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Maintenance Management and Modeling in Modern Manufacturing Systems

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1. Introduction

The cost of maintenance in industrial facilities has been estimated as 15-40% (an average of 28%) of total production costs (Mobley, 1990; Sheu and Krajewski, 1994). The amount of money that companies spent yearly on maintenance can be as large as the net income earned (McKone and Wiess, 1998). Modern manufacturing systems generally consist of automated and flexible machines, which operate at much higher rates than the traditional or conventional machines. While the traditional machining systems operate at as low as 20% utilization rates, automated and Flexible Manufacturing Systems (FMS) can operate at 70-80% utilization rates (Vineyard and Meredith, 1992). As a result of this higher utilization rates, automated manufacturing systems may incur four times more wear and tear than traditional manufacturing systems. The effect of such an accelerated usage on system performance is not well studied. However, the accelerated usage of an automated system would result in higher failure rates, which in turn would increase the importance of maintenance and maintenance-related activities as well as effective maintenance management. While maintenance actions can reduce the effects of breakdowns due to wear-outs, random failures are still unavoidable. Therefore, it is important to understand the implications of a given maintenance plan on a system before the implementation of such a plan.

Modern manufacturing systems are built according to the volume/variety ratio of production. A facility may be constructed either for high variety of products, each with low volume of production, or for a special product with high volume of production. In the first case, flexible machines are utilized in a job shop environment to produce a variety of products, while in the second case special purpose machinery are serially linked to form transfer lines for high production rates and volumes. In any case, the importance of maintenance function has increased due to its role in keeping and improving the equipment

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availability, product quality, safety requirements, and plant cost-effectiveness levels since maintenance costs constitute an important part of the operating budget of manufacturing firms (Al-Najjar and Alsyouf, 2003).

Without a rigorous understanding of their maintenance requirements, many machines are either under-maintained due to reliance on reactive procedures in case of breakdown, or over-maintained by keeping the machines off line more than necessary for preventive measures. Furthermore, since industrial systems evolve rapidly, the maintenance concepts will also have to be reviewed periodically in order to take into account the changes in systems and the environment. This calls for implementation of flexible maintenance methods with feedback and improvement (Waeyenbergh and Pintelon, 2004).

Maintenance activities have been organized under different classifications. In the broadest way, three classes are specified as (Creehan, 2005):

1. Reactive: Maintenance activities are performed when the machine or a function of the machine becomes inoperable. Reactive maintenance is also referred to as corrective maintenance (CM).
2. Preventive: Maintenance activities are performed in advance of machine failures according to a predetermined time schedule. This is referred to as preventive maintenance (PM).
3. Predictive/Condition-Based: Maintenance activities are performed in advance of machine failure when instructed by an established condition monitoring and diagnostic system.

Several other classifications, as well as different names for the same classifications, have been stated in the literature. While CM is an essential repair activity as a result of equipment failure, the voluntary PM activity was a concept adapted in Japan in 1951. It was later extended by Nippon Denso Co. in 1971 to a new program called Total Productive Maintenance (TPM), which assures effective PM implementation by total employee participation. TPM includes Maintenance Prevention (MP) and Maintainability Improvement (MI), as well as PM. This also refers to “maintenance-free” design through the incorporation of reliability, maintainability, and supportability characteristics into the equipment design. Total employee participation includes Autonomous Maintenance (AM) by operators through group activities and team efforts, with operators being held responsible for the ultimate care of their equipments (Chan et al., 2005).

The existing body of theory on system reliability and maintenance is scattered over a large number of scholarly journals belonging to a diverse variety of disciplines. In particular, mathematical sophistication of preventive maintenance models has increased in parallel to the growth in the complexity of modern manufacturing systems. Extensive research has been published in the areas of maintenance modeling, optimization, and management. Excellent reviews of maintenance and related optimization models can be seen in (Valdez-Flores and Feldman, 1989; Cho and Parlar, 1991; Pintelon and Gelders, 1992; and Dekker, 1996).

Limited research studies have been carried out on the maintenance related issues of FMS (Kennedy, 1987; Gupta et al., 1988; Lin et al., 1994; Sun, 1994). Related analysis include effects of downtimes on uptimes of CNC machines, effects of various maintenance policies on FMS failures, condition monitoring system to increase FMS and stand-alone flexible machine availabilities, automatic data collection, statistical data analysis, advanced user interface, expert system in maintenance planning, and closed queuing network models to optimize the number of standby machines and the repair capacity for FMS. Recent studies related to FMS maintenance include, stochastic models for FMS availability and productivity under CM operations (Savsar, 1997a; Savsar, 2000) and under PM operations (Savsar, 2005a; Savsar, 2006).

