The Thesis Committee for Haitham Gamal AlBarbary
Certifies that this is the approved version of the following thesis:

Simulation-based Maintenance Schedule Optimization under Supply and Demand Uncertainty

APPROVED BY
SUPERVISING COMMITTEE:

Supervisor: ______________________________
Dragan Djurdjanovic

____
David Morton

Simulation-based Maintenance Schedule Optimization under Supply and Demand Uncertainty

by

Haitham Gamal AlBarbary, B.S.

Thesis

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Master of Science in Engineering

The University of Texas at Austin

August 2011

Dedication

To my parents, my fiancée, and my friends.

Acknowledgements

I would like to express my sincere gratitude to my adviser, Professor Dragan Djurdjanovic, for his continuous guidance, commitment, encouragement, and support throughout my research. I also give special thanks to my co-adviser, Professor David Morton, for his advice and kindness, and for his insightful comments.

Also, I would like to express my gratefulness to The ExxonMobil Corporation and The Institute of International Education (IIE), for giving me the opportunity to be a part of the ExxonMobil Middle East and North Africa Scholarship Program, and for the continuous administrative and financial support throughout my studies.

Finally, I give my utmost gratitude to my parents, fiancée, and friends, whose love, encouragement, and patience made this possible, and all worthwhile.

August 2011

Abstract

Simulation-based Maintenance Schedule Optimization under Supply and Demand Uncertainty

Haitham Gamal AlBarbary, M.S.E.
The University of Texas at Austin, 2011

Supervisor: Dragan Djurdjanovic

This MS thesis studies the effect of uncertainty in the demand of finished products, supply of raw materials, and maintenance resources availability on the maintenance schedule of a manufacturing facility. A simulation model is formulated in order to realistically model manufacturing systems of various complexities, consisting of multiple interacting machines that degrade and fail over time, and are repaired using imperfectly available maintenance crews and resources. A design of experiments (DOE) based sensitivity study is conducted to find the system parameters that mostly affected the maintenance decisions and corresponding profits.

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Chapter 1: Introduction

1.1. Motivation

Since the 1990s, companies in several industries have come under an increasing pressure to offer a wide portfolio of different products in response to variable and highly uncertain customer needs (Goyal and Netessine, 2004). Also, inconsistency in the supply of the raw materials used, and the unpredictable nature of some of the supply chains have made matters more difficult for these companies (Gupta and Maranas, 2003). As a result, and in order to survive in the fierce market, it is essential for manufacturing systems to focus on cost-effective responsiveness, rather than only focusing on product quality and cost reduction (Zhou et al., 2007). Since a key part of any manufacturing system is its maintenance strategy, therefore, it is important to study the effect of uncertainties in demand and supply of raw materials on the maintenance operations.

Maintenance strategies can be divided into two main categories: corrective maintenance (CM) and preventive maintenance (PM). The CM policy performs the required maintenance operations only when the degradation in the condition of a part, or piece of equipment, leads to a functional failure. On the other hand, the PM policy is a time-driven, or interval-based, maintenance strategy that is performed without regard to equipment condition (Dhillon, 2006). Although PM policies focus on replacing parts before they fail, corrective repairs can still occur due to unexpected component failures. PM has been studied intensively in the literature; it usually incurs less downtime than CM and leads to fewer losses caused by unexpected failures. Due to the mentioned reasons, PM policies are usually preferred over CM policies (Wang, 2002).

To the best of the author's knowledge, a relationship between variability in daily demand, and the supply of raw materials, and the maintenance schedule of manufacturing systems have not been investigated in the literature. Uncertainties in demand and supply have always been simplified and replaced by average values, based on historical data, rather than incorporating the variability into the modeled manufacturing systems. To fully understand and better analyze the dynamics of real-life manufacturing systems, it would be beneficial to incorporate these uncertainties into the analyzed models.

1.2. Framework and Objectives

In this research, we focus on devising maintenance policies that take into account uncertainties in demand and supply. The maintenance decision-making will focus on a serial/parallel multi-station manufacturing system producing a single product.

Challenges faced in this research include:

- The uncertainty of the variables that are input to the system, as well as the dynamic nature of multi-stage manufacturing systems, make it difficult to analytically model and optimize the maintenance plans.
- After finding optimal solutions for relatively simple single-product manufacturing system, extending the model to analyze multi-product systems is a challenging task.

1.3. Outline

The thesis is organized as follows; a review of the literature related to the conducted research is given in Chapter 2, including the different maintenance decision policies, modeling approaches, and the different optimization methods frequently used in the past. Chapter 3 describes the simulation-based maintenance schedule optimization model, which is formulated under supply and demand uncertainty. Chapter 4 outlines the results for multi-station scenarios, and discusses any insights that can be concluded from the study. Finally, Chapter 5 concludes the report, and outlines the key contributions made by this research, as well as suggesting further topics that may be tackled in future work.

Chapter 2: Literature Review

2.1. Maintenance Scheduling

Maintenance scheduling has been a thoroughly studied topic in the past several decades. Whether to increase profits and throughput or to reach an optimal combined benefit of both factors, an optimum maintenance schedule is important in any manufacturing facility (Dekker, 1996; Wang, 2002).

Maintenance policies can generally be classified into corrective maintenance (CM) and preventive maintenance (PM). The main function of performing CM is to restore a machine back to a desired initial condition due to an unexpected breakdown. PM, however, is an appropriately scheduled event and is performed on a machine before unacceptable behavior occurs. The state of a machine after performing a maintenance action is itself a debatable topic and is usually always assumed either to be perfect, imperfect, or minimal. A perfect maintenance action restores a machine to “as good as new” condition, while a minimal maintenance action does not improve the condition of the machine, but rather keeps it at “the same as before” level and only restores the functionality of the maintained system. An imperfect maintenance action brings the system to a condition between perfect (as good as new) and minimal maintenance (Wu and Clements-Croome, 2005).

CM is observed to cause longer logistic and production delays when compared to PM, due to the higher downtime and costs associated with it. The long downtime and high costs observed in CM are mainly due to the unavailability of resources at the time of the breakdown, since it is unexpected and has not been accounted for in terms of maintenance crew, spare parts, and tools. Consequently, the cost of CM can be as high as triple that of PM (Chitra, 2003). Therefore, it is not surprising that the research literature on the topic of maintenance scheduling clearly shows that employing PM policies can increase machine life and reduce the total operational costs (Nakagawa and Yasui, 1991).

In almost all the studied literature, either analytical models were constructed to represent and optimize the desired maintenance policies, or simulations were employed to evaluate and optimize maintenance decision-making. Depending on the analytical tractability of the system and maintenance policy representation, mainly analytical or meta-heuristic methods were used to optimize the studied maintenance policy. When possible, benchmarking to conventional maintenance models was also done to verify the existence and level of benefits that could be realized from a proposed maintenance model. More details about the past research on maintenance decision making is discussed below.

2.1.1. Age-based Preventive Maintenance

Age-based PM (ABM) is perhaps the most widely studied, and most widely applied family of maintenance policies. In the case of ABM, the interval between PMs depends on how long production has run since the previous maintenance was carried out, and/or the "age" of the unit. A great deal of research has been done on various aspects of ABM modeling and optimization, including studies on the effect of different time horizons, system complexities, state of information, cost functions, or type of maintenance operations carried out. The rest of this section will present the different analytical and simulation-based solution methods used in ABM that were studied in the past.

Analytical Maintenance Modeling Methods and Corresponding Optimization Approaches

Early on in the literature, analytical solutions were mostly employed to solve maintenance optimization problems. This can be seen in Barlow and Hunter (1960), where the authors studied two preventive maintenance policies, one for maintaining simple equipment arrangements, and the other for large, more complex systems. The "limiting efficiency," or the fraction of up-time over long operating time intervals, was optimized by analytically deriving its equation in terms of the expected maintenance time, the failure distribution of the system, and the resulting up-time, and performing mathematical actions such as integration and differentiation to find the optimum solution. Refer to Barlow and Hunter (1960) for the detailed derivations of the limiting efficiency equations, and their solution approach.

Almost two decades later, Pierskalla and Voelke (1976) performed a detailed survey on the advancement in maintenance models, since Barlow and Hunter's (1960) study. In their paper they outlined the transition from discrete to continuous maintenance models, and how more models were formulated to handle different states of available information. More importantly, they focused on the analysis tools used and how they have progressed over the span of their study. It was established that mostly analytical solution methods, namely the use of calculus, integration and differentiation of complicated mathematical expressions resembling the different models and assumptions, were still the primary approach used. In their reflections on the study, the authors anticipated the evolution of the solution methods from analytical to simulation-based approaches as the availability and computation power of computers increased in the future.

