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Maintenance scheduling in manufacturing systems based on predicted machine degradation

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Abstract In this paper, we propose a new method for scheduling of maintenance operations in a manufacturing system using the continuous assessment and prediction of the level of performance degradation of manufacturing equipment, as well as the complex interaction between the production process and maintenance operations. Effects of any maintenance schedule are evaluated through a discrete-event simulation that utilizes predicted probabilities of machine failures in the manufacturing system, where predicted probabilities of failure are assumed to be available either from historical equipment reliability information or based on the newly available predictive algorithms. A Genetic Algorithm based optimization procedure is used to search for the most cost-effective maintenance schedule, considering both production gains and maintenance expenses. The algorithm is implemented in a simulated environment and benchmarked against several traditional maintenance strategies, such as corrective maintenance, scheduled maintenance and condition-based maintenance. In all cases that were studied, application of the newly proposed maintenance scheduling tool resulted in a noticeable increase in the cost-benefits, which indicates that the use of predictive information about equipment performance through the newly proposed maintenance scheduling method could result in significant gains obtained by optimal maintenance scheduling.

Keywords Cost-effective maintenance · Genetic algorithm · Machine degradation · Maintenance scheduling

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Introduction

Modern manufacturing systems are complex systems of interacting machines working together towards a common production goal. Over time, the condition of all machines degrades with usage and age and if no maintenance action is taken, this degradation process will ultimately result in a machine failure. Equipment failures interrupt the normal manufacturing process and lack of timely maintenance could result in significant loss of production and decrease of profits of the manufacturing system (Zeng, 1997). On the other hand, excessive maintenance can virtually eliminate downtime caused by equipment failure, but the corresponding cost of maintenance will increase and thus decrease the profits. Therefore, it is clear that a proper maintenance strategy in a production system is necessary for it to operate in the most cost effective manner.

In the past several decades, maintenance problems have been studied intensely (Ben-Daya, Duffuaa, and Raouf, 2000; Dekker, 1996; Lyonnet, 1991; Wang, 2002). Majority of the early work has been conducted on single-unit systems. A commonly accepted maintenance policy is the age-dependent preventive maintenance (PM) policy, under which a unit's PM times are based on its age (Badia, Berrade, and Campos, 2002; Mijailovic, 2003). In Chen and Feldman (1997) and Bruns (2002), modifications to the age-dependent PM policy were proposed based on the minimal time to repair and imperfect maintenance. In Charles, Floru, Azzaro-Pantel, Pibouleau, and Domenech (2003), a periodic PM policy is described in which degraded machines are maintained in fixed time intervals, independent of machine failures. Various modifications and enhancement to this periodic PM strategy have been proposed recently (Cavory, Dupas, and Goncalves, 2001). Condition-based maintenance (Barbera, Schneider, and Kelle, 1996; Marseguerra, Zio, and Podofillini, 2002;

Sloan and Shanthikumar, 2002; Yam, Tse, Li, and Tu , 2001) is conducted in systems where certain performance indices are periodically (Barbera, Schneider, and Kelle, 1996) or continuously monitored (Marseguerra, Zio, and Podofillini, 2002). Whenever an index value crosses its predefined threshold, maintenance action is performed to restore the machine to its original state or to push it to a new state in which its performance is satisfactory.

Today's manufacturing systems, such as automotive assembly or semiconductor fabrication plants, are highly complex systems of strongly interconnected machines Therefore any maintenance decision to be deployed in such systems should not only consider a single machine degradation, but also the dependencies between machines (Wang, 2002).

In the existing literature, two groups of maintenance policies explicitly considering multi-unit systems can be found (Wang, 2002): *group maintenance policy* and *opportunistic maintenance policies*, (Dagpunar, 1996; Gertsbakh, 1984; Sheu and Jhang, 1996). Group maintenance policy focuses on the replacement or the repair of a group of machines when one failure occurs (Gertsbakh, 1984; Sheu and Jhang, 1996). In the case of opportunistic maintenance, a shut-down caused by a component or subsystem failure can be used to perform PM on non-failed subsystems, if such operation is cost-effective, i.e., if a cost-based opportunity exists to perform maintenance on related subsystems that have not failed yet (Dagpunar, 1996; Nakagawa and Murthy, 1993). Summaries of research achievements in characterizing and optimizing effects of PM can be found in the survey papers (Sherif and Smith, 1981; Valdez-Flores and Feldman, 1989; Zheng, 1997).

Recent advances in sensing and information technology enabled manufacturers to accurately and on-line collect, store and process information that characterizes the status of the manufacturing system (Koc, Ni, Lee, and Bandyopadhyay, 2003). Such information allows one to base maintenance policies on the currently observed status of the manufacturing system and thus be responsive to any changes that take place in the system. Furthermore, recent developments in machine performance evaluation and prediction algorithms offer additional insight into possible future status of a machine or a process (Djurdjanovic, Lee, and Ni, 2003; Engel, Gilmartin, Bongort, and Hess, 2000; Liu, Djurdjanovic, Ni, and Lee, 2004; Pandit and Wu, 1993; Yu, Qiu, Djurdjanovic, and Lee, 2005). This predictive information allows one to also be proactive in addition to being responsive in maintenance decision-making. Predicting and avoiding unscheduled equipment downtime based on this information could lead to minimization of maintenance-related costs. Essentially, the on-line available information about the status of manufacturing systems allows one to approach maintenance problems using a "feedback" approach from control systems, where feedback is facilitated through the on-line information about the current and predicted equipment behavior.

