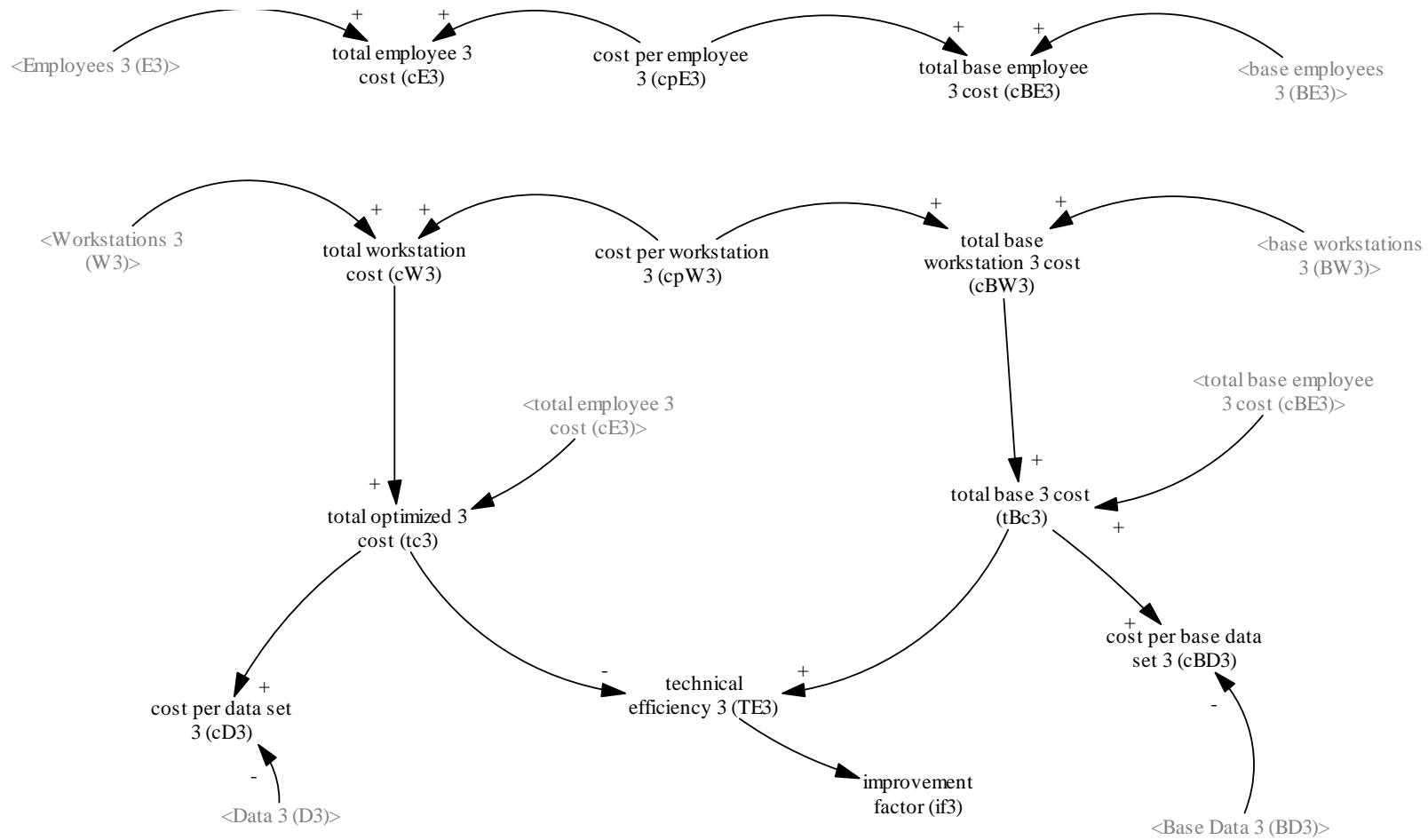**Figure 4-3(f).** Scenario 1 Cost and Technical Efficiency Structure.

special data 2
production standard
(SPS2)

<Special Data 2
Requirement (SN2)>

-

- data 2 special
workstations (SW2)

+

data 2 special
employees (SE2)

+

Special Data 2
Requirement
(SN2)

+   +

special data 2
requirement rate
(SNR2)

special data 2
production rate
(SPR2)

+

+

employee 2 special
exponent (ees2)

workstation 2 special
exponent (ews2)
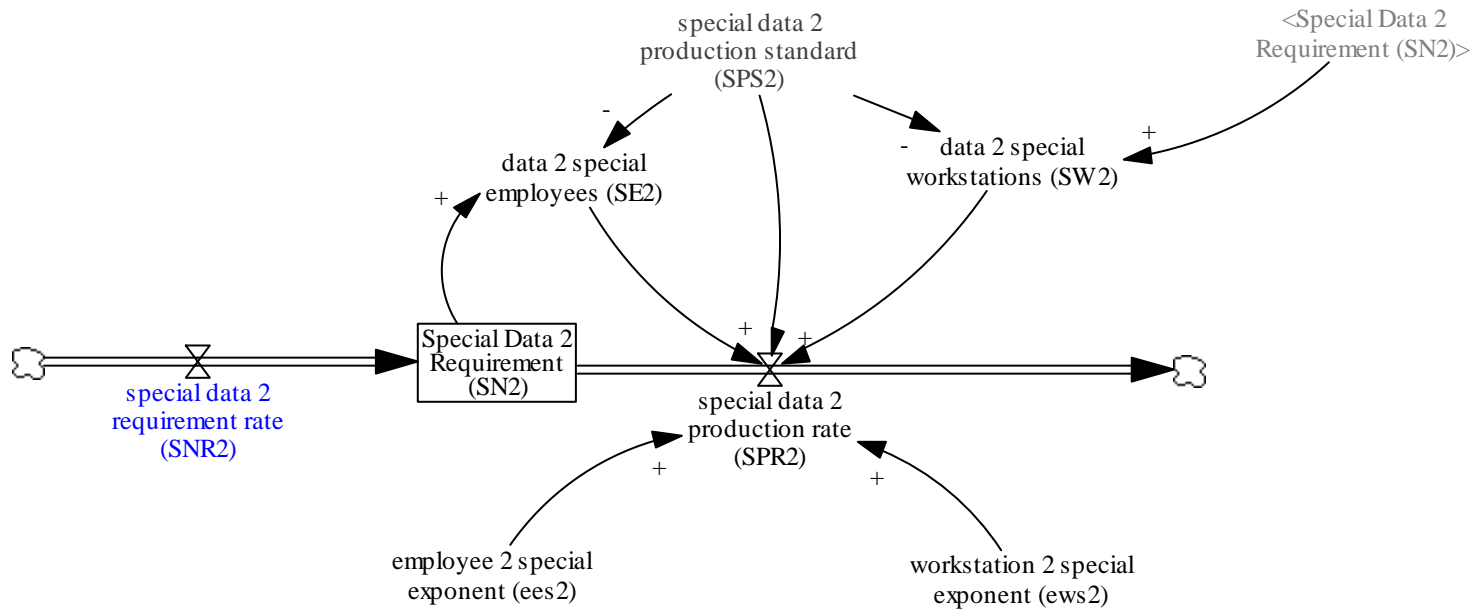
Figure 4-4(a). Scenario 2 Special Data Structure.

