Optimization of Preventive Maintenance in Chemical Process Plants

DuyQuang Nguyen and Miguel Bagajewicz*

School of Chemical, Biological and Materials Engineering, The University of Oklahoma, 100 East Boyd Street, T335, Norman, Oklahoma 73019

In this article, we use a genetic algorithm to obtain an economically optimal preventive maintenance frequency for different equipment, the parts inventory policy (number and type of spare parts to keep in stock), and labor allocation in process plants. To assess cost, we improved a previously published Monte Carlo simulation-based maintenance model (Nguyen et al. *Ind. Eng. Chem. Res.* **2008**, *47*(6), 1910−1924). Two examples, a Tennessee Eastman example and a fluid catalytic cracking unit in a refinery, are provided.

1. Introduction

In the age of high competition and stringent environmental and safety regulations, the role of maintenance as an effective tool to increase profit margin, improve plant reliability, and reduce safety and environmental hazards has become increasingly important. The perception about maintenance has shifted from being a "necessary evil" to being an effective tool to improve processing efficiency and ultimately larger profit. The trend is part of the new approach to processing named Smart Plants,[2] which advances the concept that such plants anticipate problems instead of reacting to them.

Maintenance has been defined as all actions appropriate for retaining an item/part/equipment functionality or restoring it to a given condition.[4] In other words, maintenance is used to repair broken equipment, preserve equipment conditions, and prevent their failure, which ultimately reduces production loss and downtime eventually reducing the associated safety hazards. It is estimated that over $300 billion are spent on plant maintenance and operations by U.S. industry each year and that approximately 80% of this is spent to *correct* the chronic failure of machines, systems, and human errors.[4] The annual cost of maintenance as a fraction of total operating budget can be as large as 40−50% for the mining industry[5] and 20−30% for the chemical industry.[6] The typical size of a plant maintenance group in a manufacturing organization varies from 5% to 10% of the total operating force.[4]

There is a large number of computerized maintenance management systems (CMMS) software packages devoted to help managing/organizing maintenance activities (over 360 software packages are listed on the Web site www.plant-maintenance.com). Despite this abundance, the optimization of decision variables in maintenance planning (like preventive maintenance frequency or level of availability of labor and spare parts), referred to as the maintenance optimization problem, is usually not discussed in detail in textbooks nor it is included as a feature in the aforementioned software packages. Thus, for the most part, these packages are excellent databases that help track repair orders and maintain appropriate book-keeping.

Despite the lack of optimization in practice, a large amount of maintenance models have been published in academic circles. The book by Wang and Pham,[7] and various review papers (for example, refs 8 and 9) offer an account of all these models. We now discuss the merits and shortcomings of the most popular ones:

* To whom correspondence should be addressed. Phone: 1-405-325-5458. E-mail: bagajewicz@ou.edu.

In general, a maintenance model needs to include the following:

- A maintenance policy: The most common maintenance policy is the standard periodic preventive maintenance (PM); other policies include age-dependent PM policy, sequential PM policy, replacement policy, opportunistic maintenance, predictive maintenance, etc.[7]
- A set of decision variables: They depend on the policies. The most common ones are the periodic PM time or PM frequency (in periodic PM policy) for each piece of equipment or group of equipment, the labor workforce size and the inventory level of parts.
- The objective: The most common objective is minimizing cost; maximizing profit or reliability are also used sometimes.
- The constraints: Limitations on storage of spare parts, limitations on labor or budget, among others.

The assumptions most commonly used to build these optimization models are that maintenance restores the equipment to a state "as good as new" (AGAN; or minimally "as bad as old" (ABAO)). Other assumptions that have been used are negligible maintenance time, binary states for equipment (either operating or failed), increasing failure rate of equipment, infinite time horizon, complete availability of maintenance resources, independence between units in a multiunit system, etc.

Most of the existing models are equation-based models obtained by using probability theory such as Markov chain or Renewal theory. One such Markovian model can be found in the work of Bloch−Mercier,[10] who used sequential PM policy to improve long-run availability of a repairable system. Renewal theory was used as a modeling tool by Wang and Pham,[11] who considered imperfect maintenance under age-dependent PM policy. Other models are based on stochastic process simulation: for example, Charles et al.[12] used discrete-event production-oriented simulation, while Tan and Kramer[6] used Monte Carlo simulations.