Utilizing the on-line information about dynamic system behavior for the purpose of improving maintenance (or any other operation of the manufacturing system) is not straightforward because possible maintenance options will be influenced and constrained by the structural limitations (physical and functional connections between individual pieces of equipment), performance limitations (required production) and resource limitations (maintenance crews and spare parts) in the production system, which themselves could vary over time. Furthermore, the non-analytical character of the degradation processes prohibits the immediate use of readily available methods for PM scheduling, where analytical character of reliability curves is utilized to obtain elegant, analytical solutions to maintenance scheduling (for example, see Figure 15 in Liu, Djurdjanovic, Ni, and Lee (2004) as an example of a realistic curve of cutting tool load features approaching the failure region). There is therefore a great need to develop formal and systematic methods to incorporate on-line available information about equipment condition into a dynamic maintenance schedule that exploits maintenance opportunities hidden in that information and results in a set of responsive maintenance decisions that are cost-effective *all the time*, rather than only *over time*.

In order to accomplish this task, methods need to be developed to quantitatively evaluate different maintenance scenarios based on the associated cost effects of the resulting maintenance and production operations, taking into account the current and predicted machine degradation levels, system configuration, cost of maintenance actions, profits per manufactured product, spare parts availability and maintenance resource constraints. Furthermore, one needs to devise an algorithm that can systematically search for maintenance schedules that optimize those cost-effects by minimizing the negative effects of maintenance and maximizing the benefits of production. Those methods will be introduced and demonstrated in this paper.

The remainder of the paper is organized as follows. Section "Evaluation of effects of a maintenance schedule" will describe the method used for quantitative evaluation of the cost-effects of any given maintenance schedule. In section "Genetic algorithm based search for optimal maintenance schedules", an optimization procedure for finding the optimal maintenance schedule based on score evaluated will be introduced. Results of a simulation of production and maintenance operations in a manufacturing process are enclosed in section "Result" in order to compare cost-effects of various traditional maintenance strategies and the newly proposed optimized strategy. These results are discussed in section "Discussion", while conclusions of this work and possible directions for future work are enclosed in section "Conclusions and future work".

Evaluation of effects of a maintenance schedule

The purpose of methods presented in this section will be to evaluate cost effects of any given maintenance schedule.

Operation of the manufacturing system at any time moment will be represented through a corresponding *system state*. A period of system operation between either of the following events: *machine start, machine stop, machine fail, maintenance start, maintenance finish, buffer empty* and *buffer full*, will be considered as a period in which the system operates in one *system state*. The system state will be described by a vector:

$$\mathbf{S}_i = \{IPR_1, IPR_2, \cdots, IPR_n, CCR_1, CCR_2, \cdots, CCR_m, MA\}$$

where IPR_i is the *instantaneous production rate* (IPR) of machine i, CCR_i is the *content change rate* (CCR) of buffer i, and MA is the number of maintenance persons available when the system operates in state $\mathbf{S}_i$.

The *instantaneous production rate* (IPR) of a machine represents how fast the machine is producing and is expressed through the number of parts the machine processes within one unit of time. One machine's IPR is bounded above by its maximum production rate and bounded below by 0. The *content change rate* (CCR) of a buffer shows how fast the content level of a buffer is changing. CCR is determined by the IPR-s of the machines linked to it. A positive CCR indicates the buffer is receiving more parts than it is supplying and if no other events happen, the buffer content level will rise until it is full. A negative CCR means the buffer is supplying more parts than it is receiving and if no other events happen, the buffer content levels will drop until the buffer is empty. Table 1 summarizes the conditions that need to be satisfied when system state parameters IPR and CCR are calculated.

Whenever the buffer becomes full or empty, the corresponding event signifies a change of the system state due to machine starvation or blockage, respectively, after which new values of IPR-s and CCR-s will need to be calculated. In addition, each time a machine is stopped for maintenance or due to a breakdown, as well as each time a machine is started (after a maintenance or repair event), the system state changes and CCR-s and IPR-s need to be recalculated.

Based on the elaboration above, the system operation can be viewed as a sequence of consecutive time intervals, each characterized by a state in which the manufacturing system is during that time. The predicted machine performance giving insight into the future machine failure events will have its effect on the durations of time a system spends in each state, which will in turn affect the total production gain and maintenance expenses.

The recently developed algorithms for prediction of equipment performance are aimed at predicting future machine reliability or machine failure likelihoods over time (Engel, Gilmartin, Bongort, and Hess, 2000). Figure 1 indicates how predicted distributions of performance related features obtained using methods such as Autoregressive Moving Average (ARMA) modeling prediction (Pandit and Wu, 1993), Recurrent Neural Network (RNN) prediction (Yu et al., 2005), or Match Matrix (Liu et al., 2004) based prediction, can be utilized to obtain future probabilities of unacceptable behavior or failure.