In case of serial production flow lines, literature abounds with models and techniques for analyzing production lines under various failure and maintenance activities. These models range from relatively straight-forward to extremely complex, depending on the conditions prevailing and the assumptions made. Particularly over the past three decades a large amount of research has been devoted to the analysis and modeling of production flow line systems under equipment failures (Savsar and Biles, 1984; Boukas and Hourie, 1990; Papadopoulos and Heavey, 1996; Vatn et al., 1996; Ben-Daya and Makhdoum, 1998; Vouros et al., 2000; Levitin and Meizin, 2001; Savsar and Youssef, 2004; Castro and Cavalca, 2006; Kyriakidis and Dimitrakos, 2006). These models consider the production equipment as part of a serial system with various other operational conditions such as random part flows, operation times, intermediate buffers with limited capacity, and different types of maintenance activities on each equipment. Modeling of equipment failures with more than one type of maintenance on a serial production flow line with limited buffers is relatively complicated and need special attention. A comprehensive model and an iterative computational procedure has been developed (Savsar, 2005b) to study the effects of different types of maintenance activities and policies on productivity of serial lines under different operational conditions, such as finite buffer capacities and equipment failures. Effects of maintenance policies on system performance when applied during an opportunity are discussed by (Dekker and Smeitnik, 1994). Maintenance policy models for just-in-time production control systems are discussed by (Albino, et al., 1992 and Savsar, 1997b).

In this chapter, procedures that combine analytical and simulation models to analyze the effects of corrective, preventive, opportunistic, and other maintenance policies on the performance of modern manufacturing systems are presented. In particular, models and results are provided for the FMS and automated Transfer Lines. Such performance measures as system availability, production rate, and equipment utilization are evaluated as functions of different failure/repair conditions and various maintenance policies.

2. Maintenance Modeling in Modern Manufacturing Systems

It is known that the probability of failure increases as an equipment is aged, and that failure rates decrease as a result of PM and TPM implementation. However, the amount of reduction in failure rate, from the introduction of PM activities, has not been studied well. In particular, it is desirable to know the performance of a manufacturing system before and after the introduction of PM. It is also desirable to know the type and the rate at which preventive maintenance should be scheduled. Most of the previous studies, which deal with maintenance modeling and optimization, have concentrated on finding an optimum balance between the costs and benefits of preventive maintenance. The implementation of PM could be at scheduled times (*scheduled PM*) or at other times, which arise when the equipment is stopped because of other reasons (*opportunistic PM*). Corrective maintenance (CM) policy is adapted if equipment is to be maintained only when it fails. The best policy has to be selected for a given system with respect to its failure, repair, and maintenance characteristics.

Two well-known preventive maintenance models originating from the past research are called *age-based* and *block-based replacement* models. In both models, PM is scheduled to be carried out on the equipment. The difference is in the timing of consecutive PM activities. In the aged-based model, if a failure occurs before the scheduled PM, PM is rescheduled from the time the corrective maintenance is completed on the equipment. In the block-based model, on the other hand, PM is always carried out at scheduled times regardless of the time of equipment failures and the time that corrective maintenance is carried out. Several other maintenance models, based on the above two concepts, have been discussed in the literature as listed above.

One of the main concerns in PM scheduling is the determination of its effects on time between failures (TBF). Thus, the basic question is to figure out the amount of increase in TBF due to implementation of a PM. As mentioned above, introduction of PM reduces failure rates by eliminating the failures due to wear outs. It turns out that in some cases, we can theoretically determine the amount of reduction in total failure rate achieved by separating failures due to wear outs from the failures due to random causes.

2.1 Mathematical Modeling for Failure Rates Partitioning

Following is a mathematical procedure to separate random failures from wear-out failures. This separation is needed in order to be able to see the effects of maintenance on the productivity and operational availability of an equipment or a system. The procedure outlined here can be utilized in modeling and simulating maintenance operations in a system.

Let f(t) = Probability distribution function (pdf) of time between failures.

F(t) = Cumulative distribution function (cdf) of time between failures.

R(t) = Reliability function (probability of equipment survival by time t).

h(t) = Hazard rate (or instantaneous failure rate of the equipment).