The most common optimization criteria is cost minimization, which can be maintenance cost only[6] or total cost, that is, maintenance cost, inventory cost and maintenance labor cost.[13] For systems like nuclear power plants or power generation systems where reliability is much more important than cost, the optimization criteria are reliability measures constrained by a given maintenance budget.[14]

Most of the research works dealt with maintenance planning, the upper level in the maintenance management hierarchy. In this upper level, decisions are made regarding which equipment will be prioritized for preventive maintenance, the preventive maintenance time plan over a time horizon of months or years,

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parts inventory levels, replacement strategy and purchasing policy, and maintenance work force size (the decision variables). On the other hand, we have maintenance scheduling, the lower level in the maintenance management hierarchy, deals with organizing maintenance activities on a daily or a weekly basis, e.g. allocating necessary labor and material resources to perform maintenance considering several factors: equipment to be maintained according to a predetermined maintenance plan or to be repaired, availability of equipment for maintenance operation, current available labor, and material resource. Only a few papers considered maintenance scheduling, namely the work of Gopalakrishnan et al.,[15] Ahire et al.,[16] and Yao et al.[17] All of them deal with optimal maintenance tasks scheduling under workforce constraints.

The complex stochastic maintenance models employ genetic algorithms or simulated annealing to solve the problem: Podgorelec et al.[14] used GA to optimize maintenance time plan and maintenance personnel allocation for nuclear power plants. Sum and Gong[13] simultaneously optimized maintenance timing, a part replacement strategy, and workforce size using GA. The use of simulation tools like Monte Carlo is required when dynamic situations are considered, like the interaction between resource (labor, spare parts) availability and maintenance activities or the dependence of condition-based preventive maintenance on the condition of the equipment. Thus, Monte Carlo simulation is usually coupled with genetic algorithm to optimize maintenance policy.[6,18,19] Genetic algorithms are also used to solve models with complicated maintenance policies like opportunistic maintenance policy.[6,20,21]

The policy on spare parts is an important issue in maintenance optimization because the availability of spare parts can decide whether a requested maintenance duty can be fulfilled if the part is in inventory or has to wait until the order arrives. Kennedy et al.[22] reviewed models for optimizing spare parts inventory levels. Usually, the models focus on the spare parts inventory optimization problem alone without interactions with the maintenance task organization. Only few papers addressed the simultaneous optimization of maintenance policy and spare parts inventory: Sum and Gong[13] simultaneously optimized the maintenance frequency, part replacement frequency and the purchasing quantity. Ilgin and Tunali[23] presented an integrated simulation approach based on GA for finding the optimal inventory level and periodic PM intervals. Sarker and Haque[24] simultaneously optimized block replacement as a maintenance policy and the spare provisioning policy using a simulation tool.

Realistic situations such as imperfect maintenance, where maintenance actions leave equipment in a state somewhere between "as good as new" and "as bad as old" (which is more realistic than the assumption of perfect maintenance) have also been investigated. Wang and Pham[7] gave a good review of imperfect maintenance models and classified these models into eight categories. In these models, the effect of imperfect maintenance action on the reliability function, the failure rate or the age of equipment at maintenance time was modeled using predetermined rules; for example, after maintenance actions, the failure rate reduces to some extent but not to the perfect level "as good as new" (the improvement factor method) or it may be recovered to the perfect level with a certain probability.

Despite the abundance of previous works on maintenance, the simultaneous consideration of maintenance policy, labor work force size, and spare parts inventory levels using the constraints on resource (labor, spare parts) has only been addressed by Nguyen et al.[1] A few other models contain some elements of these interactions but not all simultaneously. Indeed, although Ilgin and Tunali[23] and Marseguerra et al.[25] considered the interaction between spare parts availability and maintenance activities making use of a simulation tool, only the optimization of spare parts provisioning was targeted[25] or the labor resource constraint was not considered.[23] The works of Gopalakrishnan et al.,[15] Ahire et al.,[16] and Yao et al.[17] considered the constraint of resource availability on maintenance activities but they all targeted resource allocation (maintenance scheduling) only.

