Effects of Personnel Availability and Competency on Fleet Readiness

Lindsey Colosi[1], Ling Rothrock[1], Russell Barton[2], Jeffrey Banks[3] and Karl Reichard[3]

[1] The Harold and Inge Marcus Department of Industrial and Manufacturing, Pennsylvania State University, University Park, Pennsylvania, 16802, United States
ldc163@psu.edu
lxr28@engr.psu.edu

[2]The Mary Jean and Frank P. Smeal College of Business, Pennsylvania State University, University Park, Pennsylvania, 16802, United States
rbarton@psu.edu

[3] Applied Research Laboratory, State College, PA, 16802, United States
jcb242@psu.edu

ABSTRACT

The planning of future operations is a complex process that requires knowledge and understanding of many different factors and resources. 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 of a maintenance unit. 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. *

These analyses can be used to help make key decisions in the utilization of labor resources. Overall, these results show that the procedure presented in this research serves as a very useful tool to aid in resource planning.

* This is an open-access article distributed under the terms of the Creative Commons Attribution 3.0 United States License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

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.

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, locations 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. The focus of this research is the development of a procedure that incorporates personnel availabilities into maintenance scheduling. The results of this procedure can then be used as an aid to help decision-makers make decisions regarding personnel levels.

2 LITERATURE

Two main areas of literature were reviewed for this work. The first topic reviewed was the use of mathematical models for fleet maintenance management purposes. The second topic reviewed models that incorporated scheduling of personnel.

2.1 Mathematical Models for Fleet Maintenance Management

One area where mathematical models can effectively be used to solve real-world maintenance-related problems is in fleet maintenance management. Fleet maintenance management is prevalent across all types of industry and thus there is a variety of applications for these models. 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. Yan, Yang, and Chen (2004) developed a method for scheduling short-term maintenance manpower supplies for an airline using a mixed integer programming model. Chiesa, Quer, Corpino, and Viola (2009) used a two-phase approach to schedule different maintenance operations that needed to be performed that was a hybrid technique between heuristic approaches and exact techniques.

Chattopadhyay (1998) used linear programming to schedule maintenance activities for generators in an Indian Power Plant. Leou (2001) presented an approach that accounted for uncertainties in system constraints by utilizing a fuzzy 0-1 integer programming model that was solved by a branch and bound process. Haghani and Shafahi (2002) formulated a preventive maintenance scheduling problem for bus maintenance as an integer programming model that 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.

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. 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.

2.2 Personnel Availability Constraints

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 there are six main factors affecting the personnel capacity requirement in the maintenance department. These six factors were: amount of maintenance workload, the production system, structure of the equipment, organization of the maintenance, profile of the maintenance personnel, and 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. 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. Loucks and Jacobs (1991) developed a goal programming model that modeled 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. Bard and Purnomo (2005) presented a methodology to make daily schedule adjustments using an integer programming model solved within a rolling horizon framework for nurse staff scheduling.

Review of literature on the topic of personnel capacity and constraints has indicated that 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.

3 METHODOLOGY

The objective of this work was to develop a prognostic procedure to give decision-makers a tool that can aid in man-power decisions by creating fleet readiness predictions subject to various personnel factors. This procedure was based on two different models, a binary integer linear programming model (BILP) and a personnel simulation model. The simulation model generated different personnel availability scenarios that are used as inputs to the BILP. After iteratively optimizing the BILP, a fleet readiness prediction for each of the vehicles was generated. By analyzing the results of many runs subject to different personnel factors, the results could be used to aid in decision-making for many different maintenance planning applications.

3.1 Assumptions for BILP

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 Index Sets for BILP

i = vehicle index, i = 1, 2, 3, … , V

j = mechanic index, j =1, 2, 3, … , M

3.3 Decision Variables for BLIP

X(i,j) = 1 if *i* is repaired by mechanic *j*, 0 otherwise

FinalStat(i) = 1 if vehicle *i* has ready status

3.4 Definition of Parameters

The parameters are defined as follows:

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*

3.5 Formulation for BILP

The model formulation used in the BILP is shown in Figure 1.