Hazard rate $h(t)$ can be considered as consisting of two components, the first from random failures and the second from wear-out failures, as follows:

$$h(t) = h_1(t) + h_2(t) \tag{1}$$

Since failures are from both, chance causes (unavoidable) and wear-outs (avoidable), reliability of the equipment by time t, can be expressed as follows:

$$R(t) = R1(t)\ R2(t) \tag{2}$$

Where, $R_1(t)$ = Reliability due to chance causes or random failures and $R_2(t)$ = Reliability from wear-outs, $h_1(t)$ = Hazard rate from random failures, and $h_2(t)$

= Hazard rate from wear-out failures. Since the hazard rate from random failures is independent of aging and therefore constant over time, we let $h_1(t) = \lambda$. Thus, the reliability of the equipment from random failures with constant hazard rate:

$$R_1(t) = e^{-\lambda t} \quad \text{and} \quad h(t) = \lambda + h_2(t) \tag{3}$$

It is known that:

$$h(t) = f(t)/R(t) = f(t)/[1-F(t)] = \lambda + h_2(t) \tag{4}$$

$$h_2(t) = h(t) - h_1(t) = f(t)/[1-F(t)] - \lambda \tag{5}$$

$$R_2(t) = R(t)/R_1(t) = [1-F(t)]/ e^{-\lambda t} \tag{6}$$

$$h_2(t) = f_2(t)/R_2(t) \tag{7}$$

$$f_2(t) = h_2(t)R_2(t) = [\frac{f(t)}{1-F(t)} - \lambda][\frac{1-F(t)}{e^{-\lambda t}}] = \frac{f(t)}{e^{-\lambda t}} - \frac{\lambda}{e^{-\lambda t}}[1-F(t)]$$

where

$$f_2(t)=\frac{dF_2(t)}{dt} \qquad F_2(t) = 1 - R_2(t) = 1 - \frac{1-F(t)}{e^{-\lambda t}} = \frac{e^{-\lambda t} - R(t)}{e^{-\lambda t}} \tag{8}$$

Equation (8) can be used to determine $f_2(t)$. These equations show that total time between failures, f(t), can be separated into two distributions, time between failures from random causes, with pdf given by $f_1(t)$, and time between failures from wear-outs, with pdf given by $f_2(t)$. Since the failures from random causes could not be eliminated, we concentrate on decreasing the failures from wear-outs by using appropriate maintenance policies. By the procedure described above, it is possible to separate the two types of failures and develop the best maintenance policy to eliminate wear-out failures. It turns out that this separation is analytically possible for uniform distribution. However, it is not possible for other distributions. Another approach is used for other distributions when analyzing and implementing PM operations. Separation of failure rates is particularly important in simulation modeling and analysis of maintenance operations. Failures from random causes are assumed to follow an exponential distribution with constant hazard rate since they are unpredictable and do not depend on operation time of equipment. Exponential distribution is the type of distribution that has memoryless property; a property that results in constant failure rates over time regardless of aging and wear outs due to usage. Following section describes maintenance modeling for different types of distributions.

2.2 Uniform Time to Failure Distribution

For uniformly-distributed time between failures, t, in the interval $0 < t < \mu$, the pdf of time between failures without introduction of PM is given by: $f(t)=1/\mu$. If we let $\alpha = 1/\mu$, then $F(t)= \alpha t$ and reliability is given as $R(t)=1-\alpha t$ and the total failure rate is given as $h(t)=f(t)/R(t)=\alpha/(1-\alpha t)$. If we assume that the hazard rate from random failures is a constant given by $h_1(t)=\alpha$, then the hazard rate from wear-out failures can be determined by $h_2(t)=h(t)-h_1(t)=\alpha/(1-\alpha t)-\alpha=\alpha^2 t/(1-\alpha t)$. The corresponding time to failure pdf for each type of failure rate is as follows:

$$f_1(t) = \alpha \times e^{(-\alpha t)}, \qquad 0 < t < \mu \tag{9}$$

$$f_2(t) = \alpha^2 \times t \times e^{(\alpha t)}, \qquad 0 < t < \mu \tag{10}$$