In summary, the shortcomings of existing models are that they do not consider all the interactions and/or they do not optimize the decision variables. These shortcomings were addressed by Nguyen et al.[1] who presented a Monte-Carlo-based model that considered three practical issues:

(i) Different failure modes of equipment
(ii) Ranking of equipment for repair scheduling, according to the consequences of failure
(iii) A constraint of resource availability (including labor and spare parts) on maintenance activities as the basis for the optimization of labor work force size and spare inventory level.

Another novelty of the model of Nguyen et al.[1] is that the performance measure of maintenance policy is translated into monetary value (the economic loss) and included in the single composite objective value, which is the sum of economic loss, which is the economic performance measure of a maintenance policy and the maintenance cost. This approach allows the simultaneous optimization of the performance and the cost of maintenance policy to be formulated as an unconstrained, single objective optimization problem. Although Nguyen et al.[1] provided an analysis of factors affecting maintenance performance, they did not present an optimization method to solve the problem.

In this work, we improve on the maintenance model of Nguyen et al.[1] and add optimization. More specifically:

(i) We consider imperfect maintenance action.
(ii) We use more practical policies for spare parts inventory and labor assignment.
(iii) We add an optimization method (a genetic algorithm). The following three decision variables are optimized simultaneously: preventive maintenance time plan, labor workforce size, and inventory level.

The paper is organized as follows: we present basic concepts of process plant maintenance first; we then briefly review our previous Monte Carlo simulation-based maintenance model followed by a description of our extensions to the model. Next we present the genetic algorithm method to solve the maintenance optimization model. Finally, we provide two illustrations, a small scale example consisting of 19 pieces of equipment and an industrial scale example consisting of over 300 pieces of equipment

2. Maintenance Policies

Plant maintenance policies can be divided into three main types:[26]

(1) Corrective Maintenance (CM): maintenance is performed whenever an equipment failure is noticed to correct the failure and restore equipment function.
(2) Preventive Maintenance (PM): preplanned maintenance that is performed at a scheduled time to prevent/mitigate equipment failure, detect any small hidden failure, and retain equipment function.
(3) Predictive maintenance: in this type of maintenance, maintenance personnel monitor (online or periodically) the condition of equipment to detect in advance any future

Table 1. Ranking of Equipment for Maintenance Purposes (following the Work of Tischuk[27])

	consequence of failure		
probability of subsequent catastrophic failure	high	medium	low
high	1	2	3
medium	2	3	4
low	3	4	5

failure symptom and then perform planned repair for the failure-prone equipment.[26]

Note that there are some literature sources referring to the two types of proactive maintenance policies, preventive and predictive maintenance, as two categories belonging to a family of PM policies: time-driven PM and condition-driven PM, respectively.[3]

Various versions of time-driven preventive maintenance (PM) policy have been proposed. The book by Wang and Pham[7] provides one exhaustive list. A summarized version was presented in the review paper by Wang.[8] The (time-driven) PM policies are:

- Age-dependent PM policy: The PM times are based on the age of the unit.
- Periodic PM: A unit is preventively maintained at fixed time kT (k = 1, 2, ...), where T is the PM interval, independent of the failure history or age of the unit.
- Failure limit policy: PM is performed only when the failure rate or other reliability measures of a unit reach a predetermined level.
- Sequential PM: A unit is preventively maintained at unequal time intervals. Usually, the time intervals become shorter and shorter as time passes.

The standard periodic PM is probably the most commonly used maintenance policy in practice because of its simplicity; this policy together with the age-dependent PM policy are the most common policies in academic research.

3. Monte Carlo Simulation-Based Maintenance Model

The main features of our previous model[1] are described next:

Ranking of Repairs. Equipment units to be repaired are ranked according to the consequences of their failure: 1 is urgent and 5 is affordable to go unrepaired. The maintenance of equipment with higher ranking takes precedence over the lower ranked ones. We use the ranking of equipment shown in Table 1, which follows Tischuk,[27] who classified equipment for inspection planning purposes.