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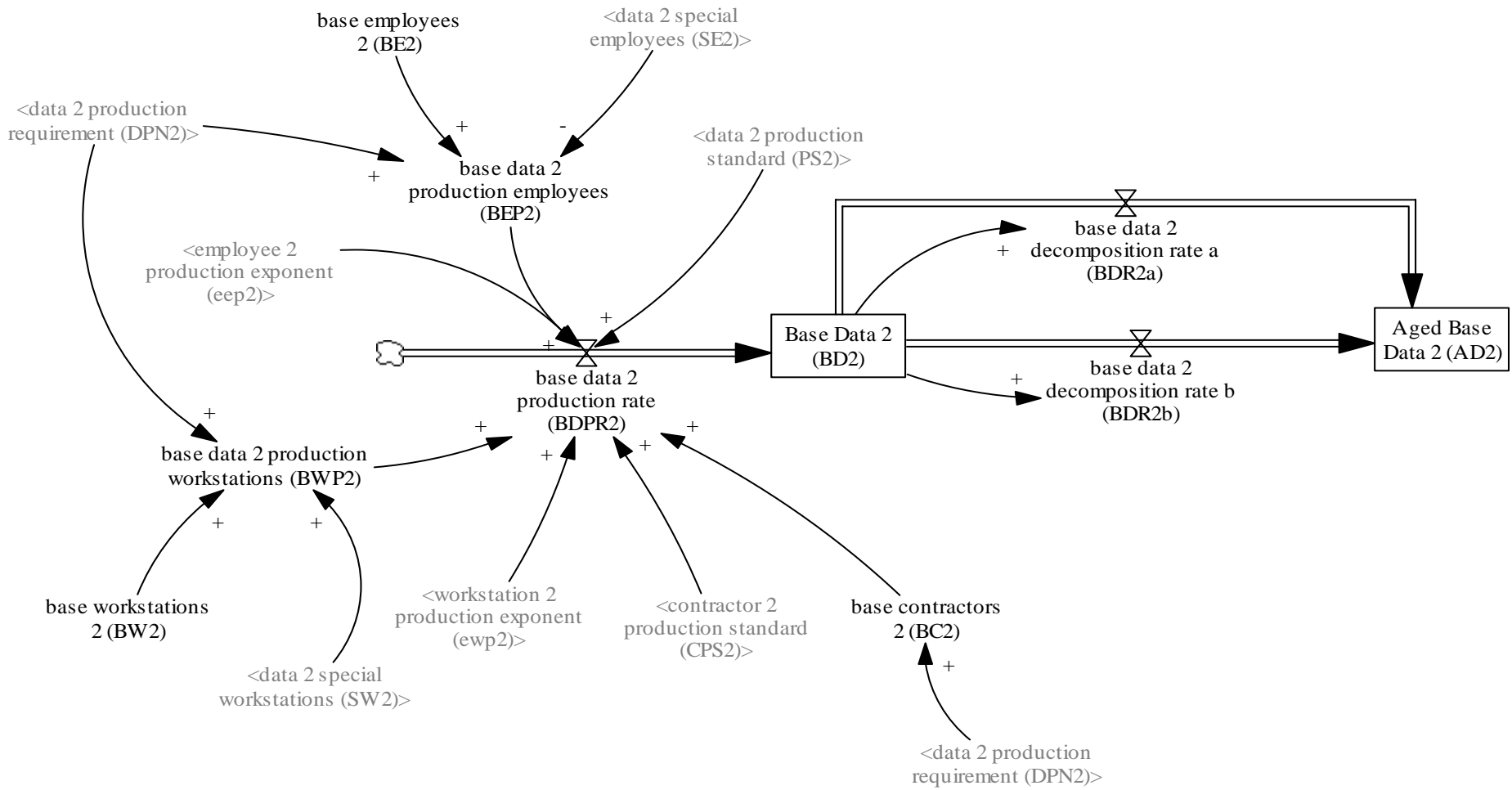
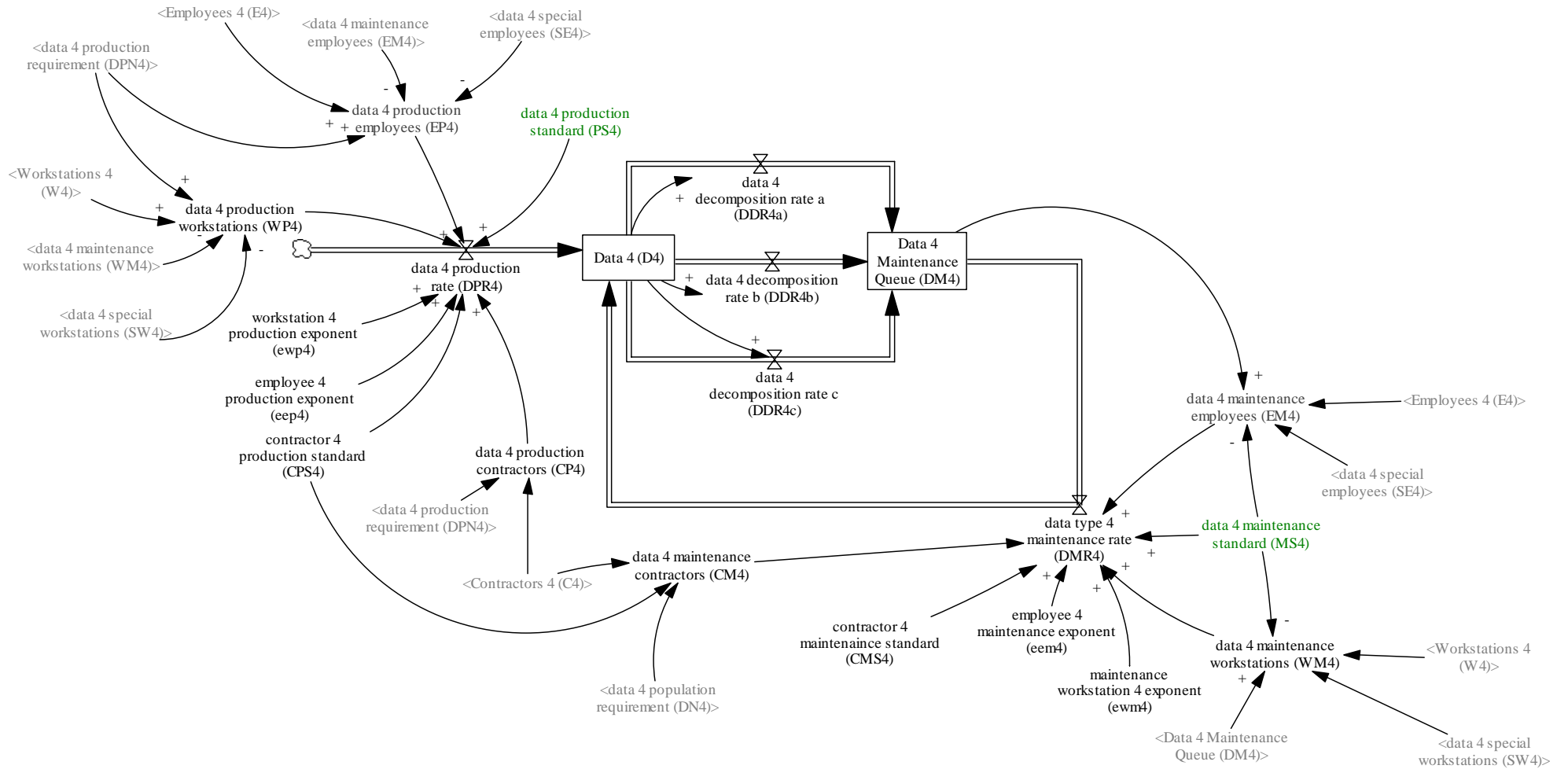**Figure 4-4(b).** Scenario 2 Base Case Structure.
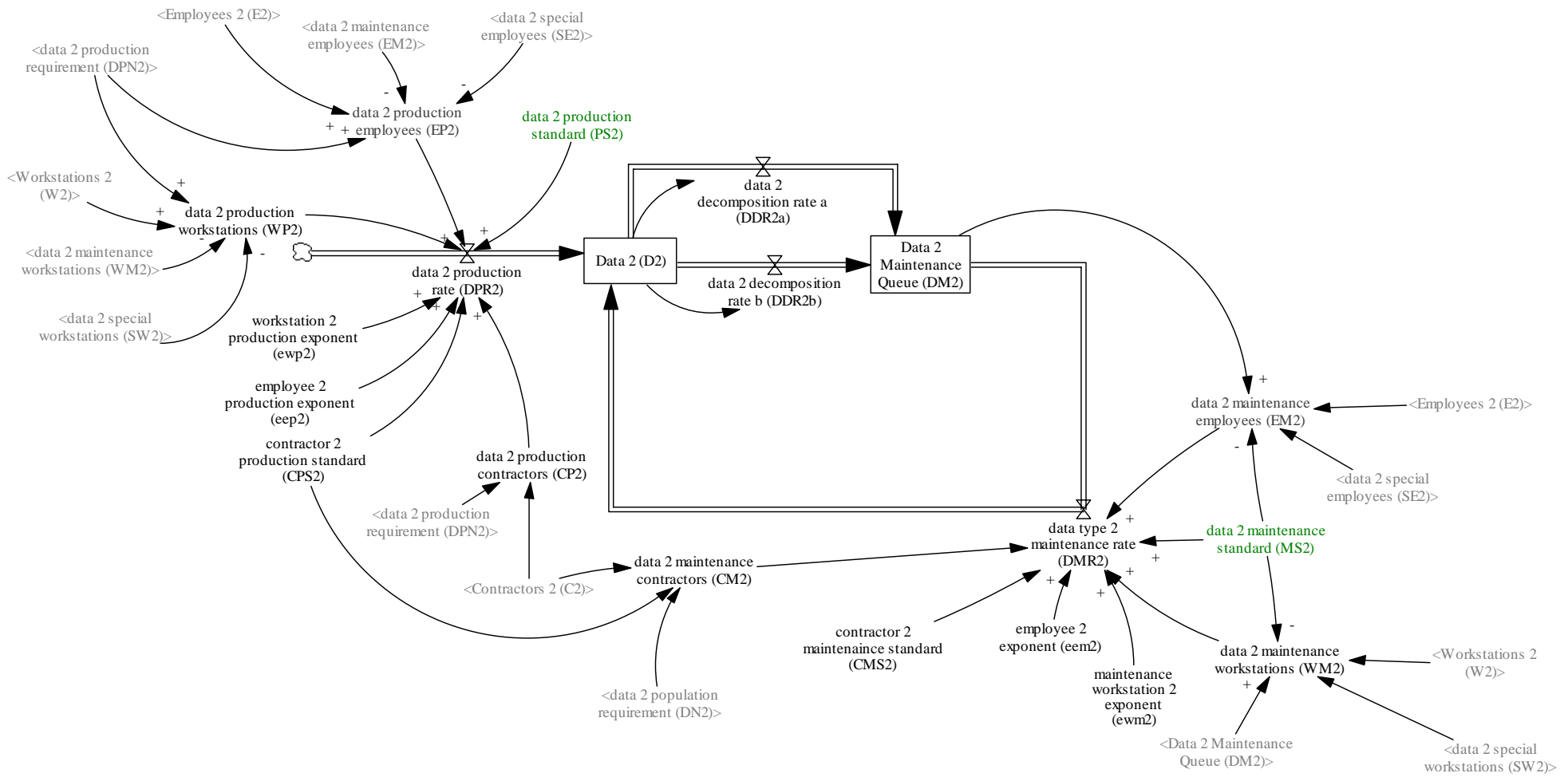
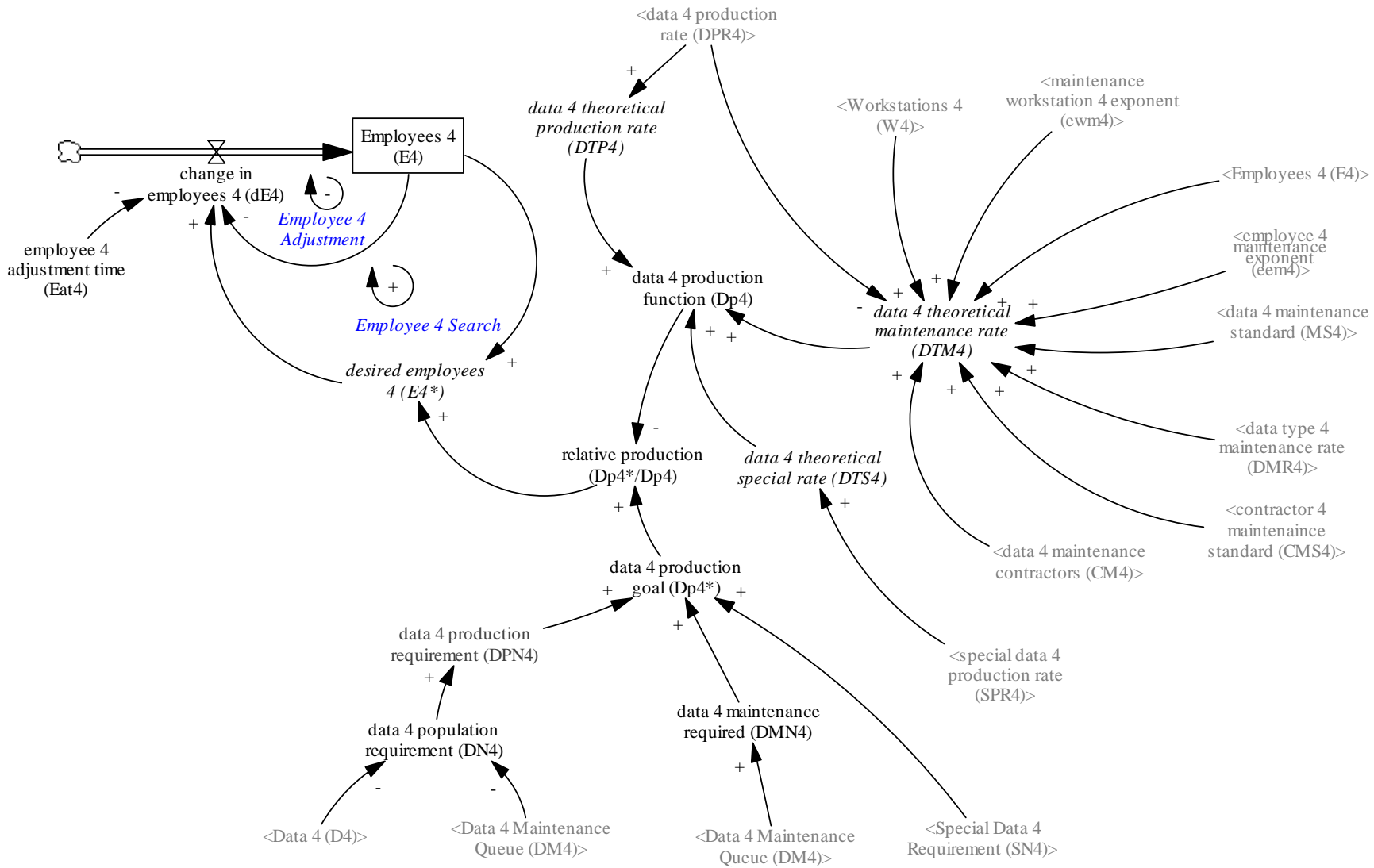**Figure 4-4(c).** Scenario 2 Excursion Structure.
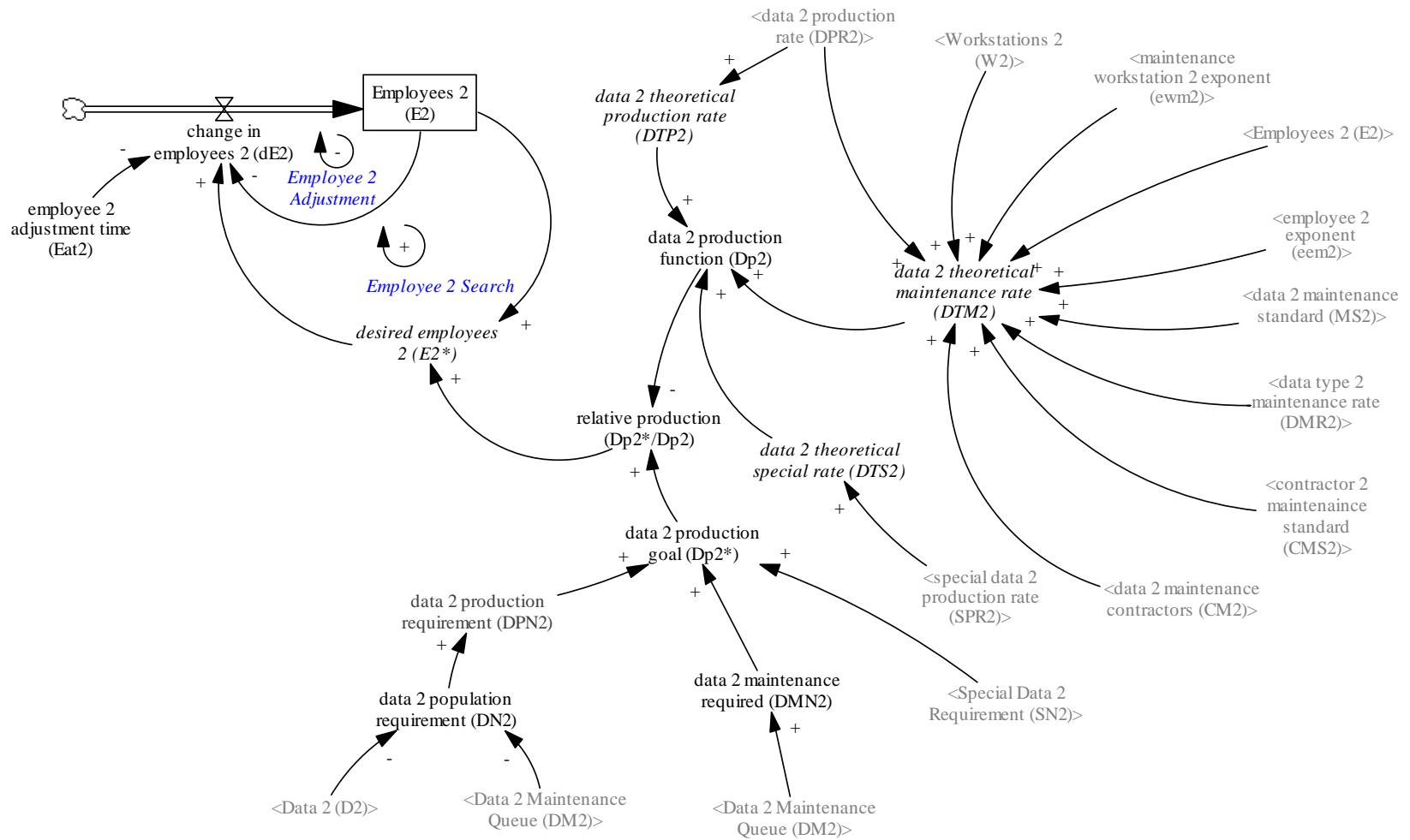
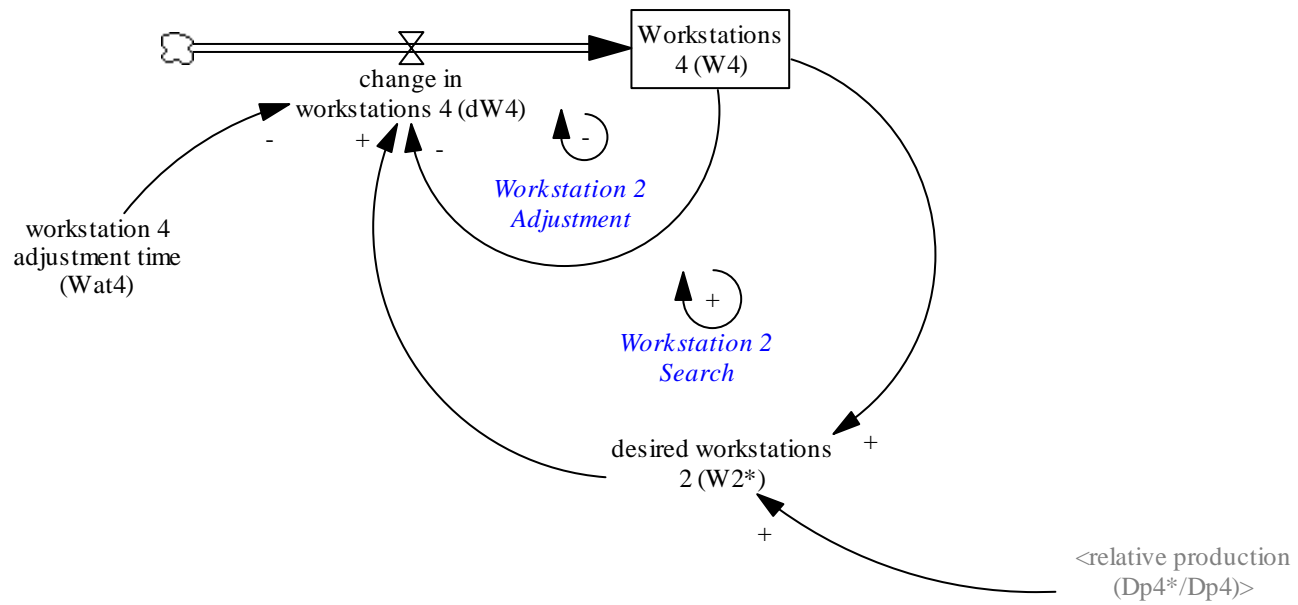**Figure 4-4(d).** Scenario 2 Employees Hill-Climbing Optimization Structure.

140

Figure 4-4(e). Scenario 2 Workstations Hill-Climbing Optimization Structure.
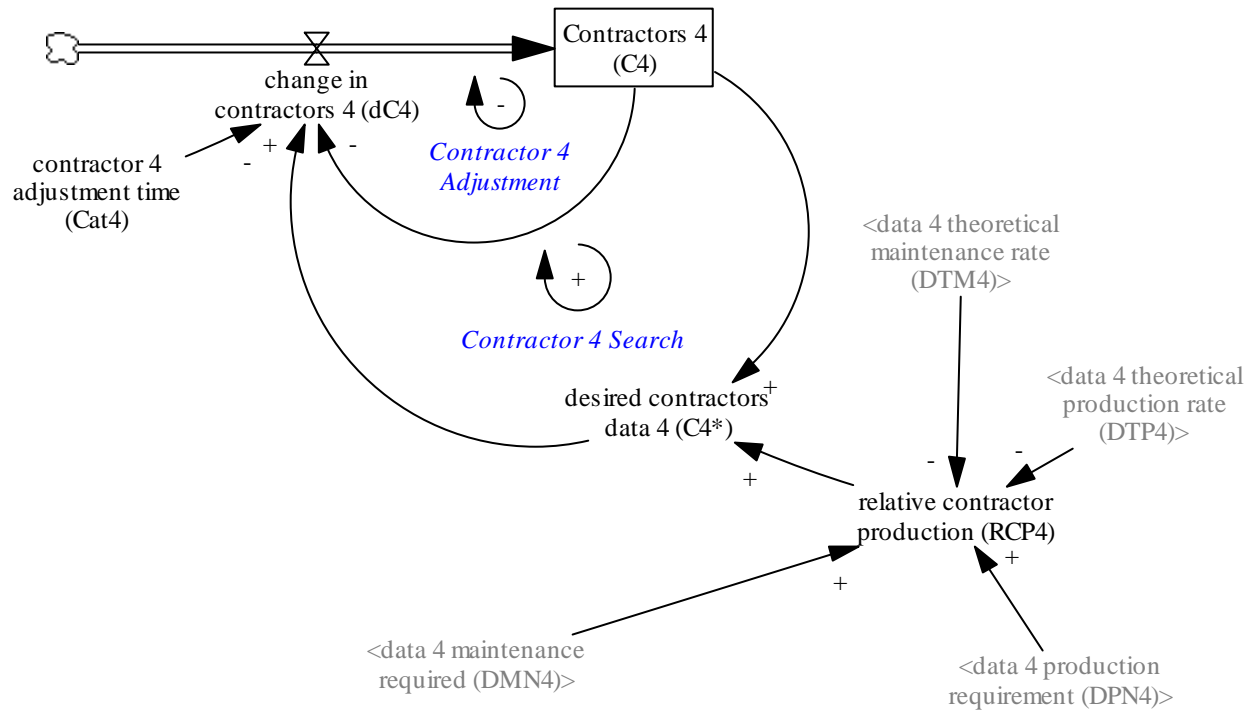
**Figure 4-4(f).** Scenario 2 Contractors Hill-Climbing Optimization Structure.

Contractors 2 (C2)

change in contractors 2 (dC2)

contractor 2 adjustment time (Cat2)

Contractor 2 Adjustment

Contractor 2 Search

desired contractors data 2 (C2*)

<data 2 theoretical maintenance rate (DTM2)>

<data 2 theoretical production rate (DTP2)>

relative contractor 2 production (RCP2)

<data 2 maintenance required (DMN2)>

<data 2 production requirement (DPN2)>

Figure 4-4(g). Scenario 2 Cost and technical Efficiency Structure.

special data 3
production standard
(SPS3)

<Special Data 3
Requirement (SN3)>

-

data 3 special
employees (SE3)

- data 3 special
workstations (SW3)

+

+

+

Special Data 3
Requirement
(SN3)

special data 3
requirement rate
(SNR3)

special data 3
production rate
(SPR3)

+

+

+

+

employee 3 special
exponent (ees3)

workstation 3 special
exponent (ews3)

Figure 4-5(a). Scenario 3 Special Data Structure.

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base employees
3 (BE3)

<data 3 special
employees (SE3)>

<data 3 production
requirement (DPN3)>

+

+

base data 3
production employees
(BEP3)

-

<data 3 production
standard (PS3)>

<employee 3
production exponent
(eep3)>

+

Base Data 3
(BD3)

Aged Base
Data 3 (AD3)

base data 3
production rate
(BDPR3)

+

base data 3
decomposition rate a
(BDR3a)

+

base data 3 production
workstations (BWP3)

+

+

+

base workstations
3 (BW3)

+

-

<workstation 3
production exponent
(ewp3)>

<data 3 special
workstations (SW3)>

Figure 4-5(b). Scenario 3 Base Case Structure.

