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Multi-objective preventive maintenance and replacement scheduling in a manufacturing system using goal programming

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ABSTRACT

This research presents a new multi-objective nonlinear mixed-integer optimization model to determine Pareto-optimal preventive maintenance and replacement schedules for a repairable multi-workstation manufacturing system with increasing rate of occurrence of failure. The operational planning horizon is segmented into discrete and equally-sized periods and in each period three possible maintenance actions (repair, replacement, or do nothing) have been considered for each workstation. The optimal maintenance decisions for each workstation in each period are investigated such that the objectives and the requirements of the system can be achieved. Total operational costs, overall reliability and the system availability are incorporated as the objective functions and the multi-objective model is solved using a hybrid Monte Carlo simulation and goal programming procedure to obtain set of non-dominated schedules. The effectiveness and feasibility of the proposed solution methodology are demonstrated in a manufacturing setting and the computational performance of method in obtaining Pareto-optimal solutions is evaluated. Such a modeling approach and the proposed solution algorithm could be useful for maintenance planners and engineers tasked with the problem of developing optimal maintenance plans for complex productions systems.

1. Introduction

Production scheduling and preventive maintenance planning are among the most common and significant problems faced in manufacturing industries in which workstations (i.e., machines, industrial robots, etc.) are considered as the main resources to carry out the production plan. The production plan and maintenance actions directly affect the workstations' operation schedules. Production planning is concerned with allocating limited resources to a set of jobs along with certain objective functions that should to be optimized, i.e., in order to meet the deadlines by minimizing the sum of tardiness or makespan. According to the configuration of the workshop (single workstation, multiple workstations, flow shop, job shop, open shop and hybrid systems), some critical objectives should be optimized and certain types of constraints must be taken into account (preemption, setups, etc.). In real manufacturing systems, workstations may be subject to some unavailability periods due to unexpected failures or just because of performing scheduled maintenance activities. In maintenance scheduling, the most important task is to establish an appropriate preventive maintenance plan which optimizes certain objective functions, like minimizing maintenance costs or keeping the workstations in a good condition all the time. However, most of the studies in maintenance optimization do not take into account the production requirements encountered in practice. Considering inherent interdependent relationship between the manufacturing operations and the maintenance scheduling, the two activities are generally planned and executed separately in real systems. The relationship between production and maintenance has been literally considered as a conflict in optimal decisions. These conflicts may result in an unsatisfied demand in production due to the interruptions resulting from the preventive maintenance interventions or workstation failures.

In this research, we develop a multi-objective model by taking into account the workstations reliability for preventive maintenance aspect, the overall availability of the system for production purposes, and total operational costs for both preventive maintenance and production planning decisions. This modeling approach allows the decision maker to achieve compromise solutions meeting at best for three important criteria by which the Pareto-optimal solutions (also known as the efficient frontier) are determined. The rest of this paper is organized as follows. Section 2 reviews the existing literature of the problem of interest. Section 3 formulates the problem containing possible preventive maintenance actions, objective functions and necessary mathematical equations. The hybrid solution method is presented in Section 4 and Section 5 presents the computational results in a manufacturing application.

2. Literature review

The effectiveness of the preventive maintenance scheduling under different conditions such as shop load, job sequencing rule, maintenance capacity and strategy was studied in several earlier

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studies (Banerjee and Burton, 1990; Burton et al., 1989; Mosley et al., 1998). These studies tested the effectiveness of simple preventive maintenance policies using discrete-event simulation, rather than optimizing them along with production scheduling decisions. There are also other research that extend the simple machine scheduling models by considering the maintenance decisions or constraints (Mannur and Addagatla, 1993). A multi-criteria approach to find optimal preventive maintenance intervals of components in a paper factory production line with total expected costs and reliability as the objective functions was proposed by Chareonsuk et al. (1997). Gharbi and Kenne´ (2005) could find an approximation for optimal control policies and values of input factors by combining analytical formulation with simulation-based statistical tools such as experimental design and response surface methodology in a production and preventive maintenance planning problem. A comprehensive research in the area of integrating preventive maintenance scheduling and production planning was found in Ruiz et al. (2007). In this study, three different policies for preventive maintenance schedules and the total manufacturing time were defined for flow shop problems. The authors applied six different adaptations of heuristic and metaheuristic algorithms to evaluate the policies over two sets of problems and concluded that ant colony optimization and genetic algorithms solve these types of problems effectively overcoming other types of metaheuristics.

Integrated preventive maintenance and job shop scheduling problem for a single-machine was tackled in Cassady and Kutanoglu (2003, 2005), Sortrakul et al. (2005), Leng et al. (2006), Batun and Azizoglu (2009) and Pan et al. (2010). In these studies, minimization of total weighted expected completion time is considered as the objective function. As a comparison, the obtained computational results of integrated model were compared with the results achieved from solving preventive maintenance scheduling and job scheduling problems independently. Furthermore, Sortrakul and Cassady (2007) tried to improve the solution procedures by solving a larger version of the integrated preventive maintenance and production scheduling model using genetic algorithms. Allaoui and Artiba (2004) proposed an integrated simulation and optimization method to solve a hybrid flowshop problem under maintenance constraints to optimize several objectives while considering flow time and jobs due dates along with setup, cleaning, and transportation times. Allaoui and Artiba (2006) also explored the non-preemptive two-stage flexible flowshop scheduling with a single machine on the first stage and multiple machines on the second stage under minimization of the makespan. The researchers also presented the complexity analysis of simultaneously scheduling multiple jobs and preventive maintenance scheduling on a two-machine flow shop setting to minimize the makespan (Allaoui et al., 2008). Jin et al. (2009) presented a single-machine integrated job shop and preventive maintenance scheduling model in order to find an optimal sequence of jobs along with an optimal maintenance plans to minimize the total weighted expected completion time of the jobs.

The theoretical aspects of optimal integrated production and preventive maintenance plans has been investigated for a single machine under a cumulative damage process with the goal of minimizing total tardiness (Kuo and Chang, 2007). In another study, five objectives functions of maintenance cost, makespan, weighted completion time of jobs, total weighted tardiness, and machine availability were considered simultaneously in a multi-objective integrated production and maintenance planning problem solved by a multi-objective genetic algorithm (Yulan et al., 2008). Benbouzid-Sitayeb et al. (2008) employed an ant colony optimization approach to solve integrated production and preventive maintenance scheduling problem in permutation flowshops. The obtained results were also compared to those of an integrated genetic algorithms developed in previous works. Bi-objective integrated production and maintenance scheduling models have been presented to determine the Pareto-optimal front of the assignment of production tasks to machines along with preventive maintenance activities in a production system (Berrichi et al., 2009; Berrichi et al., 2010). These studies developed and tested series of genetic algorithms to solve the problem. Hua et al. (2010) developed an integrated optimization model and showed the advantage and practicality of the optimal integrated policy over independent optimal production and maintenance schedules driven by separate models. The study was further expanded by considering a flowshop with multiple machines connected in series, aiming to minimize the total weighed system cost (Miaoqun et al., 2010). In another research, a bi-objective optimization model integrating flexible job shop problem with preventive maintenance scheduling was developed to minimize the makespan and system unavailability (Moradi et al., 2011). Integrating flexible flowshops and periodic preventive maintenance policies to minimize makespan of workstations using genetic algorithm and simulated annealing were presented in Naderi et al. (2009, 2011).

This research tries to incorporate preventive maintenance activities introduced in Berrichi et al. (2009, 2010), Moghaddam and Usher (2011) and develops a multi-objective preventive maintenance and replacement scheduling model aimed at finding Pareto-optimal schedules for multi-workstation manufacturing systems. It is found that none of the reviewed research studies considered the simultaneous combination of total operational costs, system reliability and overall availability of the production system in their modeling approach. In addition, most of these efforts try to model single-component or single-machine production systems which are very uncommon in real and large-scale applications. Hence the first contribution of this research is to develop a comprehensive mathematical model to be able to capture broader aspects of the production and maintenance scheduling problems in multi-component manufacturing systems without any predefined user preferences for different criteria of the system. On the other hand most of the above reviewed literature employed or developed some sort of heuristic algorithms to solve their proposed models. These algorithms are best known to their capability of obtaining good or near optimal solutions. However attainment of the exact optimal solution(s) is never guaranteed. Therefore, the second contribution of our study is to develop and test a novel solution procedure to achieve exact Prato-optimal solutions using combination of simulation and optimization methods. Computational results confirm that there are indeed trade-offs among the objectives of total operational costs, system reliability and availability. Capturing these trade-offs provides invaluable information to improve systems performance over the range of designated goals.

