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PREDICTIONS OF FLEET READINESS

USING DAILY OPTIMIZATION

A Thesis in

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by

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ABSTRACT

The planning of future operations is a complex process that requires knowledge and understanding of many different factors and resources. Likewise, daily maintenance planning is also a complicated task due to many different factors that need to be considered simultaneously. Although there is much literature on maintenance planning, existing work lacks the integration of robust personnel work schedules into scheduling algorithms. Thus the objective of this research is to develop a procedure that aids in the short-term planning of operations by predicting the future readiness level of a fleet of vehicles that are subjected to various personnel factors. This research presents a procedure that combines two different models to appropriately predict readiness levels at the end of a seven-period horizon. This first model is a Monte Carlo simulation that determines different personnel availability scenarios based on three different factors that affect the net resource pool of workers. These scenarios are then entered into a binary integer linear program (BILP) which iteratively optimizes fleet maintenance schedules on a daily basis. An overall fleet readiness level with a certain degree of probability is determined which serves as an extremely useful tool for operations planning. In addition, sensitivity analysis is presented on the different factors affecting personnel availability that can serve as useful aids in operational decision-making. Overall, these results show that the procedure presented in this research serves as a very useful tool to aid in resource planning and overall operations planning.

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Chapter 1
Introduction

Resource management and utilization is a complex and important concept found in many different areas of industry. Proper maintenance and allocation of a company's fleet of resources is a crucial aspect in its ability to meet customer demands and therefore needs to be given much attention. Whether it is a set of machines in a manufacturing plant or a group of vehicles in a rental car fleet, production and operation decisions can rely heavily on when resources are available and properly functioning. The ability to use the resources to successfully complete assigned tasks is referred to as the level of fleet readiness. Companies that can effectively maintain high levels of fleet readiness are better positioned to handle planned operations and also to adapt to unexpected situations.

Knowledge of current fleet readiness levels has many important applications, but the ability to predict future readiness levels can also serve as a very useful tool. Predictions of which resources will be available at a certain point in the future can help aid in the planning of operations. The focus of this research is to develop a tool that predicts readiness levels for a fleet of vehicles that can be used as an aid in planning future operations. These predictions of fleet readiness along with information about upcoming demand can be used to help determine which vehicles can and should be used to complete future company objectives.

The following is a summary of the organization of this work. Chapter 2 presents a summary of reviewed literature that is relevant to the underlying ideas of this research. Chapter 3 presents the methodology for the key models developed in this work. Chapter 3 also outlines the steps for implementing the procedure for fleet readiness prediction. Chapter 4 presents results and sensitivity analysis of the model. Chapter 5 discusses the significance and usefulness of the results from the methodology. Chapter 6 summarizes conclusions from this work and outlines some future areas of research.

Chapter 2
Literature Review

This chapter discusses previous research related to the techniques and methods utilized in this work. Presented first in Section 2.1, is a brief overview of the importance of fleet readiness, which is then followed by some of the techniques and methods currently used in its prediction and calculation. Next, the importance of practical mathematical models versus theoretical models is presented in Section 2.2. Section 2.3 discusses overall fleet maintenance management systems in various industries. This section also includes a review of methods utilized in three specific fields: the airline industry, the power industry, and the transit industry. Next, Section 2.4 presents literature on handling personnel capacity and availabilities. Finally, a short summary of the literature reviewed in this chapter is presented in Section 2.5.

2.1 Fleet Readiness Calculation and Prediction

The ability to ascertain the readiness level of a fleet of equipment is crucial to most companies in various industries, whether they be manufacturing-related or service-oriented. Properly calculating and predicting future readiness levels can drastically affect decisions on how production and operation are to continue at a certain point in time. Thus the ability to identify fleet readiness levels becomes an important concept with many different applications. One application in which this concept has a significant impact is for a fleet of military vehicles. Vehicle readiness is extremely crucial in mission planning and can have significant effects on the successful completion of a mission. One example can be found in the Navy in which "readiness and supportability problems have immediate consequences and affect the Navy's ability to perform its mission in logistically isolated areas (Rodgers, 1992)." Furthermore, vehicle readiness can also be a determining factor in the ability to win an armed conflict. Vehicle readiness "relies on the ability to keep the fleet of tanks, planes, ships, or missiles, maintained and ready for use and the ability to quickly repair any item damaged in service and bring it quickly back into play (Rodgers, 1992)." Thus accurate prediction of vehicle readiness serves as an extremely important part in the proper planning of tasks. Dunst & Fry (1997) provide an overview of the aspects the Navy considers when assessing readiness stating that operational availability is the measure for "determining if weapon systems are able to accommodate their intended mission from a material point of view."

Some researchers have developed techniques to establish predicted fleet readiness levels. Black and Keller (2003) presented statistical methods for determining what a specific vehicle's level of readiness would be at a certain point in time. They presented a non-homogeneous Poisson process to describe the repairable systems and a power law process to measure the improvement or deterioration of a system over its lifetime. Finally, they presented a probability equation to describe the overall readiness of a vehicle. Other researchers have developed tools to establish current mission readiness levels. Jurges (1999) introduced "The Aircraft Carrier Material Condition and Readiness Assessment Simulation Model." This model simulated the "'real factors' influencing the ship's performance and takes them into account when assessing any aircraft carrier mission." Thus this tool allowed a commanding officer to assess the potential risks associated with planning a mission on a certain carrier.

In addition to assessing and predicting readiness, some researchers presented ways to improve fleet readiness levels. Cortez, Keller, and Poblete (2008) proposed a method of improving fleet readiness based on the Theory of Constraints, originally presented by Eliyahu Goldratt in his novel "The Goal". In their work, they argued that certain characteristics of fleet support are analogous to work-in-process, inventory, and throughput in a manufacturing plant.

Then by following the model outlined in Goldratt's novel, maintenance on a fleet of Advanced Air Mobility Aircraft could be improved by first identifying and exploiting the bottleneck of the system. In this case, the bottleneck was considered to be unscheduled maintenance downtime. Then by iterative identification and exploitation of this bottleneck, improvements were made and the overall fleet's mission capability was improved.

2.2 Applied vs. Theoretical Models in Maintenance

Often times, highly theoretical and complex models are developed through research that prove to be difficult to implement in real-world applications. Scarf (1997) argued that perhaps this was the wrong approach and made an appeal to maintenance modelers to "attempt to solve real maintenance-related problems." Furthermore, he stated that the specific process of interest to the decision-maker should be of higher priority to the modeler than simply finding an application on which to apply a previously developed model. Simple models with a small number of unknown parameters or approximate solutions can prove more useful than overly complex, theoretical models developed without the input of the true stakeholder.

Dekker (1996) made a similar statement about the gap between theory and practice in developing maintenance models and then attributed that gap to six different aspects. The first aspect was that maintenance optimization models are difficult to understand and interpret and thus it is not easy for technicians and managers to fully understand them. The second aspect was that many papers have been written for math purposes only. Unfortunately, mathematical results are not appealing to industry practitioners and researchers do little to make the results worthwhile or understandable. The third reason for which the gap exists between theory and practice was that companies are not interested in publication. Dekker stated that companies should reward researchers for solving real-world problems and allow them to publish the results. A fourth reason was that maintenance covers a multitude of different aspects and that there is not one model that covers a generic maintenance modeling problem. The fifth aspect was that optimization is not always necessary and does not always result in costs savings to maintenance itself. Often times the savings appear in other aspects of operation making it more difficult for managers to fully grasp the benefits. The final reason for such a gap was that optimization models often focus on the wrong type of maintenance and thus are not viewed as helpful or as effective as possible. Therefore, in order for a model to be fully implemented and then utilized effectively in scheduling maintenance it must be practical in nature and appropriate for the specific problem at hand.

2.3 Fleet Maintenance Management Models

One area where mathematical models can effectively be used to solve real-world maintenance-related problems is in fleet maintenance management. The idea of fleet maintenance management "refers to the process of scheduling and allocating resources to the maintenance activities (repair, replacement, preventive maintenance) associated with a fleet of equipment (Cassady, Murdock, Nachlas, Pohl, 1998)." Although the term fleet is typically associated with vehicles, its general definition simply refers to multiple units of an equipment type. Thus fleet maintenance management becomes an important concept in all aspects of industry including manufacturing, transportation, and communication fields. In their work, Cassady, Murdock, Nachlas, & Pohl (1998) presented common difficulties associated with fleet maintenance management models. In addition, they outlined several domains that need to be addressed in order to obtain a comprehensive fleet maintenance management system. These domains were equipment-level maintenance scheduling, opportunistic maintenance policies, effects of obsolescence and new technology, age-based equipment retirement, and maintenance resource allocation

As mentioned previously, fleet maintenance management is an important concept in many different fields across industry. One field where such models are frequently used is the airline industry. Yan, Yang, and Chen (2004) developed a method for scheduling short-term maintenance manpower supplies for an airline. Using a mixed integer programming model, they evaluated several different flexible management strategies for performing maintenance on airplanes. A solution algorithm was developed to handle large-scale problems and was solved using CPLEX. Another approach to aircraft maintenance was taken by Chiesa, Quer, Corpino, and Viola (2009). The authors used a two-phase approach to schedule different maintenance operations that needed to be performed. Due to sub-optimal solutions from heuristics and large computational complexity of exact techniques, a hybrid solution of two techniques was created that proved more efficient than manual scheduling techniques.

Another field that is highly researched is power plant generation maintenance scheduling. Chattopadhyay (1998) used linear programming to schedule maintenance activities for generators in an Indian Power Plant. A rule-based heuristic was applied to the results of the linear program in order to create a more practical maintenance plan that could easily be implemented and effectively utilized. Leou (2001) presented a slightly different approach that accounted for uncertainties in the system constraints. When constraints caused computational complexity issues and infeasible solutions, a fuzzy 0-1 integer programming model was introduced and solved by a branch and bound process.

Bus maintenance scheduling is yet another topic that has proven to be quite relevant to this work. The idea of creating a bus maintenance schedule refers to the assignment of resources to a task in one or several connected discrete time intervals (Zhou, Fox, Lee, & Nee, 2004). This generalization implies that the techniques used to schedule bus maintenance can be used in any resource assignment process and is not limited solely to buses. Haghani and Shafahi (2002) formulated a preventive maintenance scheduling problem as an integer programming model and solved it by the branch and bound method. The model was run daily to take into account various dynamic events that could affect the results, such as unscheduled maintenance that arises due to the breakdown of a vehicle. A simulation model was developed to test the effectiveness of the model with real-world data. The method proposed by Zhou, Fox, Lee, & Nee (2004) attempted to solve the bus maintenance scheduling problem in a different fashion. Their method proposed a multi-agent system approach. This approach was comprised of four separate agents, the Order Receiver agent, the Mediator agent, the Bay agent, and the Database agent. Each agent served their own purpose and objective, but interacted with the other agents to obtain the overall maintenance schedule.

Using relevant research in other industries, such as the literature detailed above, as an analogy, Duffuaa and Al-Sultan (1997) presented general mathematical programming models for the management of maintenance planning and scheduling. They stated that the maintenance load for a particular unit can be divided into two categories: scheduled and unscheduled maintenance. The unscheduled maintenance was considered the major source of uncertainty in the scheduling process and consisted of seven main factors:

1) emergency jobs arrival times
2) availability of manpower
3) time to complete a job
4) availability of spare parts
5) delivery times of spare parts
6) availability of equipment and tools
7) reliability of equipment and tool

They strongly advocated the use of mathematical programming models to solve these types of problems and then identified several types of models that were appropriate for different situations. Constraints for these models typically represented five main areas:

1) availability of various types of skills
2) equipment and tool availability
3) availability of spare parts
4) arrival times and job requirement of all incoming jobs
5) sequence of job operations

In addition, there were six main objectives to be considered in these models, which were:

1) Minimize equipment and personnel idle time
2) Minimize total scheduling time
3) Minimize delay of certain jobs
4) Maximize equipment availability
5) Minimize the shut-down cost
6) Minimize the plant shut-down time

After outlining sources of uncertainty, types of constraints, and different possible objectives, two general mathematical models were described. The first was a general form integer programming model that used deterministic data. The second was a stochastic model based upon the former integer programming model that accommodated for the planning of various uncertainties, such as predicting future breakdowns.

The previous section detailed above has demonstrated the need for developing mathematical maintenance models and reviewed pertinent literature in that field. Literature review has shown a need for practical models that can be applied in real-world applications. It has also been demonstrated that these models are often more effective than complex, theoretical models that are not easily implemented in industry. Fleet maintenance models are useful in various fields throughout industry and three different applications have been explored in greater detail in this work. These fields included the airline industry, the power industry, and the transit industry. More applications in these fields and others can be found in the comprehensive survey of over 120 articles written by Dekker (1996). Relevant literature has also outlined general methods for applying mathematical models to maintenance scheduling and planning and common sources of uncertainty, constraints, and objectives were detailed.

2.3 Consideration of Personnel Capacity and Availability

There are many aspects to consider when scheduling maintenance operations on a fleet of vehicles. These include the demand for maintenance operations, the availability of supplies and parts, location of maintenance depots and other such aspects. However, perhaps the most important consideration is the capacity constraints of maintenance personnel. Luczak and Mjema (1999) stated that when analyzing all the aspects of an entire maintenance department, "the predominant cost centre is the maintenance personnel." Furthermore, they stated that "the determination of personnel capacity requirement in maintenance plays an important role in the reduction of operation costs within the whole production system." Therefore understanding personnel requirements and considerations is an important issue. However, due to the complexity of this issue, modeling these requirements has proven quite challenging for many researchers.