Mathematical formulations of PM problems continued to be the main approach in the following years, as could be seen in Chaudhuri and Sahu (1977). The reliability of a system was calculated under the assumption that the failure rate of the system monotonically increases between PM actions, and that PM actions are imperfect. After analyzing the formulated reliability function, it was found to be a concave function, and this property was used to find the optimal PM intervals for the studied system.

In a more recent survey, Sherif and Smith (1981) summarized the evolution of maintenance models, and corresponding optimization techniques, throughout the previous decade or so. The authors reviewed more than 500 research papers, and categorized their findings according to the type of maintenance model used and the optimization method used to optimize this model.

As the speed and computational ability of the available computing systems grew, scientists began moving towards more realistic and more complex maintenance models, and their respective optimization procedures. For example, in a more recent survey, Pham and Wang (1996) discussed the various maintenance policies and optimization methods that can be used in single and multi-component systems. The paper picks up from where Sherif and Smith (1981) left off, and observes that the majority of the studied ABM literature used renewal theory to optimize availability, total cost, or cost rate by analytically or numerically solving the renewal equation. The use of renewal theory, and semi-Markovian or Markovian decision approaches to handle ABM problems seemed to be popular in this time period.

In later studies, more complex ABM models were formulated that consider independent, monotonically decreasing operating times, or independent, monotonically increasing maintenance times of a system. To solve these types of problems, the "limiting expected maintenance cost rate" and availability were derived in an analytical form, and nonlinear programming tools were also used to optimize the objective functions (Wang and Pham, 1999). Similarly, Park et al. (2000) modeled a system having a monotonically increasing hazard rate, where performing PM slows the rate of system degradation, and the optimal PM frequency and interval was obtained. The objective in this study was minimization of the expected long-run cost per unit time, calculated over an infinite time horizon. Similar to nearly all the prior and contemporary literature at the time, the objective function was formulated analytically, and then explicit solutions for the optimal PM intervals were calculated for the special case of Weibull-distributed failure times.

There has been a shift in the ABM representation and optimization methods, from analytical and numerical methods to simulation-based and meta-heuristic algorithms, enabling considerations of more complex systems and decision-making optimized over finite time horizons (Karlj and Petrovic, 1988).

In a study by Jayabalan and Chaudhuri (1992), a production system with imperfect PM was modeled, where the expected failure duration of an "old," previously repaired, system was less than that of a brand new system. In such a configuration, the optimal PM interval is not constant, causing the researchers to opt for a novel heuristic optimization algorithm introduced in that paper. Heuristic algorithms such as genetic algorithms (GAs), simulated annealing (SA), or tabu search (TS) were also encountered as tools for optimizing PM decisions, as can be seen in Block et al. (1993), who gives a thorough review of different ABM and replacement policies.

In a more recent study, Tan and Kramer (1996) showed that GA had distinct advantages over analytical and Markovian solution techniques in terms of solution accuracy, versatility, and tractability. The authors implemented their framework to optimize PM schedules and process reliability in a chemical plant, and it proved to be easily integrated into the existing system. In addition, the approach demonstrated the ability to optimize non-deterministic objective functions, making it both versatile and generalizable in ABM optimization problems.

Similarly, a later study by Levitin and Lisnianski (2000) that focused on ABM schedules in multi-state systems used GA as their solution approach, to find the optimal sequence of PM actions that achieve the desired system reliability and minimum maintenance cost. The authors also have made considerable research in ABM literature, and their paper contains a number of references that may be of interest to the reader.

Currently, the majority of researchers seem to be focusing on sensitivity analysis for PM scheduling and replacement models in multi-component systems, and the effect of changing system parameters on the optimal solution. Also, the efficiency and accuracy of exact and heuristic algorithms is of great interest nowadays. Moghaddam and Usher (2011) have recently published an article tackling this issue, where they used factorial design of experiments (DOE) to study the effects of changing reliability parameters on the cost and optimal PM schedules. The authors also compared the accuracy and computational efficiency of GA, SA, branch-and-bound, and generalized reduced gradient methods in order to assess their performance.

Simulation-based Maintenance Modeling Methods and Corresponding Optimization Approaches

As the need to more faithfully model and optimize increasingly complex systems grew, and the availability of cheap and fast computational resources increased, researchers began to rely more on simulation-based approaches as an alternative to analytical modeling. Simulation enables researchers to consider complicated, case-specific attributes of a studied system, which were mostly overlooked by generalized analytical modeling.

In Crocker and Kumar (2000), the authors turned to computer simulation to model military aero-engine failures. Since the only data that was available to the authors was the mean time between failures, any mathematical models that could be formulated needed to be based on the exponential distribution, however, based on their knowledge and the available standards for the studied system, the exponential distribution was not an accurate assumption. This led Crocker and Kumar to use Monte Carlo simulation to model aero-engine failures, and determine the optimal maintenance scheme to be employed. They introduce the concept of "soft life" versus "hard life" for engine components, and optimize the relevant PM costs. Finally, the authors suggest augmenting their model with a heuristic optimization tool, for a faster, more efficient solution procedure, since the grid search approach that they used took them almost 10 hours to solve for only one part of the system.

Using a different simulation approach, Zhang et al. (2008) developed a fuzzy ABM policy, where they treated component life as a fuzzy variable (Sinha et al., 2000). The long-term expected long-run cost per unit time was calculated using a computer simulation, and a newly proposed simultaneous perturbation stochastic approximation algorithm was used to determine the optimal solution for the simulation model. El-Ferik (2008) also optimized the PM schedule of a production facility, subject to random failures and imperfect PM activities, using a fully programmed algorithm that was analytically developed. The simulation program integrated system parameters, such as failure probability distributions and maintenance costs, and evaluates the optimal PM frequency. Both these studies prove the versatility of simulation models over analytical approaches, since they can be fully customized to the problem at hand by programming the algorithm from the ground upwards.

Although heuristic approaches were found to be more popular in the literature, several researchers opted for DOE and statistical tools, as opposed to heuristic algorithms, in order to optimize the objective function. Gharbi and Kenné have used DOE and response surface methodology (RSM), to obtain the optimal maintenance and production policy in several applications. For example, Gharbi and Kenné (2000) used the mentioned statistical tools to obtain the optimal production and PM rates, which minimizes the total cost of inventory and backlogging, for a multiple-identical-machine manufacturing system with random breakdowns. Later on, in Gharbi and Kenné (2005), their model was extended to a multiple, non-identical-machine manufacturing system. In both cases, the authors combined discrete-event simulation and DOE based RSM to find an approximation for the optimal PM policies.

2.1.2. Condition-based Preventive Maintenance

Another approach that gained widespread interest and acceptance in recent years is condition-based PM (CBM). The "condition" of a unit in a manufacturing system is monitored, using readings from sensors attached to the equipment, and PM is carried out when the condition reaches an unsatisfactory level (Yang et al., 2007). This maintenance policy aims at performing PM only when it is necessary, and therefore can reduce maintenance costs and improve system availability (Marseguerra et al., 2002). A study of the CBM literature, with reference to analytical, heuristic, and simulation-based solution methods was carried out and will be given in this section.

Analytical Maintenance Modeling Methods and Corresponding Optimization Approaches

Analytical solutions were also mostly employed in the early CBM literature to achieve optimal maintenance policies. Earlier formulations can be seen in Bladin (1986), where machine availability was analytically optimized based on diagnostic data. Another CBM optimization policy was carried out by Chilcott and Christer (1991), where machine downtime was analytically formulated, in terms of the probability of "defects arising," repair time, production cycle, and other system-specific parameters. The mathematical formula was integrated over the planning time horizon to find the total expected downtime for the system. Since condition monitoring was not carried out via sensors in both Bladin (1986) and Chilcott and Christer (1991), routine system checkups were manually done by the machine operators to obtain degradation levels in both studies. A later study by Hontelez et al. (1996) minimized total maintenance cost for a concrete structure by finding the optimal CBM policy. Similar to the earlier studies, Hontelez et al. (1996) analytically modeled the system deterioration as a continuous Markov process, and obtained the optimal control-limit rule using a discrete Markov decision model. The Markov model was mathematically solved, since the solution process using basic linear algebra was fairly simple. For more references on the early CBM literature, one may refer to Chilcott and Christer (1991), Djurdjanovic et al. (2003), and Kim et al. (2010).