3. Problem formulation

Parameters

N : number of workstations
L : length of the planning horizon
T : number of time intervals over the planning horizon
K : number of objective functions
λ_i : scale parameter (characteristic life) of workstation i
β_i : shape parameter of workstation i
α_i : improvement factor of maintenance action on workstation i
F_i : unexpected failure cost of workstation i
M_i : maintenance (including inspection and repair) cost of workstation i
R_i : replacement cost of workstation i
TPM_i : time to perform preventive maintenance on workstation i

TR_i : time to perform replacement on workstation i
S : shutdown cost of the entire system
f_k : objective function k
$goal_k$: desired level of achievement for objective function f_k
w_k : importance weight of deviation of objective function f_k from a desired level $goal_k$
d_k^+ : positive deviation of objective function f_k from designated $goal_k$
d_k^- : negative deviation of objective function f_k from designated $goal_k$

Decision variables

$X_{i,t}$ effective age of workstation i at the start of period t
$X'_{i,t}$: effective age of workstation i at the end of period t

$$m_{i,t} = \begin{cases} 1 \text{ if workstation } i \text{ at period } t \text{ is maintained (inspected or repaired)} \\ 0 \text{ otherwise} \end{cases}$$

$$r_{i,t} = \begin{cases} 1 \text{ if workstation } i \text{ at period } t \text{ is replaced} \\ 0 \text{ otherwise} \end{cases}$$

3.1. System specifications

Suppose there is a new repairable and maintainable series system of N workstations in a newly established manufacturing system. It is important to note that other system configurations (parallel, series–parallel, parallel–series, k-out-of-n, linked network, etc.) can be modeled just by adapting different reliability and availability functions in order to reflect specific system structure. It is also assumed that each workstation in the system is subject to deterioration and has an increasing rate of occurrence of failure, $v_i(t)$, where t denotes chronological time,($t>0$). In this research because of increasing failure rate and maintainability of the system under study, it is assumed that workstations failure correspond to the well-known Non-Homogeneous Poisson Process (NHPP) expressed by:

$$v_i(t) = \lambda_i \cdot \beta_i \cdot t^{\beta_i - 1} \quad \text{for } i = 1, \ldots, N \tag{1}$$

where λ_i and β_i are the scale (characteristic life) and the shape parameters of workstation i respectively. The Non-Homogeneous Poisson Process is similar to the Homogeneous Poisson Process (HPP) with the exception that the rate of occurrence of failure is not constant but is a function of time. It would be desirable to find a schedule of future maintenance and replacement actions for each workstation over the planning horizon $[0, L]$. The interval $[0, L]$ is segmented into T discrete periods, each of length L/T. At the end of period t, the system may be either, maintained, replaced, or no action is to be performed. In most manufacturing systems maintenance activities in period t reduce the "effective age" of the workstations and subsequently "failure rate" of the system. This kind of maintenance activities are known as minimal repairs in the literature since they do not change the failure characteristic of the system. To account for the instantaneous changes in workstation age and failure rate, first the initial age for each workstation is set to zero. Then let $X_{i,t}$ denote the effective age of workstation i at the start of period t, and $X'_{i,t}$ denotes the age of workstation i at the end of period t. It is clear that:

$$X'_{i,t} = X_{i,t} + (L/T) \quad \text{for } i = 1, \ldots, N; t = 1, \ldots, T \tag{2}$$

3.1.1. Maintenance actions

Consider the case where workstation i is maintained at the end of the period t. The maintenance action effectively reduces the effective age of the workstation at the start of the next period as follows:

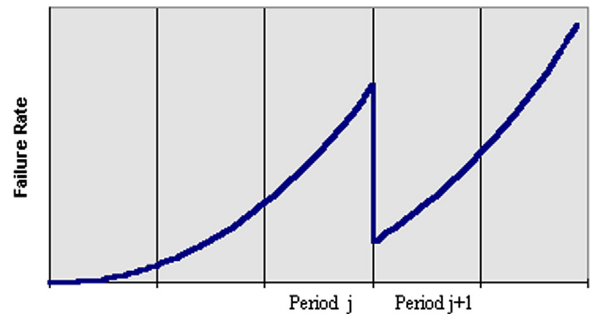

Fig. 1. Effect of preventive maintenance on workstation's increasing rate of failure.

$$X_{i,t+1} = \alpha_i \cdot X'_{i,t} \quad \text{for } i = 1, \ldots, N; t = 1, \ldots, T \quad \text{and} \quad (0 \le \alpha_i \le 1) \tag{3}$$

The term α is an "improvement factor" which allows for a variable effect of maintenance on the aging of a workstation. When $\alpha = 0$ the effect of maintenance is to return the workstation to a state of "good-as-new" and when $\alpha = 1$ maintenance has no effect and the workstation remains in a state of "bad-as-old". Note that the maintenance action at the end of period t partially lowers the rate of occurrence of failure of workstation i, as shown in Fig. 1. Furthermore, the maintenance action takes TPM_i to be done and a maintenance cost M_i is incurred at the end of that period.

Here, the proposed improvement factor function developed by Moghaddam and Usher (2010) is adopted in which a function of maintenance and replacement costs is considered to reflect the effectiveness of the maintenance activity.

$$\alpha_i = \phi(R_i, M_i) = (R_i - M_i)/R_i \quad \text{for } i = 1, \ldots, N \tag{4}$$

The above improvement factor function is based on the ratio of difference of replacement and maintenance costs, which is always between zero and one. It is designed so that if a costly maintenance action is performed on a workstation, the effective age improves more than when an inexpensive maintenance is performed. That is, more expensive maintenance results in a greater amount of age reduction and failure rate improvement. For example, overhauling an engine results in more age reduction than changing the oil does. Note that if maintenance cost is equal to the replacement cost, the numerator of the fraction becomes zero, and the maintenance action will coincide with a replacement action. On the other hand, if the maintenance cost equals zero, the ratio becomes one meaning that maintenance does not affect the effective age so it can be considered as do nothing action described next.

3.1.2. Replacement actions

If workstation i is replaced at the end of period t with a new identical workstation, then it is obvious that the effective age of the workstation at the start of the next period drops to zero as in Eq. (5) and the workstation failure behavior is returned to a state of "good-as-new" in which the rate of occurrence of failure of workstation i drops from $v_i(X'_{i,t})$ to $v_i(0)$, as depicted in Fig. 2. In addition, the replacement action needs a specific amount of time, TR_i, to be performed and the system is charged with a replacement cost of that workstation equals to the initial acquisition cost of the workstation i, denoted as R_i.

$$X_{i,t+1} = 0 \quad \text{for} \quad i = 1, \ldots, N; \; t = 1, \ldots, T \tag{5}$$

3.1.3. Do nothing

If no action is planned to be taken in period t, then a continuous increase will be expected on the rate of occurrence of failure for

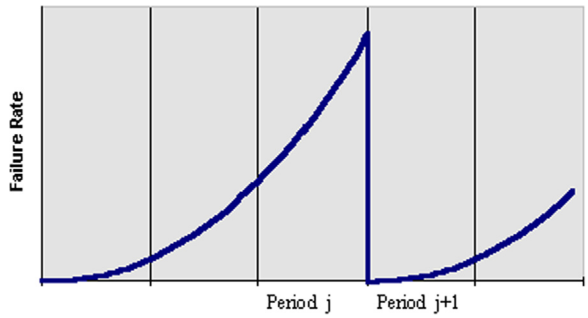

Fig. 2. Effect of preventive/corrective replacement on workstation's increasing rate of failure.

workstation i, as formulated as follows:

$$X'_{i,t}=X_{i,t}+(L/T) \quad \text{for } i=1,...,N; t=1,...,T \tag{6}$$

$$X_{i,t+1}=X'_{i,t} \quad \text{for } i=1,...,N;\ t=1,...,T \tag{7}$$

$$v_i(X_{i,t+1})=v_i(X'_{i,t}) \quad \text{for } i=1,...,N;\ t=1,...,T \tag{8}$$

When a future schedule of maintenance operations for a production system is planned, the inevitable costs caused by unexpected workstation failures must be taken into account. However it is not possible to exactly determine when such failures occur but it is possible to anticipate that if the production system carries a high rate of occurrence of failure through a period, then the system is at risk of experiencing an upcoming failure resulting to a significant amount of unexpected failures cost. On the other hand, a low rate of occurrence of failure in period t should yield a low cost of failure in that period. In order to take into account these unplanned failure costs, the calculation of expected number of failures for each workstation in each period is proposed. The unexpected failure cost for each workstation is defined as F_i (in units of \$/failure event) then $F_{i,t}$ the cost of failures attributable to a workstation i in period t can be determined as follows:

$$\begin{aligned} F_{i,t} &= F_i \cdot (\text{expected number of failures in } [X_{i,t},X'_{i,t}]) \\ &= F_i \cdot \int_{X_{i,t}}^{X'_{i,t}} v_i(t)dt = F_i \cdot \lambda_i((X'_{i,t})^{\beta_i}-(X_{i,t})^{\beta_i}) \\ &\text{for} \quad i=1,...,N;\ t=1,...,T \end{aligned} \tag{9}$$