Luczak and Mjema (1999) stated that there are six main factors affecting the personnel capacity requirement in the maintenance department. These six factors were:

(1) amount of maintenance workload

(2) the production system

(3) structure of the equipment

(4) organization of the maintenance

(5) profile of the maintenance personnel

(6) maintenance strategies

The most influential factor was considered to be the amount of maintenance workload which depended mainly on the frequency and duration of maintenance work orders.

Another aspect that further complicates maintenance personnel capacity is availability of workers. Howe, Thoele, Pendley, Antoline, & Golden (2009) studied the difference between the number of assigned personnel and the number of workers that were actually available and qualified to perform necessary tasks. They performed a study at a U.S. Air Force base and found that the percentage of available workers was often significantly lower than the number of workers assigned, sometimes as low as 41% of the baseline staff. They ascertained that there are three main factors that cause the net effective resource pool to be much lower than the total resource pool: skill-level productivity, ancillary and computer-based training, and availability. The first factor, skill-level productivity, accounted for the fact that all workers do not work at the same rate of efficiency. One worker may take longer to complete a task than a different worker performing that same task. The second factor, ancillary and computer-based training, represented the time that job training takes away from completing maintenance operations on daily basis. The study showed that maintenance workers spent, on average, between 5.24% and 7.51% of their day on training-related tasks. The third factor was availability of workers. It was found that on any given day, many workers were not actually available to perform work although they were scheduled. Fifteen different reasons for unavailability were determined including reasons such as scheduled days off, medical leave days, and full-day appointments. It was found that non-availabilities reduced the size of the resource pool by an average of 65.39%. The significance of these results implied that understanding availability issues and correcting for them is a very important aspect of maintenance scheduling that cannot be ignored.

Likewise, another study on the Air Force focused on understanding productivity differences between maintenance units. Seven potential factors were determined including: wartime versus peacetime manning factors, out-of-hide duties, on-the-job training requirements, supervisory policies, shift or scheduling and utilization efficiencies, depth and range of experience and cross-utilization, and personnel availability (Drew, Lynch, Masters, Tripp, Roll, 2008).

Although important to military applications, the concept of personnel availability is not limited only to military problems. Any company that has a workforce is subject to the factors mentioned previously. Loucks and Jacobs (1991) developed a goal programming model that accounted for a non-homogeneous work force at a fast food restaurant. Their model accounted for different availabilities of workers and various skill-sets among workers. Bard and Wan (2005) developed a midterm model for mail processing and distribution centers that scheduled the available workforce for a seven-day week. Re-planning throughout the week was considered a necessity due to “vacations, sick leave, and other types of absenteeism that reduce the size of the workforce from one day to the next” and thus the use of a midterm model was quite advantageous. Yet another industry where personnel availabilities must be considered is the healthcare industry. Generally, nursing schedules for several weeks are determined in advance. However, daily adjustments are often needed to account for demand fluctuations, sick leave, personal days, emergencies, and other types of uncertainties that can change workforce capacity. Bard and Purnomo (2005) presented a methodology to make daily schedule adjustments using an integer programming model solved within a rolling horizon framework. Always solving for the next 24 hours, the model was re-solved whenever new information became available that might have affected the supply and demand of the nursing unit.

Review of literature on the topic of personnel capacity and constraints has demonstrated several important concepts. First it has shown that personnel account for a large percentage of maintenance costs and thus should be considered in maintenance models. Three main factors that affected the resource pool were skill-level productivity, training requirements, and availability. Relevant literature has shown that staff scheduling is highly susceptible to uncertain events such as sick leave and personal vacation days. It has been demonstrated that these types of events occur not only in the field of maintenance but across all other types of industries. Developing a short-term or mid-term model or one with a rolling planning horizon is an excellent way to be able to quickly react and adapt to sudden changes in personnel availabilities.

2.5 Summary

Assessment and prediction of fleet readiness is an important concept that can have significant effects on production and operation in any industry. Fleet maintenance accounts for a high percentage of operational costs and thus is an important area to study. Although there is much literature on fleet maintenance and management, much of this research has been theoretical and does not lend itself to easy implementation in real-world applications. Review of the literature has shown that mathematical programming models are often the best choice for this particular type of problem, although very few have been developed for applications involving a dedicated workforce (e.g., the military). Furthermore, the objective of most current maintenance models is to minimize costs, not to maximize overall fleet readiness.

This research proposes a short-term maintenance scheduling procedure that has three main objectives. The first objective is to generate fleet readiness level predictions at the end of the time horizon that can aid in future operations planning. A second objective is to use sensitivity analysis of the results to analyze the effects of different personnel factors. The third and final objective is generate maintenance schedules that assist in the planning of daily maintenance operations by determining which vehicles should be repaired by which mechanics and on what days. To allow for ease of implementation in a real-world application, a simple binary integer linear programming model (BILP) is presented that is re-optimized daily to incorporate newly available information. To account for personnel factors, the mechanic resource pool is subjected to certain availability and productivity constraints which are used as inputs to the BILP to obtain more realistic results. The outcome of this procedure is a versatile planning tool that assists in decision-making on different resource utilization strategies.

Chapter 3

Methodology

In this chapter, a procedure is presented for the development of a planning tool that predicts vehicle fleet readiness levels. The first section, Section 3.1, details the background of the problem and the objectives of this work. Section 3.2 introduces a binary integer linear program that is the basis for the planning tool. A personnel simulation model used to develop resource availability scenarios is presented in Section 3.3. Section 3.4 discusses the overall procedure which combines the mathematical model and the simulation model. Finally, a summary of this chapter is presented in Section 3.5.

3.1 Problem Background

Each day company leaders try to plan operations that will be performed at some point in the future. Planning operations requires understanding of the demands of the customer, as well as the resources that will be utilized. For the purpose of demonstration, the resources in this research are assumed to be a fleet of vehicles. Since events requiring vehicle utilization can arise unexpectedly, maintaining a high level of vehicle readiness at all times becomes extremely important. Ideally all vehicles would be available for use at any time and thus asset readiness would not be a significant factor in the planning of operations. However, all vehicles are subject to breakdowns and require time and resources to be repaired to ready status. Therefore, it is important to always have updated information on a fleet of vehicles, as well as a way to predict what the readiness of the vehicles will be in the future.

In addition to operations planning, maintenance operations also need to be scheduled on a daily basis. Although it might not seem overly complex, there are many different factors that must be considered. Maintenance operations planners must determine which mechanics to schedule for a given work day. This can become complicated because not all mechanics work at the same efficiency rate. In addition, the availability of mechanics can vary greatly from one day to the next so schedules must be adjusted frequently. Another task that planners must complete is the prioritization of work. Some vehicles may be more important to repair than others. Other vehicles may be required to wait for necessary parts until they can be repaired. Thus there are many different factors that must be accounted for when planning daily operations. A planning tool to aid in the organization of these different factors can help plan the operations and lead to more efficient repairs.

The objective of this work is to develop a procedure that helps with both the planning of future operations and daily maintenance operations. This procedure is based on two different models, a binary integer linear programming mode (BILP) and a personnel simulation model. The simulation model generates different personnel availability scenarios that are used as inputs to the BILP. After iteratively optimizing the BILP, there are two main outputs that can aid in planning. The first output is a fleet readiness prediction for each of the vehicles that can be used in operations planning. The second output is a daily schedule that can assist in the coordination of maintenance tasks on a day-to-day basis. Overall, the procedure generates results that are useful in many different maintenance planning applications.

3.2 Model Formulation

This section outlines the basic mathematical model that is used in this operations planning tool. The model takes the form of a binary integer linear programming (BILP) model. This section discusses assumptions, notation, input data, decision variables, and finally the complete formulation.

3.2.1 Model Assumptions

The starting point of the model is a baseline that requires several assumptions. The assumptions made are as follows:

1) A vehicle may experience only one breakdown per day.
2) Only one mechanic may complete the repair on a certain vehicle.
3) All parts can be obtained but are subject to variable delivery lead times.
4) Breakdowns are assumed to occur throughout the day, but repairs cannot begin until the start of the next day.
5) A repair will always be started and completed during the same day.
6) All mechanics are trained to complete all the tasks.

3.2.2 Notation

The index sets used in the model are:

i = vehicle index, $i = 1, 2, 3, \ldots, V$

j = mechanic index, $j = 1, 2, 3, \ldots, M$

The vehicle index is used to represent each of the V vehicles in the organization being modeled. The mechanic index is used to represent each of the M mechanics that make up the resource pool.

3.2.3 Input Data

The input data necessary for the model are listed below.

InitStat(i) = initial status of vehicle *i*

Priority(i) = priority of vehicle *i*

DiagTime(i) = hours required to diagnose the problem for vehicle *i*

RepTime(i) = hours required to repair vehicle *i*

TowTime(i) = hours required to tow vehicle *i*

PartTime(i) = hours until the parts are delivered for vehicle *i*

Effic(j) = efficiency rate of mechanic *j*

MechHrs(j) = number of available working hours for mechanic *j*

There are several different sources used to determine the values of the input data. In a real-world application this data would be based on actual data. Vehicle statuses, necessary repairs and times, availability of mechanics, etc. would all be based on actual statuses of vehicles, times, and resource availability data.

For the purposes of this research, most of this data is generated randomly. Breakdowns of the vehicles are generated randomly according to a certain probability distribution where certain vehicles are subject to higher probability of failures. For every day, including Day 1, each vehicle has a certain probability associated with the likelihood of that vehicle to fail during the day. Each vehicle also belongs to one of Z certain subdivisions of vehicles within the organization. All vehicles within a certain subdivision are subject to the same probability of failure. General forms of the probability of failures per subdivision are shown in Table 3-1.

Table 3-1. Probability of Breakdown per Subdivision

Subdivision	**Probability of Failure**
A	$\mu_A \pm \varepsilon_A$
B	$\mu_B \pm \varepsilon_B$
C	$\mu_C \pm \varepsilon_C$
…	…
Z	$\mu_Z \pm \varepsilon_Z$

3.2.4 Decision Variables

The decision variables for the model are presented below.

$$X(i,j) = \begin{cases} 1 \text{ if vehicle } i \text{ is repaired by mechanic } j \\ 0 \ otherwise \end{cases}$$

$$FinalStat(i) = \begin{cases} 1 \text{ if vehicle } i \text{ ready status} \\ 0 \ otherwise \end{cases}$$

The *X(i,j)*'s show which vehicles are repaired by which mechanics. *FinalStat* refers to the final status of a given vehicle. If the *FinalStat* of a vehicle is 1 at the end of a period, then that vehicle's status is ready at that time. However if the *FinalStat* is 0, then the vehicle's status is non-ready and has experienced a breakdown that has not yet been repaired.

3.2.5 Formulation

The model formulation is presented below.

Maximize $\sum_i (FinalStat(i) * Priority(i))$

Subject to:

$$FinalStat(i) = InitStat(i) + \sum_j x(i,j) \qquad \forall\ i \qquad (3.1)$$

$$\sum_j x(i,j) \leq 1 \qquad \forall\ i \qquad (3.2)$$

$$\sum_i \mathrm{x(i,j)} \leq MechHrs(j) \qquad \forall\ j \qquad (3.3)$$

$$x(i,j) * [RepTime(i) * Effic(j) + DiagTime(i) * Effic(j) + \max\{TowTime(i), PartTime(i)\}] \leq MechHrs(j) \quad \forall\ i,j \qquad (3.4)$$

$$\sum_i x(i,j) * [(DiagTime(i) + RepTime(i)) * Effic(j)] \leq MechHrs(j) \quad \forall\ j \qquad (3.5)$$

$$x(i,j) \in \{0,1\} \qquad \forall\ i,j \qquad (3.6)$$

$$FinalStat(i) \in \{0,1\} \qquad \forall\ i \qquad (3.7)$$

The objective function of this model maximizes the weighted sum of the final statuses of all the vehicles for a certain period. In this model, the weights correspond directly to the priority of the vehicles. This ensures that more important vehicles are more likely to get repaired before less important vehicles. Constraint 3.1 shows the relationship between the initial status of a vehicle and the final status. If a vehicle is non-ready at the beginning of the period (*InitStat(i)= 0)* and then is fixed during the period (*X(i,j)* = 1for some *j*), the final status of the vehicle will be ready (*FinalStat(i)* = 1*)* Likewise, if the vehicle does not get repaired (*X(i,j)* = 0 for all *j*), then the final status will remain as non-ready (*FinalStat(i)* = 0). Constraint 3.2 ensures that each vehicle is repaired by only one mechanic per day. Note that this does not prevent a mechanic from working on multiple vehicles in one day. Constraint 3.3 ensures that only mechanics with available working hours during a certain day can be scheduled to repair vehicles. If a mechanic is unavailable on a certain day (*MechHrs = 0),* then no vehicles can be repaired by that mechanic (*X(i,j)* = 0 for all *i*). Constraint 3.4 ensures that the sum of the diagnosis time, repair time, and the maximum time spent waiting for part delivery or towing for a mechanic on a particular vehicle is less than or equal to that mechanic's available hours that day. Note that this constraint does not prevent the mechanic from repairing other vehicles while awaiting the arrival of parts for a specific vehicle. Constraint 3.5 ensures that the sum of all the time diagnosing and repairing for all vehicles that a mechanic repairs during a single day is less than the mechanic's available hours on that day. Constraint 3.6 forces the *X(i,j)*'s to be binary variables, that is, to only take on the value of one or zero. Similarly, Constraint 3.7 also forces the *FinalStat* variables to be binary.