Failure Modes of Equipment. Equipment may have different failure modes involving different parts. For example, it can fail because of the deterioration of mechanic parts (possible consequence is complete failure that requires equipment replacement) or malfunction of electronic parts (partial failure that can be repaired). Different failure modes need different repair costs and repair times and induce different economic losses. This poses a problem for simulations. The options are to sample each type of failure separately, which is numerically costly or look for some approximations. In this article, we opt for the latter. The sampling of different failure modes of equipment is done as in the work of Nguyen et al.:[1]

(i) We assign a probability of occurrence for each type of failure mode using information on how common a failure mode is.

(ii) At the simulated failure time of the equipment, the type of failure mode that actually occurred is sampled in accordance with the probability of occurrence of that failure.

Interfering/Noninterfering Units. When preventive maintenance (PM) is performed on specific equipment, there are two possibilities:

(i) PM action on that equipment does not affect production and the economic loss during the maintenance time is negligible; the equipment whose PM does not interfere with production is termed a noninterfering unit, an example of such equipment is a valve or pump (with a spare unit online).

(ii) PM action on that equipment significantly affects production, e.g. it causes production loss or even downtime, which leads to economic loss; the equipment whose PM interferes with production is termed an interfering unit.

The distinction between interfering and noninterfering units is incorporated into the simulation-based model, and it also has implications in the optimization procedure.

Preventive Maintenance Policy. The most important decision variable for the standard periodic preventive maintenance policy is the PM frequency (or PM time interval).

Objective Function. The objective value is the total maintenance cost plus economic loss (to be minimized). The economic loss is the loss caused by equipment failures that lead to reduced production rate or downtime. It is the economic measure of the effectiveness of maintenance, i.e. the better the maintenance plan the smaller the economic loss. Thus, by minimizing the maintenance cost plus the economic loss, one simultaneously optimizes the cost and the performance of maintenance.

The cost term includes four types of cost: PM and CM costs (e.g., the cost of parts replacement, lubricating oils, cleaning agents), the labor cost (the salary paid to employees), and the inventory cost (the cost associated with storing spare parts).

The economic loss term includes two types of losses:

(i) Economic loss associated with failed equipment that have not been repaired (for example, a fouled heat exchanger can continue operating but at reduced heat transfer rate)

(ii) Economic loss due to unavailability of equipment during repair time.

The economic loss is calculated as the loss rate ($/day) multiplied by the duration of the period within which the loss is realized. To determine economic loss rates, an analysis is carried out on each piece of equipment to determine the economical effects of equipment failure, which include reduced production rate or even shutdown, the deterioration of product quality, etc.

Input Data. For each piece of equipment, the following data are needed:

(i) Reliability data like the mean time between failures (MTBF)

(ii) Information on the failure modes and the associated probability of occurrence for each type of failure mode

(iii) The time and the associated material cost of performing corrective maintenance (CM) (for each type of failure mode) and preventive maintenance (PM)

(iv) The economic loss associated to each type of failure mode

(v) The inventory cost rate for each type of spare parts

(vi) Other input data: the waiting time for an emergently ordered spare part to arrive, the labor paid rate, the available labor hours per employee per week (default

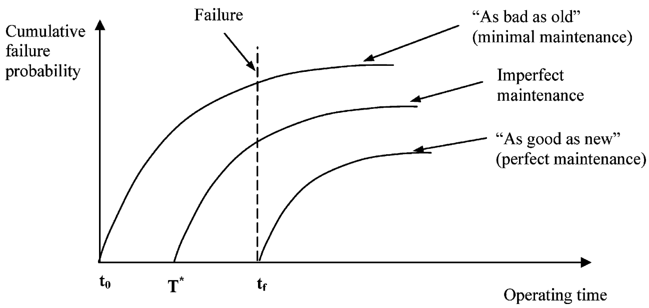

Figure 1. Imperfect maintenance cumulative probabilities.

value = 40), the ranking (for repair) and the classification (interfering or noninterfering) of the equipment.