3.1.4. System shutdown cost

In a multi-workstation production system with the failure, maintenance, and replacement costs, the integrated manufacturing operations and maintenance scheduling problem can be considered to reduce to a simple problem of finding the optimal sequence of maintenance, replacement, or do-nothing actions for each workstation, independent of all other workstations over the planning horizon. As a result one could simply find the best sequence of operations for workstation 1 regardless of the operations taken to workstation 2 and so on. This would result to N independent scheduling problems. In that case, a system of N workstations over T time periods, has $N \times 3^T$ possible maintenance schedules (i.e., $N=10$ and $T=12$ have 5,314,410 possible schedules). Such a modeling approach seems unrealistic, as there should be some overall and large penalty cost whenever an action is performed on any workstation in the system. It would seem that there should be some logical advantage to combining maintenance and replacement actions to be executed at the same time. For instance, while the system is shut down to replace one workstation it may make sense to perform maintenance or replacement actions on some other workstations, even if they are not at their individual optimum point where maintenance or replacement would ordinarily be performed. Under this scenario, the optimal time to perform maintenance or replacement actions on individual workstation is completely dependent upon the decisions made for other workstations. As such, consideration of a penalty cost of shutting down the system is proposed to be charged in period t if any workstation (one or more) is repaired or replaced in that period. Consideration of this shutdown cost makes the problem much more interesting and very difficult to solve as the optimal sequence of dependent maintenance actions must be determined simultaneously for all workstations from astronomical $3^{N\times T}$ possible combinations (i.e., $N=10$ and $T=12$ have 1.79×10^{57} possible schedules). Eq. (10) calculates the total shutdown costs charged whenever any workstation in each period is repaired or replaced and it is obvious that if more than one workstation in a period is undertaken to be repaired or replaced the function results to a single charge.

$$\text{Shutdown costs} = \sum_{t=1}^{T}\left[S\left(1-\prod_{i=1}^{N}(1-(m_{i,t}+r_{i,t}))\right)\right] \tag{10}$$

In the above cost function, the condition of $m_{i,t}+r_{i,t} \le 1$ should be held for all workstations over the intervals of the planning horizon stating that either a maintenance or a replacement action should be carried out for each workstation.

3.2. Objective functions

3.2.1. Total operational costs

From the definitions of each type of cost, the total operational costs of the system can be found over the T periods of the planning horizon. Therefore, the objective function of the total operational cost can be expressed as

$$\begin{aligned} f_1 &= \text{Total operational costs} \\ &= \sum_{i=1}^{N}\sum_{t=1}^{T}[F_i \cdot \lambda_i((X'_{i,t})^{\beta_i}-(X_{i,t})^{\beta_i})+M_i \cdot m_{i,t}+R_i \cdot r_{i,t}] \\ &\quad + \sum_{t=1}^{T}\left[S\left(1-\prod_{i=1}^{N}(1-(m_{i,t}+r_{i,t}))\right)\right] \end{aligned} \tag{11}$$

Note that $m_{i,t}$ and $r_{i,t}$ are binary variables of maintenance and replacement actions for workstation i in period t and they cannot be equal to one simultaneously. The last term of the above function indicates that if a workstation is maintained or replaced in each period, the whole system encounters with the shutdown cost.

3.2.2. System reliability

In order to compute the reliability of a series system of workstations, the reliability function for a repairable workstation i in the period t is defined as Eq. (12) and it can be extended to the reliability function of the entire production system as presented in (13); see Elsayed (2012) for more details on reliability of repairable systems.

$$\begin{aligned} R_{i,t} &= \exp\left[-\int_{X_{i,t}}^{X'_{i,t}} v_i(t)dt\right] = \exp[-\lambda_i((X'_{i,t})^{\beta_i}-(X_{i,t})^{\beta_i})] \\ &\text{for } i=1,...,N; t=1,...,T \end{aligned} \tag{12}$$

$$f_2 = \text{System reliability} = \prod_{i=1}^{N}\prod_{t=1}^{T}\exp[-\lambda_i((X'_{i,t})^{\beta_i}-(X_{i,t})^{\beta_i})] \tag{13}$$

3.2.3. System availability

Unavailability of a workstation can be observed due to the occurrence of unexpected failures in which the failed workstation should be replaced by new equipment. The replacement action in this case takes a specific amount of time to be performed denoted by TR_i.

Therefore, if no preventive maintenance or replacement action is performed on a workstation, its unavailability increases over time and subsequently results to manufacturing breakdown due to increase of occurrence of unexpected failures. On the other hand, a workstation may become unavailable due to scheduled preventive maintenance or replacement activity. Therefore, the availability function for a repairable workstation i in period t should be defined in away to reflect two causes of unavailability. Considering these aspects, the availability of workstation i is formulated as Eq. (14) and the availability function of the entire series system of workstations can be derived accordingly as presented in (15).

$$A_{i,t}=\frac{(X'_{i,t}-X_{i,t})}{(X'_{i,t}-X_{i,t})+TR_i\cdot\lambda_i\left((X'_{i,t})^{\beta_i}-(X_{i,t})^{\beta_i}\right)+(TPM_i.m_{i,t}+TR_i.r_{i,t})}\quad \text{for } i=1,...,N;t=1,...,T \tag{14}$$

$$f_3=\text{System availability}=\prod_{i=1}^{N}\prod_{t=1}^{T}\left[\frac{(X'_{i,t}-X_{i,t})}{(X'_{i,t}-X_{i,t})+TR_i\cdot\lambda_i\left((X'_{i,t})^{\beta_i}-(X_{i,t})^{\beta_i}\right)+(TPM_i.m_{i,t}+TR_i.r_{i,t})}\right] \tag{15}$$

3.3. Multi-objective optimization model

Based on the configuration of production system and the formulated equations and objective functions, the multi-objective nonlinear mixed-integer optimization model with the total operational costs, overall reliability, and system availability can be presented as

$$\begin{aligned}
\text{Min } f_1 &= \sum_{i=1}^{N}\sum_{t=1}^{T}\left[F_i\cdot\lambda_i\left((X'_{i,t})^{\beta_i}-(X_{i,t})^{\beta_i}\right)+M_i\cdot m_{i,t}+R_i\cdot r_{i,t}\right]\\
&\quad+\sum_{t=1}^{T}\left[S\left(1-\prod_{i=1}^{N}(1-(m_{i,t}+r_{i,t}))\right)\right]\\
\text{Max } f_2 &= \prod_{i=1}^{N}\prod_{t=1}^{T}\exp\left[-\lambda_i\left((X'_{i,t})^{\beta_i}-(X_{i,t})^{\beta_i}\right)\right]\\
\text{Max } f_3 &= \prod_{i=1}^{N}\prod_{t=1}^{T}\left[\frac{(X'_{i,t}-X_{i,t})}{(X'_{i,t}-X_{i,t})+TR_i\cdot\lambda_i\left((X'_{i,t})^{\beta_i}-(X_{i,t})^{\beta_i}\right)+(TPM_i.m_{i,t}+TR_i.r_{i,t})}\right]\\
&\text{subject to:}\\
X_{i,1}&=0 \qquad i=1,...,N\\
X_{i,t}&=(1-m_{i,t-1})(1-r_{i,t-1})X'_{i,t-1}+m_{i,t-1}((R_i-M_i)/R_i)X'_{i,t-1} \qquad i=1,...,N;t=2,...,T\\
X'_{i,t}&=X_{i,t}+(L/T) \qquad i=1,...,N;t=1,...,T\\
m_{i,t}+r_{i,t}&\le 1 \qquad i=1,...,N;t=1,...,T\\
m_{i,t},\ r_{i,t}&=0 \text{ or } 1 \qquad i=1,...,N;t=1,...,T\\
X_{i,t},X'_{i,t}&\ge 0 \qquad i=1,...,N;t=1,...,T
\end{aligned} \tag{16}$$

In the above optimization model, the first set of constraints indicates that the initial age for each workstation is set to be zero indicating that all workstations are brand new ones at the beginning. The second set calculates the effective age of workstations depending on which action was taken in the previous period. If a workstation was replaced in the previous period then $r_{i,t-1}=1, m_{i,t-1}=0$, so that its effective age drops down to $X_{i,t}=0$, if a workstation is minimally repaired then $r_{i,t-1}=0$, $m_{i,t-1}=1$ and its effective age becomes $X_{i,t}=((R_i-M_i)/R_i)X'_{i,t-1}$. Finally if no action was taken, $r_{i,t-1}=0, m_{i,t-1}=0$, the workstation continues its normal aging as $X_{i,t}=X'_{i,t-1}$.

4. Solution method: hybrid Monte Carlo goal programming simulation

Most real-life problems are multi-objective problems in which objectives under consideration have some sort of conflict with each other. The classic methodology to solve multi-objective optimization problems is based on preference-based approach in which a relative predetermined vector of weights is used to combine multiple objectives into a single objective function. Other methods such as ε-constraint method reformulate the multi-objective optimization problems by just keeping one of the objectives, placing the others into the set of constraints and then restricting them by user-specified values. Goal programming methods try to find the optimal solutions that attain a predefined target values for one or more objectives by minimizing deviations from these target values. All of these traditional methods then employ a point-by-point deterministic optimization approach by finding single Pareto-optimal solution. Since multi-objective optimization problems have equally important Pareto-optimal solutions, an ideal approach would be finding multiple trade-off optimal solutions at once and let the decision maker choose the desired solution based on other higher-level information. The optimal solutions obtained by the ideal approach will be independent from the user's predefined parameters. An effective multi-objective solution procedure should successfully perform three following conflicting tasks (Zitzler et al., 2000; Deb, 2001):

(1) The obtained non-dominated solutions should be close enough to the true Pareto front. Ideally, the non-dominated solutions should be a subset of the Pareto-optimal set.
(2) The obtained non-dominated solutions should be uniformly distributed over of the Pareto front in order to provide the decision-maker a true insight of trade-offs.
(3) The obtained non-dominated solutions should capture the whole spectrum of the Pareto front. This requires investigating non-dominated solutions at the extreme ends of the objective functions space.