An example of the transition from purely analytical solution methods, used in early CBM literature, to relatively simple numerical approaches that allow incorporation of more system details, yielding more practical solutions is shown in Christer and Wang (1995). The authors formulated a simple condition monitoring model for direct monitoring of a single component in a machine. A stochastic model was derived to minimize the expected cost rate over the interval between the current inspection action and the next one. In the model, the inspection interval was analytically formulated, depending on the accumulated wear on the component. The wear probability measures were statistically modeled, by fitting a regression model to historical data, and the CBM model was mathematically optimized to find the maintenance policy that minimized the cost rate of the system.

Over time, the evolution towards more complex, and more realistic system and CBM policy representations continued. Barbera et al. (1996) used dynamic programming to find the optimal solution in a single-unit system with exponential failures and fixed inspection intervals. The model's objective was to find the optimal maintenance policy that minimizes the sum of the long-run average PM and failure costs. The optimal control limit policy was achieved numerically, by solving the simplified dynamic programming model. The model was later expanded in Barbera et al. (1999) to a two-unit system, using the exact same modeling approach and solution procedure.

In recent CBM studies, product quality is also integrated in the generated models. Sloan and Shathikumar (2000) is one of the earliest works to consider the effects of equipment condition on product quality, incorporating these considerations into maintenance scheduling. A decision-making policy, determining maintenance and production schedules for a multi-product/single-machine production system was proposed, assuming known operation-dependent Markovian degradation models and known condition-dependent yields for each product. A linear program was used to obtain the optimal maintenance policy from the formulated Markov decision process model. Sloan (2004) extended this model by using a variable production target and multiple maintenance actions. The same degradation modeling approach was used (Markov decision process model) for this extended problem, and solving it showed that the product yield had a binomial distribution, which depends on the deteriorating equipment condition. The model developed by Sloan and Shathikumar (2000) was also extended in Sloan and Shathikumar (2002), where they used a simulation-based approach for a multi-stage system. Simulation-based CBM optimization will be discussed in detail in the following section.

Simulation-based Maintenance Modeling Methods and Corresponding Optimization Approaches

Similar to the trend in ABM, the need to faithfully model and optimize more complex systems, and the availability of cheap and fast computational resources, led to increased interest in simulation-based approaches as an alternative to analytical modeling and solution approaches.

For the early literature on simulation-based approaches in CBM, one may refer to Marseguerra and Zio (1993), Lam and Yeh (1994), Hontelez et al. (1996), Grall et al. (1998), and Berenguer et al. (2000).

One of the more recent examples, where researchers used simulation modeling as a useful tool to optimize more complex systems, is Sloan and Shanthikumar (2002). The single-unit CBM model, developed earlier and analytically solved in Sloan and Shanthikumar (2000), was extended to consider multiple units and an additional job dispatching decision. The performance of predetermined dispatching rules, and fixed maintenance policies, was compared with a basic CBM model to study the benefit of implementing their new joint policy. Since semiconductor manufacturing is a complex process involving hundreds of steps and multiple processes, a discrete-event simulation model was used to evaluate different policies. The effect of using in-line equipment condition and yield information to schedule maintenance was found to be beneficial over fixed-time and fixed-usage policies.

Around the same time, Barata et al. (2002) used Monte Carlo simulation to model a continuously monitored deteriorating system and developed an optimization strategy to find the optimal condition threshold levels. The authors started by formulating a single-unit system subject to stochastic degradation, and then generalized their model to account for multiple units. The total cost was optimized using a simple user-defined space search between the upper and lower maintenance threshold levels. A sensitivity analysis was also done to assess the influence of various system parameters on the resulting CBM policy. Though the tools employed in this study were fairly simple and crude, the flexibility of their simulation model enabled them to capture relevant features found in real-life systems that cannot be modeled analytically. The authors also anticipated that future improvements in condition data collection will add to the success of such simulation-based models, since more accurate system parameters would be used and hence more reliable results can be obtained.

A more in-depth approach was implemented by Marseguerra et al. (2002), where a continuously monitored multi-component system was considered. The problem was formulated as a multi-objective search simultaneously optimizing profit and availability. The degradation dynamics model was based on a Monte Carlo simulation, to better mimic the real-life scenario of a stress-dependent degradation process in load-sharing components, and could easily incorporate limitations in the available maintenance crew. Finally, a GA was employed to determine the optimal degradation level where PM has to be performed.

In one of the very recent studies, Celen and Djurdjanovic (2011) studied a multi-product, multi-station system through simulations, where a product went through several operation steps and each workstation could only execute a subset of operations. Machine degradation was modeled as an operation-dependent Markov process, where each state represented the state of degradation reached by a workstation. Similar to Sloan and Shathikumar (2000), the quality of manufactured products was assumed to depend on the machine condition. A discrete-event simulation model was used to model the suggested system, and a meta-heuristic search was employed to find optimal operation-dependent maintenance strategy. It was shown that operation-dependent maintenance decision-making outperforms traditional operation-independent policies. Such integrated maintenance scheduling and production-operation decision-making policies will be discussed in more detail in Section 2.2.

2.1.3. Hybrid Maintenance Models

Of special interest in recent maintenance literature are so-called "hybrid maintenance models" that combine ABM and CBM policies in order to benefit from both worlds. Since ABM policies do not take into account the actual condition of a system, they can sometimes lead to unnecessary maintenance of machines that still operate properly or cause production losses, due to unscheduled maintenance events caused by faults that occurred before a scheduled PM, all of which lead to reduced profits. On the other hand, since CBM only utilizes sensor information to determine optimal maintenance schedules, it generally does not factor in the historical information of machine failures and maintenance events on other units of the same type and make as is the monitored machine, which is what ABM policies rely on to model failure processes on a machine. In other words, CBM does not factor in the "aging" effect on the system. Therefore, there are great potential benefits in creating hybrid maintenance policies that combine ABM degradation characteristics with real-time CBM monitoring information to predict the remaining lifetime of a unit in a manufacturing system (Kaiser and Gebraeel, 2009). The rest of this section will summarize the findings in the area of hybrid maintenance models and solution procedures.

The proportional hazards model (PHM), first introduced by Cox (1972), is one of the tools that were found to be used in hybrid maintenance decision-making. PHM is a class of survival models in statistics that relates the time passing before the occurrence of an event to one or more of the related control variables. The fundamental approach in PHM is to assume that the hazard function of a system has two multiplicative factors: the baseline hazard rate, and (generally) an exponential function that includes the effect of the monitored variables (Kumar and Westberg, 1997). The hazard function, resulting from multiplying the two factors, represents the system survival time (Kay, 1977). The main objective of using PHM is to calculate the unknown parameters, which define the influence of the monitored variables on the failure process observed in the system (Kumar and Westberg, 1997). Cox's (1972) PHM is considered as the earliest example of a hybrid maintenance model policy, since it enabled researchers to simultaneously integrate ABM and CBM policies in a single analytical tool that can be used to find optimal PM policies. A general review of the basic literature and computer programs in the area of PHM are given in Kumar and Klefsjo (1994).

An application of hybrid, PHM-based maintenance modeling can be seen in Kumar and Westberg (1997). The authors proposed a method to estimate the optimal PM time interval, with failure characteristics of the studied system estimated using age-based total operating time, as well as condition-dependent system variables. In this study, PHM was employed to identify the most important variables, which would show whether failure characteristics of the system depended only on failure times or on the monitored variables as well. The identified significant factors were then used to formulate an estimate of the system reliability function. The optimal PM interval was obtained using the "graphical approach" (Bergman, 1977) from the "total time on test" plot (TTT-plot), which was constructed based on the estimated system reliability function.

More recently, PHM was used by Jardine et al. (1999) to develop an optimal PM policy for bearings. By conducting statistical analysis of the vibration data, the authors estimated the current risk level of a machine, with the aid of a software package (EXAKT) to identify the key vibration signals. The risk curve was then generated, using PHM to identify the unknown parameters, and cost data was used to obtain the optimal PM policy. The study concluded that it was possible to identify key condition measurements, using PHM to analyze vibration monitoring data, and therefore to possibly reduce costs by eliminating unnecessary inspections.

In a similar study, Vlok et al. (2002) used PHM, having a Weibull function, to find the optimal replacement policy for circulating pumps subject to vibration and other condition-based monitoring parameters. Based on historical data collected over a period of two years, the optimal maintenance policy was formulated using PHM to estimate the significant system parameters. The policy was validated using operations data collected after the study was completed, and the differences between theoretical and practical operations were used to assess the performance of the suggested PM policy. One can find similar CBM-based PHM applications in Jardine et al. (1987), Jardine et al. (1989), Jardine et al. (2001), and Lin et al. (2006).