The reliability function for each component is as follows:

$$R_1(t) = e^{(-\alpha t)}, \qquad 0 < t < \mu \tag{11}$$

$$R_2(t) = (1 - \alpha t) \times e^{\alpha t}, \qquad 0 < t < \mu \tag{12}$$

$$R(t) = R_1(t) \times R_2(t) \tag{13}$$

When PM is introduced, failures from wear-outs are eliminated and thus the machines fail only from random failures, which are exponentially distributed as given by $f_1(t)$. Sampling for the time to failures in simulations is then based on an exponential distribution with mean μ and a constant failure rate of $\alpha=1/\mu$. In case of CM without PM, in addition to the random failures, wear-out failures are also present and thus the time between equipment failures is uniformly distributed between zero and μ as given by f(t). The justification behind this assumption is that uniform distribution implies an increasing failure rate with two components, namely, failure rate from random causes and failure rate from wear-out causes as given by $h_1(t)$ and $h_2(t)$, respectively. Initially when t = 0, failures are from random causes with a constant rate $\alpha=1/\mu$. As the equipment operates, wear-out failures occur and thus the total failure rate h(t) increases with time t. Sampling for the time between failures in modeling and simulation is based on uniform distribution with mean μ/2 and increasing failure rate, h(t).

2.3. Non-uniform time to failure distributions

2.3.1 Normal distribution:

If the times between failures are normally distributed, it is not possible to separate the two types of failures analytically. However, the following procedure can be implemented in simulation models:
When no preventive maintenance is implemented, times between failures are sampled from a normal distribution with mean μ and standard deviation σ. When PM is implemented, wear-out failures are eliminated and the remaining random failures follow an exponential distribution with constant failure rate with extended mean time between failures. It is assumed that mean time between equipment failures after introduction of PM extends from μ to kμ, where k is a constant greater than 1.

2.3.2 Gamma Distribution:

For a gamma distribution, which is Erlang when its shape parameter α is integer and exponential when α=1, the expected value of random variable T is defined by E(T) = αβ. Thus, by changing α and β values, mean time between failures can be specified as required. When no PM is introduced, times between failures are sampled from a gamma distribution with mean time between failures of $\alpha\beta$. If PM is introduced and wear-out failures are eliminated, times between failures are extended by a constant k. Therefore, sampling is made from an exponential distribution with mean $k(\alpha\beta)$.

2.3.3 Weibull Distribution:

For the Weibull distribution, α is a shape parameter and β is a scale parameter. The expected value of time between failures, $E(T)=MTBF=\beta\Gamma(1/\alpha)/\alpha$, and its variance is $V(T)= \beta^2[2\Gamma(2/\alpha)-\{\Gamma(1/\alpha)\}^2/\alpha]$. For a given value of α, $\beta=\alpha(MTBF)/\Gamma(1/\alpha)$. When there is no PM, times between failures are sampled from Weibull with parameters α and β in simulation models. When PM is introduced, wear-out failures are eliminated and the random failures are sampled in simulation from an exponential distribution with mean=$k[\beta\Gamma(1/\alpha)/\alpha]$, where α and β are the parameters of the Weibull distribution and k is a constant greater than 1.

2.3.4 Triangular Distribution:

The triangular distribution is described by the parameters a, m, and b (i.e., minimum, mode, and maximum). Its mean is given by $E(T)=(a+m+b)/3$ and variance by $V(T) = (a^2+m^2+b^2-ma-ab-mb)/18$. Since the times between failures can be any value starting from zero, we let a=0 and thus m=b/3 from the property of a triangular distribution. Mean time between failures is $E(T)=(m+b)/3=[b+b/3]/3=4b/9=4m/3$. If no PM is introduced, time between failures are sampled in simulation from a triangular distribution with parameters a, m, b or 0, b/3, b. If PM is introduced, again wear-out failures are eliminated and the random failures are sampled from an exponential distribution with an extended mean of $k[a+m+b]/3$, where a, m, and b are parameters of the triangular distribution that describe the time between failures. The multiplier k is a constant greater than 1.

3. Analysis of the Effects of Maintenance Policies on FMS Availability

Equipment in FMS systems can be subject to corrective maintenance; corrective maintenance combined with a preventive maintenance; and preventive maintenance implemented at different opportunities. FMS operates with an increasing failure rate due to random causes and wear-outs. The stream of mixed failures during system operation is separated into two types: (i) random failures due to chance causes; (ii) time dependent failures due to equipment usage and wear-outs. The effects of preventive maintenance policies (scheduled and opportunistic), which are introduced to eliminate wear-out failures of an FMS, can be investigated by analytical and simulation models. In particular, effects of various maintenance policies on system performance can be investigated under various time between failure distributions, including uniform, normal, gamma, triangular, and Weibull failure time distributions, as well as different repair and maintenance parameters.