In the past three decades numerous multi-objective evolutionary algorithms have been developed and tested as trustable and efficient solution methods to solve multi-objective models (Deb, 2001). However, these algorithms are best known to their capability of obtaining good or near optimal solutions and attainment of the exact optimal solution(s) is never guaranteed.

In order to solve the multi-objective model (16), we consider goal programming method as a subroutine of the solution approach. The major drawback of the standard goal programming method is that the method can obtain only one non-dominated solution which is highly dependent to the decision maker's choice of the goals and the weights of deviation from the predefined goals. To rectify this dependability and in order to obtain the true Pareto-optimal front, the following hybrid Monte Carlo simulation model is proposed in which randomly generated objective goals and deviation weights are used in the goal programming submodel in each simulation replication.

Hybrid Monte Carlo goal programming simulation

Begin
Calculate the minimum and maximum values of the objective function k
$f_k^{\min}, f_k^{\max}$ for $k=1,2,3$
Current replication = 1
While (current replication ≤ designated number of replications)
Read the parameters of the optimization model (16)
$w_k=rand\,(0,1)$ for $k=1,2,3$
$$w'_k=\frac{w_k}{\sum_{k=1}^{3}w_k} \quad \text{for } k=1,2,3 \tag{17}$$
$$goal_k=rand\,(f_k^{\min},f_k^{\max}) \text{ for } k=1,2,3 \tag{18}$$

Solve the goal programming submodel (19)

$$\begin{array}{ll}
\text{Min} \quad \text{weighted goal deviations} = w'_1 d_1^+ + w'_2 d_2^- + w'_3 d_3^- & \\
\text{subject to :} & \\
f_k^{\text{normalized}} + (d_k^- - d_k^+) = goal_k^{\text{normalized}} & k = 1,2,3 \\
X_{i,1} = 0 & i = 1,...,N \\
X_{i,t} = (1-m_{i,t-1})(1-r_{i,t-1})X'_{i,t-1} + m_{i,t-1}((R_i - M_i)/R_i)X'_{i,t-1} & i = 1,...,N; t = 2,...,T \\
X'_{i,t} = X_{i,t} + (L/T) & i = 1,...,N; t = 1,...,T \\
m_{i,t} + r_{i,t} \le 1 & i = 1,...,N; t = 1,...,T \\
m_{i,t}, \ r_{i,t} = 0 \text{ or } 1 & i = 1,...,N; t = 1,...,T \\
X_{i,t}, X'_{i,t} \ge 0 & i = 1,...,N; t = 1,...,T
\end{array} \tag{19}$$

Current replication = Current replication + 1

End while

End

It is useful to mention that in the goal programming submodel (19), linear normalization method is adopted to adjust the magnitude of the objective functions values and the designated goals.

$$f_k^{\text{normalized}} = \frac{f_k - f_k^{\min}}{f_k^{\max} - f_k^{\min}} \text{ for } k = 1,2,3 \tag{20}$$

$$goal_k^{\text{normalized}} = \frac{goal_k - f_k^{\min}}{f_k^{\max} - f_k^{\min}} \text{ for } k = 1,2,3 \tag{21}$$

5. Manufacturing application and computational results

5.1. Data settings

In order to illustrate the model and show the effectiveness of the proposed solution method in a real manufacturing environment, a representative data set is developed as shown in Table 1. The reliability characteristics of the workstations were determined from the historical failures of different computer numerical control (CNC) machines including milling, metalworking lathe, drilling, surface grinding, cylindrical grinding, and welding in a manufacturing setting. In a CNC machine, a failure (also known as crash) occurs when the machine moves in such a way that is harmful to the machine, tools, or parts being manufactured, sometimes resulting in bending or breakage of cutting tools, accessory clamps, vices, and fixtures, or causing damage to the machine itself by bending guide rails, breaking drive screws, or causing structural components to crack or deform under strain. A minor crash may not damage the machine or tools, but may damage the part being machined so that it must be scrapped. Since the CNC machines are repairable systems the scale and shape parameters of the Non-Homogeneous Poisson Process (NHPP) representing the failure distribution of the workstations were obtained by fitting an NHPP function to the observed failure times. In addition to the failure characteristics of workstations, costs of possible preventive maintenance and replacement actions along with unexpected failure costs were estimated from the recorded previous actions. The unexpected failure costs are generally considered much higher than the simple replacement of unfailed but degraded components. The shutdown cost of the production system is assumed to be $10,000 over a planning horizon of 12 months. It is also assumed that a maintenance action (including inspection and repair if required) takes a complete working day but a replacement action can be done in ¼ of a working day of a two 8 hours shifts (i.e., 16 and 4 hours respectively). Under this setting, the multi-objective problem (16) has 470 variables, 240 of which are binary variables, and 360 functional constraints, 110 of which are nonlinear. Visual Basic programming environment is utilized to construct the simulation model and LINGO software is acquired to solve the goal programming submodel to be all run on a laptop computer with 1.7 GHz Intel Core Duo CPU and 2 GB RAM.

Table 1
Characteristics of workstations in the production system.

Workstation	Scale parameter	Shape parameter	Failure cost ($)	Maintenance cost ($)	Replacement cost ($)
1	0.0022	2.20	5000	625	2500
2	0.0035	2.00	4200	525	2100
3	0.0038	2.05	5600	700	2800
4	0.0034	1.90	3600	450	1800
5	0.0032	1.75	4100	513	2050
6	0.0028	2.10	5100	638	2550
7	0.0015	2.25	3500	440	1750
8	0.0012	1.80	4300	537	2150
9	0.0025	1.85	4200	525	2100
10	0.0020	2.15	5000	625	2500

5.2. Distribution of the non-dominated solutions

Fig. 3 illustrates the obtained Pareto-optimal solutions in 3-dimensional objective functions space of cost, reliability and availability using the proposed solution method; the detailed computational results are presented in Table A1 in the Appendix. In Fig. 4, the trade-off curves of the objective functions and distributions of the obtained solutions are also graphed using plot-matrix chart. As can be observed, the non-dominated solutions uniformly cover a broad area of the objective functions' space being able to capture the existing trade-off between the total operational cost, reliability, and availability of the system. As stated in Section 4 the first task in solving a multi-objective optimization problem is to identify non-dominated solutions as close as possible to the true Pareto-optimal front. Other necessary features to be carried are that the obtained non-dominated solutions must be uniformly and widely distributed in the Pareto-optimal region reflecting the existing trade-off among different objective functions. These tasks are achieved by generating uniform objective goals along with random weights for the deviations of objective functions in the simulation process and then by solving the resulting goal programming optimization model in each replication.

In order to investigate of the effect of the uniform probability distribution used to generate random goals the performance of the algorithm is also examined by generating random goals from normal distribution. Therefore Eq. (18) in the algorithm is replaced by Eq. (22) resulting to a new pattern of Pareto-optimal solutions depicted in Figs. 5 and 6; refer to the detailed computational results presented in Table A2 in the Appendix. This modification results to non-dominated solutions crowded around the mean of the normal distribution, $(f_k^{\max} + f_k^{\min})/2$, being incapable of capturing the entire trade-off of

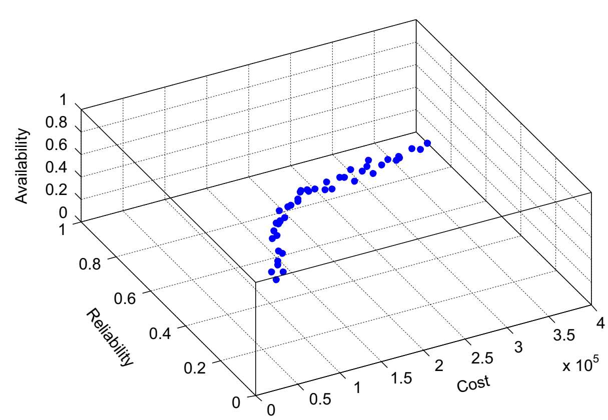

Fig. 3. Pareto-optimal solutions using generated uniform random goals.