In a recent study, Ghasemi et al. (2010) proposed a hybrid model to calculate the reliability function and the mean residual life of a unit in a system that does not have a directly observable degradation state. The unit is inspected at equal time intervals, where at each inspection point a degradation indicator is observed and collected. However, the obtained inspection information is imperfect, causing the inspection process not to directly reveal the exact degradation state the unit has reached. Therefore, a stochastic relation between the condition indicator's value and the unobservable degradation state was formulated and given by an "observation probability matrix." A hidden Markov chain model was developed to model the unobservable degradation state transition, and the probability of being at a certain degradation state during each inspection was determined using Bayes' rule. Finally, Cox's (1972) time-dependent PHM was used to model the unit's failure rate. The model was analytically solved for a Weibull hazard function, yielding the cost of the optimal replacement policy and the mean residual life of the system.

A different approach to hybrid maintenance models was presented in Lin et al. (2000). The authors analytically formulated the mean cost rate function, in terms of the hazard rates, PM intervals, effective system age, and maintenance costs. ABM was then introduced to this hybrid approach by differentiating the mean cost rate function with respect to the "effective age," in order to determine the optimal long-run average cost with respect to the system age. An analytical solution was obtained by assuming Weibull hazard functions, and the optimal PM schedule that minimizes the cost rate was obtained.

In an extension to this study, Lin et al. (2001) considered the same model but with multiple failure modes, namely maintainable and non-maintainable failure modes. In this study, it was assumed that PM only reduces the hazard rate of maintainable failure modes, but does not affect the hazard rate of non-maintainable failure modes. An analytical solution was also obtained by assuming Weibull hazard functions, and the authors mentioned that if another hazard function was to be modeled, they would optimize the maintenance policy using a numerical algorithm, which they also outlined in the paper.

2.2. INTEGRATED MAINTENANCE SCHEDULING AND OPERATIONS DECISION MAKING

Developing an intelligent and cost-effective PM strategy in highly dynamic, and highly flexible production systems presents a major challenge. Since maintenance actions inevitably interrupt the production process, and on the other hand, production-related actions affect system reliability, any policy that does not simultaneously consider both maintenance and operations decisions will not yield optimal results. This inherent interaction between maintenance and operations suggests that a new maintenance strategy, which integrates the effect of operational changes on system reliability in the maintenance decision-making process is required, as optimal maintenance schemes and operational actions cannot be simply added together to achieve an optimal policy. To tackle this problem, recent research focused on integrating operational and maintenance decisions into a single optimized process (Zhou et al., 2007).

Early in the literature, Tagaras (1988) made a study that presented the economic model, which incorporates process control and maintenance procedures, concurrently optimizing their design parameters. The target of the study was to show that the combined benefit of integrating both decision-making techniques would yield a lower cost than using both methods separately. The model was solved using a combination of direct grid search and golden section search (Chiu, 1975), and Fibonacci lattice search (Sugie, 1964) to find the effectiveness and cost of maintenance based on control-chart signals. A sensitivity analysis was also done to check the effect of minor changes in system parameters on the optimal results. This early study showed that the interaction between maintenance and operations does not always yield a positive result.

Similarly, in a later study, a joint quality control and PM policy was done by Mehdi et al. (2010). However, the system modeled in this study was operating with a just-in-time (JIT) policy, and maintenance actions were determined based on the number of non-conforming units in each lot compared to a predefined threshold value. To reduce stoppages and ensure a continuous supply of finished products during PM, a buffer is introduced to build up stock from the moment the rejection rate reaches a certain upper control limit (UCL). The paper provided methods to determine the optimal production rate and buffer size in order to minimize the expected total cost rate, based on the PM schedule and quality control limit thresholds (Mehdi et al., 2010).

Another combination of maintenance and operational decisions, namely batch production scheduling and PM, was tackled in a study by Sanmartf et al. (1997). The authors incorporated uncertainty analysis in the scheduling stage to improve the performance of the resulting schedule when faced with machine failures. The integration reduced the need for rescheduling due to equipment failure, since the probability of equipment failure (machine reliability) was forecasted and incorporated into the scheduling process. Consequently, machines with low reliabilities were avoided for certain schedules, or PM tasks were introduced into the schedule to compensate for possible future failure delays. A “schedule reliability index” was derived to be a measure of robustness used in this study, and a heuristic approach was used to optimize this index concurrently regarding batch production schedules and PM actions. This study was found to be quite interesting, since it methodologically tackled a problem that is traditionally solved in practice using intuition and experience. The paper also has additional insightful references, with regard to batch scheduling, that might be of interest to the reader.

Iakovou et al. (1999) integrated maintenance with production operations by introducing the throughput rate of a single-unit system as an additional decision variable.

A Markov decision model was formulated to describe the relationship between the PM policy and the lifetime of the unit, where the condition of the system was inspected at equal intervals, and the throughput rate assigned accordingly. Also, based on the observed condition, a decision whether to perform PM is made with the goal of minimizing the expected average profit, discounted over an infinite time horizon.

Another study integrated the production inventory with PM to optimize the "net cost benefit rate" of the system (Das and Sarkar, 1999). This was done by modeling a single-product production system, operating with an (S,s) inventory policy, and developing a mathematical model in order to determine the optimal system parameters. In a (S,s) inventory model, there is a minimum allowable inventory level 's', if the actual inventory level drops below 's' replenishment is carried out to return the inventory back to the maximum level 'S', and hence its name (S,s). Based on the available inventory level, maintenance actions are scheduled to minimize the probability of failures, consequently leading to shorter delays in satisfying customer demand and higher system productivity. This was achieved by constructing a Markov chain of the possible single-step state transitions of the system, and was solved using the steepest ascent gradient search method. The optimal "production counts," which is basically the number of parts to output from the system before performing PM, was obtained for every discrete inventory level to maximize the net benefit per unit time. A sensitivity analysis was also done to study the effects of demand arrivals, times to failure, production times, maintenance times, and the repair times on the optimal net cost benefit. Finally, the effect of varying the (s) and (S) inventory level on the optimal PM schedule was also studied. It should be noted that since the parameters used in this study led to a simple Markov decision problem, the problem was analytically solved with ease. However, the authors suggested using a relatively new simulation-based approach, called "reinforcement learning," for stochastic approximation of more complex semi-Markov decision problems.

A more recent study by Zhou et al. (2007) examined a newly introduced integrated reconfiguration and age-based maintenance (IRABM) policy, applicable to highly flexible and reconfigurable manufacturing systems, where operations can be moved from one machine to another with ease and in real-time. Given operation-dependent machine reliabilities, the method jointly optimizes operation-dependent ABM intervals and transfers operations when system reconfiguration needs to be done. "Reconfiguration" is achieved by transferring operations between different stages of a system depending on the current system reliability level. The model is controlled by three threshold-type decision variables that define the IRABM policy. When any of the predefined threshold levels is exceeded, reconfiguration occurs and operations are routed to different machines in the system, according to a configuration that maximizes throughput and minimizes total cost. Implementing the IRABM model enables the system to jointly achieve the most economical mix of maintenance decisions and production decisions.

A different type of maintenance and operations integration was used in El Ferik (2008), where the economic production quantity and PM schedules were jointly determined, assuming that the system is subject to random failures and imperfect maintenance. The system deteriorates, with an increasing failure rate, and PM is performed either when failure occurs or when a predetermined age is reached, whichever occurs first. A model was proposed that determines the optimal number of production runs, and the PM schedule that minimizes the long-run average cost.

"Options theory" is a powerful financial tool that is defined as an "instrument whose payoffs and values are derived from or depend on something else" (Ross et al., 2002). Options theory was also recently used in Jin et al. (2009) as an integrated policy to jointly tackle production scheduling and PM when demand is uncertain. The strength of the financial tool, which led the researchers to implement it in their joint decision policy, comes from its ability to tackle optimization problems in uncertain environments. An analytical option-based cost model was presented, expressing a balance between risks due to uncertainty in demand, and high costs invested in PM activities. Based on the new decision variable of whether to choose the maintenance investment option, the optimal number of PM operations was derived in order to maximize the system output. The researchers analytically compared their proposed option-based model with the conventional periodic PM policy and found that it adds flexibility to the production system, reducing the risk of production shortage or overage due to a highly stochastic demand. The paper also points out several other studies in the literature that efficiently integrate operational and maintenance decisions, which might be of interest to the reader.

When compared to the abundant literature available on pure maintenance scheduling and optimization policies, there is much less research done to address strategies for integrated maintenance scheduling with operational decisions.