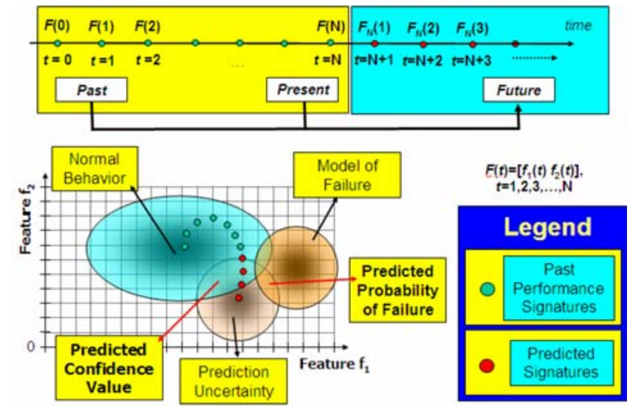


Fig. 1 Predicted probability of unacceptable behavior over time. Predicted confidence value area denotes the predicted probability that performance relevant features would stay within the normal behavior limits

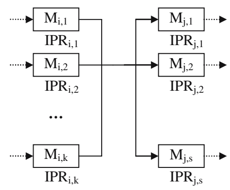
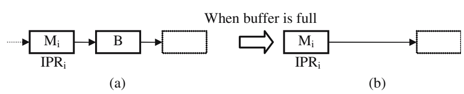
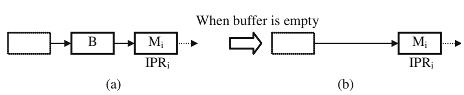
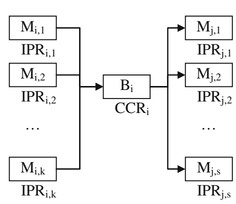
In this paper, it is assumed that for each machine in a manufacturing system, one possesses the information about future likelihoods of failure, based on either the aforementioned predictive algorithms, or based on the historical reliability of the equipment.[1] If neither the condition (sensor) based nor the reliability (history) based dependency of risks of failure over time exist for some machine, then the method proposed in this paper is not applicable (even though, one should note that it is highly unlikely that neither sensor nor history based information about a machine exist).

Machine stoppages are simulated through a discrete event simulation process, where at any given time a machine is stopped because of either of the events below occurs at that time:

- A maintenance task is scheduled (moments for maintenance actions are obtained from the maintenance schedule that is being evaluated)
- A machine failure occurs, where machine failures are simulated using Monte–Carlo simulation based on the predicted likelihoods of machine failures. A machine is restarted after an appropriate maintenance task is executed on that machine (if failure happened before a maintenance task was scheduled, then the corresponding repair is considered to be unscheduled and was simulated according

[1] If only historical reliability of machines is available, then the problem considered in this paper would degenerate to the well-known problem of preventive maintenance (PM) scheduling.

Table 1 Rules governing the determination of system state

Condition number	Condition	Equation
I	IPR of a machine M_i is always less than or equal to its maximum production rate P_i.	$IPR_i \leq P_i$
II	IPR of a machine is 0 when that machine is stopped or being repaired.	
III	Multiple machines $M_{i,t}, t = 1, 2, \cdots, k$ serially connect with multiple downstream machines $M_{j,t}, t = 1, 2, \cdots, s$ as shown. 	$\sum_{t=1}^{k} IPR_{i,t} = \sum_{t=1}^{s} IPR_{j,t}$
IVa	A buffer B connects downstream from machine M_i. 1. If the buffer is not full, the buffer imposes no additional limitation on machine M_i and effects of the system downstream from the buffer do not affect IPR_i of M_i 2. If the buffer is full, IPR_i behaves as if the buffer is a direct connection to the downstream machine(s). 	
IVb	Machine M_i connects downstream from buffer B 1. If the buffer is not empty, the buffer imposes no additional limitation on IPR_i for machine M_i and effects of the system downstream from the buffer do not affect IPR_i of M_i 2. If the buffer is empty, IPR_i behaves as if the buffer is a direct connection to the upstream machine(s). 	
V	A generic connection of a buffer to both upstream machines $M_{i,t}, t = 1, 2, \cdots, k$ and downstream machines $M_{j,t}, t = 1, 2, \cdots, s$.  CCR values must be calculated after all IPR-s are determined.	$CCR_i = \sum_{t=1}^{k} IPR_{i,t} - \sum_{t=1}^{s} IPR_{j,t}$

to an appropriate repair time distribution, while otherwise it was considered to be scheduled and was simulated according to an assumed scheduled repair time distribution). Additional consideration of the availability of maintenance persons and resources also can be taken into consideration, since the start and subsequent end of maintenance work may need to be delayed until a time moment when all required maintenance resources (personnel and spare parts) are available. Given the information whether any machine in a manufacturing system is running or not at any given time, the IPR-s of all machines that satisfy all the conditions listed in Table 1, can be calculated using, for instance, the Maximal Flow algorithm (Belegundu and Chandrupatla, 1999).

- A machine is starved (because of the buffer feeding it is empty), or blocked (because the buffer storing products from that machine is full). Based on the IPR-s and status of each machine (whether machine is running or not), the

CCR-s of all buffers are evaluated at any given time and moments when any buffer fills up or is emptied out are identified. The stopped machine is restarted whenever a part in the supply buffer is available and a place for the new product is available in the downstream buffer.