3.1 Types of Maintenance Policies

In this section, five types maintenance policies, which resulted in six distinct cases, and their effects on FMS availability are described.

i) No Maintenance Policy:
In this case, a fully reliable FMS with no failures and no maintenance is considered.

ii) Corrective Maintenance Policy (CM):
The FMS receives corrective maintenance only when equipment fails. Time between equipment failures can follow a certain type of distribution. In case of uniform distribution, two different types of failures can be separated in modeling and analysis.

iii) Block-Based PM with CM Policy (BB):
In this case, the equipment is subject to preventive maintenance at the end of each shift to eliminate the wear out failures during the shift. However, regardless of any CM operations between the two scheduled PMs, the PM operations are always carried out as scheduled at the end of the shifts without affecting the production schedule. This policy is evaluated under various time between failure distributions. Figure 1 illustrates this maintenance process.

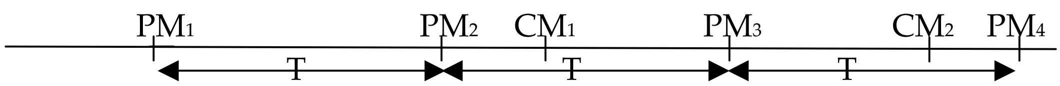

Figure 1. Illustration of PM operations under a block-based policy

iv) Age-Based PM with CM Policy (AB):
In this policy, preventive maintenance is scheduled at the end of a shift, but the PM time changes as the equipment undergoes corrective maintenance. Suppose that the time between PM operations is fixed as T hours and before performing a particular PM operation the equipment fails. Then the CM operation is carried out and the next PM is rescheduled T hours from the time the repair for the CM is completed. CM has eliminated the need for the next PM. If the scheduled PM arrives before a failure occurs, PM is carried out as scheduled. Figure 2 illustrates this process.

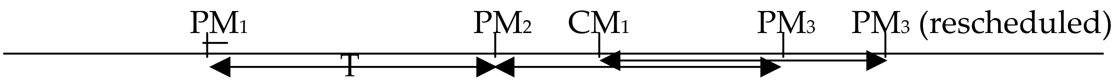

Figure 2. Illustration of PM operations under age-based policy.

v) Opportunity-Triggered PM with CM Policy (OT):
In this policy, PM operations are carried out only when they are triggered by failure. In other words, if a failure that requires CM occurs, it also triggers PM. Thus, corrective maintenance as well as preventive maintenance is applied to the machine together at the time of a failure. This is called triggered preventive maintenance. Since the equipment is already stopped and some parts are already maintained for the CM, it is expected that the PM time would be reduced in this policy. We assign a certain percentage of reduction in the PM operation. A 50% reduction was assumed reasonable in the analysis below.

vi) Conditional Opportunity-Triggered PM with CM Policy (CO): In this policy, PM is performed on each machine at either scheduled times or when a specified opportunistic condition based on the occurrence of a CM arises. The maintenance management can define the specified condition. In our study, a specific condition is defined as follows: if a machine fails within the last quarter of a shift, before the time of next PM, the next PM will be combined with CM for this machine. In this case, PM scheduled at the end of the shift would be skipped. On the other hand, if a machine failure occurs before the last quarter of the shift, only CM is introduced and the PM is performed at the end of the shift as it was scheduled. This means that the scheduled PM is performed only for those machines that did not fail during the last quarter of the shift.

The maintenance policies described above are compared under similar operating conditions by using simulation models with analytical formulas incorporated into the model as described in section 2. The FMS production rate is first determined under each policy. Then, using the production rate of a fully reliable FMS as a basis, an index, called Operational Availability Index (OAI_i) of the FMS under each policy i, is developed: $OAI_i=P_i/P_1$, where P_1 = production rate of the reliable FMS and P_i = production rate of the FMS operated under maintenance policy i (i=2, 3, 4, 5, and 6). General formulation is described in section 2 for five different times between failure distributions and their implementation with respect to the maintenance policies. The following section presents a maintenance simulation case example for an FMS system.