145
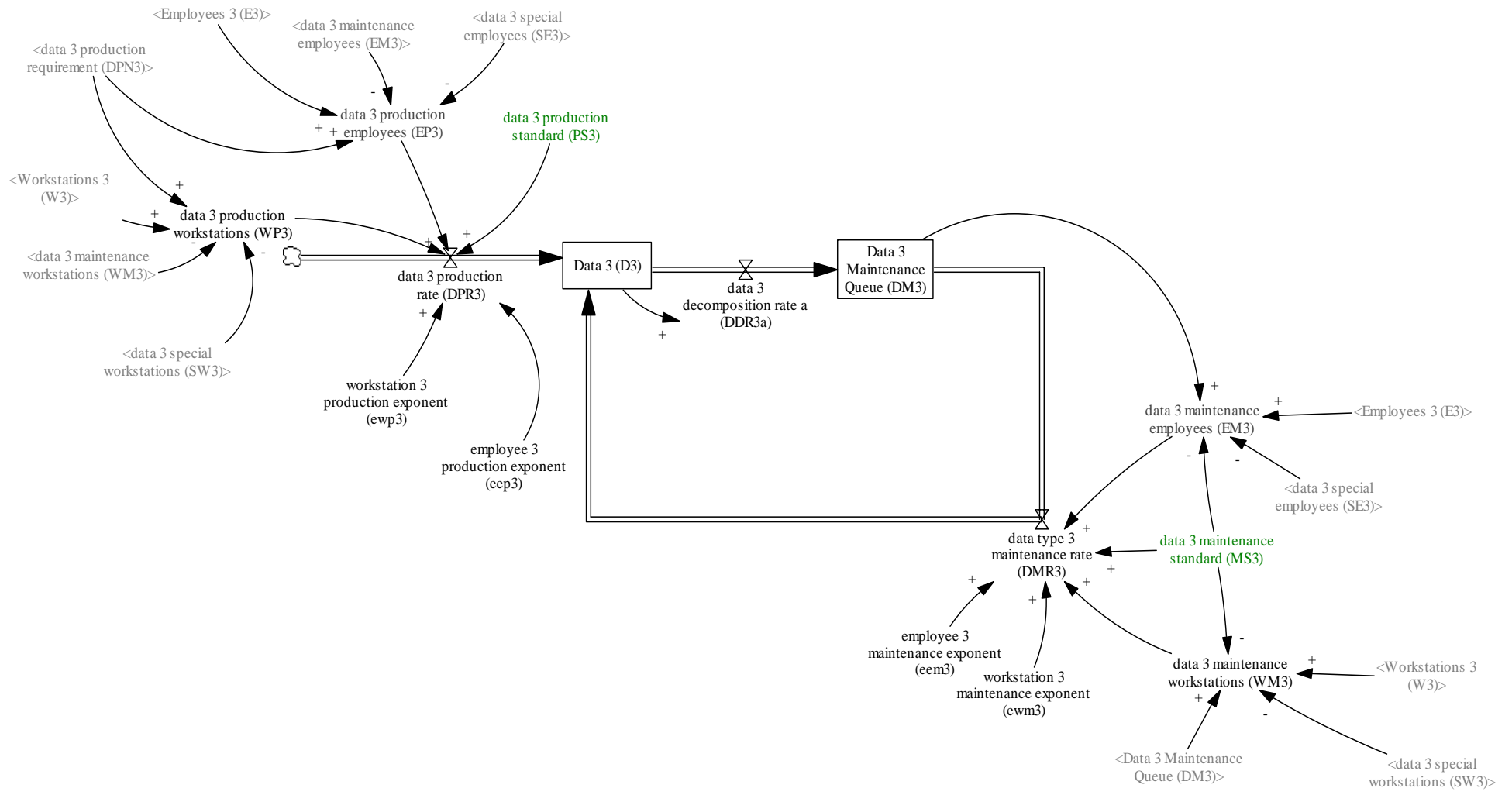
Figure 4-5(c). Scenario 3 Excursion Structure.

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Figure 4-5(d). Scenario 3 Employees Hill-Climbing Optimization Structure.

Figure 4-5(e). Scenario 3 Workstations Hill-Climbing Optimization Structure.

Figure 4-5(f). Scenario 3 Cost and Technical Efficiency Structure.
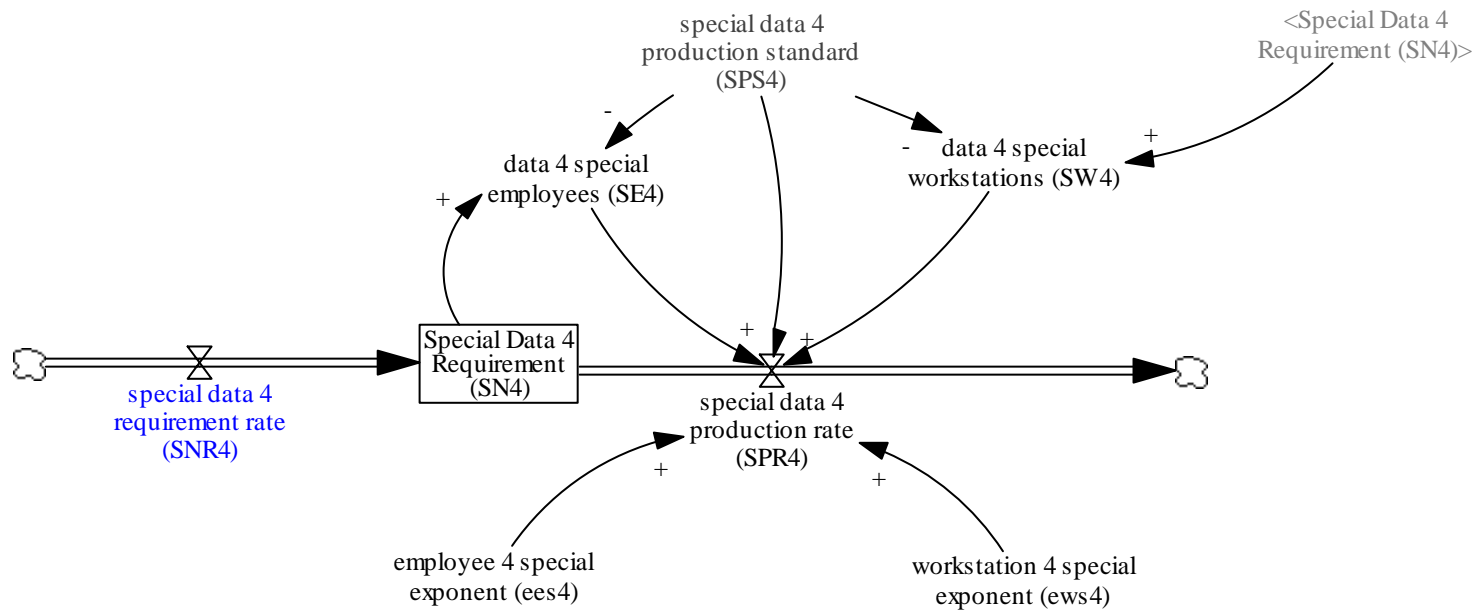
Figure 4-6(a). Scenario 4 Special Data Structure.
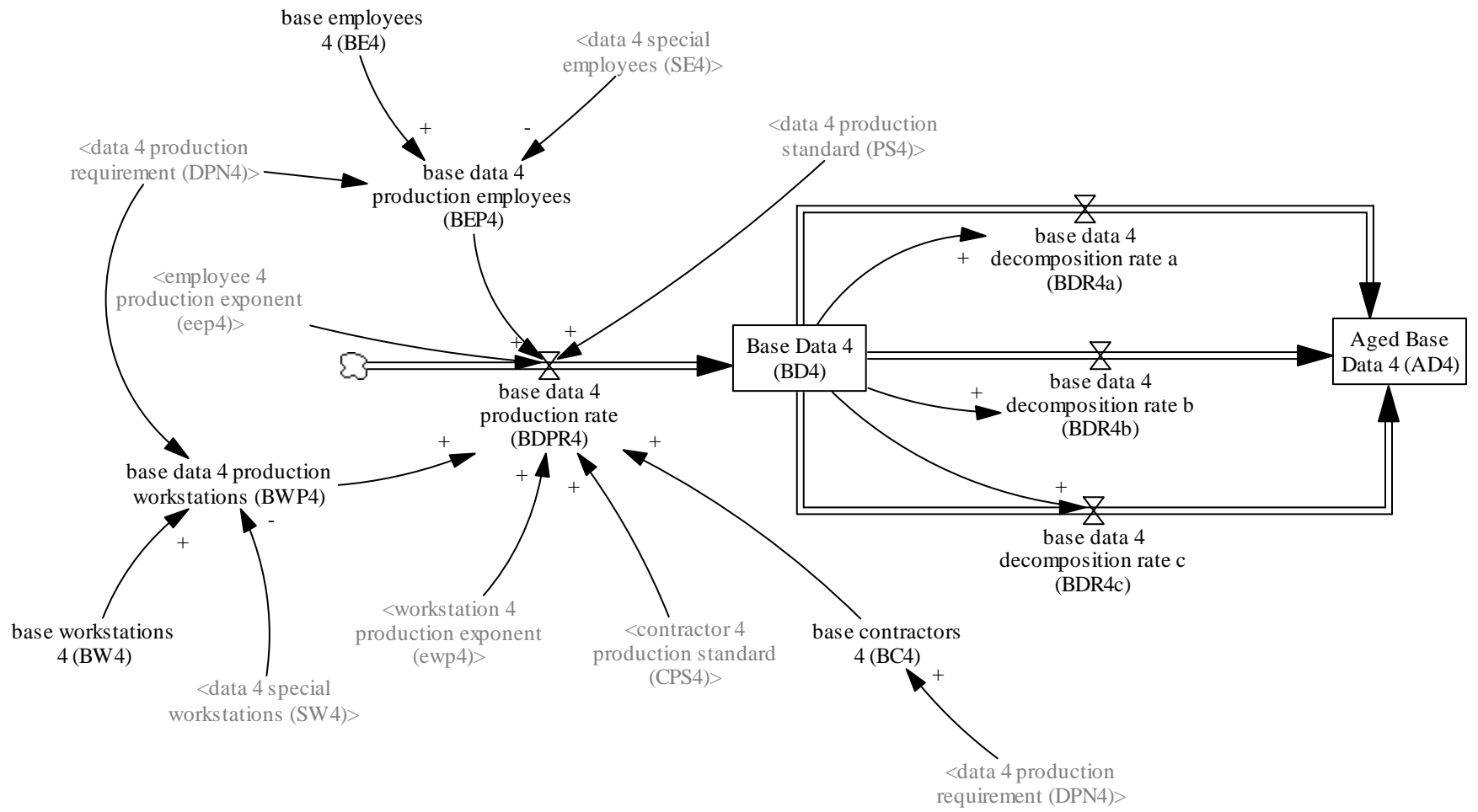
Figure 4-6(b). Scenario 4 Base Case Structure.

Figure 4-6(c). Scenario 4 Excursion Structure.

152

Figure 4-6(d). Scenario 4 Employees Hill-Climbing Optimization Structure.

153

Figure 4-6(e). Scenario 4 Workstations Hill-Climbing Optimization Structure.

Figure 4-6(f). Scenario 4 Contractors Hill-Climbing Optimization Structure.
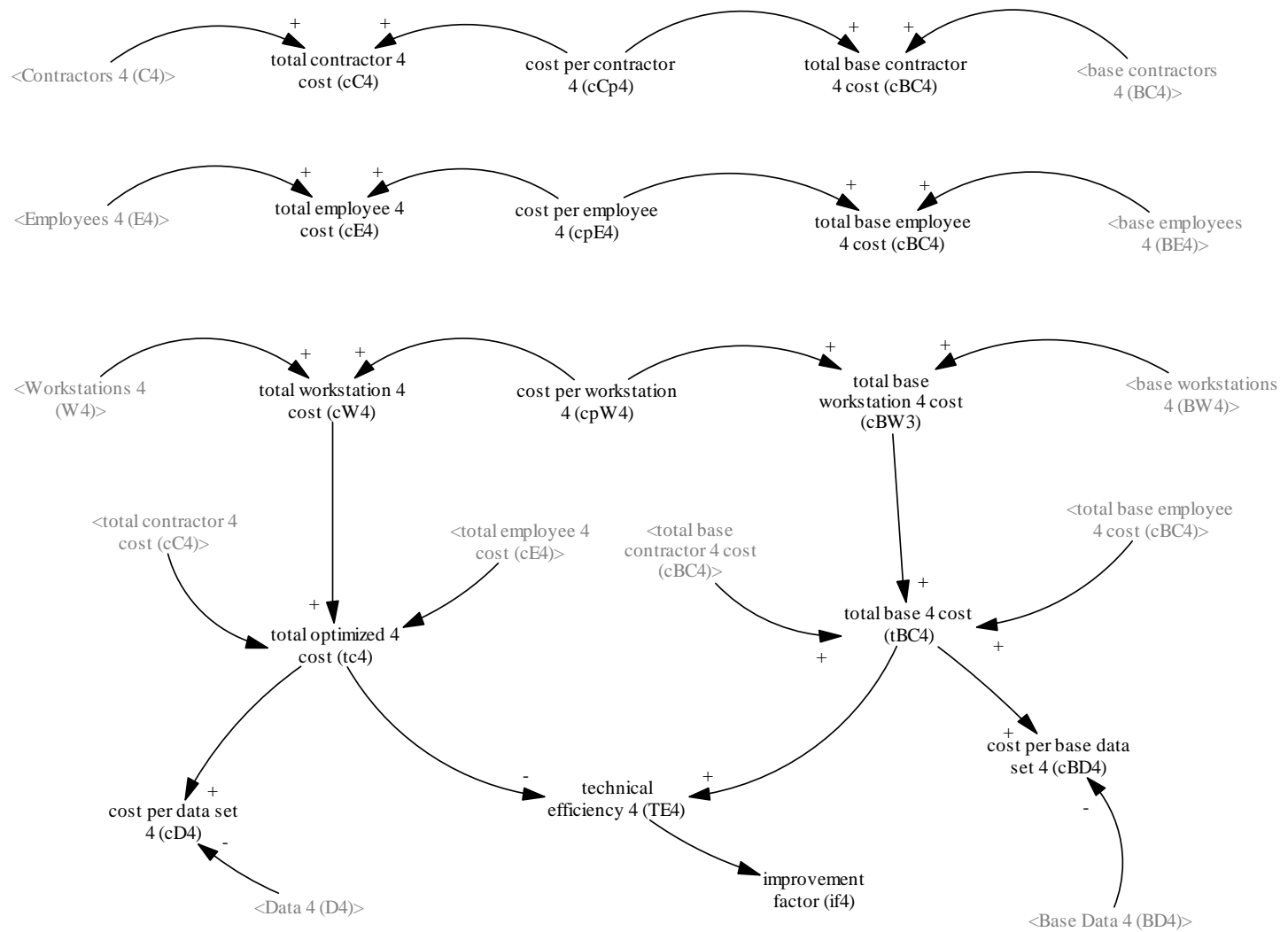
Figure 4-6(g). Scenario 4 Cost and Technical Efficiency Structure.

structures or model variability. Data decomposes at a rate of 12 months (25 percent), 24 months (50 percent), and 48 months (25 percent).

Upon initiation of the simulation, the model strives to find a steady state of operations. With a monthly production goal of 100, the system achieves a 99 cell production rate by month 9. By month 12 has reached a steady state and has a production resource mix where: $E1$ = 266 employees, $W1$ = 266 workstations, and $C1$ = 1,080 contractors.

At month 12, the first data begins to decompose. This data decomposition acts like a disturbance being introduced into the system, causing the system to seek a new steady state of operations. By month 24 when the next decomposition rate in injected, the system has not fully recovered from the first disturbance. During period 24, the system falls slightly short of its 100 cells per month production goal (98 cells are produced during period 24). The simulation reveals that the optimal resource allocation between periods 12 and 24 is to shift employees and workstations to perform the maintenance function, and to build the contractor support base. During this interval, employees and workstations increased by less than 5 percent, while 87.5 percent of those resources were shifted to data maintenance functions. All data maintenance during the 12 to 24 month interval was accomplished.

After the second decomposition rate is introduced during period 24, all employees and workstations have been reallocated to data maintenance functions. This revelation is an important outcome of this methodology as it recommends a resource allocation policy to management. The system achieves a steady state of operations by period 37. Steady state conditions reveal $E1$ = 1,038 employees, $E2$ = 1,038 workstations, and $C1$ = 1,374 contractors.

The last disturbance is introduced at period 48. With the inclusion of this disturbance, all data in the model is subject to decomposition, and the requirement to produce new data remains at 100 cells per month. These conditions, which exist between period 48 and 123 are the most stressful for the system. The system once again seeks a steady state, which is achieved for new production at period 77, but the system continues to seek a steady state for the maintenance function as more data is decomposing every period. The goal of having 12,000 cells populated by 120 is not achieved until period

123. After period 123, the contractors start to fall from their 1,374 value to zero. Since there is a adjustment time for adjusting the number of contractors, the contractors continue to provide resources in the simulation past period 123, the numbers decrease significantly during each period. Steady state conditions are achieved for the final time during period 153, with all data being maintained as it deteriorates. Final conditions require 3,269 employees and workstations. Figure 4-7 depicts the amount of production resources used by month for a 160-month time horizon.

The concept of data maintenance is especially appropriate in this scenario where the data decomposes at such a quick and frequent rate. Figure 4-8 reveals the inadequacy of the current no maintenance concept. The base data is equivalent to, or exceeds, the excursion data until period 23. After period 23, the base data climbs slowly to a peak of 2,319 cells, and then begins a slow decline. By period 148, the amount of aged base data exceeds the amount of good optimized data. In fact, by period 120, there are approximately 9,000 more good cells from the excursion structure than there are from the base structure.