Thus, each run of the discrete-event simulation results in a sequence of machine states whose duration can be calculated as the time elapsing between two adjacent state changing events (*machine start, machine stop, machine fail, maintenance start, maintenance finish, buffer empty* and *buffer full*)

The cost-effects of a maintenance schedule can then be quantitatively evaluated through a cost function calculated according to the information obtained through all predicted manufacturing system states. The following system properties affecting the cost-effects of any maintenance scenario can be extracted from the predicted sequence of manufacturing system states:

(1) Number of parts produced which equals the sum of system IPR-s for all states multiplied by the corresponding state duration. For a given state, system IPR is calculated as the summation of IPR-s of the rearmost machines in the system;
(2) System downtime which equals the summation of state durations for all states with system IPR equal to 0;
(3) Total maintenance time which equals the summation of all maintenance times between the maintenance start and corresponding maintenance end events;
(4) Total scheduled maintenance time which is the time maintenance is performed according to the schedule, before a machine failure occurred;
(5) Total unscheduled maintenance time which is the time maintenance is performed on an unscheduled (unpredicted) event.

A cost function should be used as the standard to measure whether a schedule is good or not. Such a function needs to be defined specifically from case to case. In any case, the cost function should depict the difference between benefits of producing parts and cost of maintenance operations that can be expressed as:

$$V = P - M \tag{1}$$

where P is the profit gain from production activity and M is the cost incurred by maintenance.

Due to the randomness in the model and the inherent uncertainty in the predictive information, multiple evaluation runs using various random number streams are needed to fully evaluate the possible cost effect of any given maintenance schedule. Based on multiple runs of the simulation, distribution of cost effects associated with any allocation (schedule) of maintenance actions can be obtained and properties of this distribution, such as expected value (average cost effects), variance (uncertainty in cost effects), range or percentiles of the distribution can be used to quantitatively evaluate the corresponding maintenance schedule. In this paper, we compared maintenance schedules based on the corresponding average cost effects (expected value of cost effects), even though other properties of the cost effect distribution could have easily been used.

Genetic algorithm based search for optimal maintenance schedules

Once each maintenance schedule is associated with the corresponding cost effects, one can search for a schedule associated with the most favorable cost, i.e., maintenance schedule with the highest expected profit function V described by Eq. 1. In this paper, effects of a maintenance decision (described through time-allocation of maintenance jobs) are evaluated as the expected value (average) of the distribution of cost effects (1) corresponding to that decision, as evaluated through a number of discrete-event simulations, as described in section "Evaluation of effects of a maintenance schedule". This simulation-based evaluation of effects of maintenance decisions does not require any assumptions on the character of the degradation process (no need for assumptions of Markovianity, or form of the degradation function), but it also does not yield an analytically tractable objective function. The lack of analytical tractability of the above mentioned objective function evaluated through simulation is the main motivation for utilizing a heuristic (evolutionary) search algorithm for optimization of maintenance schedules.

Genetic Algorithm (GA) based optimization (Holland, 1962) utilizes heuristic rules of survival of the fittest to produce improved approximations of the objective function optimum over a number of iterations, referred to as generations of the GA evolution. Thorough descriptions of GA-s can be found in Belegundu and Chandrupatla (1999); Yu, Qiu, Djurdjanovic, and Lee (2005); Pandit and Wu (1993), and references therein. A variation of the typical GA is used in this paper to search for the optimal maintenance schedule, maximizing the cost function of the form described by Eq. 1. It should be noted that output of any GA based optimization only approximates the optimal solution and application of these heuristic optimization methods does not guaranty optimality of the solution. Even so, the laws of natural evolution implemented through these algorithms ensure a good approximation of the optimal solution, which is why GA-s were used in this paper and in a number of other applications (Belegundu and Chandrupatla, 1999; Yu et al., 2005; Pandit and Wu, 1993).

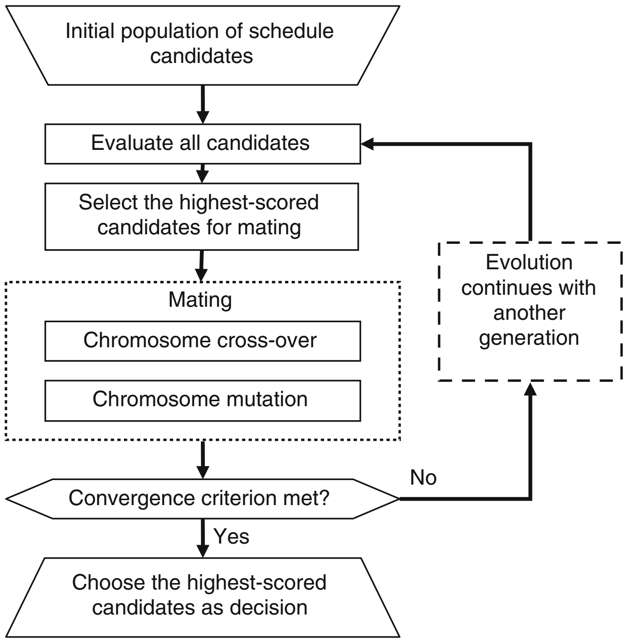


Fig. 2 Flowchart for scheduling optimization based on genetic algorithm

In this paper, each candidate schedule is represented by a *chromosome* defined as an array of integers representing the discrete starting times of maintenance actions for all given machines in the system. In other words, each cell in the chromosome corresponds to one machine in the system, while the integer number in each cell corresponds to a time moment on the discreterized time axis.