2.3. CONCLUSION

One can see from the conducted survey that maintenance decision-making has evolved greatly over the past decades. There exists a vast literature on the different maintenance scheduling policies following the ABM, CBM, and hybrid paradigms. It is also clear that modeling approaches are shifting from purely analytical models, which are inherently tractable but are often detached from reality due to the constraints imposed by numerous restrictive assumptions, toward less tractable but more realistic simulation-based models. This trend is apparent due to the increased availability of computational resources and the need for more realistic and applicable results that can be directly implemented in the industry. The adoption of simulation to model manufacturing systems will also be apparent in the research presented in this thesis.

Furthermore, the use of simulation models and advances in computational technologies led to proliferation of various meta-heuristic approaches to optimization of maintenance and production policies. The research described in this MS thesis also follows this general trend, which yields practical applicability to the resulting solutions.

Finally, it was observed that integrating both maintenance and operational policies into a single strategy enables the production system to merge strengths and deal with the limitations associated with each of the optimization problems alone, and efficiently handle the inherent interactions between them. This recent shift, from separately optimizing maintenance and operations decisions to more integrated single-strategy policies that handle operation-maintenance interactions, will also be followed in the research presented in this thesis, since product demand characteristics (operational information) will be used to make maintenance decisions.

Chapter 3: Simulation-based Maintenance Schedule Optimization under Supply and Demand Uncertainty

3.1. INTRODUCTION

The objective of this research is to study the effect of uncertainties in the demand for finished products and the supply of raw materials on the optimum maintenance schedule of a serial-parallel manufacturing system. In Section 3.2, a model for a system with N workstations, each having M machines, is presented with the relevant assumptions. Section 3.3 illustrates the methodology used to simulate the desired manufacturing system, and the optimization problem that was formulated to evaluate the simulated system. Section 3.4 demonstrates the techniques used to determine the optimal maintenance schedule and outlines the methodology behind the optimization tool utilized in this study. Finally, Section 3.5 describes the experimentation undertaken to study the system performance, and the sensitivity analysis used to test the robustness of the results.

3.2. MODEL DESCRIPTION

The focus of this study is a single product, parallel-serial manufacturing system. Machine health is randomly assigned at the beginning of the planning horizon, and work orders arrive at once and in the correct order to the first workstation. As time passes by, and work orders are being processed by the machines, the machines' health degrade and the probability of failure increases, following a stochastic distribution, until either a PM operation is done or the machine fails randomly and an CM has to be done.

There is a predefined daily target (D) that represents the total number of work orders that need to be satisfied during a finite-time planning horizon (T_{PH}). Once the production goal is met, the system stays idle until the end of the planning horizon. The production system is made up of N workstations, having an intermediate buffer between each workstation with a finite capacity (F), and each workstation has M identical machines working in parallel. To be considered a finished product, a work order has to enter workstation 1 and complete the corresponding production cycle (stay in the workstation for the duration of the corresponding cycle time) then wait in the buffer before entering workstation 2 to go through another complete production cycle, and so on, until it exits workstation N. At any workstation, a work order can be processed by any of the M parallel machines present in the workstation.

Two checks are performed before a work order is routed to workstation 1; first, whether the order is cancelled by the customer, and second, whether there are enough raw materials in the inventory to satisfy the need created by this work order. The event of order cancelation is assumed to have a known probability and different orders are canceled independently. The work order is either routed to the first workstation if it was not cancelled, or is discarded if it was cancelled by the customer[1]. Once the work order is processed by the first workstation, it is considered as work in progress (WIP), and the customer is not allowed to cancel it.

Similar to order cancellation, we assume that a known probability governs whether we have the necessary raw materials required to manufacture a work order. If raw materials for a work order are not available, the work order is delayed for a stochastic period of time (T_D) until the raw materials arrive and is then routed to workstation 1[2]. Work orders have to go through the production system sequentially, in

[1] The probability of order cancellation can easily be deduced using historical operational records in a factory.
[2] The probability of raw materials availability and distribution of the raw materials delay period (T_{RM}) can be also estimated from the historical data routinely available in today's factories.

the order of workstations, and cannot overtake other work orders (i.e. manufacturing operations must be executed in workstations 1, 2, …, N in the exact order for the product to be done).

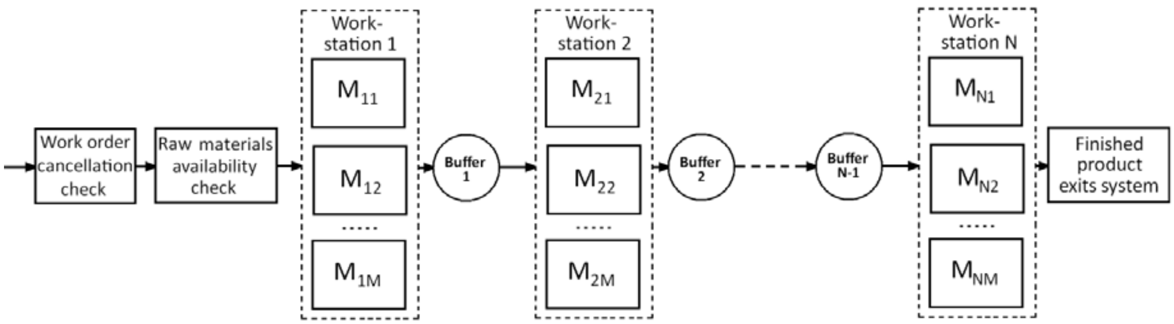


Figure 1 Single-product parallel-serial system

All the machines modeled in this system are assumed to be unreliable, and may fail randomly according to known Weibull distributions with workstation-specific shape parameters $\beta_1, \beta_2, \ldots, \beta_N > 1$ and scale parameters $\eta_1, \eta_2, \ldots, \eta_N > 0$. The random failure model supplies the time to failure of a machine after each successive maintenance operation, which returns the machine to the as-good-as-new state. Machine failures are assumed to be detected instantaneously and perfectly once the machine is out of order. Purely age-based PM is assumed in our model, which means that PM is performed on any machine after a fixed number of work orders are processed by this machine (x_i).

Preventive and corrective maintenance times (T_{PM} or T_{CM}) follow a (truncated) normal distribution, whose parameters are assumed to be known and can easily be determined using historical data. The mean CM repair time, however, is assumed to be longer than the mean PM repair time as observed in the manufacturing systems literature (Cassady et al., 2000), which makes it beneficial to pursue PMs rather than allowing failures to occur, leading to CM actions. We model maintenance crew availability (MA) using a known probability and distinct availability events are mutually independent. If a crew is available then a PM is performed immediately. Otherwise, their availability is delayed for a stochastic period of time (MD).

Incoming work orders are assumed to all arrive at once at the beginning of the planning horizon, and are processed in the first-in-first-out (FIFO) manner. Buffers exist between successive workstations and are assumed to have equal capacity (F). As a work order comes out of a buffer, it is routed to an idle machine in the following workstation. If multiple machines in a workstation are idle, the work order is routed to the machine that was most recently maintained, following heuristics developed by Celen and Djurdjanovic (2011).

3.3. METHODOLOGY

To analyze the described model, a computer simulation representation of the manufacturing system was devised. Rockwell Automation's ARENA® software was utilized to build the simulation model (Kelton et al., 2010).

The system performance under a maintenance policy is evaluated according to an objective function that represents the profit (or benefit) gained by the manufacturing facility. The objective function (B) is expressed as follows:

$$B = R_P - (C_{CM} + C_{PM} + P_C) \tag{3.1}$$

where:

- The revenue

$$R_P = N_P \times S_P \tag{3.2}$$

is the revenues from selling the finished products, equal to the number of units (N_P) produced during the planning horizon multiplied by the selling price per unit (S_P).

- The cost

$$C_{CM} = \sum T_{CM} \, M_C \tag{3.3}$$

is corrective maintenance cost, equal to the total corrective maintenance time (T_{CM}) multiplied by the hourly maintenance labor cost (M_C).

- The cost

$$C_{PM} = \sum T_{PM} \, M_C \tag{3.4}$$

is preventive maintenance cost, similar to corrective maintenance cost.

- The penalty

$$P_C = 0 \qquad if \; N_P = (D - N_C) \tag{3.5}$$

$$P_C = P \qquad if \; N_P < (D - N_C) \tag{3.6}$$

is penalty cost, equal to zero if the number of units produced (N_P) is equal to the daily target (D) minus the number of cancelled orders (N_C) (i.e. if the daily target is satisfied). The penalty is assigned a constant value (P) if the daily target is not satisfied.