Cost also plays a large impact in this scenario. A comparison was made between cost per good data cell for each time period, for the base and excursion scenarios. The cost differential (excursion cost per cell minus the base cost per cells) and data set differential (optimized data minus base data) are shown in Figure 4-9. As seen in this figure, at period 40, the cost benefits of adopting a policy that includes a maintenance
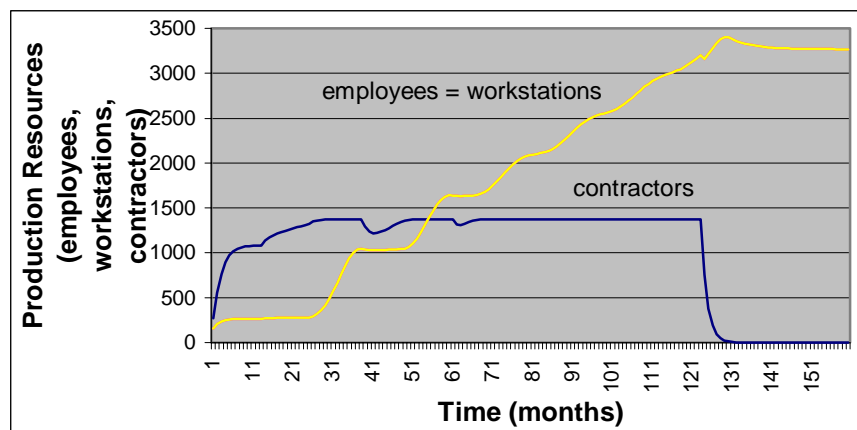
Figure 4-7. Scenario 1 Production Resources.
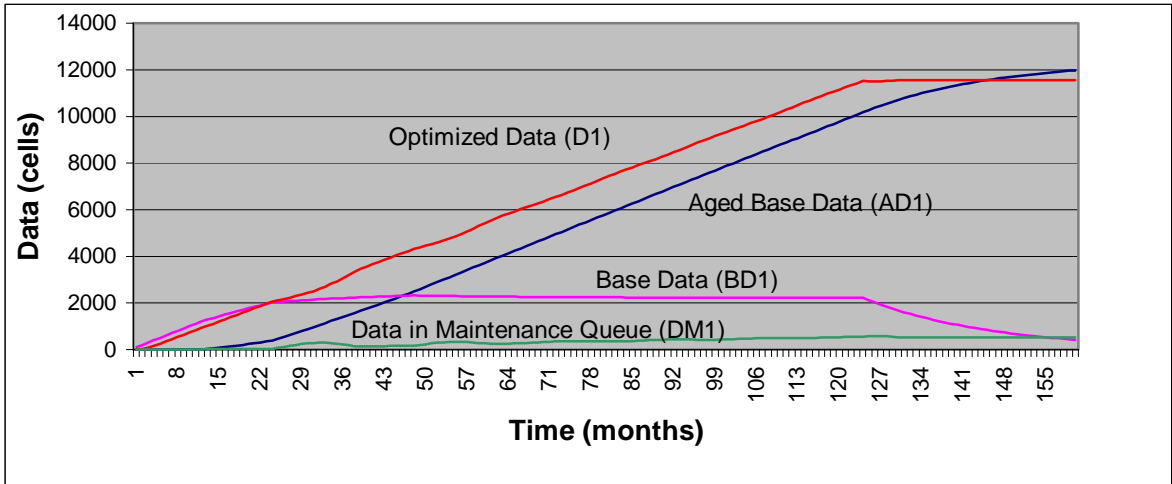
Figure 4-8. Scenario 1 Data Comparison.
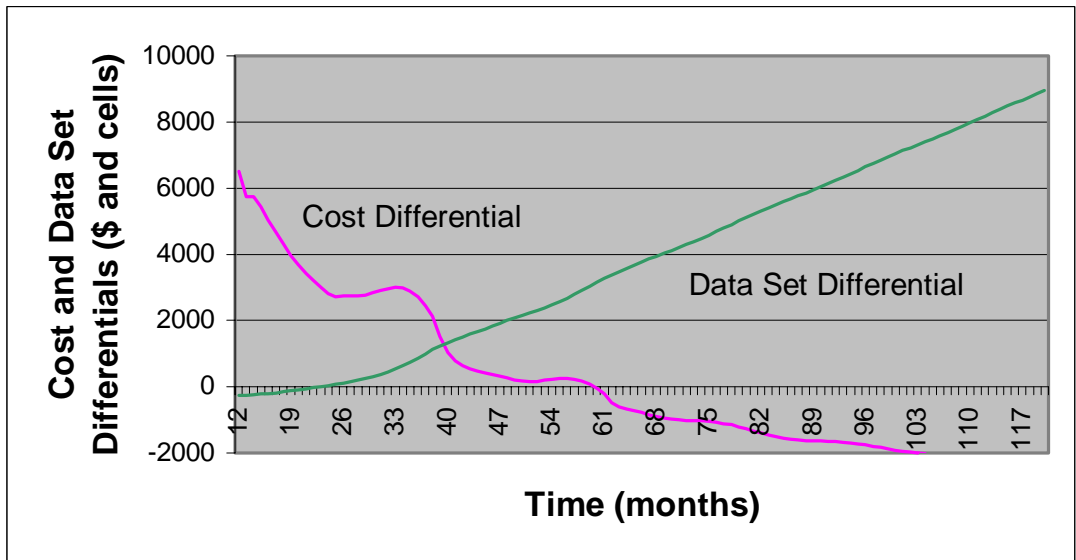
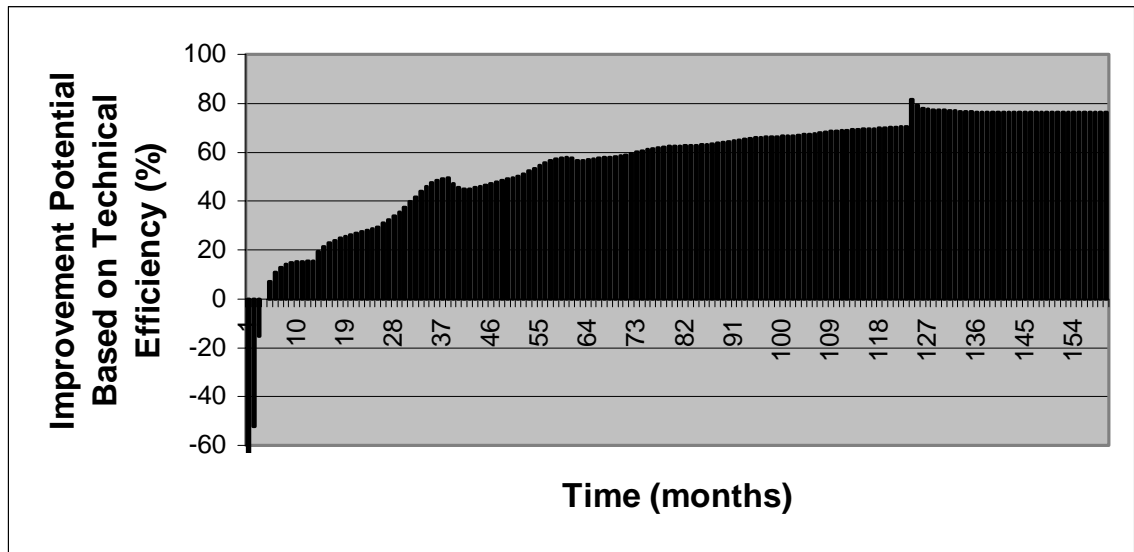**Figure 4-9.** Scenario 1 Cost per Data Set and Data Differentials.

Figure 4-10. Scenario 1 Improvement Potential Based on Technical Efficiency.

concept outweigh the cost benefits of not adopting such a policy.   Figure 4-10 shows the potential improvement of the base case based on technical efficiency calculations. While the base case is initially more efficient, adopting the optimized number of resources (employees, workstations, and contractors) can improve system performance by approximately 80 percent.

Figure 4-11 provides insights into the best time to insert new technology, if the system is following a spiral development, and a continuous technology paradigm. The graph shows that the optimum time to achieve the first spiral insertion is at period 25. Between periods 25 and 40, improvements (employees and workstations) are being implemented into the system. It achieves its full potential at period 40. The next spiral starts at approximately period 50, with the implementation lasting until approximately period 60.   The third spiral should begin at approximately period 70.   This implementation spans approximately 50 months, therefore a slow implementation is recommended.   By having a slow implementation, the organization can ensure the workstations on hand at period 120 are using the latest technology.   This is in contrast to the first two spirals which require quick technology insertions.

In addition to the technical efficiency calculation, allocative efficiency was calculated.   However, when solving for the initial conditions, a 4:1 employee to

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workstation ratio was established. The conditions for this scenario call for a one-to-one employee to workstation ratio.   Due to this strict interdependency between workstations and employees, the best ratio that could be achieved is 3 employees to 1 workstations by factoring in shift work. Additionally, since the contractor variable is not multiplicative to the cost-production function, the partial derivative of the function is zero when taken with respect to employees. Therefore contractors will have zero contribution to the system because their initial conditions is zero.   With that being said, the number of employees required with an allocative efficiency problem is 7,596, and the number of workstations is 2,515, for a total cost of $65,400,000. This is two times the cost associated with the technical efficiency solution.

From this solution, one can conclude that technical efficiency calculations work well regardless of interdependencies between input variables. In contrast, the solution to the allocative efficiency problem breaks down when input variables have strict interdependencies.

The unique focus of scenario 2 is to determine the optimal number of in-house and contractor resources for both new data production and data maintenance. Current technology is assumed thus the elasticity exponents for employees and workstations are equal to 0.5. Initial conditions for production resources (excursion structure) are: $E2 = 50$ employees, $W2 = 50$ workstations, and $C2 = 50$ contractors. Initial conditions for production resources for the base structure are: $BE2 = 202$ employees, $BW2 = 202$ workstations , and $BC1 = 202$ contractors. This scenario has the most stressful data decomposition rates of the four scenarios. Data decomposes at a rate of 12 months (50 percent), 24 months (50 percent).

Figure 4-12 shows the optimum production resources as determined by the model. As in scenario 1, there is a one-to-one correspondence between employees and workstations, thus their optimal value is equivalent throughout the scenario. The results of this scenario suggest using contractor resources as the primary source of data production. During the first 12 time periods, the in-house resources reached a steady state of 102 employees and workstations, and 331 contractor. After the first disturbance (i.e. data decomposition) was introduced at time period 12, all in-house resources were shifted to the data maintenance function. Between periods 35 and 41, the data
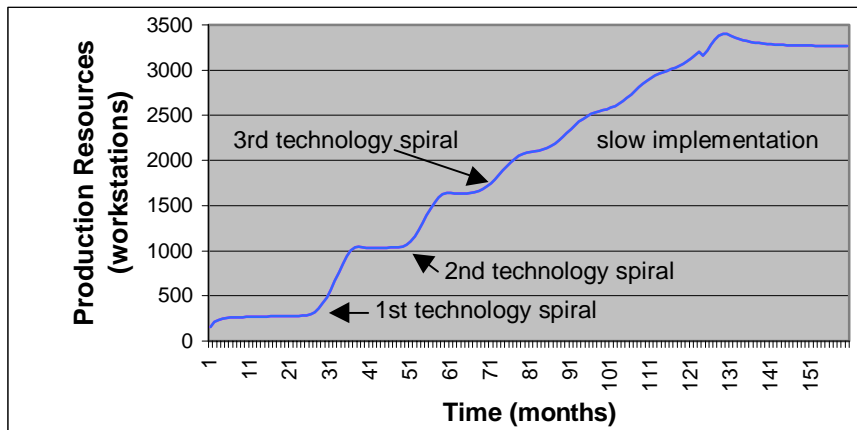
Figure 4-11. Scenario 1 Technology Spirals.

maintenance function approached steady state causing a number of employees to be shifted back the production of new data, and the contractor numbers to decrease. This anomaly is caused as a result of the system going into a brief oscillation period as the system achieved a new steady state of operations. This is caused by the natural time delay between the level variables within the model.

The steady state number of contractors required is 469, achieved at month 47. The number of employees and workstations achieves its maximum value during period 122 when 1,740 employees and workstations are required. After data production goal is realized at period 123, the system goes into a prolonged period of damped oscillation. The oscillation comes from the data maintenance requirements from time t not being fully realized until 6 months later. As such, the system has more resources than required during some periods and less during others. The system does not settle into an undamped steady state until month 303 (more than double the original data production time!), when the number of workstations and employees equal 1,549, and the number of contractors equals 277. A more practical, but less optimal, approach may be for the organization to allow its number of employees and workstations to grow to the steady state value of 1,549 employees and workstations and allow the contractor population to absorb the difference in maintenance, as this resource is more expendable.

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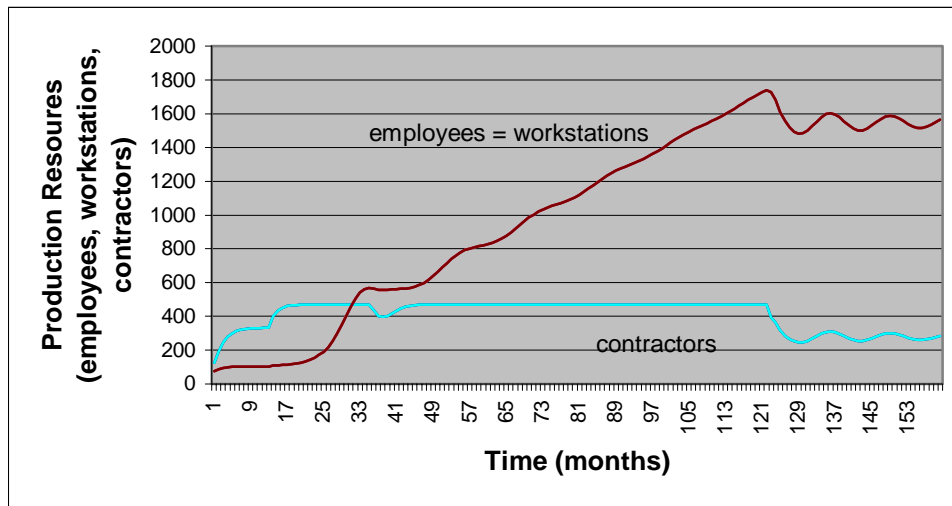
Figure 4-12. Scenario 2 Production Resources.

Figure 4-13 shows a comparison of the amount of good and aged data for the optimized and base cases. If the organization adopts the no maintenance approach, all of their base data will be outdated by the end of the time horizon. Figure 4-14 shows that the system can realize a significant improvement throughout the life-cycle of the system if the optimized option is selected.

Figure 4-15 shows the cost per data set differential compared against the amount of good data available between period 15 and 50. The two lines cross at period 34, which indicates that the data maintenance option is less expensive per good data cell at the 34th month.

Figure 4-16 shows when each technology spiral should occur. The first technology spiral occurs after period 24, the second after period 48, and the third (minor) spiral should occur after period 60. These are interesting results because intuition would dictate a different set of spirals (i.e. spiral after period 12 and period 24). However, the infrastructure required to perform all maintenance after the first data decomposition is introduced is handled by the initial system set-up, thus few additional in-house resources are required between periods 12 and 24. The maintenance requirement doubles which prompts the first spiral at period 24. At month 48 the amount of data maintenance required prompts the system to seek a new steady state, thereby prompting the second technology spiral. At approximately period 64, a new steady state is sought again.