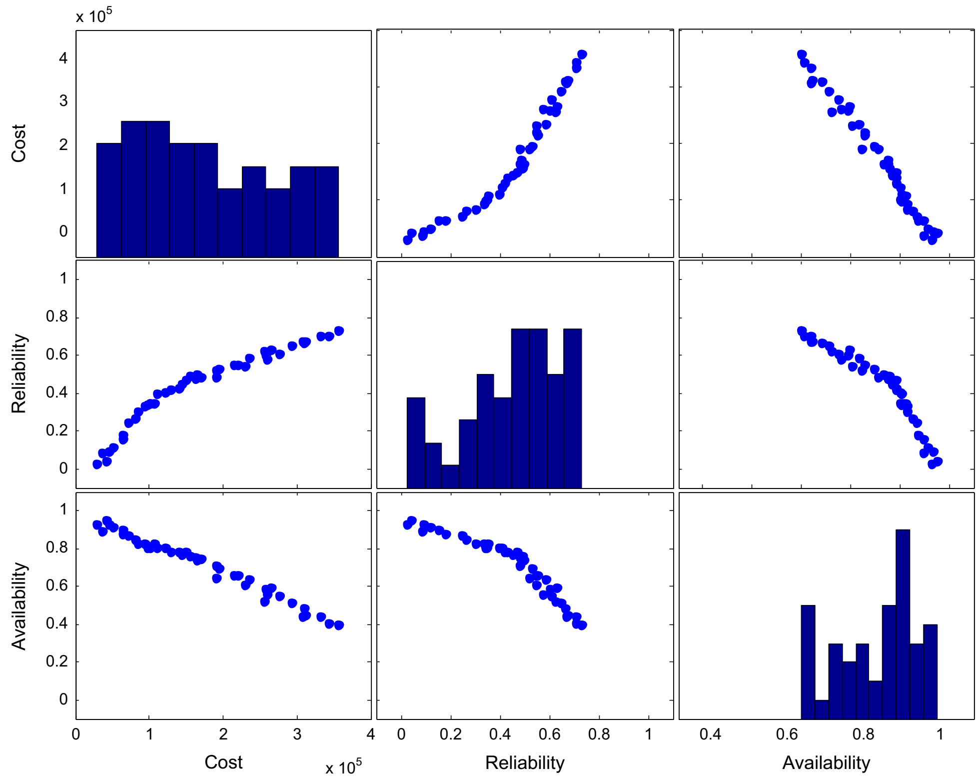

Fig. 4. Trade-off curves and distribution of Pareto-optimal solutions using generated uniform random goals.

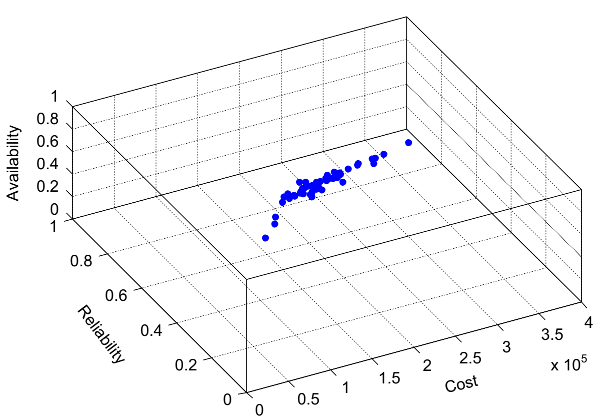

Fig. 5. Pareto-optimal solutions using generated normal random goals.

the objectives as seen in Fig. 6 so the third task in multi-objective solution procedure is not fully achieved.

$$goal_k = \Phi^{-1}(rand(0,1), (f_k^{\max}+f_k^{\min})/2, (f_k^{\max}-f_k^{\min})/6) \quad \text{for } k=1,2,3 \tag{22}$$

Another modification is performed by incorporating deterministic ideal goals and random weights as in Eq. (23) that results to another set of non-dominated solution depicted in Figs. 7 and 8 and in Table A3 in the Appendix. This alteration results to better trade-off curves than the trade-offs obtained by normal goals in reaching to the extreme values of the objectives but having some uncovered areas in objectives space suffers their uniformity pattern in covering the entire region.

$$\begin{aligned} goal_1 &= f_1^{\min} \\ goal_k &= f_k^{\max} \quad \text{for} \quad k=2,3 \end{aligned} \tag{23}$$

The above trade-off curves disclose an important aspect of the systems optimal operation plans. It can be observed that by increasing the total operational costs of the production system (because of performing more frequent preventive maintenance and replacement actions) the overall reliability improves but the availability of the system declines mainly due to increase in length and frequency of the scheduled downtimes. This may look in contrast with the general understanding of reliability and availability of systems as increase in reliability always results to availability improvement. This is true for systems with short maintenance and repair times but there are many other instances with long maintenance and repair times in which performing sequence of preventive maintenance actions in order to improve the reliability suffers the availability of the system. As a result even a system with a low reliability could have a high availability if the time to repair is short. A simple example is taking a car more often, than it is needed, to a repair shop where overall reliability is enhanced but the car will subsequently be more unavailable to the owner especially when the repair times are very long. Therefore, the direct benefit of obtaining the above trade-off curves is to provide ability to the decision maker to better understand the existing interactions among the conflicting objectives of the system to focus on the areas for large marginal improvements without significant sacrifice in other performance measures.

5.3. Structure of the non-dominated solutions

Tables 2–4 depict examples of Pareto-optimal schedules using three versions of the hybrid algorithm. Note that in presented Pareto-optimal schedules most maintenance and replacement actions tend to occur in the same period reflecting the effect of the shutdown penalty cost in the system. It is also interesting to note that once a maintenance or replacement action occurs, it is often followed by a period of inactivity. Such observations

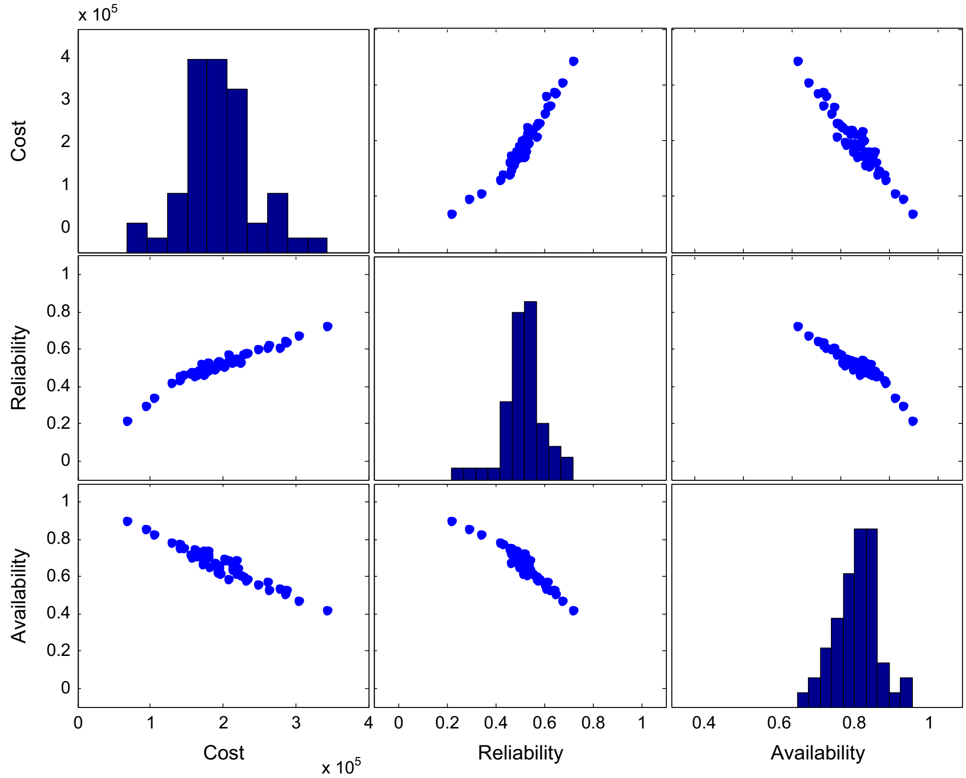

Fig. 6. Trade-off curves and distribution of Pareto-optimal solutions using generated normal random goals.

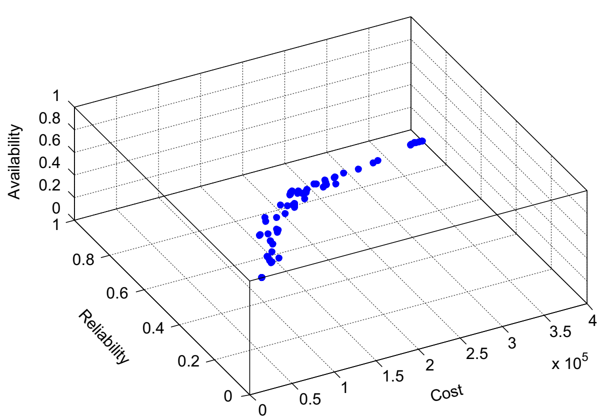

Fig. 7. Pareto-optimal solutions using ideal goals.

Table 2
An example of Pareto-optimal schedule with the uniform random goals and random deviation weights. ($w_1=0.4590$, $w_2=0.3426$, $w_3=0.1983$, $goal_1=\$100,847$, $goal_2=0.3135$, $goal_3=0.4343$) (cost=\$100,253, reliability=0.3433, availability=0.8028).

Workstation	Month											
	1	2	3	4	5	6	7	8	9	10	11	12
1	–	–	–	R	–	–	R	–	–	R	–	–
2	–	–	–	R	–	R	–	–	–	R	–	–
3	–	–	–	R	–	–	R	–	–	R	–	–
4	–	–	–	R	–	–	R	–	–	R	–	–
5	–	–	–	R	–	–	R	–	–	–	–	–
6	–	–	–	R	–	–	R	–	–	R	–	–
7	–	–	–	R	–	R	M	–	–	R	–	–
8	–	–	–	–	–	R	–	–	–	M	–	–
9	–	–	–	R	–	–	R	–	–	–	–	–
10	–	–	–	M	–	–	R	–	–	R	–	–

Table 3
An example of Pareto-optimal schedule with the normal goals and random deviation weights. ($w_1=0.4017$, $w_2=0.4587$, $w_3=0.1396$, $goal_1=\$95,977$, $goal_2=0.4186$, $goal_3=0.6808$) (cost=\$111,058, reliability=0.3680, availability=0.7731).