The objective of our study is to find the optimal PM policy for each workstation, which maximizes the objective function (B) that considers the income from production, costs of maintenance and a penalty for unmet production targets. More formally, the optimization problem is defined as follows:

Max

$B(x_1, x_2, \dots, x_N)$ (Objective function)

Subject to:

$x_l \leq x_i \leq x_u$ (Bounds)

where $i = 1, 2, \dots, N$

and x_i integer

where 'x_i' represents the number of parts to produce before performing a PM action on a machine in the i^{th} workstation, and 'x_l' and 'x_u' are the upper and lower bounds[3].

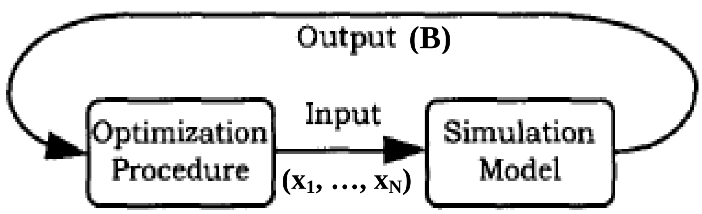
3.4. Optimization of PM Intervals

To optimize the objective function, and find the best number of parts to produce on each machine before PM is needed (x_i), OptQuest™ optimization tool integrated into ARENA® software was used (Glover et al., 1999; Schwetman, 2000; April et al., 2001; Kleijnen and Wan, 2007; http://www.opttek.com).

OptQuest™ is a generic optimizer that integrates scatter search (SS), tabu search (TS), and neural networks (NN) into a single optimization package that can heuristically solve complex optimization problems (Schwetman, 2000). Since the optimizer does not

[3] Since all the parallel machines in a workstation are identical, it is assumed that they all have to perform PM after the same value of x_i parts produced (i.e. $x_{i1} = x_{i2} = \dots = x_{iM}$), therefore, they are modeled as a single variable (x_i).

have predefined knowledge about the system it is trying to optimize, the solution procedure is detached from the system mechanics, and the optimizer treats the system as a black box. An advantage of this is that since the same optimizer can be used to optimize different types of systems, regardless of their application. A disadvantage is that the procedure cannot exploit special structures. The simulation model is used to evaluate, or rather estimate, the objective function, B, of the current solution. The optimization procedure then produces new values for this solution, (x_1, …, x_N), and this procedure repeats as depicted in Figure 2 (Glover et al., 1999).



(Glover et al., 1999)

Figure 2 Decision-making by OptQuest™ optimizer based on simulations

To guide the search through the decision-variable space, a non-monotonic search is carried out, where the objective function need not strictly decrease as the optimization algorithm iterates, and the simulation-generated outputs are used to manipulate the decision-variables that are fed back into the simulation model. According to the value of the objective function, which is tracked over time, the inputs are manipulated in an attempt to improve the objective function as the algorithm proceeds. Feasibility of candidate solutions is ensured by simply limiting the search to the “box” constraints that we have specified, and checking that all user-specific constraints are met (Glover et al., 1999).

More specifically, OptQuest™ follows the following steps. A space search is first implemented by incorporating strategic responses, probabilistic and deterministic, that take into account the objective values and the history of responses. The scatter generation process applied in OptQuet™ focuses on generating the most relevant outcomes, while at the same time achieving diverse solutions. A TS then identifies key attributes of the observed solutions, and imposes restrictions on certain selections of these attributes based on the history of observations. Finally, a NN routine is incorporated to screen out poor solutions before being evaluated by the simulation model, reducing the overall number of computational steps required. This is achieved by collecting information about the objective function values, evaluated at different variable settings, and then using this information to train a neural network, to determine how much additional data and training are still needed to terminate the optimization routine according to the user specified tolerances and optimization time requirements (Glover et al., 1999).

The OptQuest™ optimizer enables the users to control the following:

- Select the precision criteria for simulation outputs by either:
    - Specifying a fixed maximum number of replications.
    - Specifying variable number of replications (between lower and upper bounds) and the optimizer stops replicating if an inferior solution is found.
- Select the relative precision of the optimum value, and the optimizer selects the number of replications needed to achieve a half-width of the 95% confidence interval for the average output to be within a specified percentage of the true mean.

- Select different stopping rules:
    - A predefined “stopping time”
    - Stopping when the optimizer finds non-improving solutions.

(Kleijnen and Wan, 2007)

In our experiments, a number of replications (n_{rep}) was used for each iteration that was large enough to make the sample statistically significant. Also, a fixed number of iterations (n_{iter}) was used for each experiment, to ensure that a high quality maintenance policy is reached, based on initial runs of the simulation model.

3.5. EXPERIMENTATION

Sensitivity analysis and further understanding of the characteristics of the PM scheduling model described above were obtained via a systematic design of experiments (DOE) study. DOE refers to the design of an information gathering exercise, in the presence of variation. In DOE, carrying out multi-factor (factorial) experiments, instead of the traditional single-factor method, makes it more efficient in observing the effects and interactions between the studied factors (Fisher, 1935).

Five experimental parameters (factors) were chosen to be varied in the experiment and each one was allowed to take one of two levels: order cancellation probability (C), raw materials shortage (R), buffer size (F), maintenance crew availability (MA), and maintenance crew delay time (MD). A fractional factorial 2^{5-1} DOE study, having 16 experiments, was conducted (DeVor et al., 2007). We chose the aforementioned factors since they are considered to have the most significant effect on the objective function defined in equation (3.1), and also since it is important to study the interaction between them to gain insight about the effect of uncertainty on maintenance schedules. The levels are selected based on previous experience with the simulation model, and knowledge about its behavior and performance from initial trials.

For each of the 16 experiments, OptQuest™ is used to optimize the objective function for the specified system factors (C, R, F, MA, MD), and the resulting objective function value (B*) with the corresponding PM interval for each workstation (x_1, x_2, … , x_N) is obtained. We use the generated results to form a regression model of the behavior of B* with respect to C, R, F, MA, and MD, which is used to assess the main and interaction effects of experimental factors using the well known ANOVA analysis (DeVor et al., 2007). The 2^{5-1} DOE was run for four different systems of varying complexity (N=M=2, 3, 4, and 5).

Chapter 4: Results and Discussion

4.1 RESULTS

4.1.1. Model and Parameters

The parameters of the manufacturing system studied in this report are summarized in Table 1.

Simulation Parameters			
Daily target	D	120	units
Selling price	S_P	1000	$/unit
Maintenance cost	M_C	100	$/hour
Penalty value	P	500	$
Planning time horizon	T_{PH}	24	hours
PM time distribution	T_{PM1}	NORM(μ=15, σ=2)	min
	T_{PM2}	NORM(μ=23, σ=3)	min
	T_{PM3}	NORM(μ=30, σ=4)	min
	T_{PM4}	NORM(μ=38, σ=5)	min
CM time distribution	T_{CM1}	NORM(μ=60, σ=10)	min
	T_{CM2}	NORM(μ=90, σ=15)	min
	T_{CM3}	NORM(μ=120, σ=20)	min
	T_{CM4}	NORM(μ=150, σ=25)	min
Raw materials delay time distribution	T_D	NORM(μ=60, σ=5)	min
Process time distribution	T_P	TRIA(10, 20, 30)	min

Table 1 Summary of system parameters

Random failure time between arrivals		WEIB(305, 10)	min
Number of workstations	N	[2, 3, 4, 5]	
Number of machines per workstation	M	[2, 3, 4, 5]	
Optimization Parameters			
Number of replications	n_{rep}	30	
Number of iterations	n_{iter}	400	
Lower bound for number of produced parts before conducting PM operation	x_l	1	units
Upper bound for number of produced parts before conducting PM operation	x_u	20	units
DOE Parameters			
Order cancellation probability (C)	C_{low}	0%	
	C_{high}	20%	
Raw materials shortage probability (R)	R_{low}	0%	
	R_{high}	20%	
Buffer size (F)	F_{low}	2	units
	F_{high}	40	units
Maintenance Crew Availability (MA)	MA_{low}	80%	
	MA_{high}	100%	
Maintenance Crew Delay Time (MD)	MD_{low}	NORM(μ=30, σ=5)	min
	MD_{high}	NORM(μ=60, σ=5)	min

Table 1, cont.

4.1.2. Simulation and Experimental Results

The response data obtained from running the 16 experiments were recorded for each system complexity level, as seen in Table 2, Table 3, Table 4, and Table 5. For each experiment the optimization procedure was run four times, each with a different seed to generate the initial scatter search points. The objective function value (B*) was obtained for each of the 4 runs, and the average B* and standard deviation calculated. This was done to ensure that sufficient data is collected for each experiment to be used in the ANOVA analysis.