Based on this chromosome representation of a maintenance schedule, a GA based procedure outlined in Fig. 2 is used to search for schedules resulting in the highest average cost benefits expressed through the cost model (1) and evaluated using the method described in the previous section. Optimization takes place through a series of selection, crossover and mutation operations applied to successive generations of candidate schedules. Cycles of selection and mating operations upon the chromosomes representing candidate schedule solutions are repeated until some criterion for stopping the iterations is met. Stopping criteria include events when improvement of the optimum approximation between two successive GA generations is less than some predetermined value, or some previously selected maximal number of GA generations Max_Gen is exceeded.

Initial population of candidate solutions with Max_Pop individual chromosomes can be generated in various ways. For instance, a random integer between 0 and maximum number of intervals Max_Int on the time axis could be set for every cell in the chromosome. Also, initial values for chromosomes can be based on the preventive maintenance schedule, since that schedule itself can be considered as a good approximation of the optimal schedule in terms of the cost function

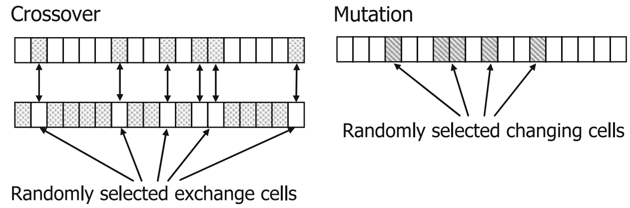


Fig. 3 Evolution schemes of chromosomes representing various candidate schedules

described in section "Evaluation of effects of a maintenance schedule".

This initial population starts a sequence of genetic *crossovers* and *mutations*, yielding ever-improved maintenance schedules. In this paper, the crossover is implemented by having the parent chromosomes exchange chromosome cells at various randomly selected positions to form two new chromosomes, while mutation is performed through random alteration of randomly selected cells in any given chromosome. Crossover and mutation schemes used in this paper are illustrated in Fig. 3.

In order to keep improving over generations the overall fitness of the chromosome population, as expressed through the corresponding cost effect values V described by Eq. 1 and only the highest scored chromosomes are selected to be the parent chromosomes that will spawn the next generation of candidate schedules. This way, the next generation of chromosomes is created, consisting of the following three types of chromosomes:

- Direct copy of the highest scored chromosomes, forming one third of the individuals in the new generation of candidate schedules;
- Children chromosomes generated by parent chromosomes crossover, also forming one third of the individuals in the next generation of candidate schedules;
- Children chromosomes generated by mutation, forming the last third of the candidate schedules in the next GA generation.

During the GA-based search executed through the above-described crossovers and mutations, there is a possibility that chromosomes symbolizing schedules that violate the *maintenance crew constraints* could be generated. Such chromosomes symbolizing unfeasible schedules are identified and corrected by adjusting starting times of maintenance operations in such a way that they do not violate maintenance resource constraints. Thus, in effect, we approach this constraint in the evolutionary optimization procedure using the chromosome repair (Michalewicz and Schoenauer, 1996).

It is a common practice for the GA parameters defining the size of the chromosome population Max_Pop and the maximal allowed number of GA generations Max_Gen to be manually chosen by the user after several test runs. Nevertheless, these parameters can also be optimized within a GA, maximizing the convergence velocity Back (1996) or some on- and off-line performance criteria (De Jong, 1975).

Results

Three types of maintenance strategies have been simulated and compared with the maintenance schedule obtained using the methods proposed in sections "Evaluation of effects of a maintenance schedule" and "Genetic algorithm based search for optimal maintenance schedules" in order to show the advantage of the newly proposed approach. The four maintenance strategies considered in this section are:

- *Corrective maintenance strategy*, which uses the simple first-come-first-serve scheme in which the maintenance is performed whenever there is a machine failure and there is a maintenance person available. If any of the two conditions is not satisfied, the machine will remain in a failed mode, not producing anything. This maintenance strategy will be referred to as ‘Strategy A’;
- *Scheduled maintenance strategy*, in which maintenance is performed in regular time intervals. This strategy will be referred to as ‘Strategy B’;
- *Condition-based maintenance*, in which maintenance crews possess information about the current condition of the equipment. Thus, instead of waiting for machine failure, it is assumed that user-defined thresholds are set on the degradation level of any given machine to trigger maintenance operations. It is different from the purely reactive maintenance in the sense that condition based information enables a portion of the maintenance action to be done as scheduled maintenance, before equipment failure actually happens. This strategy will be referred to as ‘Strategy C’;
- *Predictive maintenance strategy* based on the maintenance scheduling methods described in sections "Evaluation of effects of a maintenance schedule" and "Genetic algorithm based search for optimal maintenance schedules" of this paper, using the current and predicted equipment conditions and taking into account both production benefits and maintenance expenses. This strategy will be referred to as ‘Strategy D’.

For all four strategies, it will be assumed that any unscheduled equipment failure in the manufacturing systems will be addressed as soon as maintenance is available.