Workstation	Month											
	1	2	3	4	5	6	7	8	9	10	11	12
1	–	–	–	R	–	–	R	–	–	R	–	–
2	–	–	–	R	–	M	M	–	–	R	–	–
3	–	–	–	R	–	–	R	–	–	R	–	–
4	–	–	–	R	–	R	M	–	–	R	–	–
5	–	–	–	R	–	–	M	–	–	M	–	–
6	–	–	–	R	–	–	R	–	–	R	–	–
7	–	–	–	R	–	–	R	–	–	R	–	–
8	–	–	–	–	–	R	–	–	–	M	–	–
9	–	–	–	R	–	–	M	–	–	R	–	–
10	–	–	–	R	–	–	R	–	–	R	–	–

Table 4
An example of Pareto-optimal schedule with the ideal goals and random deviation weights. ($w_1=0.1361$, $w_2=0.7606$, $w_3=0.1033$, $goal_1=\$18,207$, $goal_2=1$, $goal_3=1$) (cost=\$164,342, reliability=0.5342, availability=0.6570)

Workstation	Month											
	1	2	3	4	5	6	7	8	9	10	11	12
1	–	R	–	R	–	R	–	R	–	R	–	–
2	–	R	–	R	–	R	–	R	–	R	–	–
3	–	R	–	–	–	R	–	R	–	R	–	–
4	–	R	–	–	–	R	–	M	–	R	–	–
5	–	M	–	M	–	M	–	R	–	–	–	–
6	–	R	–	R	–	–	–	R	–	R	–	–
7	–	R	–	R	–	R	–	R	–	R	–	–
8	–	M	–	M	–	M	–	R	–	–	–	–
9	–	–	–	R	–	–	–	R	–	R	–	–
10	–	R	–	R	–	R	–	R	–	R	–	–

can perhaps lead to the development of simple heuristic solution procedures for large-scale problems in future research extensions.

5.4. Evaluation of the proposed hybrid algorithm

In order to quantitatively evaluate and compare three different patterns for generated random objective goals employed in the proposed hybrid algorithm the hyper volume metric is adopted. The hyper volume metric calculates an approximation of the hypercube volume formed by the non-dominated solutions in the objective functions space (Van Veldhuizen, 1999). This metric can measure the necessary tasks in solving multi-objective optimization problems; closeness to the true Prato-optimal front, spread of non-dominated solutions, and extent of the generated solutions. A volume, v_i, can be constructed by each non-dominated solution and a selected reference point such as f_{nadir} to form the diagonal corners of the hypercube. Then the approximate volume of the hypercube can be found as the union of all these Q volumes as presented in Eq. (24). This performance measure has been used and recommended by many researchers to evaluate Pareto sets obtained by multi-objective evolutionary algorithms (Zitzler et al., 2000; Van Veldhuizen and Lamont, 2000). However the concept can be applied to any type of multi-objective optimization solution method.

$$HV = \text{volume}\left(\cup_{i=1}^{|Q|} v_i \right) \tag{24}$$

In order to calculate the hyper volume metric, a reference point such as the nadir solution should be selected. In this research, the nadir solution, f_{nadir} (C=\$356,710, R=0.0190, A=0.4003) is selected as the reference point (the worst obtained values for each objective function). Because of different order of magnitude of total operational costs, system reliability and availability, the normalized values of the non-dominated solutions along with normalized nadir point $f_{\text{nadir}}^{\text{normalized}}$ (C=1, R=0, A=0) are used to calculate the $HV_{\text{normalized}}$ (with maximum possible value of one). Then the volume formed by the reference point and the non-dominated solutions is to be calculated. To prevent overlapping of the volumes, the non-dominated solutions are sorted so the $f_{1,1}$ is the first value of the first objective function (cost), $f_{2,1}$ is the first value of the second objective function (reliability) and $f_{3,1}$ is the first value of the third objective function (availability). The rest of the volumes are calculated with respect to the adjacent sorted non-dominated solutions using the following equation:

$$\begin{aligned} HV_{\text{normalized}} = \Big| & (f_{1,1}^{\text{normalized}} - C_{\text{nadir}}^{\text{normalized}}) \times (f_{2,1}^{\text{normalized}} - R_{\text{nadir}}^{\text{normalized}}) \\ & \times (f_{3,1}^{\text{normalized}} - A_{\text{nadir}}^{\text{normalized}}) \Big| + \sum_{i=2}^{|Q|} \Big| (f_{1,i}^{\text{normalized}} - f_{1,i-1}^{\text{normalized}}) \\ & \times (f_{2,i}^{\text{normalized}} - R_{\text{nadir}}^{\text{normalized}}) \times (f_{3,i}^{\text{normalized}} - A_{\text{nadir}}^{\text{normalized}}) \Big| \end{aligned} \tag{25}$$

Table 5 presents the normalized hyper volumes formed by the non-dominated solutions using random goals generated from uniform and normal distributions and also by the constant ideal goals. Observing the hyper volume values, it can be concluded that the hybrid algorithm using uniform random goals generates non-dominated solutions that form the largest hypercube, HV= 0.499016, proving the capability of the uniform distribution in generating diverse and well-distributed solutions while being close enough to the true Pareto-optimal front.

Table 5
Evaluating closeness and diversity of the non-dominated solutions.

Distribution pattern	Hyper volume (HV)
Uniform random goals	0.499016
Normal random goals	0.434812
Ideal goals	0.436751

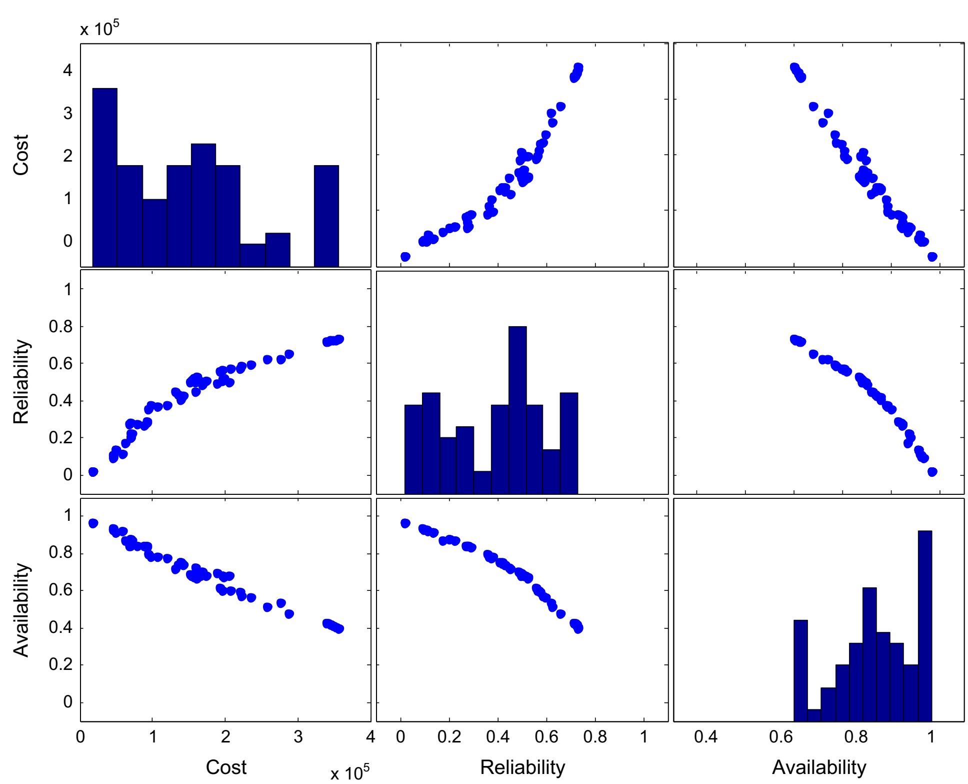

Fig. 8. Trade-off curves and distribution of Pareto-optimal solutions using ideal goals.

6. Conclusions and future research

In this research, a new multi-objective nonlinear mixed-integer optimization model to determine Pareto-optimal preventive maintenance and replacement schedules for a repairable production system is presented. In order to solve the multi-objective model, a Monte Carlo simulation procedure integrated with goal programming method is proposed. The model and the solution technique is found to be an effective approach in solving preventive maintenance and replacement planning problems encountered in manufacturing systems. The method identifies non-dominated solutions close the true Pareto optimal front and uniformly distributed over the objectives space capturing the existing trade-off among different objective functions. Such a modeling approach and proposed solution method will be useful for maintenance planners and engineers tasked with the problem of developing recommended maintenance plans for complex productions systems.

A direct extension to this research would be incorporation of probability distributions to some deterministic parameters of the model such as shutdown cost due to unsatisfied stochastic and time-varying demands. In addition, the observed patterns of the optimal schedules can provide a possible venue for developing simple heuristic solution procedures for large-scale problems in future research efforts.

Acknowledgments

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Appendix A. Detailed computational results of the manufacturing application

See Tables A1–A3

Table A1
Pareto-optimal solutions using generated uniform random goals.