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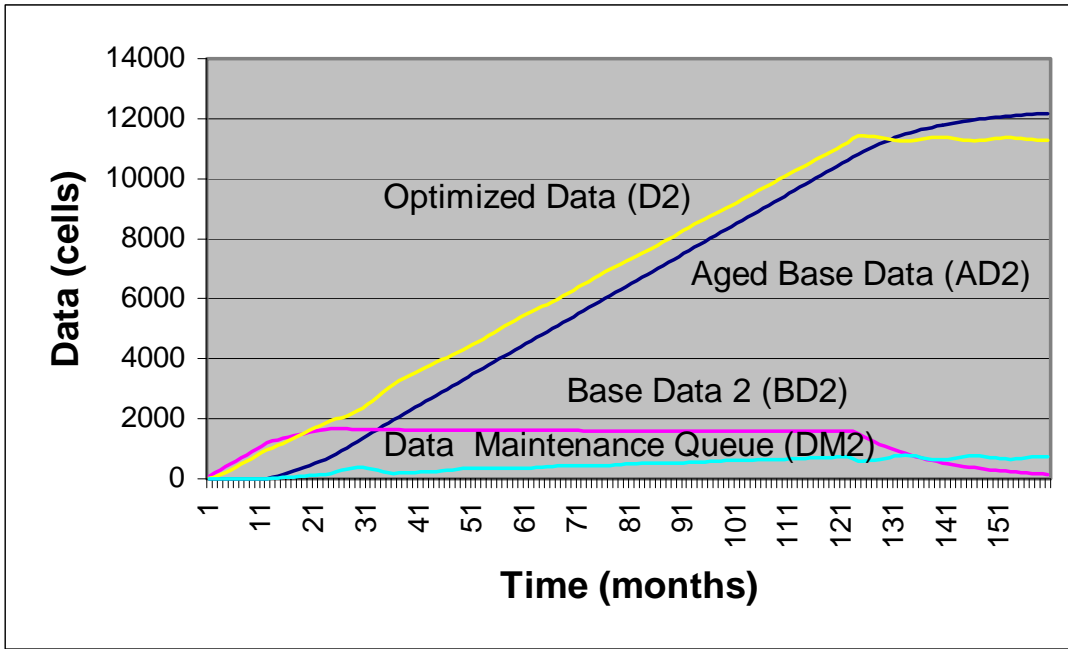
Figure 4-13. Scenario 2 Data Comparison.
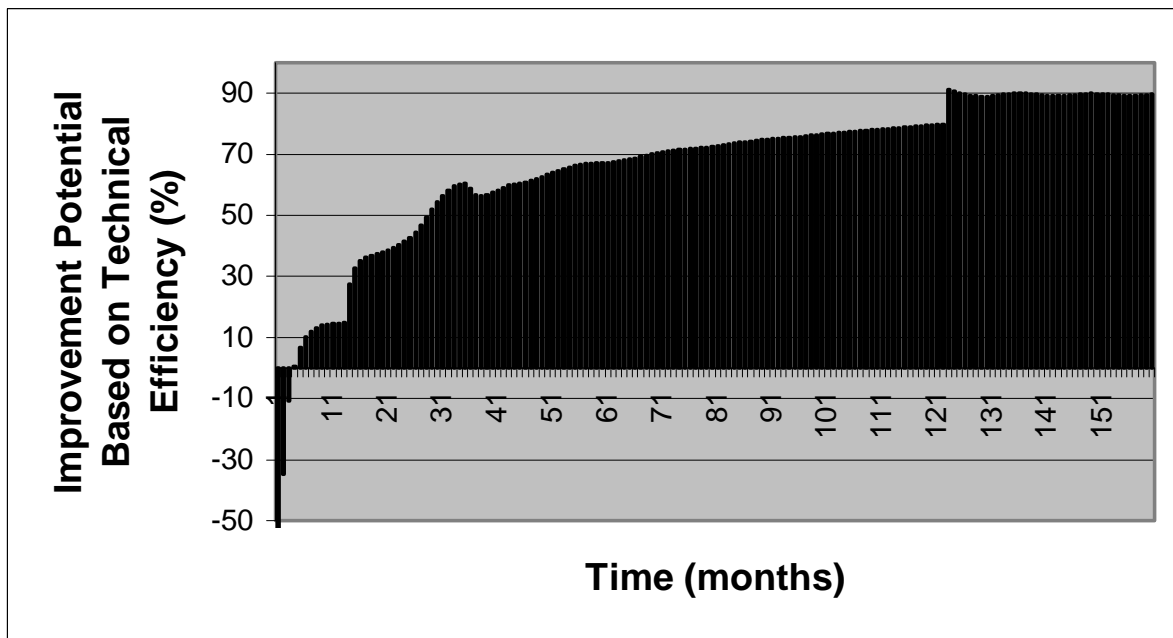
Figure 4-14. Scenario 2 Improvement Potential based on Technical Efficiency.
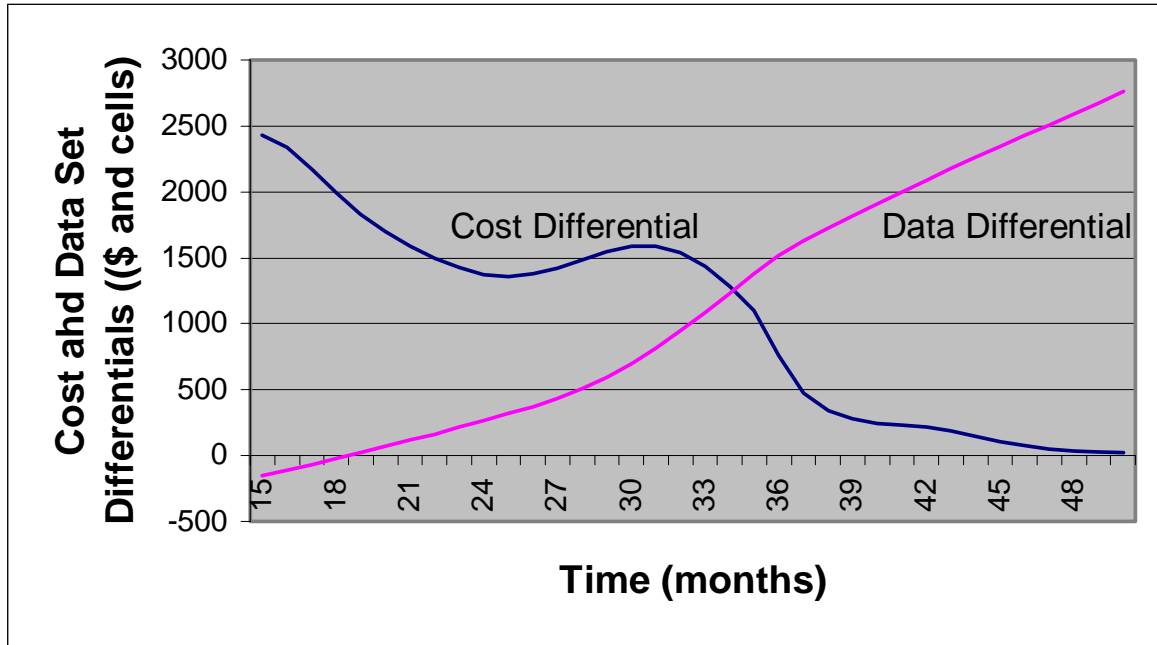
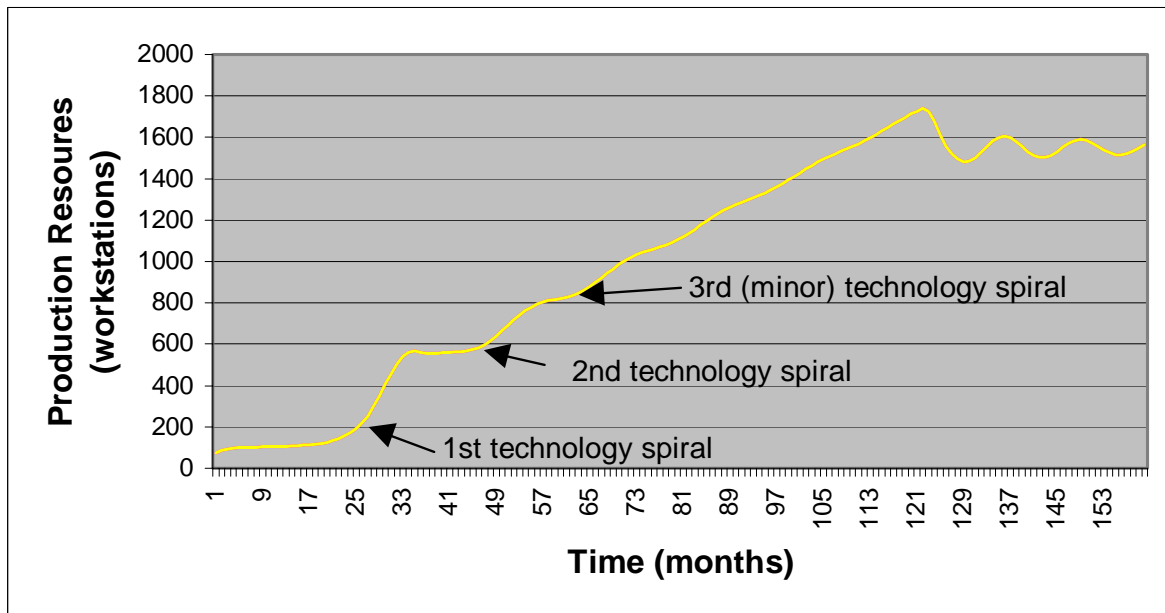**Figure 4-15.** Scenario 2 Cost per Data Set and Data Differentials.

Figure 4-16. Scenario 2 Technology Spirals.

Period 64 corresponds to the period when the one-half of the production goal is realized. This spiral is a long slow spiral that does not end until the full production goal is realized.

Scenario 3 was designed to assess the impact of advanced technology (automated change detection, automated information extraction) on the system. As such the contractor variable was eliminated from this scenario to isolate those effects. Initial conditions for production resources (excursion structure) are: $E3$ = 10 employees and $W3$ = 30 workstations. Initial conditions for production resources for the base structure are: $BE3$ = 105 employees and $BW3$ = 304 workstations. The one-to-one employee-workstation ratio is relaxed for the advanced technology scenarios. Instead, a one-to-three employee-workstation ratio is assumed. This is an indication that technology has advanced to the point where each employee can monitor and perform either new data production or maintenance concurrently. This scenario has the least stressful data decomposition rate of the four scenarios. Data decomposes at a rate of 60 months (30 percent).
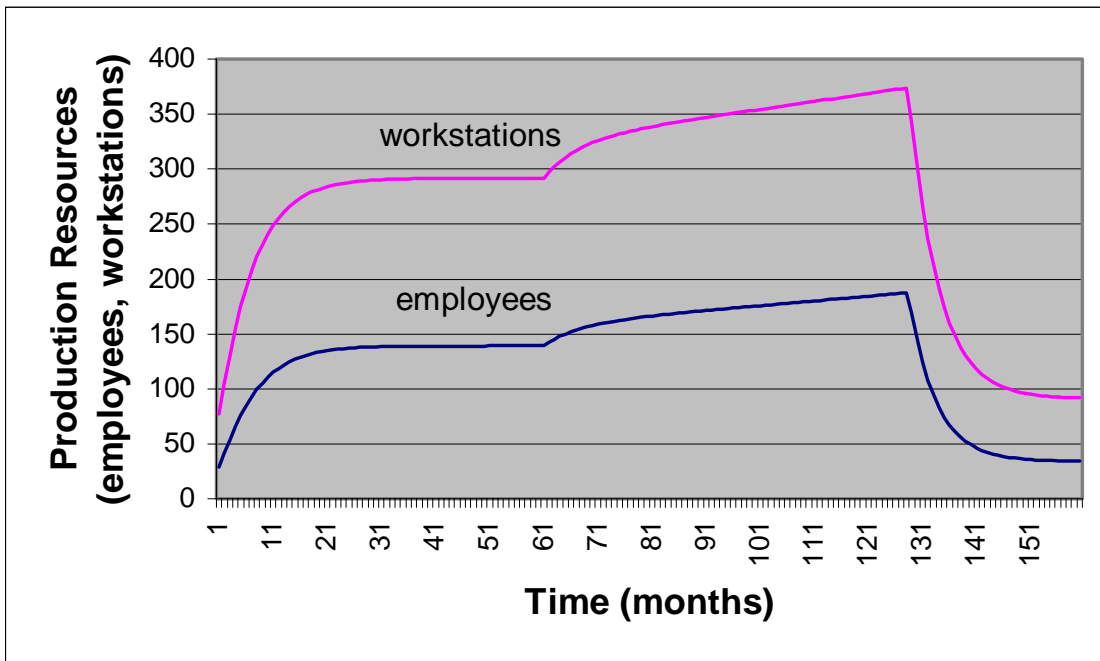
Figure 4-17. Scenario 3 Production Resources.

Figure 4-17 illustrates the optimized production resources for scenario 3. Unlike the previous scenarios, the system is slow to adjust to the initial implementation not achieving a production steady state until after period 30. This slow growth occurred in part due to the longer time delay required when implementing new technology. The system has its first disturbance introduced at period 60 when the first data produced begins to decompose. The system does not achieve a steady state of operations before period the data production goal is achieved at period 128. At its maximum, the system employs 188 employees and 343 workstations. After period 128, the number of employees and workstations are reduced to 91 workstations, and 34 employees to sustain the maintenance steady state. Given that the cost per workstation is less expensive than the cost per employee, acquiring more advanced technology is a more sound decision for this scenario.

Figure 4-18 shows the data trends for both the base data and the excursion (optimized) data. Due to the slow decomposition, the base data achieves a level of 10,104 cells before declining after month 129.

Figure 4-19 shows the cost per data set and the data differentials for scenario 3. Unlike the previous options, the cost differential is negligible. However, the benefit of data maintenance is realized after month 86, the cost per data set and data differentials are equal.
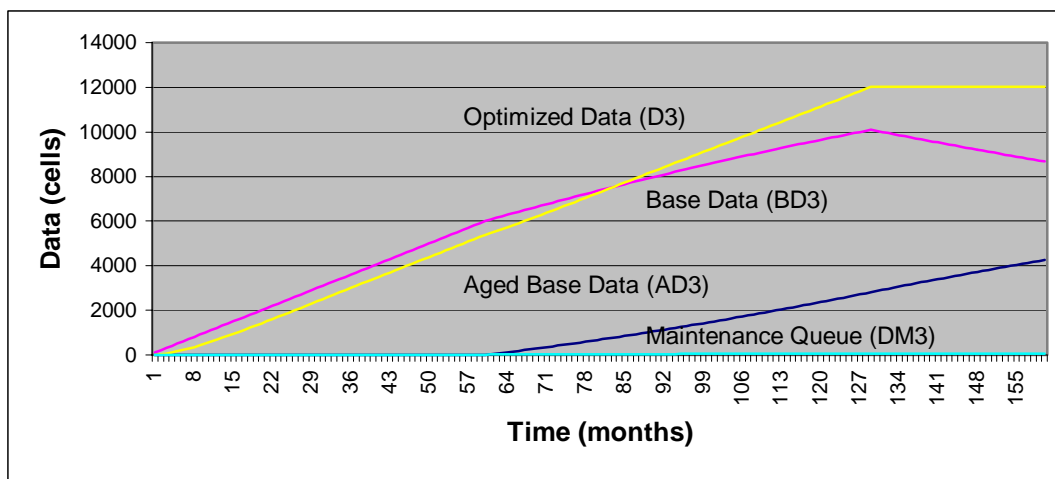
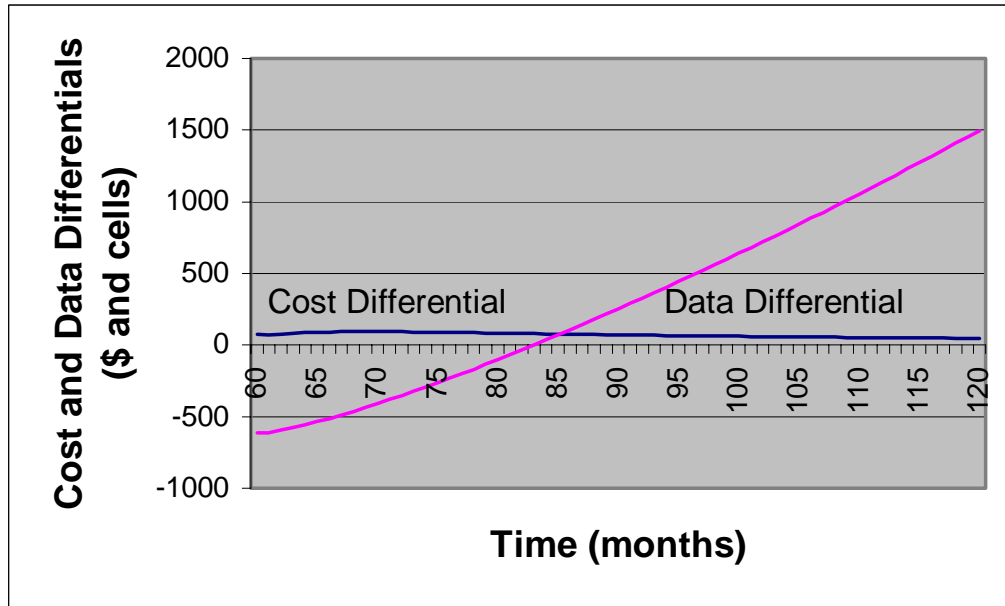

Figure 4-18. Scenario 3 Data Comparison.

Figure 4-19. Scenario 3 Cost per Data Set and Data Differentials.
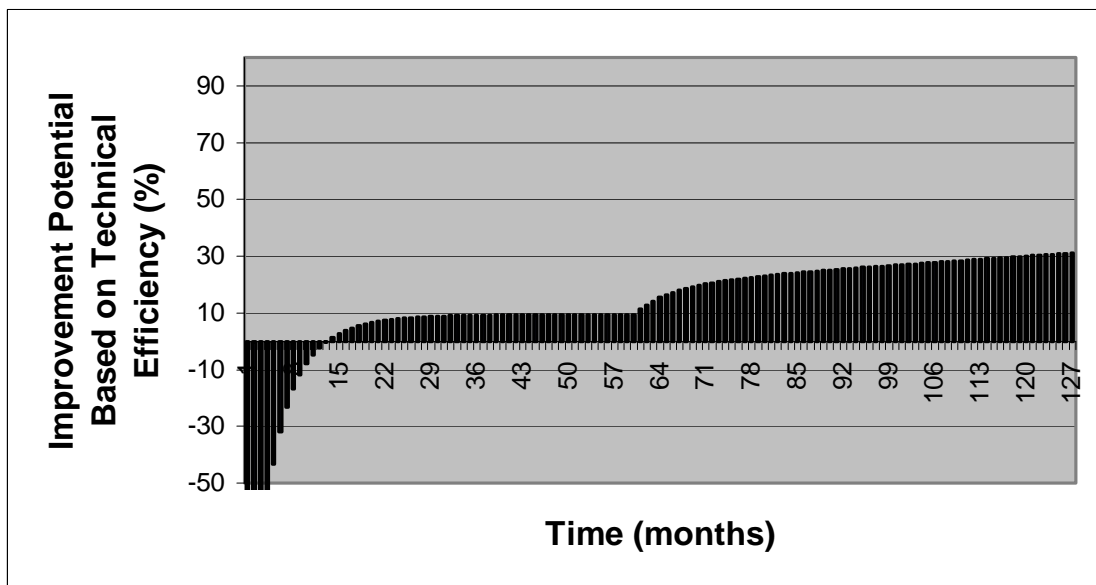

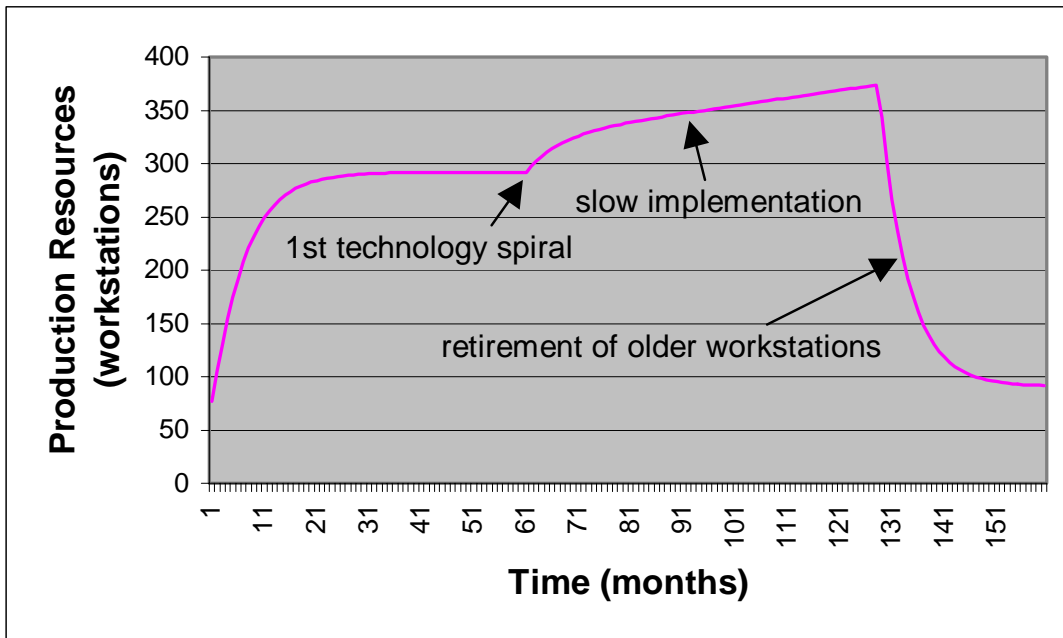**Figure 4-20.** Scenario 3 Improvement Potential based on Technical Efficiency.