3.2 Simulation Modeling of FMS Maintenance Operations

In order to analyze the performance measures of FMS operations under different maintenance policies, simulation models are developed for the fully reliable FMS and for each of the five maintenance related policies described above. Simulation models are based on the SIMAN language (Pegden et al., 1995). In order to experiment with different maintenance policies and to illustrates their effects on FMS performance, a case problem, as in figure 3 is considered. Table 1 shows the distance matrix for the FMS layout and Table 2 shows mixture of three different types of parts arriving on a cart, the sequence of operations, and the processing times on each machine. An automated guided vehicle (AGV) selects the parts and transports them to the machines according to processing requirements and the sequence. Each part type is operated on by a different sequence of machines. Completed parts are placed on a pallet and moved out of the system. The speed of the AGV is set at 175 feet/minute. Parts arrive to the system on pallets containing 4 parts of type 1, 2 parts of type 2, and 2 parts of type 3 every 2 hours. This combination was fixed in all simulation cases to eliminate the compounding effects of randomness in arriving parts on the comparisons of different maintenance policies. The FMS parameters are set based on values from an experimental system and previous studies.

One simulation model was developed for each of the six cases as: i) A fully reliable FMS (denoted by FR); ii) FMS with corrective maintenance policy only (CM); iii) FMS with block-based policy (BB); iv) FMS with age-based policy (AB); v) FMS with opportunity-triggered maintenance policy (OP); and vi) FMS with conditional opportunity-triggered maintenance policy (CO). Each simulation experiment was carried out for the operation of the FMS over a period of one month (20 working days or 9600 minutes). In the case of PM, it was assumed that a PM time of 30 minutes (or 15 minutes when combined with CM) is added to 480 minutes at the end of each shift. Twenty simulation replicates are made and the average output rate during one month is determined. The output rate is then used to determine the FMS operational availability index for each policy. The output rate is calculated as the average of the sum of all parts of all types produced during the month. The fully reliable FMS demonstrates maximum possible output (P_i) and is used as a base to compare other maintenance policies with $OAI_i = P_i/P_1$.

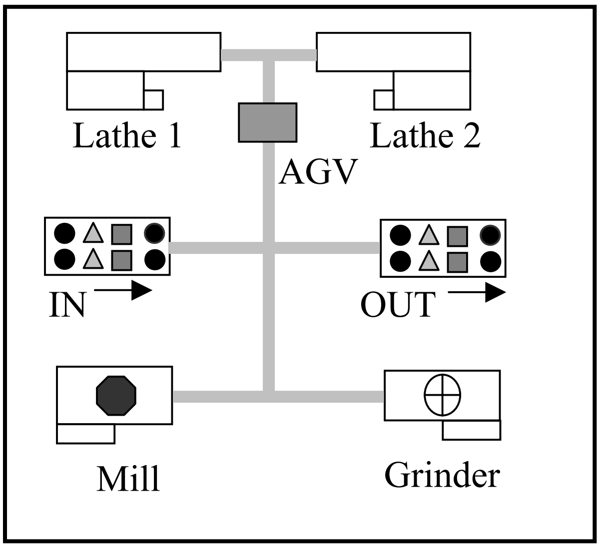

Figure 3. A flexible manufacturing system

	In	Lathe	Mill	Grind	Out
In	-	100	75	100	40
Lathe	-	-	150	175	155
Mill	-	-	-	50	90
Grind	-	-	-	-	115
Out	-	-	-	-	-

Table 1. Distance matrix (in feet).

Part Type	Lathe(L)	Milling(M)	Grinding(G)
1 (L-M-G)	Norm(30,5)	Norm(15,3)	Unif(10,15)
2 (M-G-L)	Norm(25,8)	Tria(2,10,15)	Norm(10,2)
3 (G-L)	Unif (5,10)		Norm(15,3)

Table 2. Processing time and operation sequences.

In *the first simulation experiment*, times between failures are assumed to be uniformly distributed between 0 and T for all machines with MTBF of T/2. Uniform distribution permits theoretical separation of chance-caused failures from wear-out failures. In the absence of any preventive maintenance, a machine can fail anytime from 0 to T. However, when PM is introduced, wear-out failures are eliminated; only the failures from chance causes remain, which have a constant hazard rate and exponential distribution with MTBF of T. In this experiment, the value of T is varied from 500 to 4000 minutes, in increments of 500 minutes. Repair time is assumed to be normal with mean 100 and standard deviation of 10 minutes for all machines. If PM is introduced on a machine, it is assumed that the PM is done at the end of each shift and it takes 30 minutes for each machine. If PM is triggered by the CM and done at this opportunity, PM time reduces to half, i.e., 15 minutes, since it is combined with the CM tasks. Mean production rate values are normalized with respect to fully reliable (FR) FMS values and converted into OAIs. These results are shown in figure 4. As it is seen from figure 4, performing CM alone without any PM is the worst policy of all. Observing all the policies in the figure, the best policy appears to be the opportunity triggered maintenance policy (OT). Between the age and block-based policies, the age-based policy (AB) performed better. Among all the policies with PM, block-based policy (BB) appears to be the worst policy.