A simple production line consisting of ten machines and shown in Fig. 4 is used for simulation and bench-marking of the four maintenance policies described above. For each machine, a distribution describing failure events on that machine over time and a distribution describing the corresponding repair events are assumed. Parameters of these distributions are listed in Table 2. Moreover, as mentioned in section "Evaluation of effects of a maintenance schedule", it is assumed that information about risks of unacceptable behavior of each machine over time is available. Finally, it is assumed that there is only one maintenance person available.

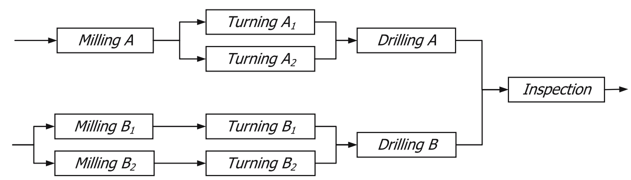


Fig. 4 Manufacturing system used for evaluation and benchmarking of strategies A, B, C and D

The cost-effects of any maintenance schedule were assessed as

$$P \times \sum_i \left[IPR_{system,i} \times (t_{i+1} - t_i)\right] - (C_s \times M_s + C_u \times M_u) \qquad (2)$$

where the following notation is used:

P	the profit per product;
$IPR_{system,i}$	the system IPR for system state i;
t_i	the starting moment of system state i;
M_s	the total scheduled maintenance time spent on maintaining machines;
C_s	the corresponding unit cost for M_s;
M_u	the total unscheduled maintenance time;
C_u	the corresponding unit penalty cost for M_u.

Simulations have been conducted for 4 different cases, which were designed to evaluate the effects of different components in the cost function (2).

In Case 1, the basic system is analyzed with cost factors set as $P = \$10$ for each product made, $C_s = \$100$ for each man-hour spent on scheduled maintenance, $C_u = \$1000$ for each man-hour spent on unscheduled maintenance. Hence, the cost factors used in the simulation were: $P = \$10$, $C_s = \$100$ and $C_u = \$1000$.

In the Case 2, the following set of cost factors was used: $P = \$10$, $C_s = \$1000$ and $C_u = \$1000$. The cost factors are chosen in such way that the cost of scheduled and unscheduled maintenance is the same, which means that the penalty for unscheduled maintenance is essentially removed. Under such circumstances, the benefits of predicting equipment failures will not exist any more since cost effects of performing maintenance before or after equipment will be the same. Thus, this case indicates how the ration between the cost-factors C_s and C_u would influence the cost-benefits of utilizing the predictive information about equipment condition.

Table 2 Parameters used in the testing system

Station name	Cycle time (sec)	Life (part)	Variation of life (part)	MTTR (h)	Variation of MTTR (h)
Milling A	36	10000	100	1.0	0.2
Turning A_1	72	7000	50	1.0	0.2
Turning A_2	72	7000	50	1.0	0.2
Drilling A	36	15000	150	2.0	0.2
Milling B_1	48	15000	70	1.2	0.2
Milling B_2	48	15000	70	1.2	0.2
Turning B_1	48	10000	20	2.0	0.2
Turning B_2	48	10000	20	2.0	0.2
Drilling B	24	15000	100	1.0	0.2
Inspection	14.4	20000	200	0.5	0.2

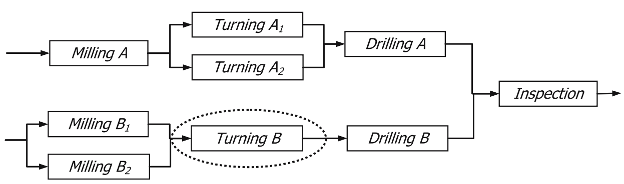


Fig. 5 Case 3 test system with one pair of machines merged into the "Turning B" machine

In Case 3, the same set of parameters as in Case 1 is used, except that one pair of machines in the basic system is merged into a single machine, thus forming a new bottleneck in the system, as shown in Fig. 5. In normal operation condition, the line performs exactly the same as the original line. However the robustness of the system considered in Case 3 is reduced because now the failure of the merged machine will cause a larger portion of the system to stop. As the criticality of one of the machines in the production system is increased, it is expected that prediction of equipment behavior will become more beneficial in the case where failure of the merged station could cause downtime of the entire system. In essence, this case will point out how structure of the system affects the cost-benefits of utilizing the predictive information about equipment condition.

In the Case 4, the same set of parameters as in Case 1 is used, except that unscheduled maintenance takes 50% more time to finish than the same maintenance performed according to the schedule, thus depicting the fact that more maintenance time is needed for unscheduled events. This Case is constructed in order to demonstrate the effects of downtime on system-level benefits of various maintenance schedules. It is expected that prediction of equipment performance and elimination of unscheduled maintenance events through maintenance schedules provided by the newly proposed Strategy D will yield more prominent system-level benefits in this case.