4. Improvements to Our Previous Model

The features of our previous model[1] that have been improved in this work are the following:

- Labor assigned to maintenance activities: The previous assumption that "maintenance worker can take care of both types of maintenance activities (PM and CM) and can provide maintenance service to any kind of equipment" is relaxed. In the new model, a worker has necessary skills for PM and CM of only a specific group of equipment (e.g., he/she can take care of only rotating machines like pumps and compressors). In addition, each group of equipment is assigned to a group of maintenance employees, whose size is to be optimized.
- Spare parts policy: We use a more realistic spare parts inventory and acquisition policy described below in a separate section.
- Imperfect maintenance: This was added to our model and is described in the next section.

We now discuss some of the above issues in more detail.

5. Imperfect Maintenance

Our imperfect maintenance modeling follows the improvement factor method proposed by Malik,[28] who suggested that the maintenance action reduces the failure rate to some degree but not all the way to zero (not new). More specifically, in this approach, the reliability measure (the failure rate, the failure probability, or the reliability function) of the system after maintenance lies between "as good as new" and "as bad as old". Following the same idea, in our model, the cumulative failure curve of equipment after maintenance lies between the cumulative failure curves corresponding to the two cases: "as good as new" and "as bad as old" as shown in Figure 1.

The cumulative failure curves of the equipment corresponding to the three cases are as follows: $F_1(t) = 1 - e^{-\lambda(t-t_0)}$ (minimal maintenance), $F_2(t) = 1 - e^{-\lambda(t-t_f)}$ (perfect maintenance) and $F_3(t) = 1 - e^{-\lambda(t-T^*)}$ (imperfect maintenance); T^* lies between t_0 and t_f. We define the improvement factor γ ($0 \leq \gamma \leq 1$, to be input by the user) as follows: $(T^* - t_0) = \gamma(t_f - t_0)$ (thus, $T^* = t_0 + \gamma(t_f - t_0)$). If $\gamma = 0$, we have minimal maintenance, and if $\gamma = 1$, we have perfect maintenance. The cumulative failure distribution $F_3(t) = 1 - e^{-\lambda(t-T^*)}$ is used to sample the next failure event of the equipment after an imperfect maintenance action. Note that in this approach the failure rate is a constant, the imperfectness of maintenance action is reflected through the "initial" times T^*, t_0, and t_f. In other words, the smaller the "initial" time is, the sooner the next failure occurs.

In this work, corrective maintenance is assumed to be perfect ("as good as new") while preventive maintenance is assume to be imperfect. Corrective maintenance is assumed to be perfect because CM usually involves replacement of failed components by new parts or even new piece of equipment (CM can also be treated as imperfect but with a better improvement factor than the factor used in modeling the PM). We leave this improvement for future work.

6. Improved Spare Parts Policy

In our previous work, provisioning policy for spare parts associated with corrective maintenance is considered with only one decision variable: whether to keep inventory for the spare parts or the whole new equipment ready for repairing or replacing the failed equipment. It was assumed that if one decides to keep inventory for a specific spare part/equipment, then a minimal inventory level is maintained: one redundant copy is kept, and when it was used to replace the failed one, the new one is ordered immediately to maintain the inventory level of one. This type of policy is appropriate when equipment does not share common spare parts with the others. However, it is usually the case that an equipment shares common spare parts with the others because they all belong to the same type/group of equipment (like pumps and valves). In such a case, the common spare parts can be kept together at one storage place and the number of a specific common spare part to keep can be less than the number of pieces of equipment it services; hence the problem of determining optimal inventory level arises.

In the current model, another type of spare parts policy is considered with one decision variable: the inventory level for each spare part (the number of the spare parts to keep). We assume that this optimal inventory level (determined by the maintenance optimization model or user-specified) is well-maintained: if the inventory level falls below the prespecified minimal level, then a purchasing order for the spare part (to be stocked) is made immediately to replenish the stocking level. This minimal stocking level is a parameter specified by the user (default level = 1).

7. Decision Variables

Taking into account these modifications, the three decision variables considered in the model are the following:

(i) The PM time schedule for each equipment. This involves two parameters: the time to perform the first PM (called PM starting time) and the PM time interval. The PM starting time and PM time interval are expressed as a fraction of MTBF (e.g., PM time interval = aMTBF), the fraction a is to be optimized (for each equipment).
(ii) Inventory level for each spare part.
(iii) Number of maintenance employees in each group.