3.3 Personnel Simulation

As previously mentioned, one of the objectives of this work is to also gain an understanding of the effects of personnel considerations on overall fleet readiness. Using the study completed by Howe, Thoele, Pendley, Antoline, & Golden (2009) as a reference, a simple Monte Carlo simulation was developed to create different personnel availability scenarios. Three main factors were included as part of this work: skill-level productivity, training requirements, and availability of mechanics.

To account for the availability factor, a Microsoft Excel spreadsheet was created that simulates different scenarios of personnel availability based on the percentages given in Howe et al.'s (2009) study. A percentage of available workers is randomly determined for each day by sampling a uniform distribution with a minimum value of 24% and a maximum value of 49%. This percentage is then converted to a number of available mechanics for that day. Since there is assumed to be resource pool of ten mechanics, the resulting number of mechanics actually available to perform maintenance operations on any given day is two, three, four, or five. In addition to determining the number of mechanics available on a given day, this simulation also determines which of the ten mechanics are available and which are not.

The process mentioned in the previous paragraph accounts for a mechanic's availability status for a particular day, which is either available or not available. If a mechanic is determined to be available on a certain day, then it is assumed that the mechanic's number of available hours for that day is eight hours. However, this does not account for the training requirements that detract from a worker's available hours. Therefore, a certain percentage of available hours is subtracted from the original value of eight hours, depending on the skill-level of the specific worker and the training requirements. Using operational data from the study performed by Howe et al. (2009) as baseline values, it is assumed that workers with skill-level ratings of one spent 7.51% of their day on training requirements and thus are actually only available for seven hours per day, after rounding to the nearest hour. Workers with all other skill-level ratings are assumed to spend 5.24% of their day on training activities and thus their actual number of available hours is still considered eight after rounding.

In this fashion, the Monte Carlo simulation not only determines which mechanics are available on certain days, but also how many hours they are available on a given day. An Excel macro was developed to automate this process for seven days at once and thus a personnel availability scenario is created for one whole week at a time. Several different weekly scenarios are generated by this simulation model and then used as input data for the BILP that was described in the previous section.

3.4 Procedure for Fleet Readiness Prediction

The main contribution of this research is the development of a procedure that is used to approximate the optimal daily maintenance schedule that maximizes the number of available vehicles at the end of the final period of the planning horizon. Although this approach is myopic in nature, it is much more practical in its application than a more dynamic approach that focuses on the entire seven-day period rather than daily optimization. This is the best approach for a maintenance scheduler because on any given day, the scheduler will always try to maximize the number of vehicles available at the end of the day. In addition, it may also be the only feasible approach to scheduling since it is difficult to predict breakdowns and daily changes in personnel availabilities.

The procedure presented here is a combination of the mathematical model presented in Section 3.2 and the simulation model presented in Section 3.3. Figure 3.1 is a flow diagram of the steps performed in this procedure. The first step of this method is to run the personnel simulation to obtain a personnel availability scenario. The results of this simulation are used to populate the necessary input parameters that correspond to the mechanics. Using the results obtained for Day 1, the appropriate number of available working hours (model input: *MechHrs*) is entered for each mechanic for Day 1. In addition, mechanic efficiencies (*Effic)* are also entered based on the appropriate skill-levels of the workforce.

Next, the rest of the initial inputs are determined for the BILP. This includes priorities (*Priority)* and initial statuses of vehicles (*InitStat)*, known diagnosis times *(DiagTime)*, repair times (*RepTime)*, part delivery times (*PartTime)*, and towing times (*TowTime)*. Once all the initial input data have been entered, the BILP is optimized for that day. It is assumed that new breakdowns occur throughout the day, but that repairs on them cannot begin until the beginning of the next day. Thus at the end of an optimization period, breakdowns that occurred during that period are accounted for in the initial status of the vehicles for the next period. For example, if the initial status of Vehicle 1 at the beginning of Day 1 is ready and then it experiences a breakdown during the afternoon on Day 1, the initial status of Vehicle 1 at the beginning of Day 2 will be non-ready. In addition to updating vehicle statuses due to breakdowns, part delivery times and towing times are adjusted by subtracting 24 hours from their total time to represent the completion of the previous day. Lastly, the maintenance availability for the next day will also be updated based on the results from the personnel simulation.

In this fashion, the BILP is optimized iteratively a total of seven times until the last day is optimized. In between the optimization of each period, maintenance availability is adjusted according to the scenario produced by the personnel simulation. In addition, new breakdowns are introduced and input data is adjusted if necessary. At the end of the optimization of Day 7, a prediction of the readiness of the fleet of vehicles is obtained. Each vehicle has either a ready or non-ready status. Therefore, in running the procedure process many times, an average probability at a certain confidence level is generated that represents the probability that a certain vehicle will have a ready or non-ready status at the end of the planning horizon. This value is extremely useful to planners in that it gives the probability that a certain vehicle will be available at the start of the mission, subject to many independent sets of events that could occur between the current day and the start of future operations.

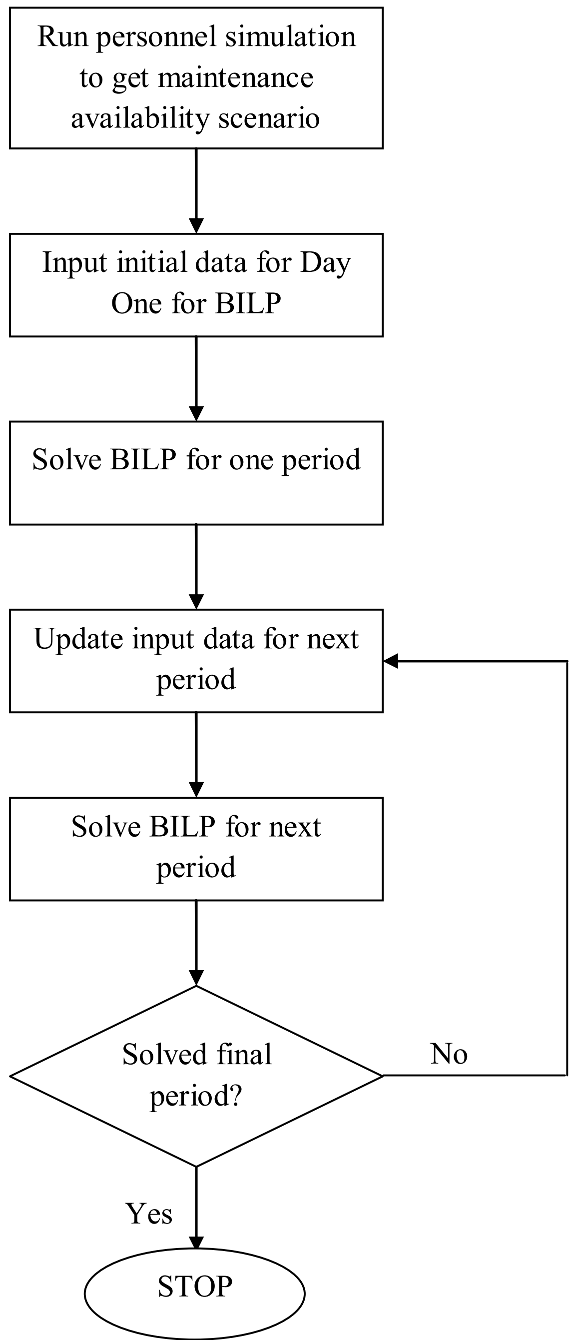

Figure 3-1: Flow Diagram of Procedure

3.5 Summary

This chapter presented the methodology used in developing an operations planning procedure that helps predict vehicle fleet readiness at the end of a seven-day planning horizon. This procedure is based on the combination of two different models, a binary linear integer programming model (BILP) and a Monte Carlo personnel simulation model. The personnel simulation is used to generate resource availability scenarios that are used as inputs to the BILP. Iteratively solving the BILP with the inputs from the personnel simulation produces a prediction of vehicle fleet readiness. Solving the BILP for many different personnel availability scenarios produces fleet readiness predictions that have a probability associated with the expected final status for each vehicle. These results prove very helpful in planning future resource usage.

Chapter 4

Results

In this chapter, an example problem and experimental results are presented. There are six main sections within this chapter. A baseline scenario that is used for example results in later sections is presented in Section 4.1. In Section 4.2, an example of a fleet readiness prediction is demonstrated. Section 4.3 shows sensitivity analysis results for personnel skill-levels, personnel training requirements, and combinations of those two factors. Section 4.4 discusses daily maintenance operations planning. Finally, a summary of the results is presented in Section 4.5.

4.1 Procedure Example

4.1.1 Vehicle Background Information

This section presents an example used to demonstrate the procedure for fleet readiness prediction that was presented in Chapter 3. This example problem is based off a real-world problem and is modeled according to the real-life constraints of the organization. This organization consists of twenty-nine vehicles and ten mechanics and uses a planning period of seven days.

The maintenance organization being modeled has twenty-nine vehicles, which are numbered 1 through 29, with each number representing a specific vehicle. The twenty-nine vehicles are also divided into five subdivisions which are Units A, B, C, D, and E. Each vehicle has a priority for repair based on the deemed importance of the vehicle. The priority of each vehicle is either “High”, “Medium”, or “Low” and does not depend on a vehicle’s unit. The vehicles that have a “High” priority are: 1, 8, 13, 20, and 26. The vehicles that have a “Medium” priority are: 2, 7, 14, 19, and 25. All other vehicles are rated as “Low” priority. The priority rating for each vehicle corresponds to a numerical value as well which represents the *Priority* input value for the BILP. “High” priority corresponds to a value of 5, “Medium” corresponds to a value of 3, and “Low” corresponds to a value of 1.

In addition to a priority, each vehicle also has a certain probability of breakdown. This value represents the probability that a given vehicle is going to experience a breakdown on any given day and is based on historical data of the breakdowns of the vehicles. In this organization, all of the vehicles within a specific unit have the same probability of failure due to similar type vehicles and utilization within individual units. To determine whether a vehicle experiences a breakdown during a certain day in this example, a random variable is generated from a uniform probability distribution with values between zero and one. If the random variable is less than or equal to the probability of failure, then the vehicle experiences a failure during that day. If the random variable is greater than the probability of failure, the vehicle does not experience a failure during that day. Table 4-1 shows the unit, priority rating, and probability of breakdown for each vehicle in this organization.

Table 4-1. Priority and Probability of Breakdown per Vehicle

Unit	Vehicle	Priority	Prob. of Breakdown
A	1	High	0.15
A	2	Med	0.15
A	3	Low	0.15
A	4	Low	0.15
A	5	Low	0.15
A	6	Low	0.15
B	7	Med	0.1
B	8	High	0.1
B	9	Low	0.1
B	10	Low	0.1
B	11	Low	0.1
B	12	Low	0.1
C	13	High	0.15
C	14	Med	0.15
C	15	Low	0.15
C	16	Low	0.15
C	17	Low	0.15
C	18	Low	0.15
D	19	Med	0.05
D	20	High	0.05
D	21	Low	0.05
D	22	Low	0.05
D	23	Low	0.05
D	24	Low	0.05
E	25	Med	0.1
E	26	High	0.1
E	27	Low	0.1
E	28	Low	0.1
E	29	Low	0.1

4.1.2 Mechanic Background Information

The maintenance organization being modeled in this example has ten mechanics. Each of the mechanics has a different level of work experience and thus works at a different pace than the others. To account for these differences, each of the workers was given a skill-level rating by their manager based on their general performance and industry standards for mechanics. The rating was a discrete value between the numbers one and five. Lower ratings corresponded to slower, less efficient mechanics that did not have much experience and were still learning or training. Higher ratings corresponded to faster, more efficient mechanics that had much experience with repairs. Therefore the most experienced mechanics received fives and the least experienced mechanics received ones, while mechanics in the middle received twos, threes, or fours. The ratings for mechanics 1 through 10 were: 5, 3, 4, 4, 2, 2, 1, 1, 1, and 1 respectively.

To turn these standard ratings of mechanics into input data for the model, each rating was transformed into an efficiency multiplier. Based on industry-wide standards for how long it should take a mechanic of a certain skill-level to complete a given task, a multiplier was determined to represent a mechanic at a certain skill-level's ability to complete that task in a certain percentage of the standard time. Skill-level ratings of 5 were given a multiplier of 0.2 and ratings of 4 were given a multiplier of 0.4. Ratings of 3 were given a multiplier of 0.6, while ratings of 2 were given a multiplier of 0.8. Finally, ratings of 1 were given a multiplier of 1. Both ratings and multipliers for each mechanic are summarized in Table 4-2.