Figure 4-21. Scenario 3 Technology Spirals.

The improvement potential based upon technical efficiency is depicted in Figure 4-20. Although the data decomposition rate is slow, adopting the excursion concept of operations over the base concept of operations will still yield a 30 percent improvement of data output and maintenance.

System output potential grows slowly after the initial technology implementation. A steady state of operations is finally achieved for new data production after period 30. The first disturbance is introduced into the system at period 60, when the first data begins to decompose. Since there are no contractor assets, the in-house capacity must be adjusted to meet the new demand. Therefore the first technology spiral should occur at period 60. This should be a slow implementation, integrating the most modern technology between periods 60 and 128. After the system's production goal is achieved, the organization should downsize to meet the new steady state required for the data maintenance environment. This is a good opportunity for the organization to retire many of the older workstations introduced as much as a decade earlier.

Scenario 4's unique focus is on determining the optimal in-house resource-contractor ratio, when advanced technology is assumed, and contractors support both new

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data production and data maintenance. Initial conditions for production resources (excursion structure) are: *E4* = 40 employees, *W4* = 120 workstations, and *C4* = 50 contractors. Initial conditions for production resources for the base structure are: *BE4* = 270 employees, *BW4* = 518 workstations , and *BC1* = 259 contractors. As in scenario 3, the one-to-three employee-workstation ratio is assumed. The employee and workstation adjustment times are the most stressing of the scenarios, requiring 12 months to fully implement new assets into the system. Data decomposes at a rate of 36 months (30 percent), 72 months (40 percent), and 108 months (30 percent).

Figure 4-22 shows the productions resources used during this scenario. The system is dominated by contractor support until period 128 when the data production goal is achieved. This contractor intensive focus occurs because of the contractors ability to be more responsive to the organization's needs. (Contractors can respond to a disturbance introduced into the system within two months, where in-house resources take one year to be fully operational.) The number of contractors dramatically increases after the first data begins to decompose at period 36, while the in-house resources only increase modestly. To meet the additional demand of data maintenance, all in-house production capacity was transferred to data maintenance, and additional contractors were hired to produce all new data sets. The number of in-house resources increases after the second disturbance at period 72. The reason that the contractors did not adjust is because of the restriction that stipulates that all new data production must be completed prior to contractors perform data maintenance. In-house resources achieve a maximum of 675 workstations and 225 employees at period 123. Contractors achieve a maximum of 813 at period 46 as a result to the first disturbance being introduced into the system. A steady state is achieved for data maintenance with 558 workstations, 186 employees, and 145 contractors.

The comparison between data is shown in Figure 4-23. The success of the data maintenance concept of operations is easily seen here, as the base data only achieves about 6,000 good data cells in the system at its maximum. In fact, the amount of aged base data surpasses the amount of good base data as the last new data production is being accomplished.
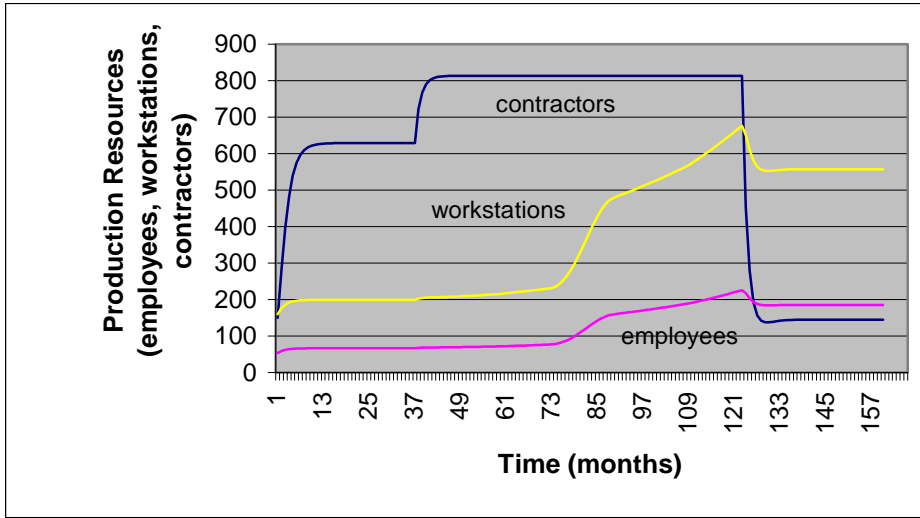
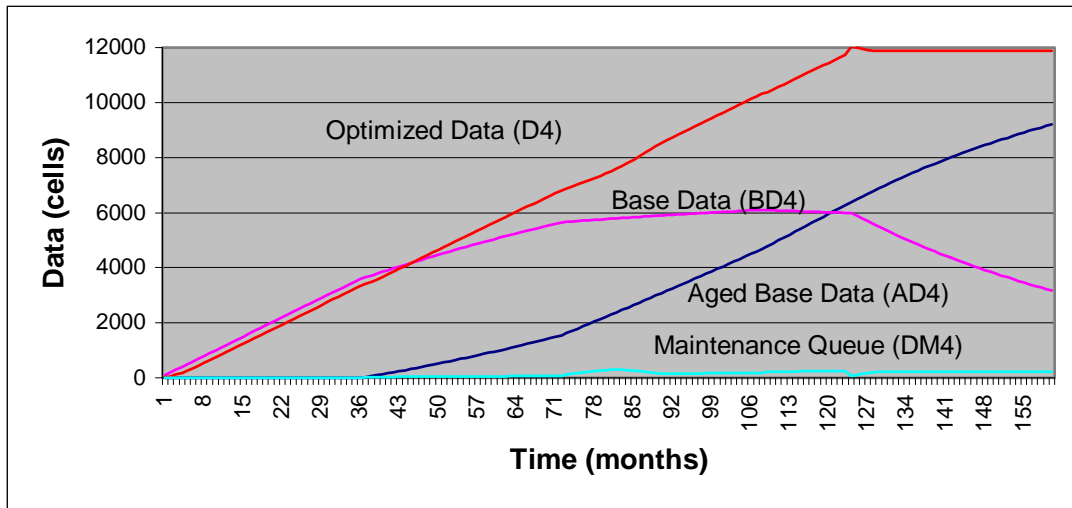**Figure 4-22.** Scenario 4 Production Resources.

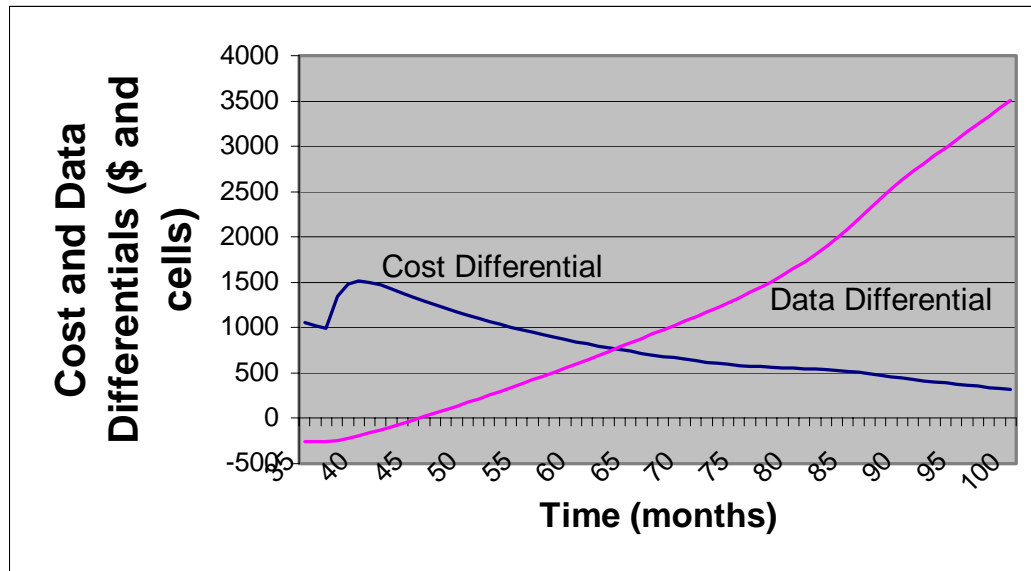**Figure 4-23.** Scenario 4 Data Comparison.

Figure 4-24. Scenario 4 Cost per Data Set and Data Differentials.

Figure 4-24 shows the cost per data set and data differentials. The two lines intersect at period 65, indicating that the cost-to-data benefits are realized after this period. Thus as in all of the other scenarios it is more cost effective to perform data maintenance as opposed to the base concept of operations.

The improvement potential due to technical efficiency is impressive in this scenario in spite of the long adjustment period. Figure 4-25 shows an improvement potential of 30 percent per month is realized within the first year of operation. By the end of data production, the excursion case exceeds the base case by more than 50 percent.

Two technology spirals are recommended for this scenario (Figure 4-26). The first, and more aggressive, spiral should occur at approximately period 75 in response to the second wave of data decomposition. The second, and slower implementation spiral occurs at period 90.

In each of the scenarios presented, the excursion concept of operations (i.e. data production and maintenance) exceeded the base concept of operations (i.e. data production only). Not only was the quality of data better in each case after 10 years, data maintenance proved to be more cost effective and technically efficient. In each scenario, the recommended times for technology implementation was presented in the form of
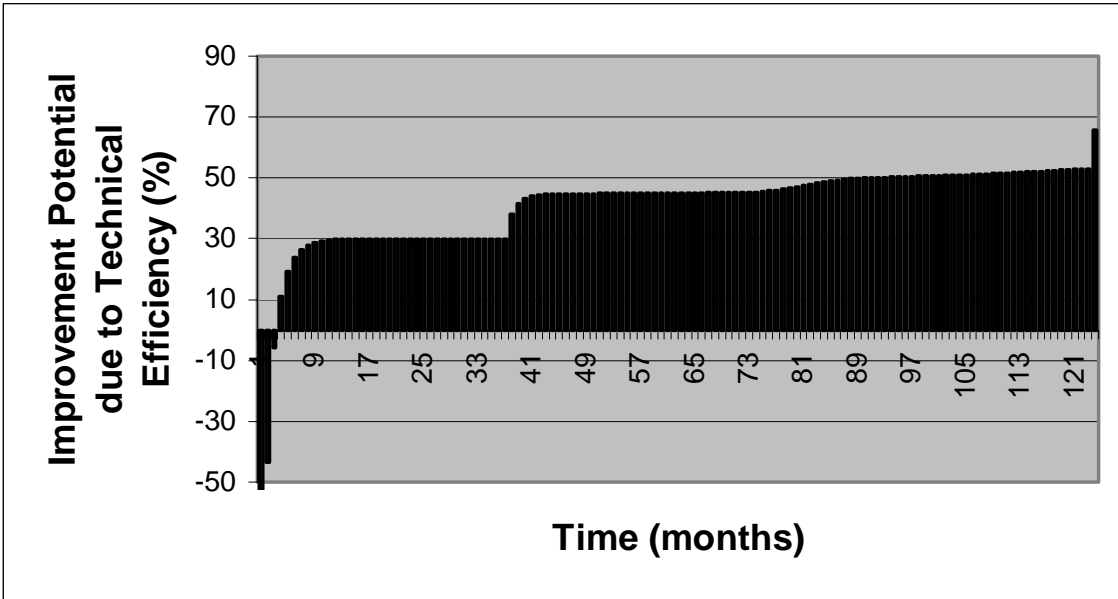
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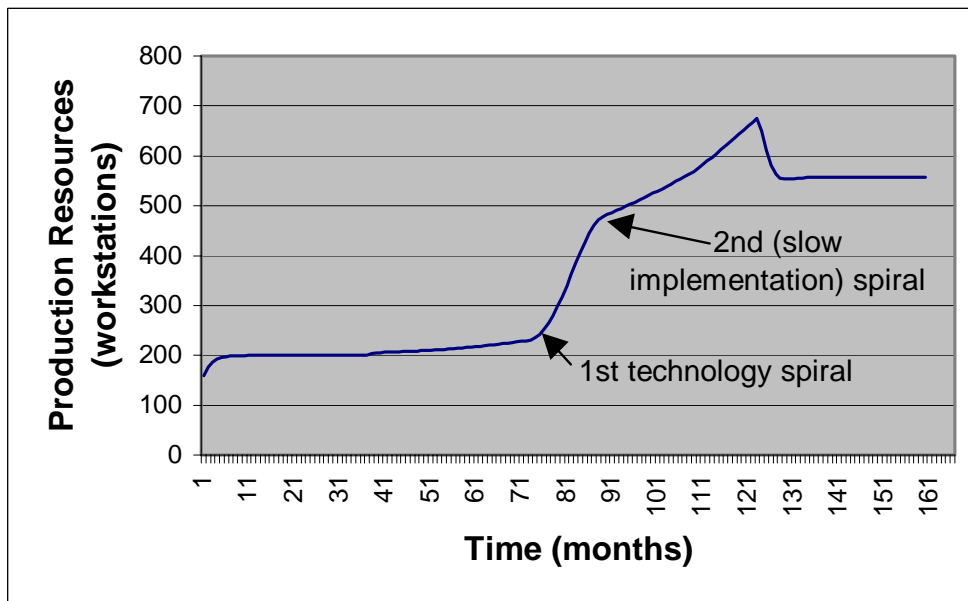**Figure 4-25.** Scenario 4 Improvement Potential based on Technical Efficiency.

Figure 4-26. Scenario 4 Technology Spirals.

technology spirals. These spirals often defied intuition by suggesting improvement times that most likely would not have been selected with managerial judgement. The spirals also presented the case for how aggressive the implementation must occur.

4.2.5 Model Validation

In general, the model validation task is conducted under the premise that all models of the real world are inaccurate to some extent. These inaccuracies occur because: (i) models are only developed to the fidelity required to answer the question being posed, therefore not every parameter that effects the real world system is modeled; (ii) models generally only consider variables endogenous to the system, thus exogenous effects on the system are not considered.

Model validation is typically considered as either conceptual validation or results validation (Defense Modeling and Simulation Office, 1996). Conceptual validation is the determination that the model accurately reflects the concepts, system structure (to include function of the system and the interaction between components), and output requirements. During conceptual validation the model is tested for boundary adequacy, structure assessment, dimensional consistency, and parameter assessment (Sterman, 2000). Results validation compares the responses of the simulation with expected or known behavior (Defense Modeling and Simulation Office, 1996). During results validation the model is tested for integration errors, extreme conditions, behavior anomalies, surprise behavior, and sensitivity analysis (Sterman, 2000).

"A simulation model is not an abstraction developed by an analyst working in isolation; in fact, the modeler must work closely with people who are intimately familiar with the system" (Law and Kelton, 2000, p. 274). Subject matter experts are equally important in the model development and validation processes. Specifically, subject matter experts are crucial to satisfying the boundary adequacy, structure assessment, and parameter assessment tests.

During this case study, the boundaries, structures, and parameters of the system were gleaned from informal conversations and technical exchange meetings with subject matter experts, and through formal and informal documentation. On the surface, this approach appears to be straightforward. However, difficulties immediately arise due to

conflicting information in the documentation, differing mental models of the subject matter experts, and the dynamic nature of systems as they are being developed and implemented. These obstacles were overcome by focusing on the questions the model was designed to answer and modeling only to the fidelity required in answering these questions. While the systems and concepts of operation were emerging during this thirty-month case study, the fundamental questions, and the structural basis of those questions did not change. Hence, factors that are endogenous to the system for the purposes of answering the questions presented were always endogenous to system regardless of the changes made to the planned system structure. Likewise, the system structure aggregated to a level required in answering the questions remained fundamental throughout.

The fundamental question during parameter assessment is "do all parameters have real world counter parts?" (Sterman, 2000). This question becomes rather interesting when testing future concepts because not all parameters have current real world counterparts. For example, the data maintenance rate variable does not exist in the real world system. However, if the real world system were to institute a concept of operations that includes data maintenance, this variable would be included. Therefore when testing the model for parameter and dimensional consistency, the relevancy of the variables, and their corresponding dimension, were considered against the variables that would have to be included if such a production concept were implemented.

A more problematic parameter assessment issue was introduced as part of the optimization structures. To facilitate the search for the optimal value of the variable, a "desired" variable was introduced. This "desired" variable has no real world meeting, but is used to perform a search for the optimal value of the variable. However, the "desired" variable's dimensions are consistent with the dimensions of the real variables that they interface with in the model.

Results validation starts with integration testing. This testing assumes two forms: time step and integration method (Sterman, 2000). The time step test was conducted by cutting the time step (one-month) in half. When this was performed, the model behaved as it did with the original time step. This confirms that the time step selected is the appropriate time step for this model. If, the production and maintenance standards were

of a shorter duration (e.g. 100 hours/cell versus 1,000 hours/cell), the one-month time step would potentially make a difference.

In SD modeling it is also important to test the integration method used. These simulations use Euler integration. This integration is usually adequate for most SD simulations, and the errors that are introduced into the models are inconsequential (Sterman, 2000). To test the model for integration method applicability, the simulations were run using the Runge-Kutta integration method. The Runge-Kutta method requires more computations per time step, thus reducing the error between time steps (Sterman, 2000). When the Runge-Kutta method was applied to this simulation, the model yielded results that differed only at the hundredth decimal place.

One surprise behavior discovered during the results validation effected the number of employees and workstations. One of the assumptions for all scenarios is that the number of workstations will be greater than or equal to the number of employees. This assumption was made because when simulating the current operational scenario, the employee to workstation is one-to-one. When advanced technology is incorporated, the workstation-employee ratio is many-to-one. After the initial simulation runs were completed, the number of employees was greater than the number of workstations. This anomaly is most dramatically illustrated (Figure 4-27) by the results from scenario 3, as

Figure 4-27. Unequal Adjustment Times for Interdependent Variables.

this scenario does not consider contractor support, and does consider the insertion of advanced technology.