8. Monte Carlo Simulation Procedure

The changes introduced to the model (labor assignment, spare parts provisioning policy, imperfect preventive maintenance) require a few modifications to the simulation procedure presented in the work of Nguyen et al.[1] Two modifications are made:

(i) A maintenance employee is responsible for maintenance of only a specific type of equipment instead of all types of equipment.
(ii) Pieces of equipment belonging to the same type are grouped into one group, e.g. group of valves, pumps, exchangers, instead of being considered separately. This is done so that employees with appropriate skill for each group of equipment are assigned to it. In addition, one

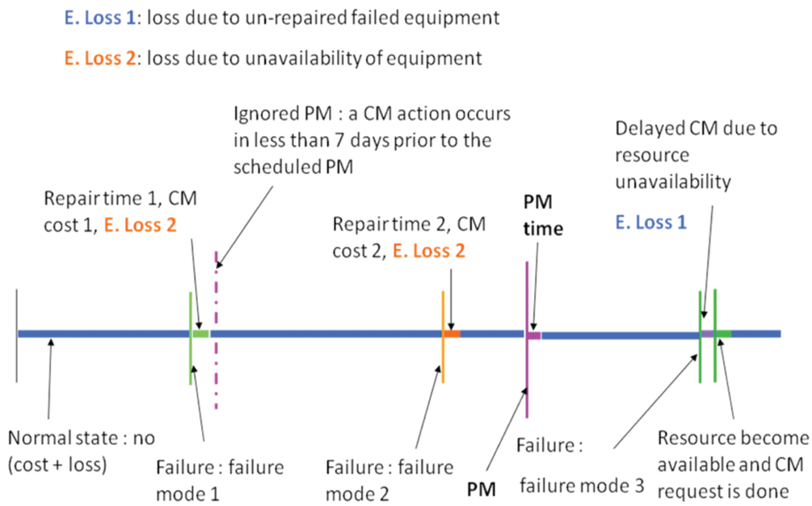

Figure 2. Sample Monte Carlo simulation result.

can better determine the inventory level for the common spare parts of the equipment.

The simulation procedure is the following:

- Failure times of equipment are sampled using the "current" reliability function of equipment. Note that, due to imperfect maintenance assumption, the reliability function changes with time.
- At failure times of equipment, the type of failure modes that caused equipment failure is sampled in accordance with the probability of occurrence.
- The cost of corrective maintenance, the repair time, and the economic losses are determined corresponding to the type of failure modes identified.
- Preventive maintenance requests for equipment are generated in accordance with the predetermined preventive maintenance schedule (predetermined PM policy).
- The planning time horizon is divided into time intervals of weeks.
- In each week
  - (i) All the CM requests (when equipment failed) and all the scheduled PM requests are identified.
  - (ii) CM and PM requests for equipment with highest priority will be fulfilled. Continuing with CM requests and PM requests of equipment with lower priority until the resource available is used up (labor resource and materials resource are considered). More specifically, for a maintenance request in the list to be fulfilled, the following steps are done: (1) check if the needed (both labor and spare parts) resources are available, (2) if resources are available, the maintenance request is fulfilled; otherwise, the maintenance request has to be delayed until the resources are available. The resources are available when there is at least one piece of needed spare part available (the current inventory level is at least one) and the number of available maintenance labor hours is at least equal to the needed time to repair/maintain the equipment. Resources that are consumed in repairing/maintaining a piece of equipment are modeled as follows: the current level of spare part inventory (if available) is subtracted by one (assuming that only one unit of spare part is consumed in that maintenance action); the available labor hours of the corresponding employee in charge of that equipment is subtracted by the needed time to repair/maintain the equipment. If the level of spare part inventory falls below the prespecified minimal level, a purchasing order is made, thus after some waiting time for the order to arrive to replenish the stocking, the inventory level increases up to the "optimal" level.
  - (iii) If a CM request or PM request is not fulfilled, it has to be delayed to next week. A delayed CM request is scheduled to be fulfilled at the early of next week or when the needed parts for repairing the equipment are available. A delayed PM request is scheduled to be fulfilled exactly 7 days after the original PM schedule.
  - (iv) If a CM action on equipment was performed prior to the scheduled PM request for that equipment by a predetermined period (current value is 7 days), that PM request will be ignored.
  - (v) If CM action for an equipment has been delayed longer than a predetermined period (current value is 21 days), the priority level of that equipment will be upgraded one level.
- The next week is considered, and the calculation is repeated. The procedure continues until the end of the planning time horizon is reached.