Table 4-2. Skill-level Ratings and Efficiency Multipliers per Mechanic

Mechanic	**Rating**	**Multiplier**
1	5	0.2
2	3	0.6
3	4	0.4
4	4	0.4
5	2	0.8
6	2	0.8
7	1	1
8	1	1
9	1	1
10	1	1

4.1.3 Failure Background Information

In this example, a vehicle breakdown represents one of twenty-four distinct component failures that were deemed to be the most common failures for this maintenance organization. Once it is determined that a vehicle is going to fail on a certain day, a random variable is generated to determine what type of failure the vehicle is going to experience. This random variable is generated from a discrete uniform distribution with values between one and twenty-four since there twenty-four different failure types. Since some repairs take longer than others, each failure type has an associated repair time based on standard times determined necessary to fix each problem. Failure types, probabilities, and repair times are summarized in Table 4-3.

Table 4-3. Probability of Failure and Repair Times per Failure Type

Failure Type	Probability of Failure	Repair Time
1	0.04	6.2
2	0.04	11.0
3	0.05	3.6
4	0.04	0.7
5	0.03	11.3
6	0.05	6.6
7	0.08	7.6
8	0.01	0.8
9	0.04	0.6
10	0.02	0.7
11	0.02	1.5
12	0.02	1.5
13	0.06	8.8
14	0.02	15.2
15	0.02	4.7
16	0.04	8.0
17	0.02	11.7
18	0.1	1.2
19	0.02	1.0
20	0.03	1.5
21	0.05	1.5
22	0.1	2.3
23	0.04	0.4
24	0.06	1.5

In addition to failure types and repair times, part delivery times and towing times are also generated for vehicles that experience a breakdown. Both part delivery times and towing times are used for only a percentage of the broken vehicles, since some parts are assumed to be available immediately and some vehicles are assumed to not require towing. Fifty percent of vehicle repairs require a part deliver time, which is generated randomly according to a uniform distribution with a minimum of zero hours and a maximum of thirty-six hours. Likewise, only thirty-three percent of vehicles require towing times, which are generated randomly according to a uniform distribution with a minimum of zero hours and a maximum of twenty-four hours.

4.1.4 Model Input Data

The information presented in the three previous sections represents the background information on the vehicles, mechanics, and failures for this organization. Next, a baseline scenario was created using the background information and then solved using the procedure.

A baseline scenario was created using the methodology outlined previously. This scenario was used to represent a specific instance of what the input data for the model might look like at a certain point in time. In this instance, there were four vehicles with non-ready statuses at the beginning of Day 1. These vehicles were vehicles 12, 19, 21, and 27. Vehicle 12 had experienced failure type 22. This failure type had a repair time of 2.3 hours and a diagnosis time of 1 hour. There was no part delivery time or towing time necessary for this vehicle. Vehicle 19 had experienced failure type 1 which had a repair time of 6.2 hours and a diagnosis time of 1 hour. In addition, the time until part delivery was 14 hours and the time until the vehicle was to be towed back was 14 hours. Vehicle 21 had experienced failure type 11 which had a repair time of 1.5 hours and a diagnosis time of 1 hour. In addition, the part delivery time was 35 hours and the towing time was 21 hours. The final vehicle was vehicle 27 which had experienced failure type 3. The necessary repair time was 3.6 hours and the diagnosis time was 1 hour. The part delivery time was 25 hours, but there was no towing time necessary for this vehicle. This information represented the input data for the BILP and is summarized in Table 4-4.

Table 4-4. Input Parameters for Baseline Scenario

Vehicle	***InitiStat***	**Priority Rating**	***Priority***	**Failure Type**	***RepTime***	***DiagTime***	***PartTime***	***TowTime***
1	1	High	5	0	0	0	0	0
2	1	Med	3	0	0	0	0	0
3	1	Low	1	0	0	0	0	0
4	1	Low	1	0	0	0	0	0
5	1	Low	1	0	0	0	0	0
6	1	Low	1	0	0	0	0	0
7	1	Med	3	0	0	0	0	0
8	1	High	5	0	0	0	0	0
9	1	Low	1	0	0	0	0	0
10	1	Low	1	0	0	0	0	0
11	1	Low	1	0	0	0	0	0
12	0	Low	1	22	2.3	1	0	0
13	1	High	5	0	0	0	0	0
14	1	Med	3	0	0	0	0	0
15	1	Low	1	0	0	0	0	0
16	1	Low	1	0	0	0	0	0
17	1	Low	1	0	0	0	0	0
18	1	Low	1	0	0	0	0	0
19	0	Med	3	1	6.2	1	14	14
20	1	High	5	0	0	0	0	0
21	0	Low	1	11	1.5	1	35	21
22	1	Low	1	0	0	0	0	0
23	1	Low	1	0	0	0	0	0
24	1	Low	1	0	0	0	0	0
25	1	Med	3	0	0	0	0	0
26	1	High	5	0	0	0	0	0
27	0	Low	1	3	3.6	1	25	0
28	1	Low	1	0	0	0	0	0
29	1	Low	1	0	0	0	0	0

The remaining pieces of input data necessary for this example problem were the available working hours per day per mechanic. All other input data values for Day 1 were the same in all runs of this example. However, the schedule of availability of mechanics was changed for each run since the effects of different schedules was being considered. The formula for calculating sample size in steady-state simulations was used to determine the number of runs necessary to generate results at a 90% confidence level and an acceptable error value of 0.10. An initial set of runs was performed and the initial estimate of the variance was found to 0.80. Therefore, it was found that 220 runs needed to be performed to achieve the specified confidence level. Then using the personnel simulation described in Section 3.3, 220 different weekly personnel scenarios were generated. An example scenario is shown in Table 4-5.

Table 4-5. Sample Personnel Schedule for Baseline Scenario

Mechanic	Day1	Day2	Day3	Day4	Day5	Day6	Day7
1	0	0	8	0	8	8	0
2	8	0	0	0	0	8	0
3	8	0	0	8	0	8	8
4	0	0	0	8	0	0	0
5	0	0	0	0	8	0	0
6	8	0	8	0	0	0	0
7	0	0	7	7	7	0	0
8	0	0	7	7	0	7	7
9	0	0	7	7	7	0	0
10	0	0	0	0	0	7	7

4.2 Baseline Scenario Readiness Results

Presented next in this work is a fleet readiness prediction for the baseline scenario. 220 runs of the procedure were performed using the baseline scenario presented above in Section 4.1.4 as the initial input parameters. Each run evaluated a different weekly personnel schedule, as well as different sets of random breakdowns throughout the seven-day horizon. The final status of each vehicle was collected from each run and averaged to find a sample average. This value represents the average probability that a particular vehicle will have a ready status at the end of the seventh day when subjected to random personnel availabilities and vehicle breakdowns. All probabilities also include a plus-or-minus value that can be added or subtracted to the average in order to determine the 90% confidence level. These values are summarized in Table 4-6.

Table 4-6. Probability of Ready Status at the end of the 7-day Period per Vehicle

Vehicle	Probability of Ready Status	Confidence Interval (+/-)
1	0.814	0.043
2	0.805	0.044
3	0.786	0.046
4	0.773	0.047
5	0.750	0.048
6	0.727	0.050
7	0.836	0.041
8	0.823	0.042
9	0.814	0.043
10	0.845	0.040
11	0.759	0.048
12	0.845	0.040
13	0.745	0.048
14	0.755	0.048
15	0.764	0.047
16	0.755	0.048
17	0.786	0.046
18	0.786	0.046
19	0.918	0.030
20	0.914	0.031
21	0.882	0.036
22	0.927	0.029
23	0.864	0.038
24	0.914	0.031
25	0.795	0.045
26	0.832	0.042
27	0.795	0.045
28	0.859	0.039
29	0.823	0.042

As expected, those units with a lower probability of breakdown (e.g. Unit D) had the highest readiness probabilities. Similarly, those units with higher probabilities of breakdown (e.g. Units A and C) had the lowest readiness probabilities. These results are demonstrated in Figure 4-1.

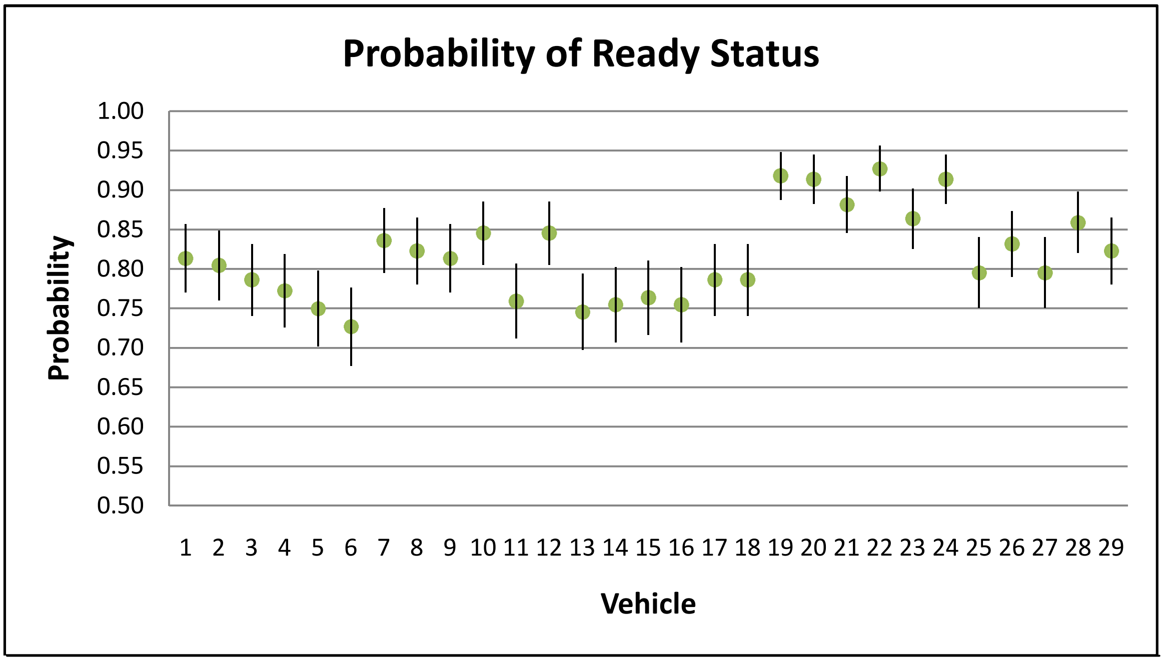

Figure 4-1. Probability of Ready Status after 7-days for Baseline Scenario

4.3 Sensitivity Analysis of Personnel Factors

This section reviews the results of sensitivity analysis that was performed on the factors affecting the skill-level and training requirements of the personnel. It is divided into three subsections. Section 4.3.1 discusses sensitivity analysis on the skill-level factor. Section 4.3.2 discusses sensitivity analysis on the training requirements factor. Lastly, Section 4.3.3 discusses sensitivity analysis on combinations of both factors.

4.3.1 Analysis of Mechanic Skill-Level

The objective of this part of the sensitivity analysis was to determine how different combinations of skill-levels across the ten mechanics affected the overall readiness level of the vehicles at the end of the seventh day. As mentioned previously in Section 4.1, the skill-level ratings of mechanics 1-10 in the baseline scenario were 5, 3, 4, 4, 2, 2, 1, 1, 1, and 1, respectively. Therefore, the average skill-level rating across all the mechanics in the baseline scenario was 2.4. In order to determine the significance of the skill-levels of the mechanics, analysis was performed with different combinations of mechanic skill levels. Four different combinations were created using the average skill-level across ten mechanics as the defining characteristic. The four scenarios tested were a 50% decrease, a 25% decrease, a 25% increase, and a 50% increase in average skill-level. Each of these scenarios represented a combination of skill-levels across the ten mechanics that averaged to a given value of 1.2, 1.8, 3.0, and 3.6, respectively. These scenarios are summarized in Table 4-7.

Table 4-7. Scenarios for Mechanic Skill-Level Analysis

	Mechanic Skill-Level				
Mechanic	***Baseline***	***50% decrease***	***25% decrease***	***25% increase***	***50% increase***
1	5	2	4	5	5
2	3	2	4	5	5
3	4	1	2	4	5
4	4	1	2	4	4
5	2	1	1	3	4
6	2	1	1	3	3
7	1	1	1	2	3
8	1	1	1	2	3
9	1	1	1	1	2
10	1	1	1	1	2
Average	**2.4**	**1.2**	**1.8**	**3**	**3.6**

Each of these skill-level combinations was run 220 times using the personnel schedules generated for the baseline scenario in order to hold the availability and training requirements constant. Once all the runs were completed for each scenario, the average probability of readiness per vehicle and related confidence intervals were calculated. Then the minimum, maximum, and average across all 29 vehicles was determined for each scenario.

The scenario with the absolute minimum probability of readiness across all 29 vehicles was the 50% decrease, with a minimum value of 0.56. The scenario that had the maximum probability across all vehicles was the 25% increase scenario, with a value of 0.95. The scenario with the lowest average probability was the 50% decrease with a value of 0.73. The two scenarios with the highest average were the 25% increase and the 50% increase with values of 0.83. These results are summarized in Table 4-8.

Table 4-8. Summary of Results for Skill-Level Analysis

	Scenario				
	50% Decrease	*25% Decrease*	***Baseline***	*25% Increase*	*50% Increase*
Average Rating	*1.2*	*1.8*	*2.4*	*3*	*3.6*
Min Prob. of Readiness	0.56	0.67	0.73	0.74	0.72
Max Prob. of Readiness	0.92	0.93	0.93	0.95	0.93
Avg Prob. of Readiness	0.73	0.80	0.82	0.83	0.83

In addition to collecting the minimum, maximum, and average probabilities for each scenario individually, average probabilities per vehicle were graphed alongside all the other different skill-level scenarios. This graph showed several main themes, all of which were expected. The first is that the 50% decrease scenario consistently had lower average probabilities than the other four scenarios. Likewise, the 25% decrease scenario generally had lower probabilities than the 50% increase, 25% increase, and baseline scenario. Meanwhile, the 50% increase scenario generally had the highest probabilities and the 25% increase generally had the second highest probabilities. These results are demonstrated in Figure 4-2.