$$\text{Maximize } \sum_i (FinalStat(i) * Priority(i)) \quad (1)$$

Subject to:

$$FinalStat(i) = InitStat(i) + \sum_j x(i,j) \quad \forall\, i \quad (2)$$

$$\sum_j x(i,j) \leq 1 \quad \forall\, i \quad (3)$$

$$\sum_i x(i,j) \leq MechHrs(j) \quad \forall\, j \quad (4)$$

$$x(i,j) * [RepTime(i) * Effic(j) + DiagTime(i) * Effic(j) + \max\{TowTime(i), PartTime(i)\}] \leq MechHrs(j) \quad \forall\, i,j \quad (5)$$

$$\sum_i x(i,j) * [(DiagTime(i) + RepTime(i)) * Effic(j)] \leq MechHrs(j) \quad \forall\, j \quad (6)$$

$$x(i,j) \in \{0,1\} \quad \forall\, i,j \quad (7)$$

$$FinalStat(i) \in \{0,1\} \quad \forall\, i \quad (8)$$

Figure 1. Model Formulation for BILP

3.6 Personnel Simulation

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 simulated different scenarios of personnel availability based on the percentages given in the study. A percentage of available workers was randomly determined for each day by sampling a uniform distribution with a minimum value of 24% and a maximum value of 49%. This percentage was then converted to a number of available mechanics for that day.

In addition, this simulation also determined which of the ten mechanics were available and which were not. If a mechanic was determined to be available on a certain day, then it was assumed that the mechanic's number of available hours for that day was either seven or eight hours depending on the training requirement for that mechanic's skill-level. Using operational data from the study as baseline values, it was assumed that workers with skill-level ratings of one spent 7.51% of their day on training requirements and thus were actually only available for seven hours per day, after rounding to the nearest hour. Workers with all other skill-level ratings were assumed to spend 5.24% of their day on training activities and thus their actual number of available hours was still considered eight after rounding. Several different weekly scenarios were generated by this simulation model and then used as input data for the BILP.

4 SAMPLE PROBLEM

A sample problem was used to demonstrate the procedure used to generate fleet readiness predictions. The results were then analyzed to determine the effects of different personnel scenarios.

4.1 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. 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 four different combinations of average mechanic skill levels. 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 1.

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. These results are summarized in Table 2.

Table 1. Scenarios for Mechanic Skill-Level Analysis

Mechanic Skill-Level					
Mech	***Baseline***	***50% dec***	***25% dec***	***25% inc***	***50% inc***
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
Avg	**2.4**	**1.2**	**1.8**	**3**	**3.6**

Table 2. Summary of Results for Skill-Level Analysis

	Scenario				
	50% Dec	*25% Dec*	***Baseline***	*25% Inc*	*50% Inc*
Average Rating	*1.2*	*1.8*	*2.4*	*3*	*3.6*
Min Prob.	0.56	0.67	0.73	0.74	0.72
Max Prob.	0.92	0.93	0.93	0.95	0.93
Avg Prob.	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. The results are demonstrated in Figure 2.

4.2 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. For this example, 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 3.