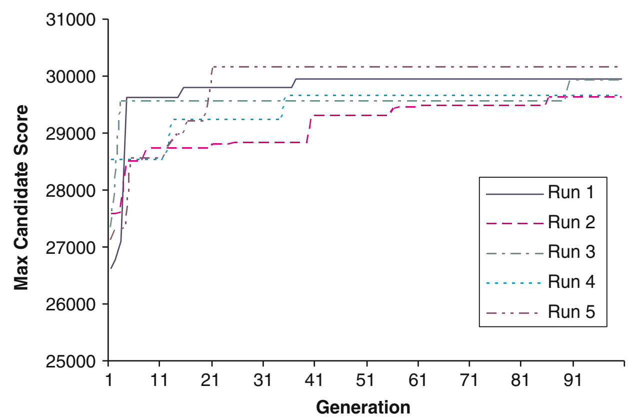


Fig. 6 Convergence of maximum candidate score through generations in different runs

The GA parameters defining the number of individuals in each population Max_Pop and the maximal number of generations allowed in the GA Max_Gen were selected ad hoc after several trial runs and have been set to

$$Max\_Pop = 64, \quad Max\_Gen = 100 \tag{3}$$

Figure 6 shows convergence of cost-effects over five different GA runs searching for an optimal maintenance schedule in the system considered in Case 1. It is visible that fitness of maintenance schedules expressed through the corresponding cost-benefits defined by Eq. 2 is increasing as generations of the GA elapse.

The results obtained from the four sets of simulations pertaining to the Cases 1–4 are listed in Tables 3–6.

Discussion

From the result of the first test case given in Table 3, it is visible that an improvement of the overall cost-benefits can be achieved using the GA optimized maintenance scheduling 'Strategy D'. With 'Strategy B', some maintenance is done as scheduled work to prevent machine failures. However, the fixed length of the time interval between two successive maintenance tasks on one machine could not always match the actual machine life. Thus, maintenance is either done too early, when there is still remaining useful life in the equipment, or too late, after failure already occurred and maintenance is performed as an unscheduled task. Thus, the corresponding cost effects of maintenance are characterized by high expense in maintenance and reducing the overall gain expressed by Eq. 2. In 'Strategy C', more scheduled maintenance occurs due to the use of direct machine conditions as indications of the imminent machine failures. Shorter and more flexible maintenance intervals on each machine increase the overall maintenance time but resulted in fewer unscheduled maintenance events. Thus, it achieved a higher profit than the purely reactive 'Strategy A' or 'Strategy B' characterized by fixed schedules. As for 'Strategy D', the corresponding increase of productivity is even bigger. Even though the overall maintenance time and unscheduled maintenance time both increased, the schedule of the maintenance is arranged in such a way that the system productivity grew, which proved to be more than enough to compensate for the increased maintenance expense.

In the Case 2, the cost factors are changed so that the costs for scheduled maintenance and unscheduled maintenance are the same. As can be seen from Table 3, both 'Strategy B' and 'Strategy C' achieved lower system gain than purely reactive 'Strategy A'. Removing the cost penalty on unscheduled maintenance resulted in no benefits in performing any maintenance action before machine breakdowns actually happen. Then, the cost-benefits associated with any maintenance schedule are determined only by the system productivity and overall maintenance time. The increased maintenance activities in both 'Strategy B' and 'Strategy C' reduce the system productivity relative to the one corresponding to 'Strategy A', thus causing the corresponding profit to be decreased. In this extreme case, the benefits of using 'Strategy D' are non-existent since there is no benefit in performing scheduled rather than unscheduled maintenance.

In the Case 3, two identical machines working in parallel in the original configuration (identified as Turning B_1 and Turning B_2 in Fig. 4), are merged into one machine (identified as Turning B in Fig. 5). Obviously, the Turning B machine from Case 3 is more critical in the new system than the original two machines were in the original system from Case 1 because when it fails, a larger portion of the production system is down, and the production losses are higher (essentially, machine Turning B is a local bottleneck in the system considered in Case 3). Maintenance schedule offered by the newly proposed 'Strategy D' calls for timely maintenance based on the predicted equipment conditions, while avoiding excessive usage of maintenance because schedules calling for excessive maintenance and thus resulting in low system-level cost-benefits as defined by Eq. 2 do not propagate through the GA-based optimization procedure. Thus, the overall profit it made exceeded all other strategies. Furthermore, due to the existence of the more critical Turning B machine, the benefits of avoiding the costly downtimes increased even further, which resulted in increased system-level cost-benefits associated with the maintenance 'Strategy D', as compared to the corresponding benefits observed in Case 1.

Table 3 Comparison of maintenance strategies A, B, C and D in Case 1

Type	Scheduled maint. (H)		Unscheduled maint. (H)		Produced part		Effective gain		Improvement
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Strategy A	0.00	0.00	7.33	1.00	3016.16	267.56	\$22833	\$3429	
Strategy B	2.68	1.12	6.01	1.34	2848.88	165.25	\$22214	\$2280	−2.71%
Strategy C	6.76	2.35	2.78	1.63	2880.58	240.07	\$25346	\$3069	11.01%
Strategy D	5.58	1.04	2.81	1.24	3315.39	144.30	\$29787	\$2285	30.46%

Table 4 Comparison of maintenance strategies A, B, C and D in Case 2

Type	Scheduled maint. (H)		Unscheduled maint. (H)		Produced part		Effective gain		Improvement
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Strategy A	0.00	0.00	7.28	0.78	3135.24	185.35	\$24067	\$2255	
Strategy B	2.75	1.25	5.50	1.31	2885.03	164.26	\$20595	\$1861	−14.43%
Strategy C	6.99	2.67	2.85	1.97	2896.69	226.90	\$19125	\$3671	−20.53%
Strategy D	1.27	1.10	6.19	1.26	3221.34	216.13	\$24745	\$3018	2.82%