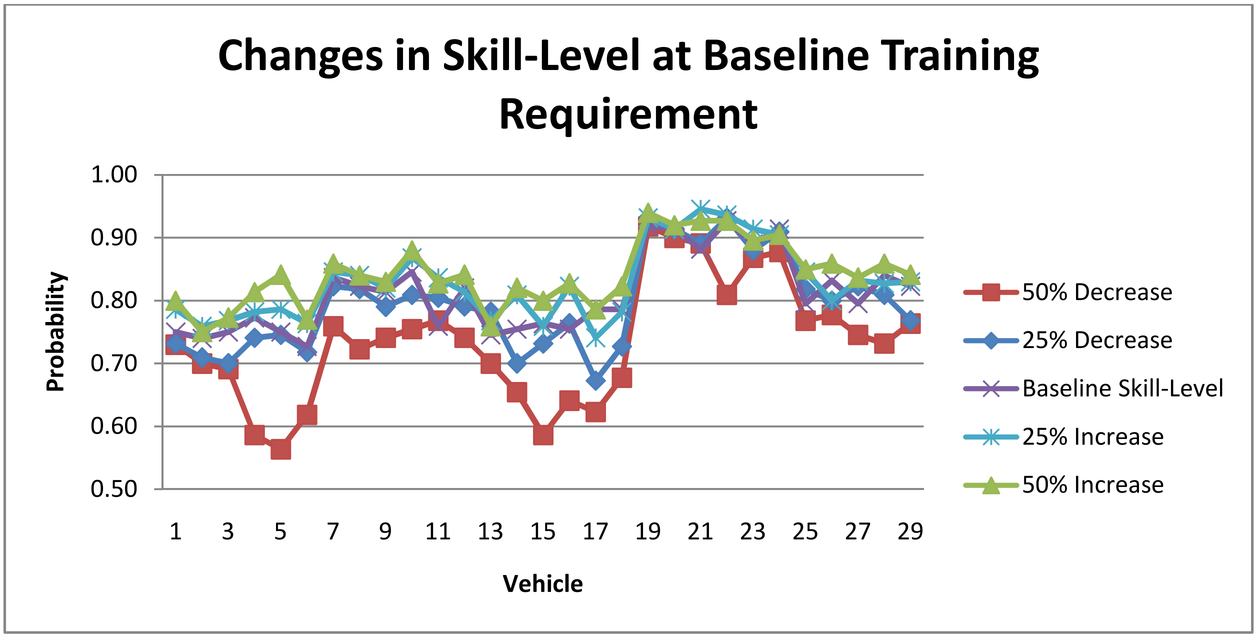

Figure 4-2. Average Probability per Vehicle in Different Skill-Level Scenarios

4.3.2 Analysis of Training Requirements

The objective of this part of the sensitivity analysis was to determine how different training requirements for the mechanics affected the overall readiness level of the vehicles at the end of seven days. As mentioned previously, the baseline assumption for training requirements was that mechanics with a skill-level rating of 1 spent one hour of their working hours on training and all other mechanics (skill-level ratings 2-5) spent zero hours of their working hours on training. Therefore, in order to test the effects of training requirements, three new training scenarios were developed. The first scenario was a zero-hour requirement in overall training requirements. This meant that the training hour requirement for all mechanic skill-levels was zero hours. The next scenario was a one-hour requirement, which meant that all mechanics had a requirement of one hour. Finally, the third scenario consisted of a two-hour training requirement for all mechanics. These scenarios are summarized in Table 4-9.

Table 4-9. Scenarios for Training Requirement Analysis

	Training Requirements (Hrs per day)			
Skill-Level	***0-hour***	***Baseline***	***1-hour***	***2-hour***
1	0	1	1	2
2	0	0	1	2
3	0	0	1	2
4	0	0	1	2
5	0	0	1	2

Each of these training requirement scenarios was run 220 times using the personnel schedules generated for the baseline scenario. However, prior to each run, the values assigned to each mechanic were first adjusted to meet the new training requirements. This means that mechanic availabilities and skill-levels were the same as the baseline scenario, but each mechanic was subjected to a slightly different training hour requirement.

Upon completion of all runs for each scenario, the average probability of readiness per vehicle was calculated across all 220 runs. Then the minimum, maximum, and average across all 29 vehicles was determined for each scenario. The scenario with the minimum probability of readiness across all 29 vehicles was the 2-hour scenario with a value of 0.70. The 1-hour scenario had the maximum probability value of 0.95. The scenario with the lowest average probability was the 2-hour requirement with a value of 0.81. The three scenarios with the highest average were the 0-hour requirement, the baseline requirement, and the 1-hour requirement with a value of 0.82. These results are summarized in Table 4-10.

Table 4-10. Summary of Results for Training Requirement Analysis

	Scenario			
	0-hr	***Baseline***	*1-hr*	*2-hr*
Training Requirement: Skill-level 1	*0*	*1*	*1*	*2*
Training Requirement: Skill-levels 2-5	*0*	*0*	*1*	*2*
Min Prob. of Readiness	0.72	0.73	0.73	0.70
Max Prob. of Readiness	0.94	0.93	0.95	0.93
Avg Prob. of Readiness	0.82	0.82	0.82	0.81

In addition to collecting the minimum, maximum, and average probabilities for each scenario individually, average probabilities per vehicle were graphed alongside all the other different training requirement scenarios. This graph showed several main themes. The first theme was that the 2-hour training requirement scenario consistently had lower average probabilities than the other three scenarios. In contrast, the 0-hour training requirement scenario generally had the highest probabilities. Meanwhile, the baseline and 1-hour training requirement scenarios tended to have probabilities between the other two scenarios. Although differences in values between scenarios did occur, these differences were much smaller than the differences in probabilities between skill-level scenarios. This seemed to suggest that changes in skill-level had a more significant impact on readiness levels than changes in training requirements. The training requirement results are demonstrated in Figure 4-3.

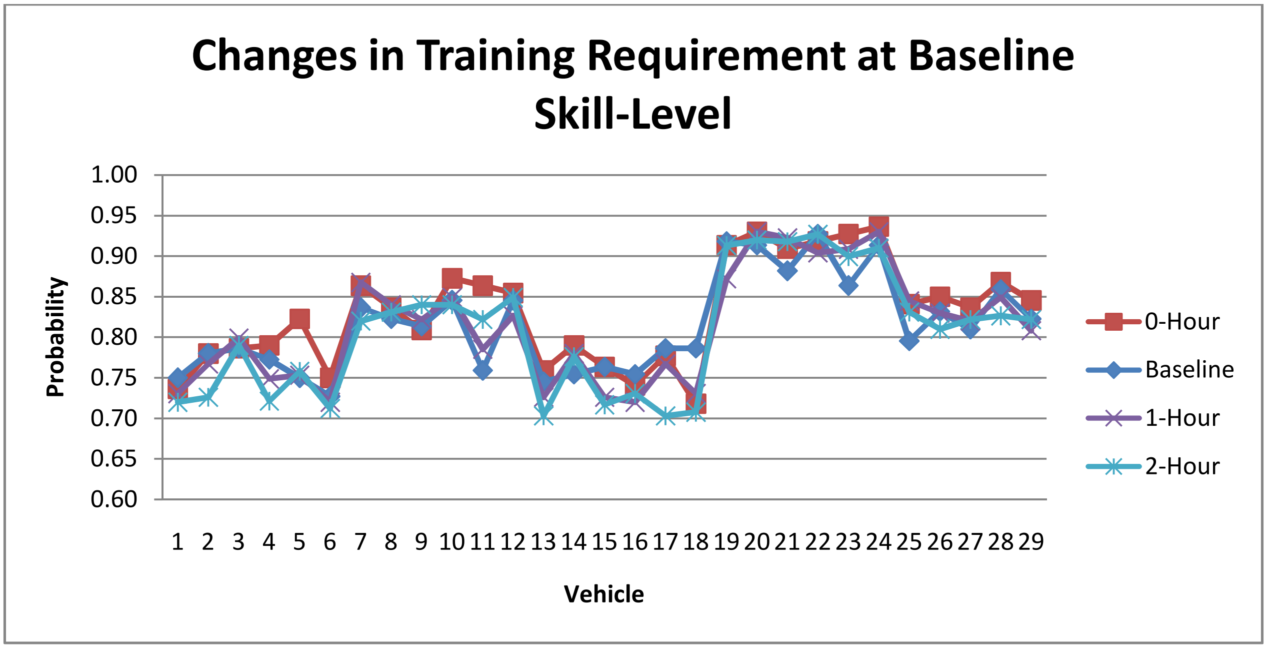

Figure 4-3. Average Probability per Vehicle in Different Training Requirement Scenarios

4.3.3 Analysis of Skill-Level and Training Requirements

The objective of this part of the sensitivity analysis was to determine how different combinations of mechanic skill-levels and training requirements affected the overall readiness level of the vehicles at the end of the seventh day. Twenty different combinations were tested using the different scenarios described in the previous two sections. These combinations are listed in Table 4-11.

Table 4-11. Combinations of Multi-Factor Analysis

Combo #	Skill-Level Scenario	Training Requirement
1	Baseline	Baseline
2	25% decrease	Baseline
3	50% decrease	Baseline
4	25% increase	Baseline
5	50% increase	Baseline
6	Baseline	0-hour
7	25% decrease	0-hour
8	50% decrease	0-hour
9	25% increase	0-hour
10	50% increase	0-hour
11	Baseline	1-hour
12	25% decrease	1-hour
13	50% decrease	1-hour
14	25% increase	1-hour
15	50% increase	1-hour
16	Baseline	2-hour
17	25% decrease	2-hour
18	50% decrease	2-hour
19	25% increase	2-hour
20	50% increase	2-hour

Like in the previous two analyses, each of these skill-level and training requirement combinations was run 220 times using the appropriate personnel schedule for the situation. Once all the runs were completed for each multi-factor combination, the average probability of readiness per vehicle was calculated. Then the minimum, maximum, and average of all 29 vehicles was determined for each combination.

When reviewing the results, it is important to keep in mind that generally a decrease in skill-level decreases the efficiency of the mechanics resulting in a lower overall readiness. Conversely, a decrease in training requirements generally increases overall readiness since mechanics spend less time in training and more time repairing vehicles. Upon reviewing the results, it was found that the combination with the minimum probability of readiness equal to 0.54 was the 50% decrease in skill-level-2-hour training requirement. Two combinations resulted in a maximum probability of 0.95. These combinations were the 50% increase in skill-level-0-hour training requirement and the 25% increase in skill-level-0-hour training requirement. The combination with the lowest average probability equal to 0.69 was the 50% decrease in skill-level-2-hour training requirement. Finally, there were several combinations that resulted in the highest average probability, a value of 0.83. The results for all the combinations are summarized in Table 4-12.

Table 4-12. Summary of Results for Multi-Factor Analysis

More Time to Repair ⟷ Less Time to Repair

			Training Requirement											
			0-hour			**Baseline**			**1-hour**			**2-hour**		
			Min	*Max*	*Avg*	*Min*	*Max*	*Avg*	*Min*	*Max*	*Avg*	*Min*	*Max*	*Avg*
Less Efficient	**Skill-Level**	**50% Decrease**	0.63	0.93	0.76	0.56	0.92	0.73	0.55	0.89	0.72	0.54	0.89	0.69
↑		**25% Decrease**	0.71	0.94	0.81	0.67	0.93	0.80	0.68	0.93	0.79	0.65	0.94	0.76
		Baseline	0.72	0.94	0.82	0.73	0.93	0.82	0.73	0.95	0.82	0.70	0.93	0.80
↓		**25% Increase**	0.73	0.95	0.83	0.74	0.94	0.83	0.73	0.93	0.82	0.70	0.94	0.82
More Efficient		**50% Increase**	0.70	0.95	0.83	0.72	0.93	0.83	0.72	0.93	0.83	0.71	0.94	0.82

In addition to collecting the minimum, maximum, and average probabilities for each combination individually, graphs for multiple combinations at a time were created. In each of these graphs one specific scenario for either skill-level or training requirement was held constant. Then the other factor (skill-level or training) was graphed at its different levels. For example, skill-level was held constant at 50% decrease and then the average probability per vehicle at 0-

hour, baseline, 1-hour, and 2-hour training requirements were plotted. This resulted in nine different graphs which can be found in Figures A-1 through A-9 of the Appendix.

4.4 Daily Maintenance Operations Planning

Although generation of fleet readiness predictions was the main contribution of this work, another slightly less important function of this procedure was to also serve as a tool for daily maintenance scheduling. This section details a brief example of how a sample maintenance schedule might be generated using the methods in this research. Once again, the baseline scenario described in Section 4.1.4 was used for this example.