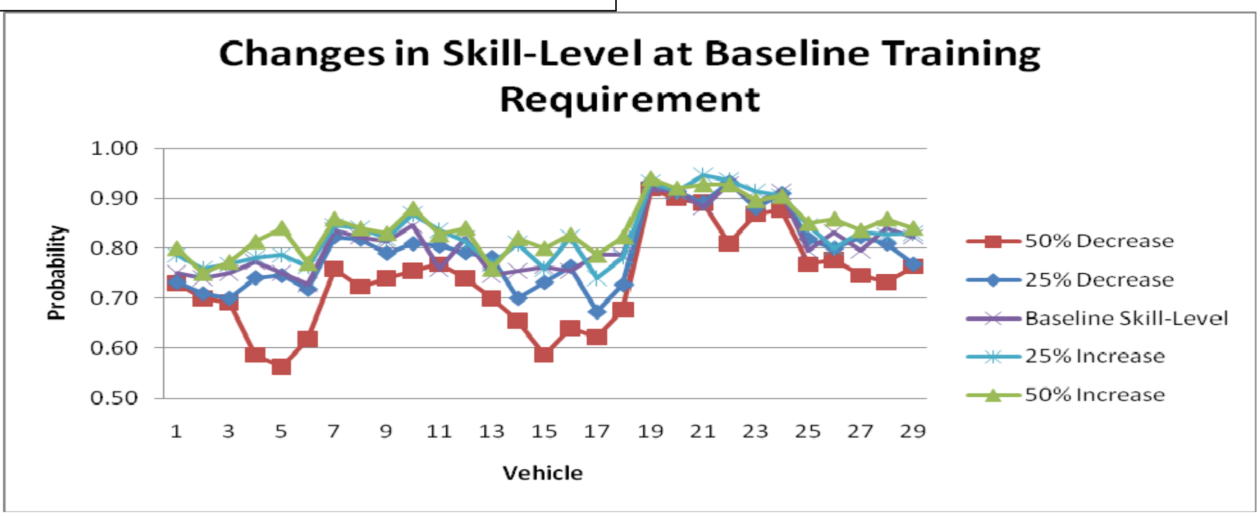

Figure 2. Average Probabilities for Different Skill-Level Scenarios

Table 3. Scenarios for Training Requirement Analysis

	Training Requirement Scenario			
	0-hr	***Baseline***	*1-hr*	*2-hr*
Tr. Req: SL 1	*0*	*1*	*1*	*2*
Tr. Req: SL 2-5	*0*	*0*	*1*	*2*
Min Prob.	0.72	0.73	0.73	0.70
Max Prob.	0.94	0.93	0.95	0.93
Avg Prob.	0.82	0.82	0.82	0.81

Table 4. Summary of Results 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. These results are summarized in Table 4.

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 3.

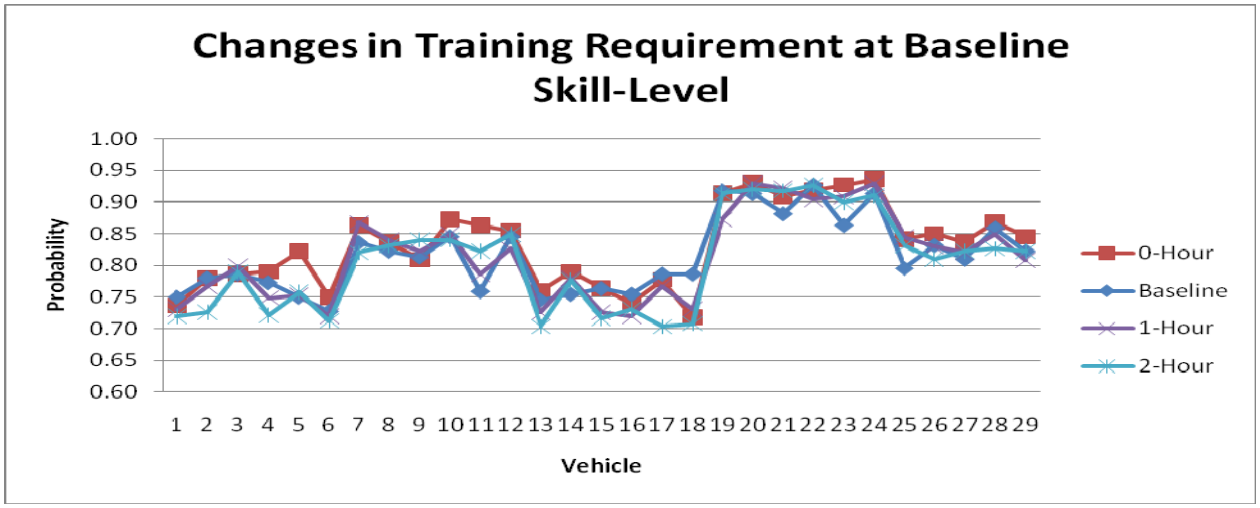

Figure 3. Average Probabilities for Training Requirement Scenarios

Regardless of which factor is being analyzed, these values and trends could be particularly useful if an operations planner had 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 could 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 could 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.

4.3 Analysis of Skill Level and Training Requirement Combinations

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. 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 5.

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. 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.

Table 5. Probabilities for Skill-Level and Training Requirement Combination 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

5 CONCLUSION

The objective of this research was to develop a procedure that evaluated the sensitivity of vehicle readiness levels 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. The results of these types of analyses can aid decision makers in determining proper allocation of their labor resources and thus save a planner time and effort while also leading to better overall readiness levels.