Upon thorough investigation, it was learned that the cause of this anomaly was the adjustment times associated with the model drivers. Originally, the adjustment time for the workstations *(Watu)* was twice the adjustment time for the employees *(Eatu)*. When simulating this policy, the full employee contribution to the system is realized before the full workstation contribution. As such, the simulation immediately uses the assets, which skew the amount of production that could be accomplished. Through causal relationships, this influence can be traced to the relative production variable that causes the workstation and employee optimization structures to be falsely acted upon.

In reality, if employees and workstations are not balanced, the system will experience decreasing returns to scale, as employees will be idle as there are not enough workstations. Recall from the strong input disposability axiom *(DA.2(b))*, when inputs are not increased proportionally, outputs may decrease. Output did not decrease in each of the scenarios, however, the ratio between system inputs and outputs did decrease.

This problem is both an organizational policy issue as well as a modeling issue. The organization may wish to hire additional employees before the arrival of the capital equipment for training and organizational familiarization. During this orientation period, these employees should not be considered to contribute to production, as the organization will experience decreasing returns to scale. This reinforces the basic concept that you cannot implement technology faster than the implementation rate of the slowest component.

The modeling issue is equally important as it reveals a limitation of the model. If the adjustment times for variables that require a strong interaction with each other are not equal, the optimization results will be skewed. A sound practice for determining the adjustment time is to default all adjustment times to the variable requiring the longest adjustment. In an attempt to rectify this model shortfall, a delay was introduced into the optimization structure. This proved not to be a feasible solution since the delay introduces an error into the model that prevents it from simulating past the initial time period. Modeling decreasing returns to scale was also considered between time periods.

This is achievable but complicated. The solution used in this study was to redefine the adjustment time to the time of the slowest adjusting variable.

Sensitivity analysis is performed by systematically changing the values of model input variables to observe the effect upon the models behavior (Defense Modeling and Simulation Office, 1996). Multivariate sensitivity simulations, also known as Monte Carlo simulation, uses the probability distribution that characterizes the likely value for each parameter to represent the best, worst and most likely simulation outcomes (Vensim, 1998, Sterman, 2000).

Monte Carlo simulation was used to test the sub-systems used in this case study. In each case the data production and maintenance standards were varied to determine the confidence bounds for the key variables (employees, workstations, and in three of the four cases, contractors). Each Monte Carlo simulation was simulated with 200 iterations. The sensitivity graphs shown for each of the scenarios illustrate the amount of uncertainty associated with each variable. Thus the wider the bands, the greater the range of possibilities. The percentage delimitations show the confidence bounds. Thus for a confidence bound shown as 75 percent, there is a 75 percent probability that the variable will have a value between the boundaries that delimit that percentage (Vensim, 1998; Sterman, 2000).

In scenario 1, the data production standard was assumed to have a normal distribution with a minimum value of 2,400 hours per cell, a maximum value of 1,800 hours per cells, a mean of 2,000 per cells and a standard deviation of 200 hours. The data maintenance standard was also assumed to have a normal distribution with a minimum value of 1,200 hours per cell, a maximum value of 700 hours per cell, a mean of 1,000 hours per cell and a standard deviation of 100 hours. Figure 4-28 shows the dynamic confidence bounds for employees 1. The greatest variability in employees 1 occurs after period 130 when there is a 50 percent chance that the number of employees required is between 2,800 and 3,400 per period. Similar results are found for workstations (Figure 4-29) which has a one-to-one correspondence with employees. The uncertainty comes from the high data decomposition rate that occurs after the 12,000 cells become populated at period 123. The dynamic confidence bounds for contractor 1 (Figure 4-30) shows variability during the growth periods as data production is being transferred from
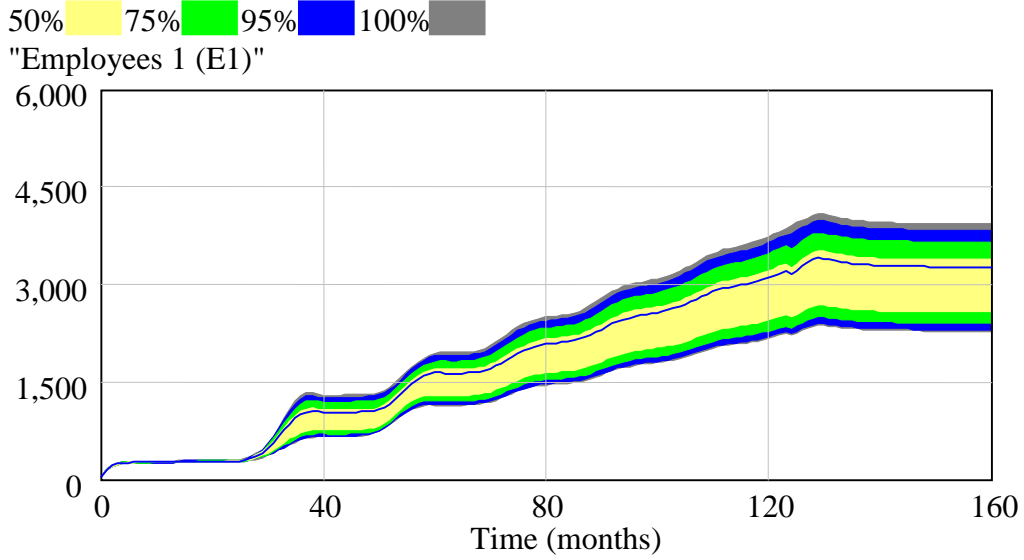
"Employees 1 (E1)"

Figure 4-28. Dynamic Confidence Interval for Employees 1.
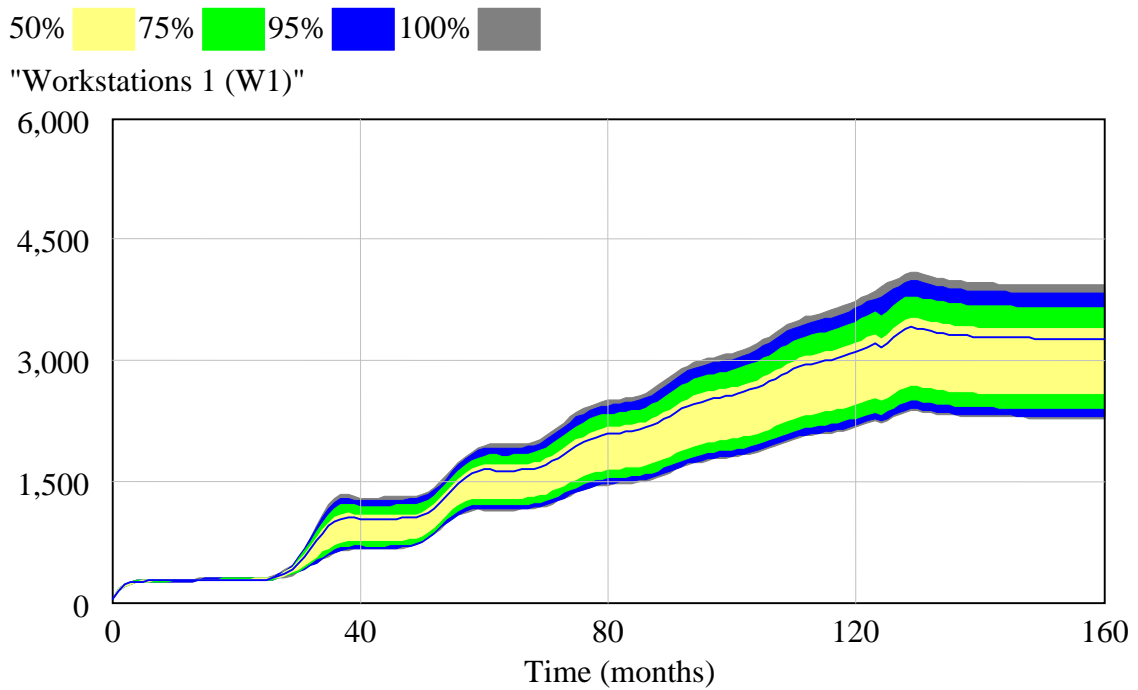
"Workstations 1 (W1)"

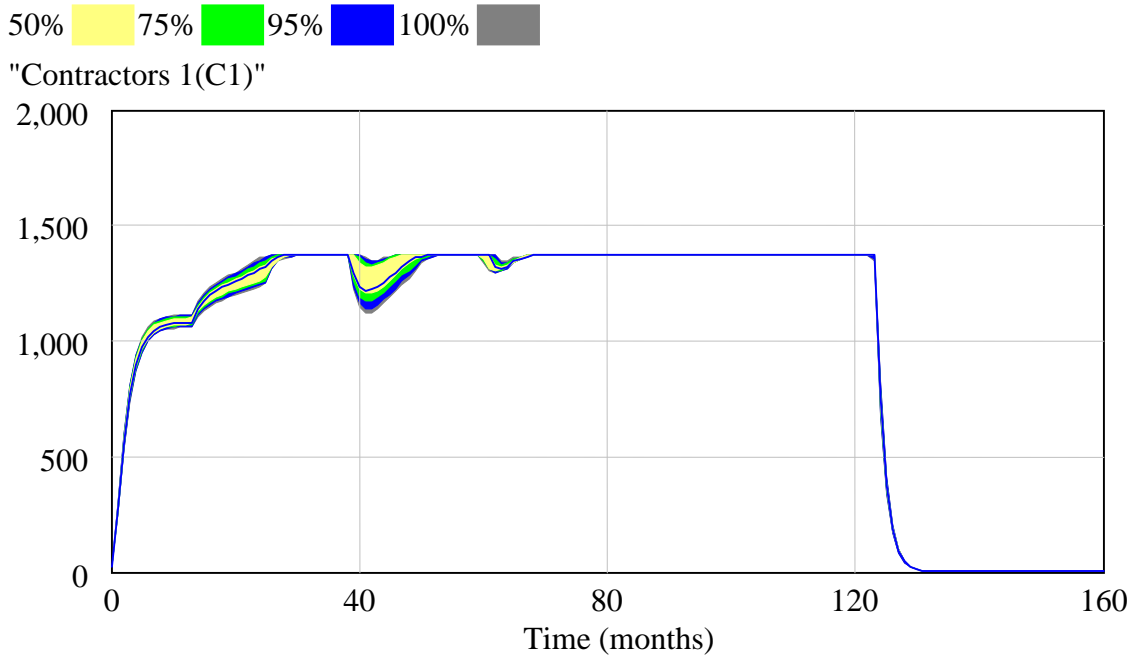**Figure 4-29.** Dynamic Confidence Interval for Workstations 1.

Figure 4-30. Dynamic Confidence Interval for Contractors 1.

an in-house employee-contractor mix to all contractors. Contractor variability is also demonstrated between periods 40 and 50. During this period, overshoot occurs within the model. This overshoot is believed to occur to the system adjusting to production after additional data decomposition is introduced.

In scenario 2, the data production and maintenance rates were assumed to have a normal distribution. The data production standard has minimum production time of 750 hours and maximum production time of 370 hours, a mean of 560 hours, and a standard deviation of 75 hours. The data maintenance standard has a minimum time of 500 hours, a maximum time of 200 hours, a mean equal to 400 hours, and a standard deviation equal to 45 hours. Figures 4-31 and 4-32 show the dynamic confidence bounds for employees 2 and workstations 2 respectively. As in the Monte Carlo simulation for scenario 1, the confidence interval widens after the full requirement for data cells are populated. This increase in uncertainty is believed to come from the fact that the system is experiencing a damped oscillation behavior due to the hill-climbing structure over and under compensating for the maintenance requirements due to the adjustment time of the variables . Figure 4-33 shows the dynamic confidence intervals for contractor. Like in
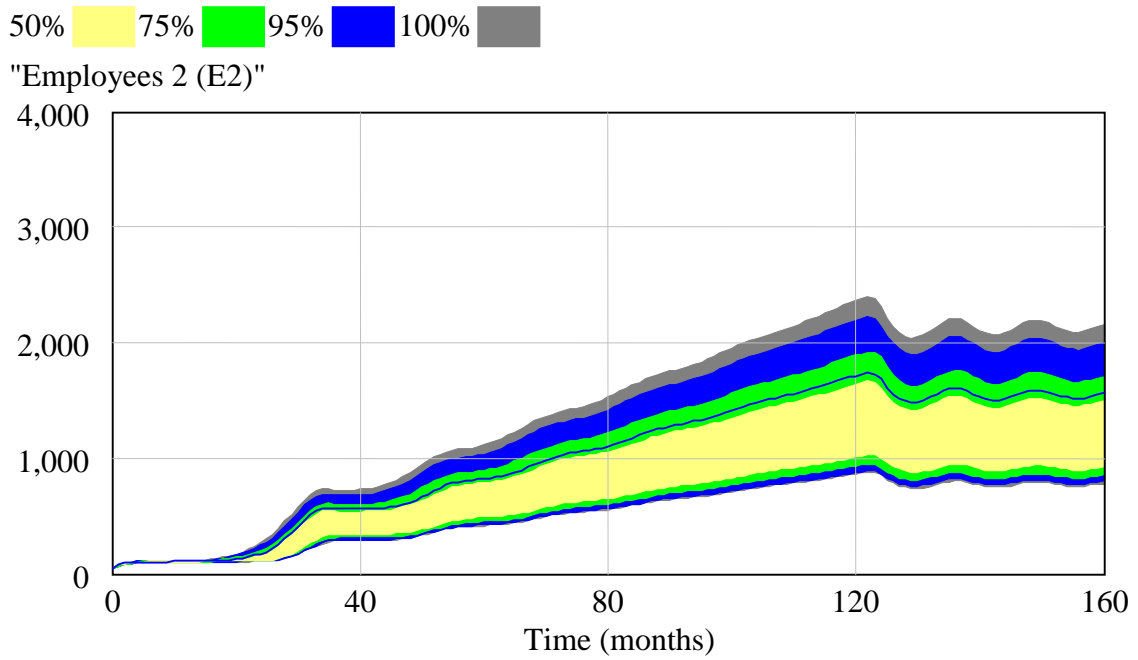
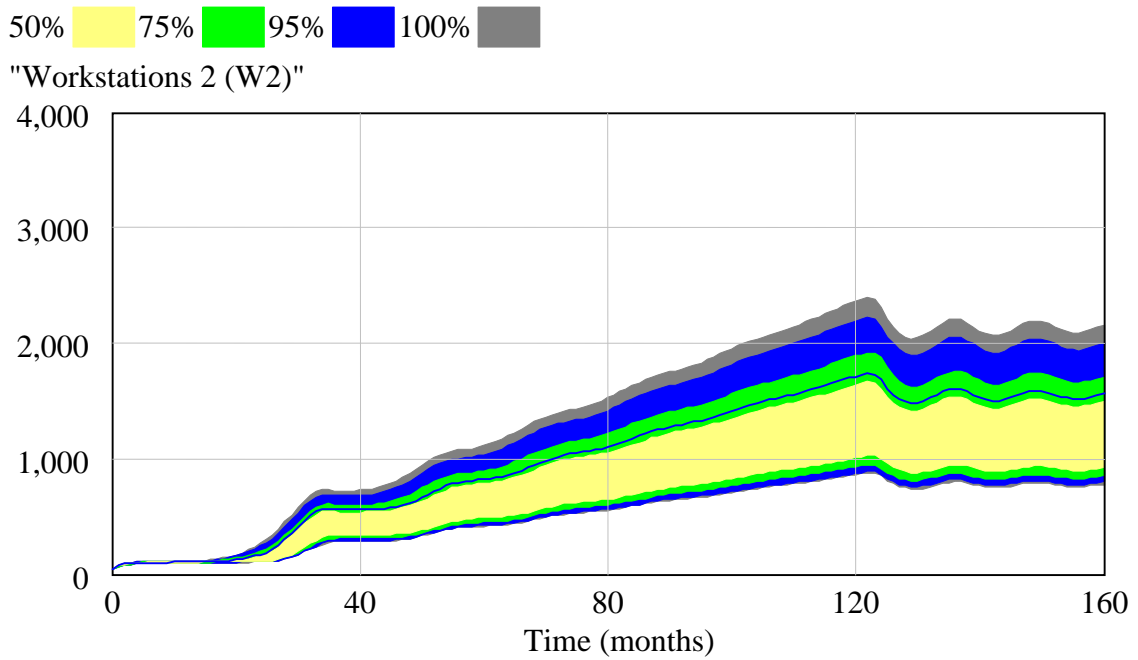**Figure 4-31.** Dynamic Confidence Interval for Employees 2.