Using the model for daily maintenance operations planning, the planner would input the initial inputs for the start of Day 1 and then optimize the model. The planner would then use the results of the model to schedule activities. For example, the model might result in mechanic 2 repairing vehicle 12 and mechanic 7 repairing vehicle 19. Thus the maintenance scheduler would schedule mechanic 2 to repair vehicle 12 and mechanic 7 to repair vehicle 19. All other mechanics would be scheduled to perform other tasks around the shop but not to fix any specific vehicles. Meanwhile, throughout the course of Day 1, vehicles 7 and 9 also experienced failures. Thus at the beginning of Day 2 the planner would update the inputs to the model and re-optimize it resulting a new a schedule for Day 2. In this fashion, the maintenance operations planner could determine each day's work by optimizing the model for a given set of constraints on a given day.

4.5 Summary of Results

This chapter presented the results from an example application of the methodology. The first section outlined the background information for the problem and the formulation of a baseline scenario that was used in the example scenario. Next, a sample fleet readiness prediction was presented showing the average probability of readiness for a fleet of vehicles based on 220 runs of the baseline scenario. The third section presented the results of sensitivity analysis. These results showed analysis of runs for different values of mechanic skill-levels, different values of mechanic training requirements, and for different combinations of skill-levels and training requirements. Finally, the fourth section presented a brief example of how a daily maintenance schedule might be generated.

Chapter 5
Discussion

In this chapter, the different results outlined in Chapter 4 are discussed. Section 5.1 discusses the importance and usefulness of the fleet readiness prediction. Section 5.2 discusses the sensitivity analysis performed on the personnel factors and their implications. Section 5.3 discusses the relevance of daily maintenance planning by a maintenance planner. Finally, Section 5.4 gives a brief summary of the chapter.

5.1 Discussion of Fleet Readiness Prediction

. The results from 220 independent runs of the baseline scenario were compiled and presented in Section 4.2. This section discusses the usefulness and importance of those results. As explained previously, each run of the baseline scenario produced an average probability for each vehicle indicating the likelihood that a particular vehicle will be ready at the end of the seven-day planning period. Analyzing the values for a single vehicle across all 220 runs produces a good prediction of what the vehicle's status will be since the 220 runs were all subjected to different personnel scenarios and random vehicle breakdowns.

Examining the results in Table 4-6, which summarizes the probability of a ready status for each of the 29 vehicles, an operations planner can obtain some useful insights about the state of the fleet at the beginning of the time period being planned. In Table 4-6, it is shown that vehicles 19, 20, and 24 have the probability of being ready equal to 0.918, 0.914, and 0.914 respectively. These results indicate that these vehicles are the most reliable and the most likely to be ready at the start time. An operations planner might look at these vehicles and decide to use these certain vehicles over other vehicles with a lower probability of being ready. Doing so lowers the probability that at the start of a planned operation, a vehicle that was planned to be used is broken down and alternative planning must be done quickly.

Table 4-6 not only indicates which vehicles are most reliable, but also which vehicles are least reliable. Vehicles 5 and 6 each have the low probability of being ready, equal to values of 0.756 and 0.727, respectively. This means that there is approximately a one out of four chance that each of these vehicles will not be functioning at the start of the future operation. Therefore, a planner might look at these vehicles and decide not to plan to use these vehicles since they have a higher probability of not being ready. Again, this will lessen the likelihood that operations will be planned around a vehicle that is more likely to be broken at the start of the operational period.

Knowing which vehicles are most reliable and which vehicles are least reliable gives a good indication of what can be expected of the vehicles. This information can be used to decide which vehicles to use and which vehicles to not use. If a vehicle's associated probability does not meet a probability threshold for a given task, that vehicle is not included in the task. However, if the task calls for all the vehicles to be utilized, this information can also serve as a guide in determining how each vehicle should be used. More reliable vehicles should be given tasks that are more critical to the success of the total operation. Likewise, less critical tasks that will not affect the success of the total operation should be allotted to the less reliable vehicles. In this way, an operations planner can use these fleet readiness predictions to help not only determine which vehicles should be used for a given operation, but also what tasks should be designated to each vehicle in order to increase the probability of successful completion of the objectives of the total operation.

5.2 Discussion of Sensitivity Analysis

This section discusses the trends and uses of the personnel factors sensitivity analysis presented in Section 4.3, which focused on three main sets of results. The first set of results was from sensitivity analysis on the skill-levels of the mechanics and was summarized in Table 4-8. The values in this table demonstrated some trends that were to be expected. In general, when moving from left to right, the probabilities in the table increased. This result makes sense because the left-most column of the table represented the 50% decrease scenario, which is the scenario with the lowest average mechanic skill-level. The right-most column represented the 50% increase scenario, which means it was the scenario with the highest average mechanic skill-level. Although the general trend persisted throughout the table, there were a few values that did not follow it. These values are believed to be the result of much variability in the occurrence of vehicle breakdowns.

Table 4-10 showed the results from the sensitivity analysis of the training requirements. Like the results from the mechanic skill-level analysis, the training requirement results also demonstrated some general trends. When moving from left to right, probability values tended to decrease. This trend makes sense since moving from left to right represented moving from the least amount of training required to the most amount of training required, or the 0-hour requirement scenario to the 2-hour requirement scenario. Although the trend persisted, it occurred to much less of an extent than the trend in the skill-level results. This would therefore imply that a change in mechanic skill-level has a far greater impact on overall readiness level than a change in training requirements.

Regardless of which factor is being changed, these values and trends are particularly useful if the planner has a certain readiness probability threshold he wishes to maintain. If the organization's current average readiness is 0.80 and they wish to increase that value by 0.03, they would need to increase their current average skill-level by at least 25%. It is also possible that an organization has several under-utilized mechanics and can complete tasks with a threshold minimum probability value of 0.65. In this case a planner might recommend reassigning mechanics in order to obtain a 25% decrease in average skill-level which would still result in a 0.67 minimum probability of readiness. Similar choices and determinations can be made using the results and trends of the training requirement analysis. For example, if a company is looking to increase training requirements but maintain a minimum probability of readiness of 0.70, the planner would know that a 2-hour increase in training requirements would achieve this goal.

A third set of results was generated from the analysis of combinations of skill-level and training requirements and was summarized in Table 4-12. These results demonstrated the effects of simultaneous changes in both skill-level and training requirements. Two general trends were observed in this data. The first trend was that most values decreased when moving from left to right. This makes sense because moving from left to right represented an increase in training requirements which meant mechanics had less time to repair vehicles. The second trend was that most values increased when moving from top to bottom within the table. This trend also makes sense since moving in this fashion represented increasing the average skill-level the mechanics.

Combining these two trends, it would make sense that the lowest probability values would be found in the top-right corner of the table. In contrast, the highest probability values would be found in the bottom-left corner of the table. Looking at the results, it can be seen that this was indeed the case. The lowest average probability value was 0.69 and was found in the 50% decrease-2-hour scenario in the top-right. The highest average probability value was 0.83 and was found in the 50% increase-0-hour scenario in the bottom-left. This value was also found in some of the cells surrounding that specific cell, but still in the same general area of the table.

Particular values and trends can be extremely useful in both future company operations planning and maintenance operations planning. A planner could look at the effects of changes in skill-levels of mechanics or training requirements individually, or he or she could look at the combined effects. For example, if a new set of training courses is being implemented which amounts to a 2-hour increase in overall training requirements, a planner might look and see that this will cause the average probability to be 0.80. If this average probability does not meet a determined probability threshold, say 0.82, the planner might recommend increasing the average skill-level by 25%. Thus the increase in training requirements can be compensated for by increasing the skill-level, and the overall average probability level will remain about the same at 0.82. In a similar fashion, if the threshold level is set to be 0.75, then the planner might recommend a 25% decrease in skill-level. This would then allow the under-utilized mechanics to spend their time on other jobs such as preventive maintenance tasks or training other mechanics.

5.3 Discussion of Daily Maintenance Operations Planning

This section discusses the uses of the model for daily maintenance planning presented in Section 4.4. The information that can be gained in this way is useful in that it indicates which vehicles should be fixed on a certain day. It also tells which mechanic should repair that vehicle. Since not all mechanics work at the same rate of efficiency, designating mechanics to specific jobs becomes important. For example, assume there are two repairs that need to be made, one quick repair and one long repair. Furthermore, one mechanic has an efficiency rating of 5 and the other mechanic has a rating of 2. In order to get both of these vehicle repaired as soon as possible, it is better to let the first mechanic handle the more complicated repair since he is more experienced and works much more efficiently. The less experienced mechanic can work on the repair that takes less time and will be able to get that vehicle working much sooner than if he did the longer repair on the other vehicle. Therefore, at the end of the day, it is much more likely that both vehicles will be fully repaired. The optimization model automatically makes these decisions and designates which vehicles should be repaired by which mechanic in order to maximize the number of vehicles repaired at the end of the day. Thus instead of a maintenance scheduler spending time and effort trying to determine the daily maintenance activities, he can look at the results of the optimization, assign tasks to all the mechanics, and repairs can begin sooner.

5.4. Summary

The sections in this chapter discussed and demonstrated the importance of the results presented in Chapter 4. First the usefulness of readiness predictions in operations planning was discussed. A planner can make informed decisions on which vehicles to select for certain tasks based on the likelihood that they will be operational at the start of a task. Next, the results of the sensitivity analysis were discussed. These results proved to be very useful in decision-making regarding personnel factors by helping to determine what the effects of changes in certain factors would be on overall readiness levels. Finally, an example of how daily maintenance operations might be scheduled was discussed. Maintenance operation schedulers can use this tool to help better organize daily operations within the maintenance unit.

6.1 Conclusions

The planning of future operations is an important and sometimes complex process that is found in all types of industry. One particularly essential aspect to this process is the planning of resource utilization. Knowledge about the future state of resources at the start of any operation can be very helpful in making informed decisions on how to best achieve the goals of a particular operation. The capacity to predict overall readiness for a fleet of resources proves to be an extremely useful aid in planning operations in any type of industry, whether it is for machines in manufacturing plants or vehicles in a motor pool. Good predictions about readiness levels lead to better planning which ultimately leads to better outcomes.

The objective of this research was to develop a procedure that produces predictions of readiness levels for a fleet of vehicles that can be used as an aid to planning future operations. These readiness predictions can be used to make informed decisions about which vehicles to utilize for specific tasks at a certain time in the future. A second objective for this planning procedure was to test readiness levels' sensitivity to certain factors that affect the net resource pool. Relevant literature has shown that personnel constraints can have a significant effect on results and thus skill-levels, training requirements, and availabilities of mechanics were incorporated to the procedure to determine their effects on overall results. Finally, this planning procedure can also serve as an aid for planning daily maintenance operations. Proper allocation of labor resources saves a planner time and effort and also leads to better overall readiness levels.

The procedure presented in this work has demonstrated a strong ability to meet these objectives. An example scenario was used to demonstrate the ability of the procedure to create a fleet readiness prediction. These results can serve as very useful aids in overall operations planning and in daily maintenance scheduling. The results of this process can help make informed decisions on resource utilization for both vehicles and mechanics. In addition, they also save a planner much time per day and provide him or her with some confidence in their decisions. The sensitivity analysis also proved a useful aid in operational decisions for maintenance planning. Strategic decisions on changes to training requirements and/or average skill-levels can be evaluated with this process and help maintain overall readiness levels of a certain threshold. Overall, this procedure has proven a very useful aid in the planning of many different aspects of maintenance operations.

6.2 Future Research

Although this research has demonstrated its ability to serve as a tool in operations planning, there are many other extensions that might enhance or extend its capabilities further. Expanding the process to a larger scale might be extremely useful for larger fleets of resources. Although, this would surely make the problem more complex, it would be useful for gaining knowledge on a more robust scale.

Another area for future research might include using stochastic values for repair times instead of deterministic ones. This would introduce even more variability into the system and would tend to generate even more realistic results. Furthermore, relaxing some of the assumptions in the binary integer linear program might also increase the realness of this model. One assumption that might be relaxed is the assumption that all mechanics are trained to make all repairs. However, in some cases, mechanics may be specialized for certain jobs and not able to do all repairs. Thus refining the BILP to account for these differences might prove more useful for certain situations. Originally this model was designed to be a simple and easy-to-use tool for aid in operations planning and although relaxing the assumptions will certainly increase the complexity of the process, it might also lead to some new and useful results.

A third area that also might help enhance this process would be to incorporate other types of maintenance tasks. The current process only accounts for unscheduled breakdowns that are not planned for in advance. Incorporating planned maintenance operations would help create a more realistic and useful tool that can be used to plan multiple aspects of maintenance work.