$P = \$10$, $C_m = \$1000$, $C_i = \$1000$

Table 5 Comparison of maintenance strategies A, B, C and D in Case 3

Type	Scheduled maint. (H)		Unscheduled maint. (H)		Produced part		Effective gain		Improvement
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Strategy A	0.00	0.00	6.42	1.20	1670.95	171.26	$10288	$2582	
Strategy B	0.85	0.85	5.40	1.04	1684.30	99.00	$11361	$1500	10.43%
Strategy C	5.53	2.27	2.11	1.66	1607.05	163.96	$13407	$2439	30.32%
Strategy D	6.68	0.77	2.43	1.11	1751.04	92.53	$14410	$1923	40.07%

Table 6 Comparison of maintenance strategies A, B, C and D in Case 4

Type	Scheduled maint. (H)		Unscheduled maint. (H)		Produced part		Effective gain		Improvement
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Strategy A	0.00	0.00	10.90	1.07	2634.86	350.01	$15451	$4006	
Strategy B	1.86	1.11	9.05	1.87	2644.84	216.68	$17212	$3416	11.39%
Strategy C	6.44	2.42	4.21	1.83	2797.37	311.63	$23118	$3579	49.61%
Strategy D	5.52	1.32	4.31	2.18	3099.46	248.77	$26135	$4278	69.14%

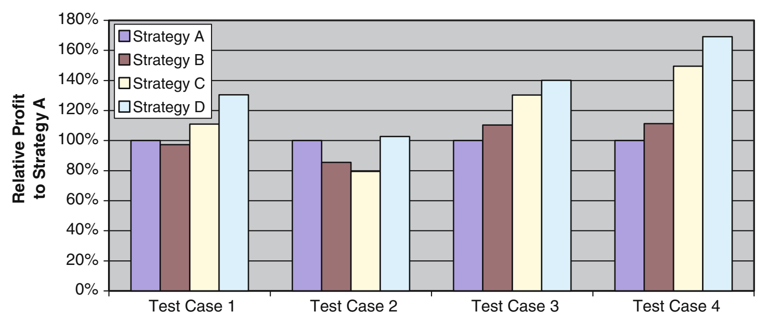


Fig. 7 Relative profit chart between maintenance strategies for the four test cases

In Case 4, the increased time needed for unscheduled tasks implied that unscheduled maintenance tasks would incur more machine downtime and thus effectively emphasize the detrimental costs associated with unscheduled maintenance that takes place after equipment failures occur. Maintenance schedule offered by the ‘Strategy D’ showed the ability of the newly proposed maintenance scheduling method to avoid unscheduled downtime and thus achieve high system-level cost-benefits, as defined by Eq. 2. Furthermore, since the impact of unscheduled downtime was increased in this case, the cost-effect benefits of utilizing the maintenance schedule offered by the newly proposed scheduling ‘Strategy D’ improved even more dramatically, compared to the improvement observed in the Case 1 (the cost-benefits improved by as much as 69% over the corrective ‘Strategy A’, while in Case 1 the corresponding improvement was 30.5%).

Relative effects of the four maintenance strategies for the four test cases are shown in Fig. 7. In each Case, the cost-benefits for corrective ‘Strategy A’ are set to 100%. One can conclude from these results that the overall production and maintenance profits can be increased through the implementation of the proposed method. Furthermore, the more critical the unscheduled system downtime and maintenance are, the benefits of the newly proposed method will be more prominent.

Conclusions and future work

A methodology for maintenance scheduling based on the use of the predicted equipment degradation is presented in this paper.

A simulation based method is proposed for integrating the information about the predicted performance of equipment in a manufacturing system is integrated with other production and maintenance information in order to assess the cost-effects of different maintenance schedules. The cost-effect model takes into account the interaction between machines, buffers and maintenance crews and assets based on the production schedule, maintenance schedule and predicted machine performance. Such quantification that uses predicted equipment performance and addresses its effects on the overall performance of the production and maintenance operations in a manufacturing system, provides a quantitative base on which maintenance schedules for system with degradation can be compared and selected.

Subsequently, a Genetic Algorithm based optimization method is used to find enhanced maintenance schedules for a manufacturing system with a fixed structure. Heuristic rules of natural evolution facilitated improvement of maintenance schedules, as demonstrated through the simulation results. Results indicate great potentials of enhancing the cost-effects of maintenance schedules through integration of predicted machine performance.

Industrial implementation and demonstration of the newly proposed methods in a real factory environment remains to be done in the future. Furthermore, the newly proposed strategy can be extended to address proactive maintenance in highly flexile and reconfigurable manufacturing systems, where the manufacturing process can be altered in response to the observed or anticipated equipment degradation. This approach would add system reconfiguration as one possible maintenance action in addition to the more traditional maintenance options of machine repair and replacement. Finally, extension of the methods proposed in this paper to service systems is another opportunity for further enhancing the benefits of maintenance operations through the usage of predictive condition information.

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