Replication	*w*1	*w*2	*w*3	Cost goal	Reliability goal	Availability goal	Cost	Reliability	Availability
1	0.2923	0.5789	0.1288	332,434	0.8790	0.8379	332,569	0.7059	0.4385
2	0.5080	0.3626	0.1294	121,939	0.4164	0.3142	122,708	0.4078	0.8024
3	0.0830	0.4224	0.4946	26,669	0.0821	0.9653	44,880	0.0912	0.9326
4	0.5597	0.1552	0.2851	94,689	0.4084	0.6234	94,425	0.3348	0.8278
5	0.0484	0.8479	0.1037	302,088	0.6765	0.4387	312,279	0.6765	0.4460
6	0.5693	0.3315	0.0991	106,959	0.7381	0.9179	107,459	0.3504	0.8258
7	0.2904	0.0753	0.6343	104,532	0.7930	0.2387	101,704	0.3482	0.8028
8	0.1694	0.5635	0.2671	69,847	0.9791	0.3222	162,691	0.4791	0.7518
9	0.3176	0.2440	0.4385	234,941	0.7639	0.0475	234,918	0.5863	0.6353
10	0.2044	0.3128	0.4828	185,687	0.0364	0.7844	41,686	0.0434	0.9503
11	0.6343	0.0241	0.3415	37,142	0.6515	0.2680	29,587	0.0243	0.9305
12	0.2939	0.1479	0.5582	63,186	0.9565	0.1019	63,890	0.1546	0.8987
13	0.3486	0.1550	0.4964	80,115	0.3421	0.0112	80,477	0.2648	0.8509
14	0.3237	0.2469	0.4294	383,613	0.6639	0.4836	309,057	0.6647	0.4841
15	0.3475	0.3656	0.2868	307,460	0.9006	0.4188	307,332	0.6719	0.4388
16	0.5486	0.0858	0.3656	64,253	0.2052	0.2199	64,263	0.1796	0.8754
17	0.7919	0.1559	0.0522	86,444	0.1809	0.6924	84,432	0.3014	0.8289
18	0.2820	0.3128	0.4053	149,559	0.4734	0.9146	143,878	0.4505	0.7673
19	0.4969	0.4530	0.0502	258,540	0.6018	0.0183	258,230	0.6025	0.5884
20	0.5570	0.3670	0.0760	155,801	0.9953	0.3344	155,751	0.4892	0.7590
21	0.2860	0.5342	0.1798	111,089	0.2865	0.7488	110,819	0.3978	0.8045
22	0.3917	0.4443	0.1640	374,270	0.9260	0.0257	356,710	0.7311	0.4003
23	0.2725	0.0867	0.6408	256,555	0.8504	0.7481	170,717	0.4834	0.7488
24	0.5877	0.2719	0.1404	110,925	0.4054	0.3394	129,180	0.4201	0.7855
25	0.5467	0.2741	0.1792	293,454	0.7781	0.6534	292,676	0.6493	0.5130
26	0.1439	0.5267	0.3294	183,591	0.6109	0.8040	215,110	0.5507	0.6569
27	0.0148	0.6784	0.3068	145,915	0.9109	0.0205	343,880	0.7072	0.4090
28	0.4325	0.2986	0.2689	20,039	0.9928	0.4494	164,494	0.4972	0.7367
29	0.1314	0.2190	0.6496	264,900	0.7594	0.0466	264,942	0.6294	0.5924
30	0.1026	0.1352	0.7622	160,532	0.4441	0.2160	194,685	0.5294	0.6948
31	0.5074	0.1598	0.3328	36,652	0.0846	0.1117	36,539	0.0851	0.8948
32	0.0537	0.3227	0.6236	221,733	0.7412	0.9599	71,722	0.2488	0.8700
33	0.4289	0.5354	0.0357	47,952	0.8199	0.5476	97,503	0.3403	0.8086
34	0.4705	0.2834	0.2461	103,841	0.8324	0.6384	101,704	0.3482	0.8128
35	0.8242	0.1314	0.0444	49,370	0.1936	0.9587	50,251	0.1167	0.9116
36	0.1111	0.4446	0.4443	42,666	0.8344	0.0566	256,241	0.6227	0.5214
37	0.3299	0.3820	0.2882	230,770	0.8738	0.0958	230,697	0.5452	0.6061
38	0.0157	0.7416	0.2427	282,329	0.2191	0.7843	150,185	0.4682	0.7848
39	0.4538	0.5238	0.0223	164,424	0.7846	0.3716	191,032	0.5196	0.6463
40	0.5339	0.0361	0.4300	330,133	0.5766	0.2763	259,845	0.5774	0.5617
41	0.2101	0.5714	0.2185	364,187	0.8785	0.7775	356,710	0.7311	0.4003
42	0.5347	0.2821	0.1833	276,947	0.6626	0.0963	276,947	0.6105	0.5522
43	0.2777	0.2425	0.4797	117,834	0.5858	0.2428	190,805	0.4822	0.7101
44	0.1083	0.2048	0.6869	181,830	0.9292	0.0661	220,006	0.5473	0.6568
45	0.3098	0.1359	0.5543	130,475	0.3763	0.3130	139,667	0.4278	0.7857

Table A2
Pareto-optimal solutions using generated normal random goals.

Replication	$w1$	$w2$	$w3$	Cost goal	Reliability goal	Availability goal	Cost	Reliability	Availability
1	0.0870	0.3522	0.5608	98,644	0.6751	0.2692	304,871	0.6753	0.4684
2	0.1309	0.7283	0.1407	226,251	0.5820	0.8637	232,649	0.5823	0.5902
3	0.3167	0.6360	0.0473	137,181	0.5947	0.3075	156,715	0.4749	0.7006
4	0.0068	0.0393	0.9539	192,578	0.4418	0.4517	174,105	0.4728	0.6838
5	0.1929	0.7362	0.0709	127,096	0.6263	0.6613	262,462	0.6254	0.5301
6	0.0718	0.1600	0.7682	222,314	0.5388	0.7353	174,871	0.4879	0.7367
7	0.2406	0.3782	0.3812	201,405	0.3905	0.4820	174,477	0.4637	0.6762
8	0.5920	0.1754	0.2326	231,958	0.6104	0.6454	219,760	0.5358	0.6462
9	0.2496	0.4937	0.2566	161,523	0.6650	0.4898	285,347	0.6488	0.5046
10	0.3071	0.1678	0.5251	180,813	0.6119	0.3884	180,873	0.4954	0.6516
11	0.1839	0.2375	0.5787	227,159	0.5706	0.4315	227,142	0.5709	0.6011
12	0.6956	0.1896	0.1148	182,149	0.3229	0.2877	179,683	0.4841	0.7392
13	0.2442	0.5573	0.1985	306,182	0.4018	0.5750	218,766	0.5505	0.6200
14	0.0149	0.7060	0.2791	156,535	0.6121	0.4474	260,538	0.6121	0.5729
15	0.5928	0.0558	0.3514	94,682	0.6693	0.6240	94,813	0.2940	0.8558
16	0.7062	0.1356	0.1582	105,709	0.5135	0.3998	105,600	0.3401	0.8239
17	0.2981	0.3573	0.3446	199,160	0.5063	0.5599	196,822	0.5147	0.6151
18	0.4656	0.5172	0.0172	161,157	0.6954	0.2384	171,676	0.5094	0.6653
19	0.2020	0.3325	0.4655	248,881	0.6100	0.6625	192,875	0.5227	0.6623
20	0.0664	0.5337	0.3998	173,400	0.3605	0.7040	163,455	0.4758	0.7125
21	0.2435	0.4968	0.2597	180,056	0.5939	0.5749	206,576	0.5696	0.5854
22	0.1519	0.4536	0.3944	268,919	0.5611	0.6583	194,876	0.5350	0.6570
23	0.5268	0.2658	0.2074	157,021	0.3579	0.6847	154,557	0.4689	0.7178
24	0.2453	0.6100	0.1447	280,333	0.4816	0.8396	166,472	0.4857	0.7073
25	0.3608	0.4154	0.2238	151,109	0.3675	0.4314	146,048	0.4659	0.7572
26	0.3614	0.5893	0.0494	198,842	0.3860	0.5008	179,678	0.4875	0.7176
27	0.3280	0.6000	0.0720	173,098	0.3500	0.6492	160,871	0.4563	0.7480
28	0.6117	0.1160	0.2723	247,688	0.6328	0.6935	201,003	0.5089	0.6957
29	0.6173	0.0284	0.3543	175,918	0.1595	0.4120	171,029	0.4894	0.7241
30	0.2549	0.1759	0.5692	189,002	0.4951	0.6342	188,220	0.5045	0.6569
31	0.0665	0.6119	0.3216	272,417	0.7224	0.4224	343,863	0.7222	0.4207
32	0.4017	0.4587	0.1396	95,977	0.4186	0.6808	129,640	0.4182	0.7842
33	0.4093	0.5418	0.0488	212,261	0.4916	0.6870	203,365	0.5221	0.6900
34	0.2472	0.4147	0.3381	185,561	0.6853	0.6420	208,170	0.5372	0.6862
35	0.4475	0.0331	0.5194	251,453	0.3684	0.4737	224,725	0.5289	0.6077
36	0.4577	0.1912	0.3511	191,493	0.7221	0.5764	189,245	0.4959	0.6761
37	0.3447	0.3307	0.3246	233,306	0.4500	0.5845	212,583	0.5433	0.6409
38	0.4184	0.4848	0.0968	286,366	0.4264	0.6414	195,088	0.5275	0.6457
39	0.1436	0.4374	0.4190	326,997	0.6076	0.5309	279,058	0.6104	0.5389
40	0.5110	0.0613	0.4277	68,435	0.7748	0.7259	68,380	0.2186	0.8964
41	0.4922	0.3930	0.1149	243,937	0.4777	0.4450	232,386	0.5777	0.5832
42	0.1200	0.5221	0.3579	150,080	0.1222	0.6816	140,454	0.4311	0.7789
43	0.0421	0.3235	0.6344	208,385	0.4226	0.6462	168,220	0.4850	0.7304
44	0.3130	0.4555	0.2315	217,972	0.5416	0.1597	217,900	0.5417	0.6889
45	0.2890	0.3361	0.3749	151,793	0.6157	0.1128	193,002	0.5278	0.6203
46	0.4929	0.4753	0.0318	247,703	0.6829	0.6869	247,754	0.6052	0.5617
47	0.5025	0.3509	0.1466	140,290	0.3281	0.5262	140,293	0.4585	0.7521
48	0.2431	0.0368	0.7200	223,161	1.0234	0.6610	212,830	0.5287	0.6624
49	0.5444	0.3610	0.0946	293,614	0.6398	0.8434	286,830	0.6407	0.5259
50	0.5085	0.3849	0.1066	81,335	0.4257	0.4898	164,517	0.4628	0.7267
51	0.6362	0.1943	0.1696	179,186	0.5926	0.3357	179,796	0.5271	0.7006
52	0.5637	0.4038	0.0326	153,207	0.6521	0.5343	171,102	0.5210	0.7246