Appendix

Probability Graphs for Multi-Factor Combination Analysis

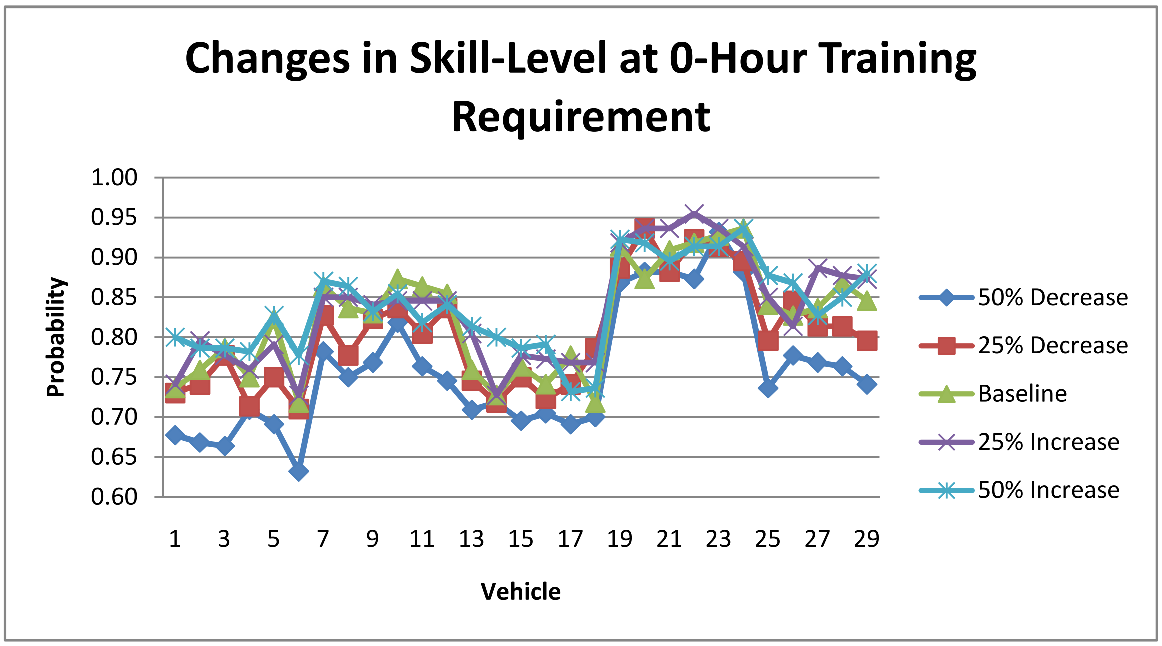

Figure A-1. Skill-Level Scenario Comparison at Constant 0-Hour Training Requirement

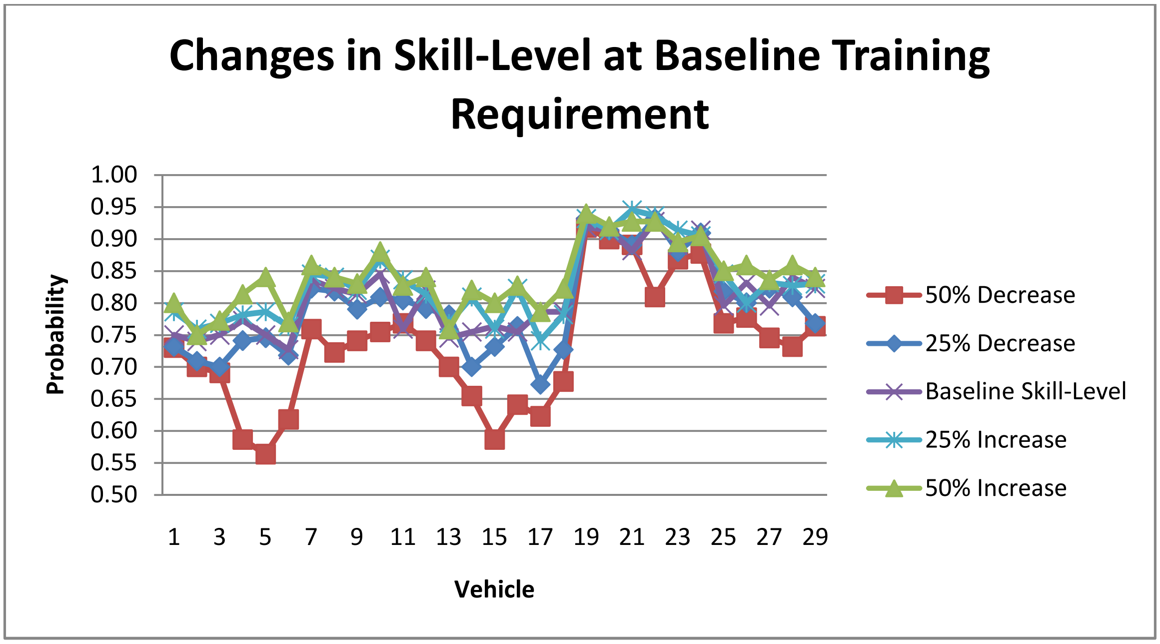

Figure A-2. Skill-Level Scenario Comparison at Constant Baseline Training Requirement

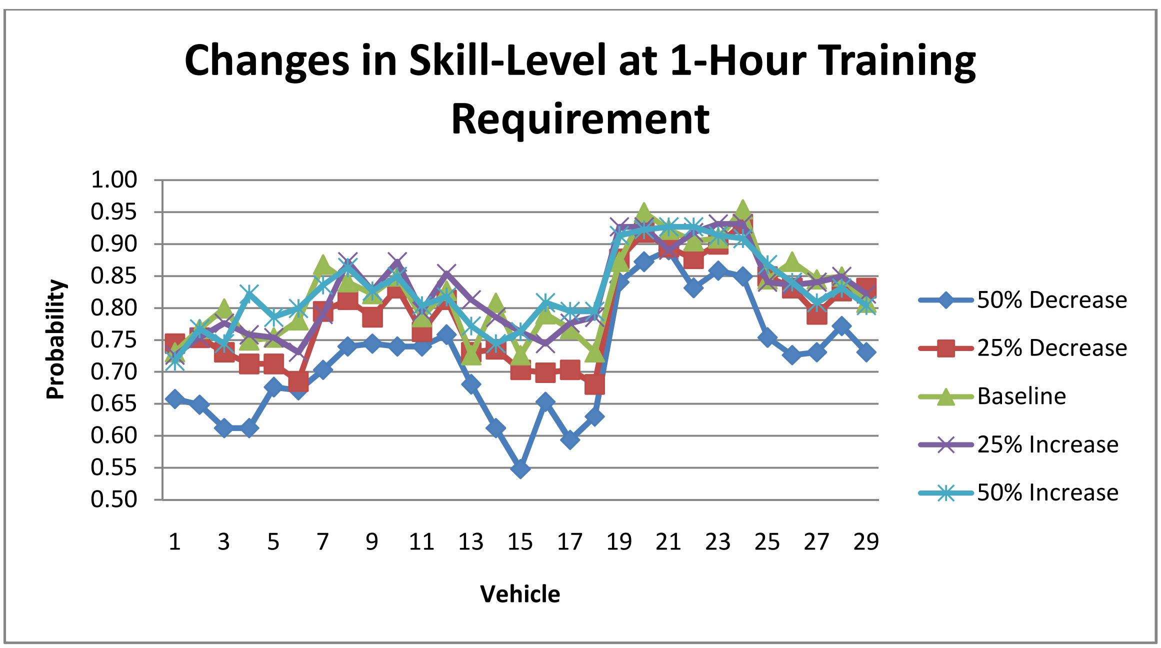

Figure A-3. Skill-Level Scenario Comparison at Constant 1-Hour Training Requirement

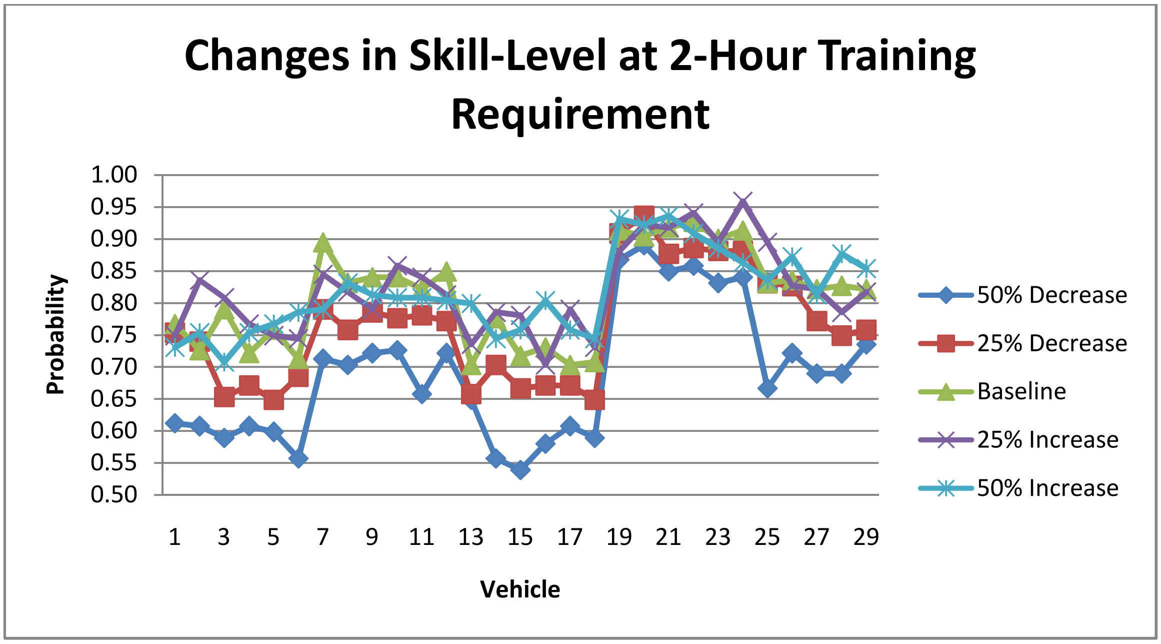

Figure A-4. Skill-Level Scenario Comparison at Constant 2-Hour Training Requirement

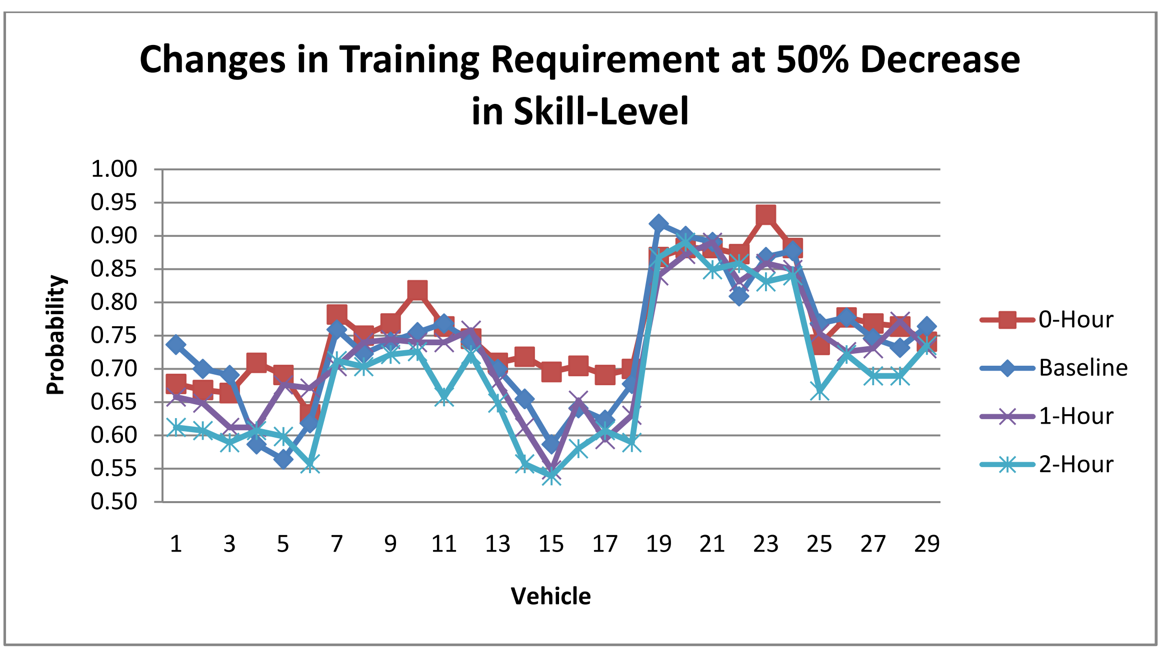

Figure A-5. Training Req. Scenario Comparison at Constant 50% Decrease Skill-Level

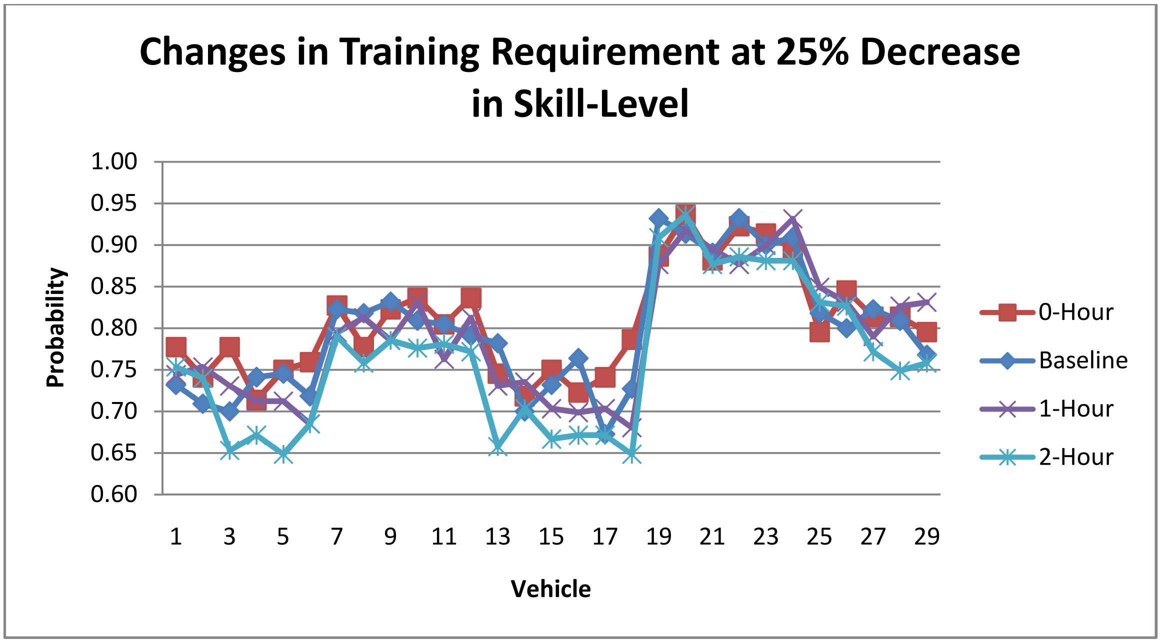

Figure A-6. Training Req. Scenario Comparison at Constant 25% Decrease Skill-Level