As the MTBF increases, all the policies reach a steady state level with respect to operational availability, but the gap between them is almost the same at all levels of MTBF. In the case of CM only policy, the operational availability index sharply increases with the initial increase in MTBF from 500 to 1000.

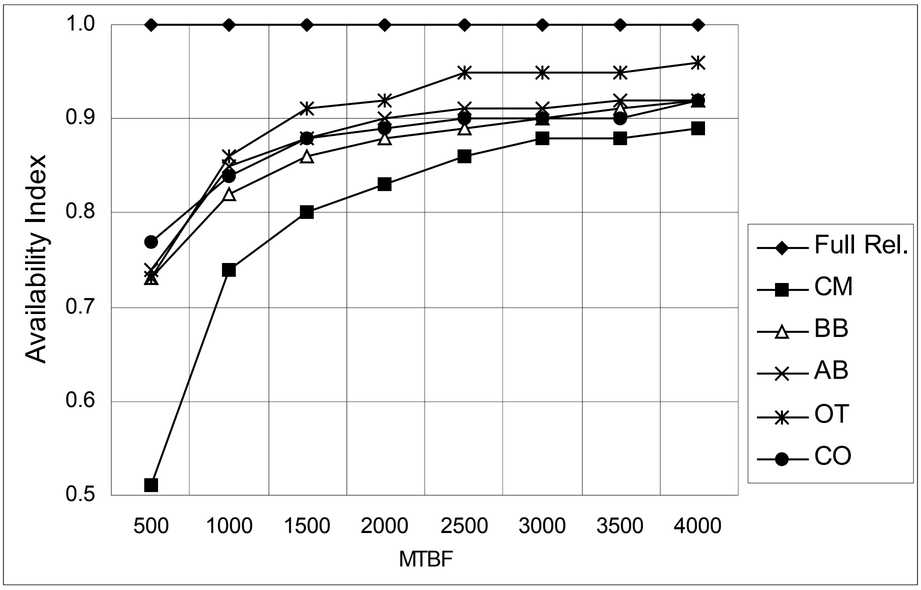

Figure 4. Operational availability index under different maintenance policies.

As indicated above, when PM is introduced, time between failures become exponential regardless of the type of initial distribution. Experiments with different distributions show that all distributions give the same performance results under the last four maintenance policies, which include some form of PM. However, FMS performance would differ under different failure distributions when a CM policy is implemented. This is investigated in *the second experiment*, which compares the effects of various time to failure distributions, including uniform, normal, gamma, Weibull, and triangular distributions, on FMS performance under the CM policy only. All of the FMS parameters related to operation times, repair, and PM times were kept the same as given in the first experiment. Only time to failure distributions and related parameters were changed such that MTBF was varied between 500 and 4000.

In the case of the gamma distribution, $E(T) = \alpha\beta$. Thus, $\alpha = 250$ and $\beta= 2$ resulted in a MTBF of 500; $\alpha = 750$ and $\beta= 2$ resulted in a MTBF=1500; $\alpha = 1250$ and $\beta= 2$ resulted in a MTBF=2500; and $\alpha = 2000$ and $\beta= 2$ resulted in a MTBF=4000, which are the same values specified in the second experiment for the normal distribution. For the Weibull distribution, which has MTBF=$E(T)= \beta\Gamma(1/\alpha)/\alpha$, two the parameters α (shape parameter) and β (scale parameter) have to be defined. For example, if MTBF=500 and α=2, then, $500=\beta\Gamma(1/\alpha)/\alpha$

=βΓ(1/2)/2. Since Γ(1/2)=√π, β=1000/√π. Thus, for MTBF=500, β=564.2. Similarly, for MTBF=1500, β=1692.2, for MTBF=2500, β=2820.95, and for MTBF=4000, β=4513.5 are used. Triangular distribution parameters are also determined similarly as follows: E(T) = (a+m+b)/3 and V(T)= ($a^2+m^2+b^2$-ma-ab-mb)/18. Since the times between failures can be any value starting from zero, we let a=0 and m=b/3 from the property of triangular distribution. E(T)= (m+b)/3=[b+b/3]/3=4b/9=4m/3. In order to determine values of the parameters, we utilize these formula. For example, if MTBF =500, then 500=4b/9 and thus b=4500/4 = 1125 and m=b/3=1500/4=375. Similarly, for MTBF=1500, b=3375 and m=1125. For MTBF=2500, b=5625 and m=1875. For MTBF=4000, b=9000 and m=3000. Table 3 presents a summary of the related parameters.