N=M=2									
Experiment No.	Factors					Response		Decision Variables (Parts Between PMs)	
	C	R	F	MA	MD	Average Objective Function – B*($)	Standard Deviation	x_1	x_2
1	0	0	2	80	60	108175.64	2476.55	8	9
2	20	0	2	80	30	95447.94	1700.12	9	7
3	0	20	2	80	30	108140.99	1763.84	9	9
4	20	20	2	80	60	96083.34	8585.75	9	9
5	0	0	40	80	30	116620.68	2266.10	11	9
6	20	0	40	80	60	95561.13	3409.50	6	8
7	0	20	40	80	60	110304.36	3386.37	10	10
8	20	20	40	80	30	91414.66	3138.76	8	6
9	0	0	2	100	30	118582.35	768.67	8	9
10	20	0	2	100	60	97839.47	2068.76	9	10
11	0	20	2	100	60	108062.56	2242.05	6	9
12	20	20	2	100	30	91741.43	3061.29	5	8
13	0	0	40	100	60	118022.96	1275.24	7	9
14	20	0	40	100	30	92431.51	3405.44	10	5
15	0	20	40	100	30	111796.85	3022.48	10	7
16	20	20	40	100	60	96808.60	756.74	10	11

Table 2 Objective Function and (x_1, x_2) when N=M=2

The ARENA model having N=M=2 was run for each of the 16 DOE experiments, and the number of parts between PMs (x_1, x_2) that optimized the objective function were obtained. As seen from the Table 2, the factors were varied in experiment, according to the DOE design that we used, which will enable us to find the significant factors that have the most influence on the objective function. It is clear that the cancellation probability (C) has a visible influence on the value of B, since the high values cause the value of B* to drop by an approximately $10,000. The effect of other factors is not as clear, but will be shown in the ANOVA analysis presented in the coming section. The parts between PMs (x_1, x_2) vary between 6 and 11, but most of the time they are within the 8-10 range. The standard deviation ranges from approximately $750 to $8,600, which is still relatively low since the mean is in the order of $100,000.

N=M=3										
Experiment No.	Factors					Response		Decision Variables (Parts Between PMs)		
	C	R	F	MA	MD	Average Objective Function – B*($)	Standard Deviation	x_1	x_2	x_3
1	0	0	2	80	60	117710.68	132.04	7	8	8
2	20	0	2	80	30	94685.53	837.98	6	9	8
3	0	20	2	80	30	113534.58	442.63	8	10	8
4	20	20	2	80	60	92955.51	390.15	5	6	6
5	0	0	40	80	30	118195.69	18.41	10	9	8
6	20	0	40	80	60	94409.56	815.80	13	9	8
7	0	20	40	80	60	116233.93	211.66	8	5	8
8	20	20	40	80	30	93518.09	994.05	5	6	5
9	0	0	2	100	30	118329.21	41.40	9	10	9
10	20	0	2	100	60	94968.45	802.51	7	8	6
11	0	20	2	100	60	114568.22	611.28	9	10	9
12	20	20	2	100	30	92961.60	881.19	9	6	6
13	0	0	40	100	60	118315.43	31.64	11	9	9
14	20	0	40	100	30	94781.01	703.39	12	9	8
15	0	20	40	100	30	116392.06	256.59	10	5	8
16	20	20	40	100	60	93648.82	1373.64	10	6	9

Table 3 Objective Function and (x_1, x_2, x_3) when N=M=3

Similar to the previous model, C seems to have the most obvious effect on B* in the more complex N=M=3 model shown in Table 3. However, the parts between PMs range is wider (5-13), meaning that in some cases the machines have to be maintained more frequently, while in others they can be left for longer periods before performing PM. The standard deviation is generally lower, having a smaller range than the previous model, ranging from approximately $50 to $1,400.

N=M=4											
Experiment No.	Factors					Response		Decision Variables (Parts Between PMs)			
	C	R	F	MA	MD	Average Objective Function – B*($)	Standard Deviation	x_1	x_2	x_3	x_4
1	0	0	2	80	60	116170.64	106.10	8	7	7	7
2	20	0	2	80	30	93866.06	1241.97	10	8	9	8
3	0	20	2	80	30	110369.12	747.16	11	8	8	5
4	20	20	2	80	60	89235.52	1398.42	7	5	6	6
5	0	0	40	80	30	116541.33	48.70	11	9	8	7
6	20	0	40	80	60	93627.30	499.94	9	8	8	7
7	0	20	40	80	60	112725.27	588.12	7	5	5	6
8	20	20	40	80	30	90355.77	1041.22	10	5	6	9
9	0	0	2	100	30	116730.46	194.42	7	8	8	9
10	20	0	2	100	60	94049.72	649.71	7	8	7	7
11	0	20	2	100	60	110830.44	490.32	7	6	8	8
12	20	20	2	100	30	89725.91	740.17	8	7	6	7
13	0	0	40	100	60	116739.44	101.26	11	7	8	8
14	20	0	40	100	30	94173.93	523.78	9	9	9	8
15	0	20	40	100	30	111974.97	455.73	9	5	6	8
16	20	20	40	100	60	89824.84	1126.81	8	7	9	7

Table 4 Objective Function and (x_1, x_2, x_3, x_4) when N=M=4

Similar to the previous two models, the N=M=4 model has B* in the same order of magnitude of $100,000. Similar to the previous model, the standard deviation in the N=M=4 model ranges from approximately $50 to $1,400. The parts between PMs, however, have a smaller range, ranging from 5 to 11. The effect of changing C is also apparent on the value of B*.

N=M=5												
Experiment No.	Factors					Response		Decision Variables (Parts Between PMs)				
	C	R	F	MA	MD	Average Objective Function – B*($)	Standard Deviation	x_1	x_2	x_3	x_4	x_5
1	0	0	2	80	60	110967.63	169.52	5	5	5	5	5
2	20	0	2	80	30	89451.08	1271.54	6	5	9	8	5
3	0	20	2	80	30	105778.07	512.41	5	5	5	5	5
4	20	20	2	80	60	83181.37	1135.31	6	10	9	9	6
5	0	0	40	80	30	112189.01	190.33	7	9	7	7	6
6	20	0	40	80	60	89217.84	632.89	9	8	7	8	7
7	0	20	40	80	60	107786.31	628.53	6	5	5	6	5
8	20	20	40	80	30	86296.43	1234.02	6	7	6	6	6
9	0	0	2	100	30	112734.80	418.19	8	9	7	8	7
10	20	0	2	100	60	89747.24	960.21	6	10	6	7	6
11	0	20	2	100	60	105528.51	712.19	7	6	6	6	6
12	20	20	2	100	30	85774.26	975.80	5	5	5	6	6
13	0	0	40	100	60	112765.47	240.54	11	10	8	9	7
14	20	0	40	100	30	89733.85	1067.87	12	13	9	11	6
15	0	20	40	100	30	107200.29	642.53	5	6	5	6	6
16	20	20	40	100	60	86777.79	721.19	11	6	7	6	9

Table 5 Objective Function and (x_1, x_2, x_3, x_4, x_5) when N=M=5

Similar to the previous models, the effect of C on B* is also apparent, and the order of magnitude of B* is also in the $100,000 range, but having slightly lower values as the system complexity increases. Also, the variations in the standard deviation seem to be getting lower as the system becomes more complex, as seen by the smaller range (approx. $170-$1,300). The range of parts between PMs seems to be the same, compared to the previous model, ranging from 5 to 13.

4.1.3. Regression Model and Sensitivity Analysis

By using a fitted linear model, shown earlier by equation (3.7), an ANOVA analysis for the experiment was performed (DeVor et al., 2007). The regression coefficients were obtained using MINITAB v14 software, and recorded in Table 6, Table 7, Table 8, and Table 9. The tables show the main and interaction effects, and their p-values that were obtained for the three system complexity levels. A 5% significance level was used to identify factors that significantly affect the response, meaning if a factor had a p-value < 0.05 it was assumed to be significant.

N=M=2		
Term	Effect	p-value
Constant	**113622**	**0**
C	**-630.70**	**0**
R	**-48.69**	**0**
F	53.54	0.17
MA	**97.28**	**0.04**
MD	-480.83	0.47
C*R	**11.17**	**0.01**
C*F	**-6.14**	**0.01**
C*MA	**-8.07**	**0.05**
C*MD	**10.76**	**0**
R*F	1.22	0.57
R*MA	-5.38	0.19
R*MD	4.85	0.08
F*MA	-1.06	0.62
F*MD	2.67	0.07
MA*MD	3.20	0.24

Table 6 Main and interaction effects for N=M=2 (highlighted items are significant effects)

As seen in Table 6, cancellation probability (C), raw material availability (R), and maintenance crew availability (MA) are the significant main effects for the system consisting of 2 workstations, with 2 machines in each workstation. Also, the interaction between cancellation probability and all other factors (R, F, MA, and MD) were significant.