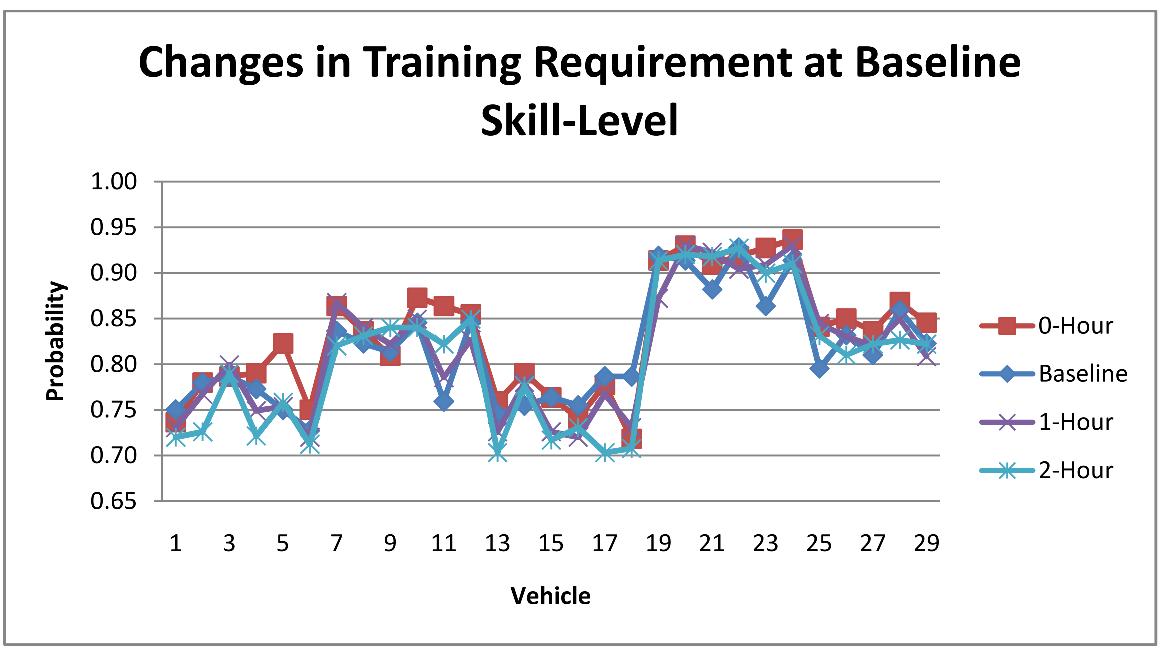

Figure A-7. Training Req. Scenario Comparison at Constant Baseline Skill-Level

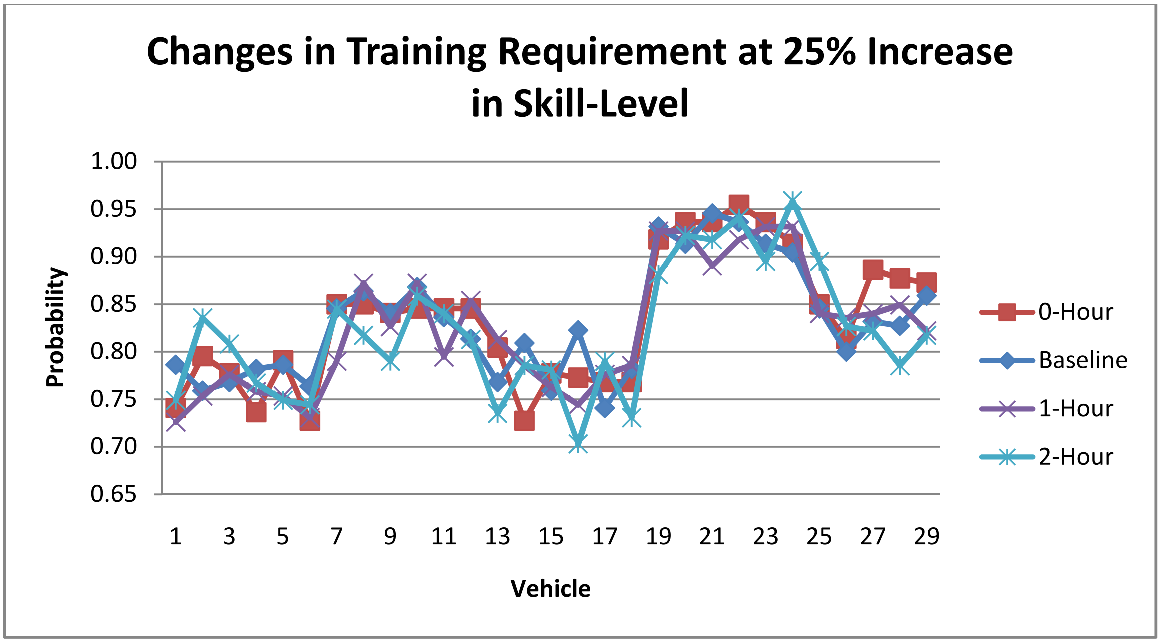

Figure A-8. Training Req. Scenario Comparison at Constant 25% Increase Skill-Level

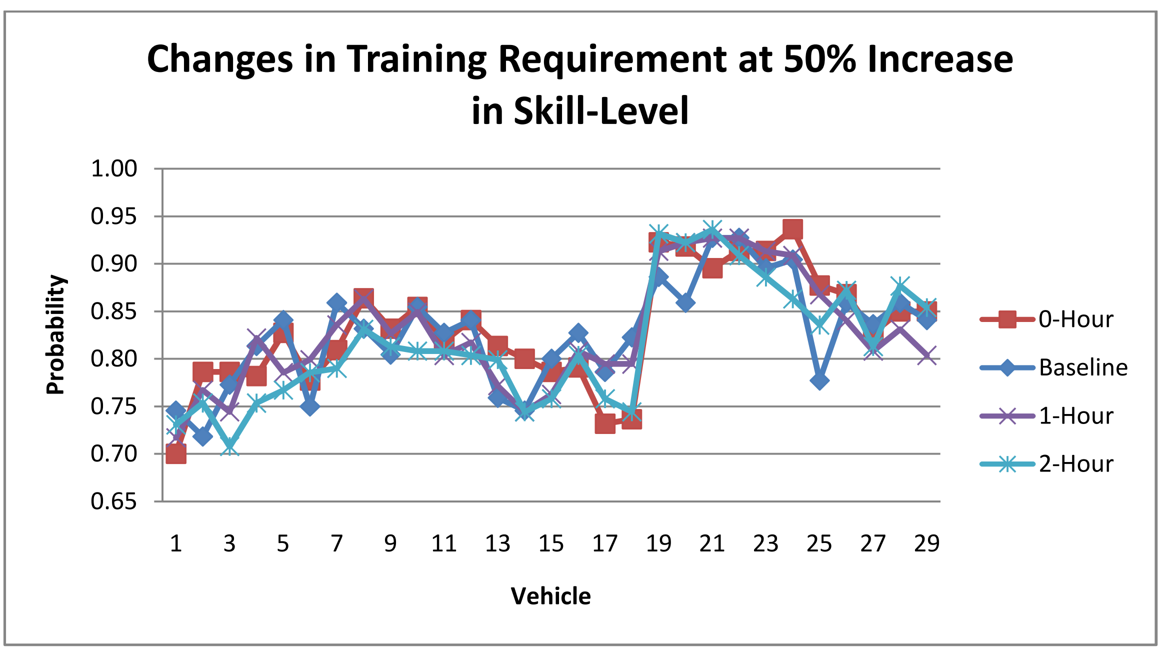

Figure A-9. Training Req. Scenario Comparison at Constant 50% Increase Skill-Level

Bibliography

Bard, J., & Purnomo, H. (2005). Hospital-wide reactive scheduling of nurses with preference considerations. *IIE Transactions , 37* (7), 580-608.

Bard, J., & Wan, L. (2005). Weekly scheduling in the service industry: an application to mail processing and distribution centers. *IIE Transactions , 37* (5), 379-396.

Black, S. E., & Keller, K. J. (2003). Calculating and Predicting Mission and Fleet Readiness. *AUTOTESTCON (Proceedings)* (pp. 687-693). Institute of Electrical and Electronics Engineers Inc.

Cassady, C., Murdock, W., Nachlas, J., & Pohl, E. (1998). Comprehensive Fleet Maintenance Management. *SMC'98 Conference Proceedings. 1998 IEEE International Conference on Systems, Man, and Cybernetics* (pp. 4665-4669 vol. 5). New York, NY: IEEE.

Chattopadhyay. (1998, November). A Practical Maintenance Scheduling Program: Mathematical Model and Case Study. *IEEE Transactions on Power Systems , 13* (4), pp. 1475-1580.

Chiesa, S., Quer, S., Corpino, S., & Viola, N. (2009). Heuristic and exact techniques for aircraft maintenance scheduling. *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering , 223* (7), 989-999.

Cortez, J., Keller, K., & Poblete, J. (2008). Establishing an Approach to Systematically Improve the Effectiveness of Fleet Support. *Proceedings IEEE AUTOTESTCON 2008* (pp. 169-175). Piscataway, NJ: IEEE.

Dekker, R. (1996). Applications of maintenance optimization models: a review and analysis. *Reliability Engineering & System Safety , 51* (3), 229-240.

Duffuaa, S., & Al-Sultan, K. (1997). Mathematical programming approaches for the management of maintenance planning and scheduling. *Journal of Quality in Maintenance Engineering , 3* (3), 163-176.

Dunst, J., & Fry, K. (1997). An Approach to Assessing Readiness Based Logistis Support Policies. *Naval Engineers Journal , 109* (1), 195-203.

Haghani, A., & Y, S. (2002). Bus maintenance systems and maintenance scheduling: model formulations and solutions. *Transportation Research, Part A (Policy and Practice) , 36A* (5), 453-482.

Howe, J. A., Thoele, B. A., Pendley, S. A., Antoline, A. F., & Golden, R. D. (2009). Beyond Authorized versus Assigned: Aircraft Maintenance Personnel Capacity. In A. B. Badiru, & M. U. Thomas, *Handbook of Military Industrial Engineering* (pp. 15.1-15.13). Boca Raton: CRC Press.

J.G., D., Lynch, K., Masters, J., Tripp, R., & Roll Jr, C. (2008). *Options for Meeting the Maintenance Demands of Active Associate Flying Units.* Santa Monica, CA: RAND Corporation.

Jurges, G. (1999). Performance Based Simulation Modeling Quantifies Aircraft Carrier Life Cycle Cost and Readiness. *Naval Engineers Journal , 111*, 27-38.

Leou, R.-C. (2001, August). A Flexible Unit Maintenance Scheduling Considering Uncertainties. *IEEE Transactions on Power Systems , 16* (3), pp. 552-559.

Loucks, J., & Jacobs, F. (1991). Tour Scheduling and Task Assignment og a Heterogeneous Work Force: A Heuristic Approach. *Decision Sciences , 22* (4), 719-738.

Luczak, H., & Mjema, E. (1999). A quantitative analysis of the factors affecting personnel capacity requirement in maintenance department. *International Journal of Production Research , 37* (17), 4021-4037.

Moore, B., & Basye, R. (1995). The Role of EDI in Readiness Logistics. *Proceedings of the IEEE 1995 National Aerospace and Electronics Conference* (pp. 943-946 vol 2). New York, NY: IEEE.

Rodgers, P. (1992). US Navy 2M/ATE Program: Fleet Self-Sufficiency, Readiness, and Progressive Maintenance. *Conference Record AUTOTESTCON '92. The IEEE Systems Readiness Technology Conference* (pp. 383-387). New York, NY: IEEE.

Scarf, P. A. (1997). On the application of mathematical models in maintenance. *European Journal of Operational Research , 99* (3), 493-506.

Sydow, K. (2008). Shipboard Maintenance: What Do Surface Warfare Officers Need to Know--and When Do They Need to Know It? *Naval Engineers Journal , 120* (2), 89-98.

Yan, S., Yang, T.-H., & Chen, H.-H. (2004). Airline short-term maintenance manpower supply planning. *Transportation Research Part A: Policy and Practice , 38* (9-10), 625-642.

Zhou, R., Fox, B., Lee, H., & Nee, A. (2004). Bus maintenance scheduling using multi-agent systems. *Engineering Applications of Artificial Intelligence , 13* (6), 623-630.