Distribution	MTBF	Parameters that result in the specified MTBF		
Gamma		α	β	
	500	250	2	
	1500	750	2	
	2500	1250	2	
	4000	2000	2	
Weibull	500	2	564.2	
	1500	2	1692.2	
	2500	2	2820.95	
	4000	2	4513.5	
Triangular	MTBF	a	b	m
	500	0	1125	375
	1500	0	3375	1125
	2500	0	5625	1875
	4000	0	9000	3000

Table 3. Parameters of the distributions used in simulation.

Comparisons of five distributions, uniform, normal, gamma, Weibull, and triangular, with respect to CM are illustrated in figure 5, which plots the OAI values normalized with respect to fully reliable system using production rates. All of the distributions show the same trend of increasing OAI values, and thus production rates, with respect to increasing MTBF values. As it seen in figure 5, uniformly distributed time between failures resulted in significantly different FMS availability index as compared the other four distributions. This is because in a uniform distribution, which is structurally different from other distributions, probability of failure is equally likely at all possible values that the random variable can take, while in other distributions probability concentration is around the central value. The FMS performance was almost the same under the other four distributions investigated. This indicates that the type of distribution has no critical effects on FMS performance under CM policy if the distribution shapes are relatively similar.

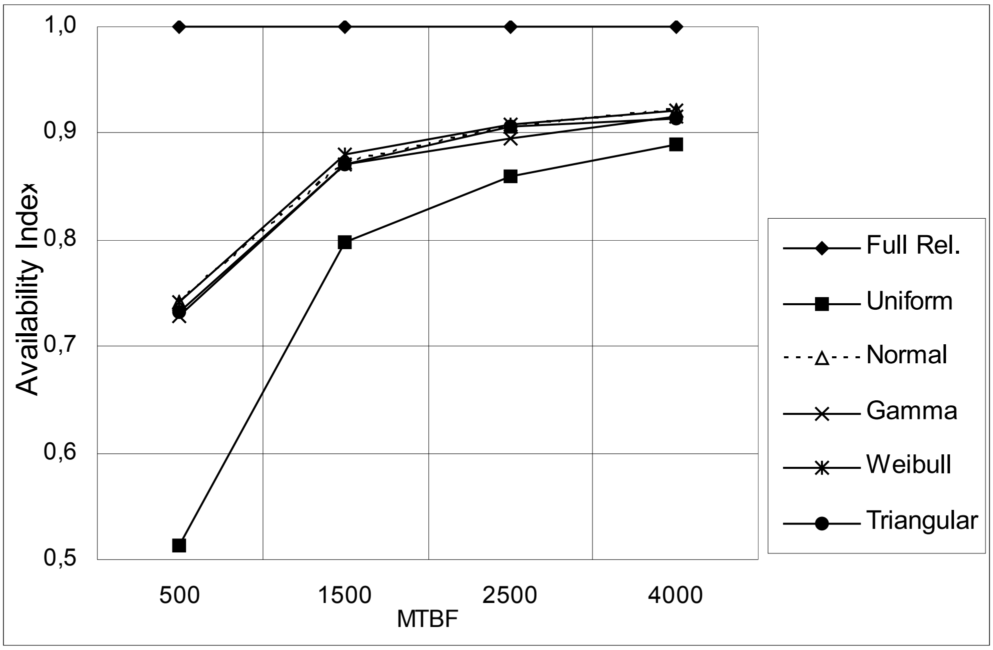

Figure 5. FMS OAI under various time to failure distributions and CM policy

The results of the analysis show that maintenance of any form has significant effect on the availability of the FMS as measured by its output rate. However, the type of maintenance applied is important and should be carefully studied before implementation. In the particular example studied, the best policy in all cases was the opportunity-triggered maintenance policy and the worst policy was the corrective maintenance policy. The amount of increase in system availability depends on the maintenance policy applied and the specific case studied. Implementation of any maintenance policy must also be justified by a detailed cost analysis.