Table A3
Pareto-optimal solutions using ideal goals.

Replication	$w1$	$w2$	$w3$	Cost goal	Reliability goal	Availability goal	Cost	Reliability	Availability
1	0.1681	0.8275	0.0044	18,208	1.0000	1.0000	288,303	0.6562	0.4801
2	0.1525	0.6337	0.2138	18,208	1.0000	1.0000	18,208	0.0190	0.9675
3	0.0625	0.6656	0.2718	18,208	1.0000	1.0000	345,999	0.7246	0.4173
4	0.4029	0.5016	0.0955	18,208	1.0000	1.0000	173,628	0.5068	0.6845
5	0.0677	0.6435	0.2888	18,208	1.0000	1.0000	207,333	0.5703	0.6050
6	0.5024	0.3039	0.1938	18,208	1.0000	1.0000	88,452	0.2679	0.8448
7	0.4891	0.2210	0.2899	18,208	1.0000	1.0000	45,956	0.1107	0.9264
8	0.0062	0.7211	0.2727	18,208	1.0000	1.0000	352,426	0.7285	0.4070
9	0.0077	0.5183	0.4741	18,208	1.0000	1.0000	196,822	0.5096	0.6789
10	0.0417	0.6170	0.3413	18,208	1.0000	1.0000	341,727	0.7199	0.4242
11	0.5052	0.4660	0.0289	18,208	1.0000	1.0000	171,098	0.5001	0.6901
12	0.4816	0.2644	0.2539	18,208	1.0000	1.0000	70,467	0.2232	0.8720
13	0.1177	0.4314	0.4509	18,208	1.0000	1.0000	78,357	0.2736	0.8450
14	0.0414	0.6188	0.3398	18,208	1.0000	1.0000	339,255	0.7158	0.4277
15	0.7614	0.2326	0.0060	18,208	1.0000	1.0000	58,019	0.1126	0.9189

Table A3 (*continued*)

Replication	*w*1	*w*2	*w*3	Cost goal	Reliability goal	Availability goal	Cost	Reliability	Availability
16	0.4125	0.3234	0.2641	18,208	1.0000	1.0000	69,114	0.2023	0.8786
17	0.0259	0.4680	0.5061	18,208	1.0000	1.0000	138,292	0.4178	0.7549
18	0.0448	0.6475	0.3077	18,208	1.0000	1.0000	348,141	0.7259	0.4138
19	0.1436	0.8556	0.0009	18,208	1.0000	1.0000	196,403	0.5629	0.6049
20	0.3913	0.5535	0.0553	18,208	1.0000	1.0000	160,095	0.5276	0.6679
21	0.2618	0.4085	0.3298	18,208	1.0000	1.0000	155,894	0.5156	0.6789
22	0.4828	0.3414	0.1758	18,208	1.0000	1.0000	92,659	0.2918	0.8315
23	0.3333	0.2773	0.3894	18,208	1.0000	1.0000	49,225	0.1370	0.9128
24	0.2153	0.5699	0.2149	18,208	1.0000	1.0000	61,981	0.1732	0.8702
25	0.3976	0.2729	0.3294	18,208	1.0000	1.0000	49,346	0.1337	0.9126
26	0.0251	0.6273	0.3476	18,208	1.0000	1.0000	339,598	0.7164	0.4277
27	0.3375	0.6111	0.0514	18,208	1.0000	1.0000	275,718	0.6212	0.5390
28	0.5057	0.4655	0.0288	18,208	1.0000	1.0000	196,397	0.5136	0.6789
29	0.2516	0.4159	0.3326	18,208	1.0000	1.0000	168,125	0.4867	0.7015
30	0.4589	0.3732	0.1678	18,208	1.0000	1.0000	158,911	0.4496	0.7247
31	0.1278	0.2593	0.6129	18,208	1.0000	1.0000	44,767	0.0932	0.9328
32	0.4409	0.4040	0.1551	18,208	1.0000	1.0000	49,204	0.1374	0.9128
33	0.1750	0.7778	0.0473	18,208	1.0000	1.0000	258,384	0.6238	0.5171
34	0.2326	0.5773	0.1902	18,208	1.0000	1.0000	220,456	0.5757	0.5951
35	0.0102	0.4232	0.5666	18,208	1.0000	1.0000	140,743	0.4207	0.7488
36	0.4032	0.3927	0.2041	18,208	1.0000	1.0000	140,032	0.4199	0.7487
37	0.2385	0.4051	0.3564	18,208	1.0000	1.0000	142,424	0.4291	0.7427
38	0.3800	0.5027	0.1173	18,208	1.0000	1.0000	166,527	0.4998	0.6788
39	0.1701	0.3803	0.4495	18,208	1.0000	1.0000	107,875	0.3661	0.7861
40	0.3136	0.4863	0.2001	18,208	1.0000	1.0000	189,163	0.4922	0.6958
41	0.7735	0.1871	0.0394	18,208	1.0000	1.0000	46,500	0.0987	0.9255
42	0.2794	0.3967	0.3239	18,208	1.0000	1.0000	120,249	0.3753	0.7797
43	0.0735	0.5006	0.4260	18,208	1.0000	1.0000	134,543	0.4328	0.7366
44	0.1048	0.6455	0.2497	18,208	1.0000	1.0000	130,649	0.4526	0.7188
45	0.5102	0.3288	0.1610	18,208	1.0000	1.0000	138,111	0.4075	0.7548
46	0.0057	0.6972	0.2971	18,208	1.0000	1.0000	345,999	0.7246	0.4173
47	0.3534	0.2907	0.3560	18,208	1.0000	1.0000	91,748	0.2804	0.8382
48	0.2142	0.2400	0.5458	18,208	1.0000	1.0000	45,961	0.1106	0.9264
49	0.1704	0.4127	0.4169	18,208	1.0000	1.0000	49,236	0.1365	0.9128
50	0.1510	0.7433	0.1056	18,208	1.0000	1.0000	222,051	0.5881	0.5710
51	0.0195	0.5427	0.4379	18,208	1.0000	1.0000	198,673	0.5228	0.6734
52	0.4177	0.5744	0.0079	18,208	1.0000	1.0000	157,972	0.5243	0.6734
53	0.0778	0.3684	0.5538	18,208	1.0000	1.0000	68,328	0.2751	0.8450
54	0.1884	0.7099	0.1017	18,208	1.0000	1.0000	70,386	0.2811	0.8382
55	0.0853	0.6499	0.2648	18,208	1.0000	1.0000	236,011	0.5975	0.5663
56	0.3489	0.4178	0.2332	18,208	1.0000	1.0000	163,932	0.5106	0.6845
57	0.4551	0.3941	0.1508	18,208	1.0000	1.0000	159,798	0.4969	0.6958
58	0.1023	0.7236	0.1741	18,208	1.0000	1.0000	192,132	0.5592	0.6150
59	0.2782	0.4198	0.3019	18,208	1.0000	1.0000	153,855	0.5082	0.6845
60	0.3231	0.3799	0.2970	18,208	1.0000	1.0000	151,815	0.5009	0.6901
61	0.0145	0.2803	0.7052	18,208	1.0000	1.0000	70,779	0.2246	0.8721
62	0.0156	0.2975	0.6869	18,208	1.0000	1.0000	69,359	0.2053	0.8787
63	0.0237	0.5322	0.4440	18,208	1.0000	1.0000	97,013	0.3785	0.7863
64	0.3446	0.2968	0.3586	18,208	1.0000	1.0000	93,070	0.3560	0.7990

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