The procedure presented in this work has demonstrated a strong ability to meet this objective. An example scenario was used to demonstrate the ability of the procedure to create fleet readiness predictions based on different skill-level and training requirement scenarios. 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. 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.

ACKNOWLEDGMENT

This work is based upon work supported by the NAVSEA Contract N00024-02-D-6604, Delivery Order 0443. The content of the information does not necessarily reflect the position or policy of the Government, and no official endorsement should be inferred.

REFERENCES

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.

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.

Drew, J.G., 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.

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

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.

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.

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.

Lindsey D. Colosi was born in Newark, Delaware. She completed her undergraduate studies at Virginia Tech in Blacksburg, Virginia where she received her Bachelor of Science degree in Industrial and Systems Engineering in 2008. She then attended the Pennsylvania State University in University Park, Pennsylvania where she earned a dual Master of Science degree in Industrial Engineering and Operations Research in 2010.

Ling Rothrock has been an associate professor in the Harold and Inge Marcus Department of Industrial and Manufacturing Engineering at Pennsylvania State University since 2008 and was an assistant professor in the department from 2002 to 2008. He served on the faculty at the Biomedical, Industrial, and Human Factors Department at Wright State University from 2000 to 2002. From 1995 to 2000, he served in the U.S. Army as an executive officer in a maintenance company, a logistics officer in support of an Air Defense Artillery brigade (PATRIOT), and a research scientist in the Army Research Laboratory. Prof. Rothrock's research areas include human-in-the-loop discrete event simulations, display visualization, and human-machine performance evaluation. His simulation software has been used by the U.S. Navy for training and modeling. He has also been funded by the National Science Foundation to investigate decision strategies in dynamic tasks. He has published over 60 technical articles in the area. Dr. Rothrock is an Associate Editor for the Institute of Electrical and Electronics Engineers (IEEE) Transactions on Systems, Man, and Cybernetics (Part A), a senior member of IEEE, the past president of the Computer and Information Systems Division of the Institute of Industrial Engineers and a member of the American Society for Engineering Education.

Jeffrey Banks is the Department Head of Complex Systems Engineering & Monitoring and he has 17+ years experience in applying advanced signal processing techniques, intelligent systems technology, and embedded diagnostics / prognostics tools to condition monitoring applications for the US Navy, US Marine Corps, US Army, NASA and Industry. His education includes a B.S.M.E. from Villanova University and a M.S. in Acoustics from The Pennsylvania State University. His research engineer duties include developing machinery health management systems and diagnostic and prognostic technology for various DoD assets including the U.S. Marine Corps Expeditionary Fighting Vehicle (EFV), Light Armored Vehicle (LAV), AV-8B Harrier, U.S. Army Heavy Expanded Mobility Tactical Truck (HEMTT), and Heavy Brigade Combat Team M1A2 Abrams, M2/M3 Bradley Fighting Vehicle, M88 Hercules platforms. He has developed two short courses at all NASA facilities in the areas of Condition Based Maintenance (CBM) and Reliability Centered Maintenance (RCM). Additional responsibilities include conducting degrader analyses for a variety of complex systems and platforms including aircraft engines and combat ground vehicles. He has also designed and developed diagnostic instrumentation systems for machinery failure test beds and field data acquisition systems. Mr. Banks has first authored and published more than 50 conference papers and technical reports.

Karl Reichard has more than 15 years of experience in the development of advanced sensors, measurement systems, and signal processing algorithms. An Assistant Professor of Acoustics at Penn State and Head of the Complex Systems Monitoring and Automation Department at the University's Applied Research Laboratory, Dr. Reichard leads advanced research and development efforts in embedded systems, electro-optics, intelligent acoustic and vibration sensors, and signal processing and classification algorithms for active noise and vibration control, manufacturing machinery monitoring, and surveillance systems. Prior to joining Penn State ARL in 1991, he was employed by the U.S. Army Aberdeen Proving Grounds and Virginia Polytechnic Institute and State University, his alma mater. Dr. Reichard has published more than 25 papers in refereed journals, conference publications, and technical reports.