N=M=3		
Term	Effect	p-value
Constant	**110925**	**0**
C	**-1071.82**	**0**
R	**-213.765**	**0**
F	**57.8516**	**0**
MA	**76.398**	**0.05**
MD	88.70	0.76
C*R	**3.78856**	**0**
C*F	**-1.38**	**0**
C*MA	-0.71	0.39
C*MD	-0.14	0.80
R*F	**1.90**	**0**
R*MA	-0.04	0.96
R*MD	0.66	0.24
F*MA	-0.38	0.39
F*MD	-0.21	0.47
MA*MD	-0.97	0.08

Table 7 Main and interaction effects for N=M=3 (highlighted items are significant effects)

Similar to the previous results, C, R, and MA were significant for a system complexity level N=M=3 (3 workstations, with 3 machines in each workstation), in addition to the buffer size (F). However, there were fewer significant interaction effects related to C.

N=M=4		
Term	Effect	p-value
Constant	**110274**	**0**
C	**-1082.16**	**0**
R	**-199.21**	**0**
F	**74.22**	**0**
MA	66.15	0.44
MD	69.02	0.72
C*R	**2.32**	**0.02**
C*F	**-0.91**	**0.07**
C*MA	0.14	0.88
C*MD	-0.93	0.14
R*F	**1.47**	**0**
R*MA	-1.14	0.23
R*MD	0.38	0.54
F*MA	-0.73	0.14
F*MD	0.06	0.85
MA*MD	-0.74	0.23

Table 8 Main and interaction effects for N=M=4 (highlighted items are significant effects)

As in all our systems, for the model having a complexity N=M=4, C and R are also the main significant effects, in addition to F. Also, C*F, C*R, and R*F are the significant interactions in this model.

N=M=5		
Term	Effect	p-value
Constant	**112263**	**0**
C	**-1230**	**0**
R	**-268.05**	**0**
F	**57.62**	**0**
MA	**11.88**	**0**
MD	**-103.31**	**0**
C*R	**4**	**0**
C*F	-0.35	0.51
C*MA	1.49	0.14
C*MD	-0.62	0.36
R*F	**2**	**0**
R*MA	-0.57	0.57
R*MD	-0.15	0.82
F*MA	**-1**	**0**
F*MD	**1**	**0**
MA*MD	0.81	0.23

Table 9 Main and interaction effects for N=M=5 (highlighted items are significant effects)

The most complex model (N=M=5) had the highest number of significant effects. All main effects (C, R, F, MA, MD) were significant, with C*R, R*F, F*MA, and F*MD being the significant interactions.

4.2 DISCUSSION

As seen from the results, cancellation probability (C), and raw material availability (R) are significant in all models, while the buffer size (F) is significant in the more complex models. This is understandable since C and R directly affect the output of the system, and hence affect the total number of work orders produced during the planning horizon, thus strongly affecting the overall profit. The negative effect of these parameters on the profit is visible from the negative sign of the corresponding coefficients. The size of those effects generally increases in value as the complexity of the system increases, meaning that they reduce the profit by a larger value in more complex systems. This is also understandable since larger, more complex systems have more machines that are prone to random failures, which add to the maintenance costs of the system that are subtracted to obtain the overall profit. Therefore, there is a constant pressure to continuously produce work orders to generate enough income to counteract the costs of maintenance.

In the simplest model (N=M=2), the buffer size (F) is not significant. However, it is very significant in the other, more complex models (N=M=3, 4, 5). Similar to the previously mentioned point, as the system complexity and the number of failure-prone machines increases, the dependence of the system on intermediate buffers to store WIP between the stages increases. More complex systems should be robust. Intermediate buffers help in achieving this, and thus become an important factor. Also, since as the system complexity increases the number of intermediate buffers increases, the effect of changing F becomes more evident as more buffers in the system are varied at the same time.

The effect of maintenance crew availability (MA) is expected to decrease as the system complexity increases, since more complex models have more machines in parallel in each workstation, and hence a work order has more options to pass through to the next workstation even if it found that one of the machines is delayed waiting for the maintenance crew to come an fix it. As seen in the effect tables, MA seems to be significant to the objective function, whereas the N=M=4 model does not show that. This observation necessitates some caution in drawing any substantial conclusions. However, what is common across all models is that the coefficient decreases as the system complexity increases, meaning that the effect of the maintenance crews not being available to fix a machine right away is getting less and less relevant, which is aligned with our intuition.

No reasonable conclusion can be reached from observing the effect of maintenance crew delay time (MD) on the objective function value, since there is no observable trend across the different system complexities. However, since the delay time only comes into effect if the maintenance crew is unavailable, its effect on the profits are not frequent, which may explain our inability to observe any general trends with respect to it. Further studies are needed to better understand this factor.

Chapter 5: Conclusions and Future Work

5.1. Conclusions

In the past two decades, manufacturing companies have come under an increasing pressure to reliably satisfy highly variable and highly uncertain customer demand in order to survive in the severely competitive market. Moreover, the often unpredictable nature of supply chains makes matters more difficult for these companies with regard to satisfying customer demand. In order to survive in the fierce market, it is therefore essential for manufacturing systems to have smooth-flowing, reliable production lines that operate continuously without frequent stoppages caused by unavailability in maintenance crew personnel or spare parts, which is common in real-life facilities. Therefore, effectively applying the correct maintenance strategy is essential in any manufacturing system, which incorporates the effect of uncertainties in customer demand, supply of raw materials, as well as variations in the availability of maintenance resources.

To formulate the maintenance decision problem, a faithful model of the relevant manufacturing system has to be obtained and analyzed. It has been observed in the literature that the advancement in computational technologies aided the shift from pure analytical modeling of manufacturing systems to more complex simulation models, which helps to more accurately model real-life systems, and achieve more practical results. The advancement in computational power also led to the development of a range of meta-heuristic optimization approaches that can be integrated with highly detailed system simulations to heuristically optimize maintenance and production policies.

To investigate the effect of uncertainty in customer demand, supply of raw materials, and unavailability of maintenance resources, a simulation model was constructed for a manufacturing system comprised of N workstations, each having M machines. The optimal maintenance strategies where sought to maximize the value of an objective function depicting benefits of production and losses due to machine failures, maintenance actions, and order cancellations. A meta-heuristic optimizer (OptQuest™) was utilized in this study, to obtain maintenance schedules that maximized the total benefits gained by the production system.

A design of experiments study was then utilized to gain insight on the behavior of the modeled system, and the effects of various system and environmental parameters on the maintenance decisions. Selected system parameters were changed, and the reactions of the system to these changes were statistically analyzed, in order to find the significant effects. It was found that for all system complexity levels the cancellation probability (C) and the raw material availability (R) are significant factors, negatively affecting the profits corresponding to the resulting maintenance decisions. It was also found that the buffer size (F) is not significant for the simplest system, but becomes significant for more complex systems. Finally, the effect of the maintenance crew availability (MA) diminishes as the system complexity increases. All the aforementioned findings are supported by engineering intuition on manufacturing system physics.

5.2. ORIGINAL CONTRIBUTIONS

In this MS thesis, a simulation-based framework was developed that integrates uncertainties in work order demand, supply of raw materials, and maintenance crew availability in order to obtain the optimal maintenance schedule, and the most significant variables affecting the generated profit.

Finally, the sensitivity of the suggested model was studied, by increasing the system complexity, and the significant system parameters were obtained which helped in gaining useful insight on the behavior of such a system in real-life manufacturing facilities.

5.3. Future Work

Future work beyond the research work presented in this report can be summarized as follows:

- The proposed framework can be expanded to more complex systems having more workstations. Also, work orders can have the flexibility to bypass certain workstations, as part of a more complex process plan, and only be routed to certain workstations making the facility operate more as a flexible manufacturing system (FMS).
- More than one product type can be manufactured in the manufacturing facility, where each product type would have a different process plan, thus a different order of processing through the workstations.
- Quality issues can be incorporated into the integrated policies, where quality, reliability and cost can be incorporated with maintenance and production scheduling. Also, the assumptions of perfect product quality can be relaxed to investigate more comprehensive integrated policies, and consider the effect of machine failures on the product quality.

- Reconfiguration of the line layout can also be integrated in parallel, serial, or hybrid systems, to add a new option for maintenance decisions.
- More elaborate cost functions could be tried, in order to incorporate more complex situations faced in real-life manufacturing facilities.
- More specialized and efficient heuristic tools can be can be explored to achieve better, and faster convergence in more complex integrated optimization problems.

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