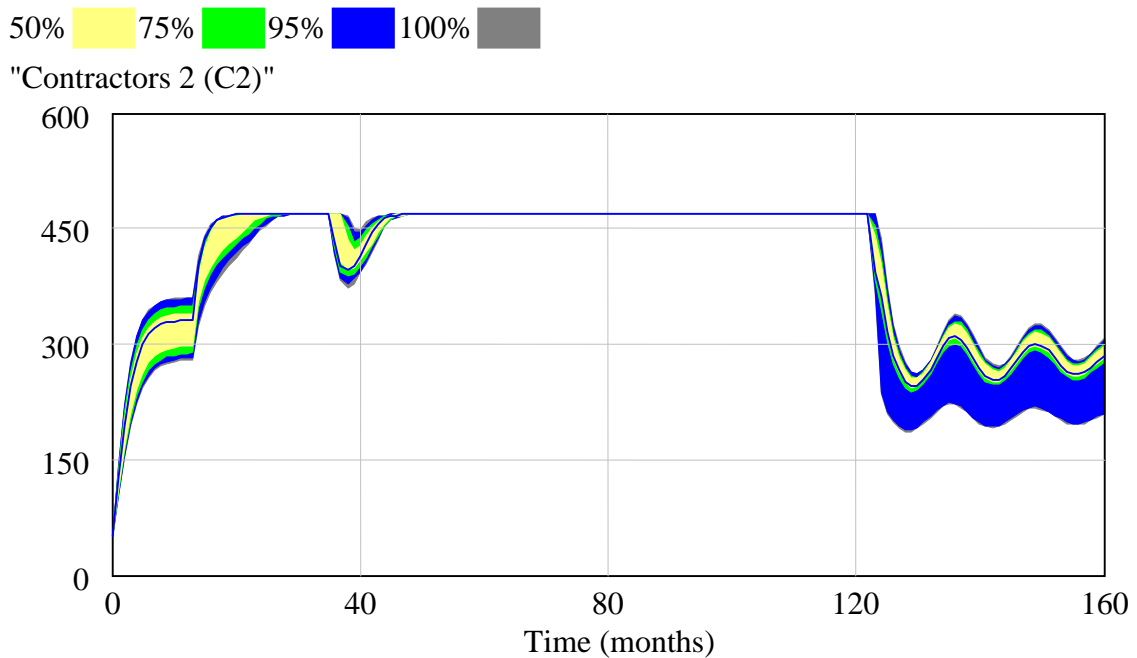**Figure 4-32.** Dynamic Confidence Interval for Workstations 2.

Figure 4-33. Dynamic Confidence Interval for Contractors 2.

scenario 1, as the contractors adjust due to the data decomposition, the confidence interval widens. When all of the contractors are moved to a data maintenance function, this variable also oscillates about the mean while the system is experiencing the damped oscillation behavior.

Unlike scenarios 1 and 2, scenario 3 does not include the contractor variable but does include advanced technology insertion. The data production standard has minimum production time of 450 hours and maximum production time of 300 hours, a mean time of 400 hours, and a standard deviation of 60 hours. The data maintenance standard has a minimum time of 225 hours, a maximum time of 100 hours, a mean equal to 200 hours, and a standard deviation equal to 60 hours. Figures 4-34 and 4-35 show the dynamic confidence bounds for employees and workstations respectively. Both diagrams show a wide confidence interval during the data production months (periods 1-123). The variable's uncertainty widens after period 60. This increase in uncertainty is expected because after this period because as good data in the system increases, so does the amount of data being decomposed during each period. The drop in resources after period 123 is coincident with reducing the resources required for data maintenance. The confidence interval for workstations during the exclusively data maintenance months
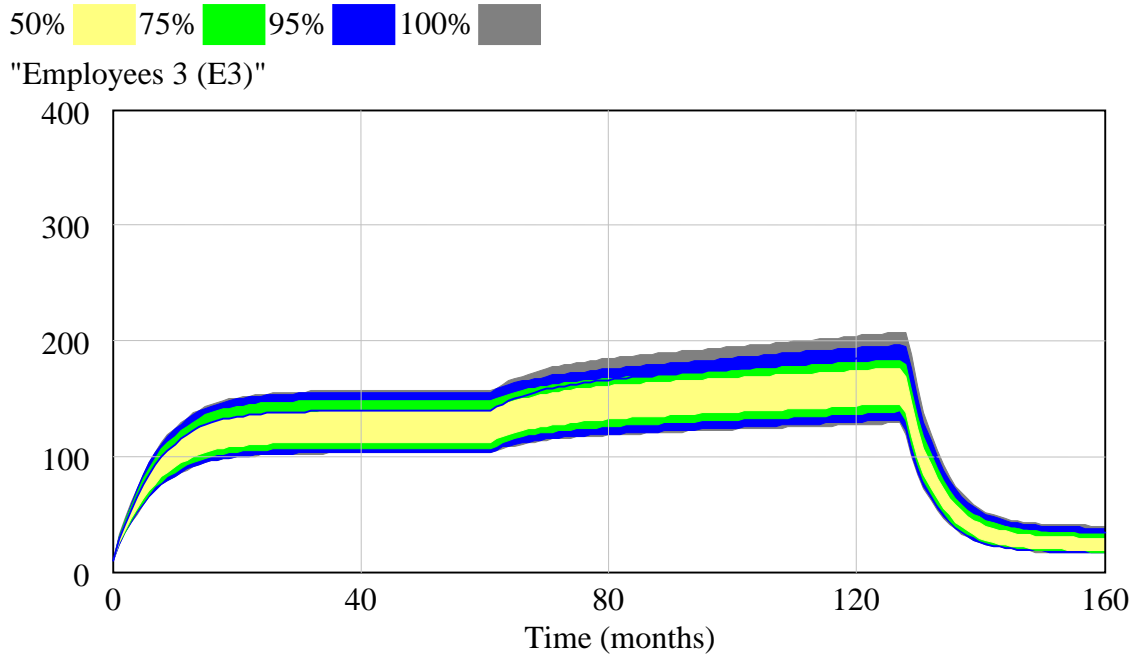
"Employees 3 (E3)"

Figure 4-34. Dynamic Confidence Interval for Employees 3.
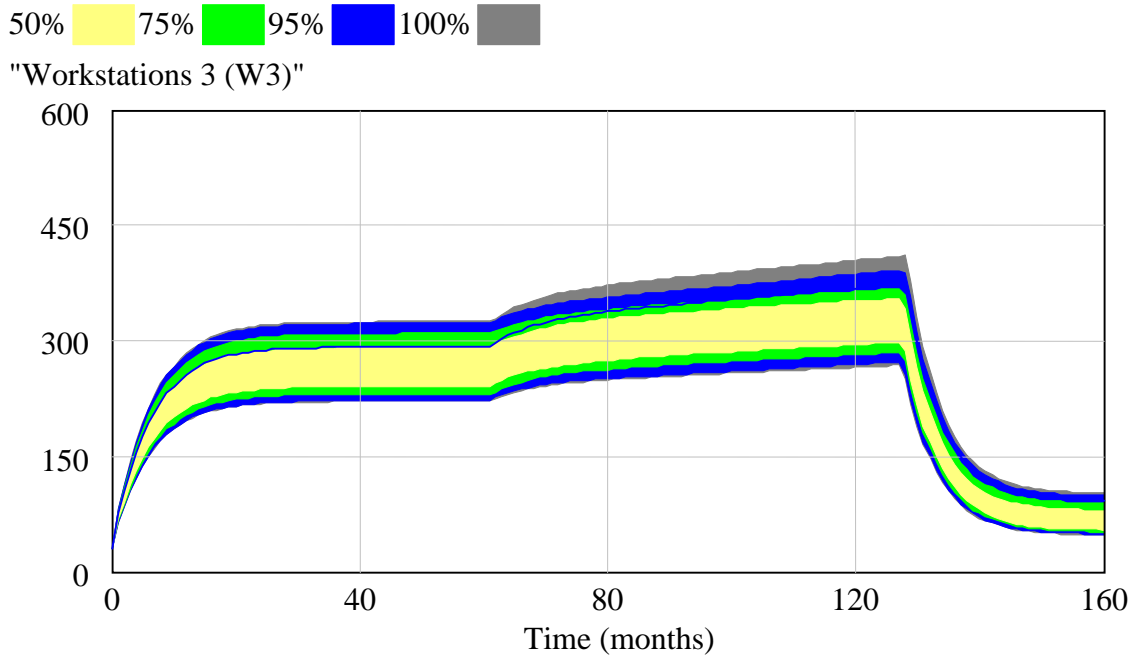
"Workstations 3 (W3)"

Figure 4-35. Dynamic Confidence Interval for Workstations 3.

(periods 123 and beyond) varies by only 75 workstations and 25 employees. This demonstrates a process that is well defined and is relatively free of uncertainty.

Scenario 4 uses employees and workstations with advanced technology and contractors to achieve the new production and maintenance goals. . The data production standard has minimum production time of 1,200 hours and maximum production time of 750 hours, a mean of 1,000 hours, and a standard deviation of 100 hours. The data maintenance standard has a minimum time of 550 hours, a maximum time of 200 hours, a mean equal to 400 hours, and a standard deviation equal to 50 hours. Figures 4-36 through 4-38 depict the dynamic confidence bounds for employees, workstations, and contractors respectively. While the employee and workstations both show a different resource total, they both exhibit the same trend with respect to confidence bounds. The process begins by exhibiting very little uncertainty for employees and workstations. After the first disturbance is introduced at period 36, the in-house resources are shifted to data maintenance. This shift in resources does is not significantly affected by uncertainty. The variation of employees and workstations increases significantly after the second disturbance is introduced at month 72. At this point the amount of data decomposition increases significantly and so does the in-house resources required to meet the rising goals. After the data production goal is satisfied (at period 123), the confidence interval remains wide. This is believed due to the relatively large standard deviation of the maintenance standard.

Validating the future, as is the case when employing predictive models, is a difficult task at best. Possibly the best that could be achieved is mitigating the risk of an invalid model by performing a sensitivity analysis such as was performed here. Ideally, similar systems have been implemented and the behaviors and trends could be used for comparison. But for one of a kind, and first of the kind, technologies, validation continues through an iterative approach of aggressively collecting data from the real world system and comparing it to the predictive model. As the model has demonstrated, the results are chaotic after a disturbance is introduced. This includes when the system is first introduced into the process (i.e. at the initial time). Therefore extreme care must be taken when collecting data around those periods.

In summary, sensitivity analysis was conducted on the key variables from each scenario. The contractor variable in all scenarios demonstrated that they have the lowest amount of uncertainty associated with them. This uncertainty may exist because contractors are only tasked with performing one task at a time. In every scenario (except scenario 3 when contractors were not employed) the rule was that contractors were to complete new production first. Since new data production has a constant goal of 100 cells per month, the contractor rate is expected to have less uncertainty. In scenarios 2 and 4, contractors also contributed to data maintenance. The employee and workstation variables demonstrated their highest degree of uncertainty during the data maintenance phases of each scenario. This uncertainty comes from the increase due to the data decomposition increasing after each period while data production was occurring concurrently. Once the system achieved it data production goal, the high degree of uncertainty in the employee and workstation variables due to the model over and under compensating as a function of the optimization algorithm.

The decision-maker should recognize the risk associated with the uncertainty demonstrated in this section. Decision-makers could mitigate their risk of uncertainty by sizing their system to at a median level, and not making significant adjustments after each period. Decreasing the adjustment times for workstations can further reduce uncertainty. Since the workstation adjustment time is the key driver for in-house resource adjustment, decreasing this time will allow those assets to be more responsive to a changing environment.
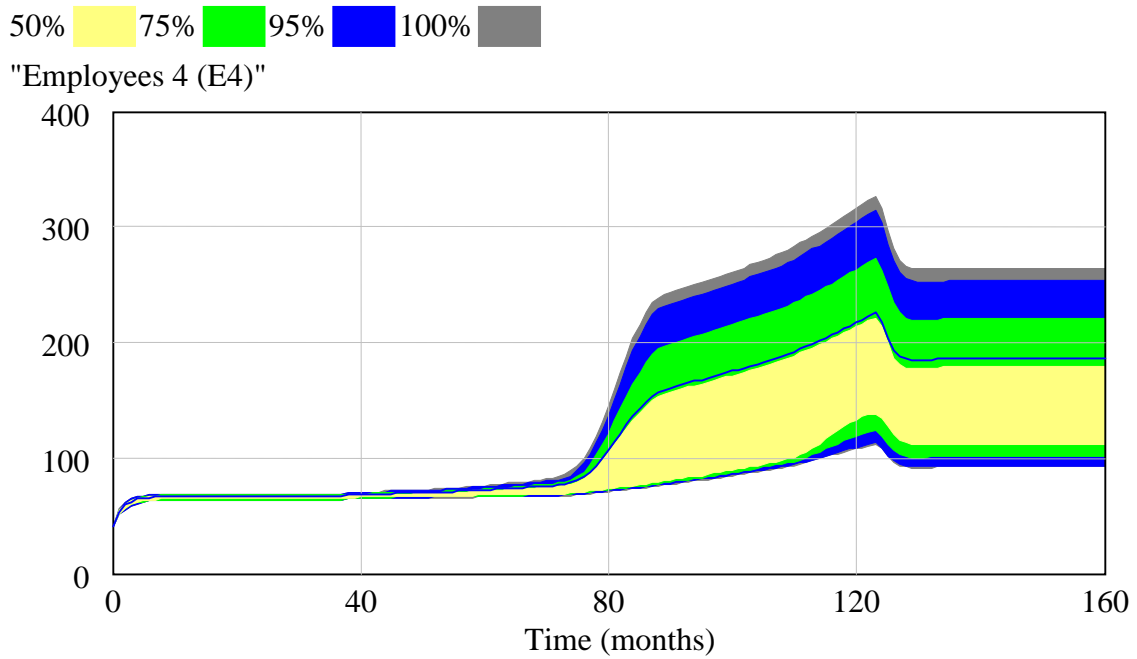
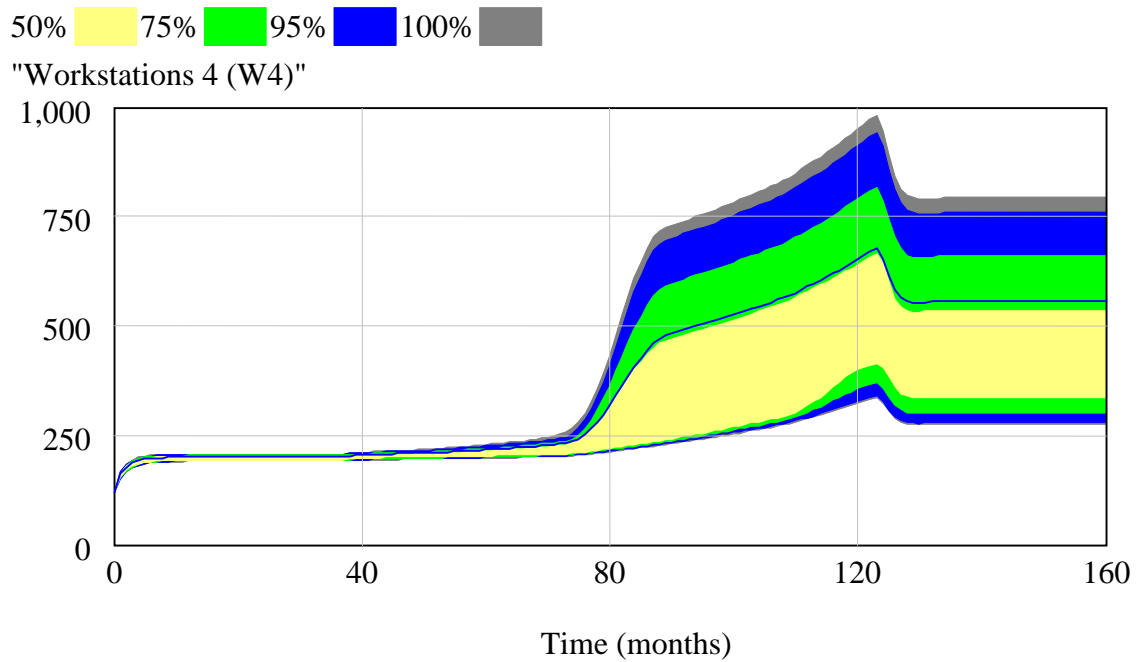**Figure 4-36.** Dynamic Confidence Interval for Employees 4.

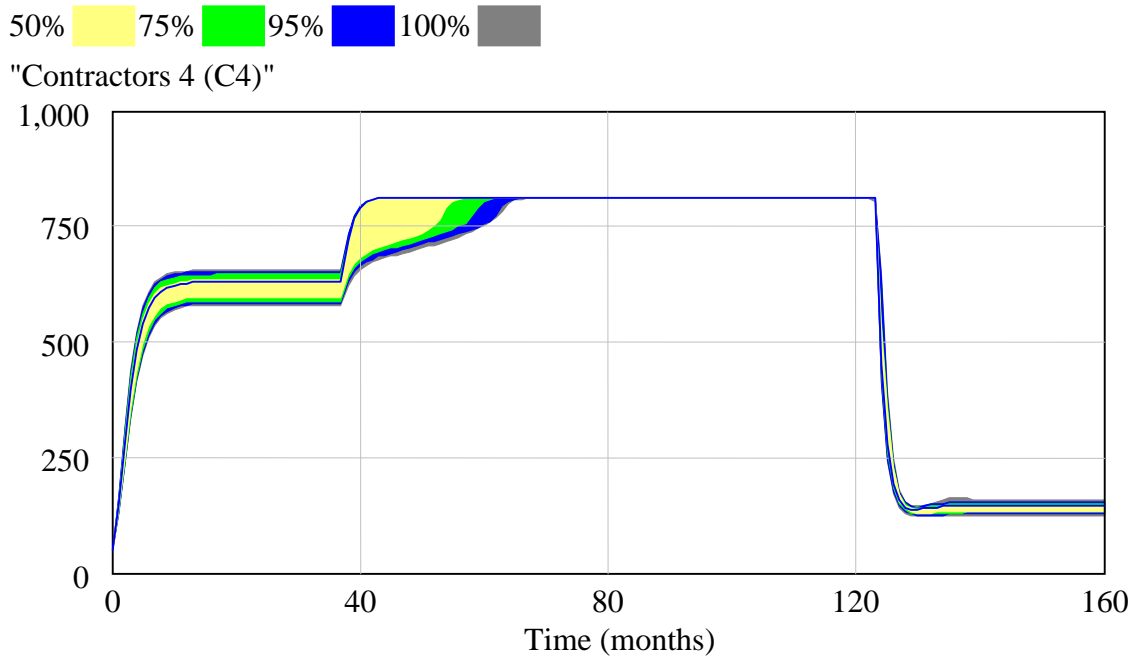**Figure 4-37.** Dynamic Confidence Interval for Workstations 4.

Figure 4-38. Dynamic Confidence Interval for Contractors 4.