A sample of the simulation result is depicted in Figure 2.

9. Optimization

As mentioned above, the following three decision variables need to be optimized: preventive maintenance time plan, labor workforce size, and inventory level. The objective is to minimize the total maintenance cost plus economic losses.

We use a genetic algorithm (GA) because this method is well-established and was shown to have good performance (although it does not guarantee optimality). In brief, a genetic algorithm is based on mimicking the principles of genetics, natural selection, and evolution; it "allows a population composed of many individuals to evolve under specified selection rules to a state that maximizes the 'fitness', i.e. minimizes the cost function".[29] The algorithmic procedure and detailed description of the well-known genetic algorithm method can be found in various textbooks such as the Haupts' book.[29] Details of calculation steps/operators in our genetic algorithm method are described below.

Variable Encoding and Decoding. All the decision variables in the model, the PM starting time (P_{ini}) and PM time interval (PMI), the spare part inventory level (SPIL) for each spare part, and the number of employees (NE) in each group, are integer variables. The P_{ini} and PMI are expressed as fractions of the MTBF (PMI = aMTBF and P_{ini} = bMTBF). The inventory level SPIL is also "normalized": the inventory level for a "common" spare part is expressed as a fraction c of the number of pieces of equipment it services. There are two justifications for the normalization of the variables:

(i) The fractions a, b, and c give a better understanding of the magnitude of the variables than their absolute values.

(ii) Because the values of the variable PMI, P_{ini} and SPIL can vary greatly; normalizing the variables reduces their range of variability, which ultimately helps the GA converge faster.

The reasonable range of a and b is [0, 2] while the reasonable range of c is [0, 1]. The fractions a and b (for each equipment) and c (for each spare part) together with the number of employees NE (for each group) are to be optimized. We decided to use the standard binary GA, that is, the variables a, b, c, and NE are coded using a binary representation. The variable NE, the number of employees, is represented by a string of binaries using a decimal-to-binary transformation. The reasonable range of number of employees is [1, 8]; thus, a string of three binaries is used to represent NE (recall that NE is the number of employees in a group, not the total labor workforce size). For practical reasons, we postulate that the variables a, b, and c can take only discrete values (like 0.1, 0.2, 0.3, etc.). There are two justifications for this:

(i) It is a common industrial practice that the preventive maintenance time schedules P_{ini} and PMI take only discrete values like 30 days, 60 days, etc.

(ii) The model contains both real variables (a, b, and c) and integer variables (NE). A GA using continuous variables has more difficulty to converge than a GA using binary variables, especially for large problems, thus the discretization of a, b, and c allows us to use a binary GA.

We confine the possible values of a and b (representing P_{ini} and PMI) to be one of the following 16 discrete values: 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5, 0.55, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1, for interfering units (vector U), and 0.5, 0.6, 0.7, 0.8, 0.85, 0.9, 0.95, 1.0, 1.05, 1.1, 1.15, 1.2, 1.3, 1.4, 1.5, 1.6, for noninterfering units (vector V). The value of c is confined to take one of the following eight discrete values: 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8 (vector W); the possible values of a, b, and c can be easily changed by the user if desirable. Thus, the problem of determining the optimal values of a, b, and c turns into the problem of selecting values for a, b, and c from the pools of discrete values. This is done in two steps, which are illustrated for the variable a for interfering units:

(i) The value of a is indicated by its location (the index i) in the corresponding vector containing possible values of a (vector U), e.g. if $i = 2$ then $a = U[2] = 0.15$.

(ii) A gene consisting of four binaries is used to represent the index i whose value ranges from 1 to 16. The variables b and c are treated in the same way (four binaries are needed to represent b, and three binaries, for c).

GA Operators and GA Parameters. The binary GA described in this paper is not problem-specific (the possible value of the variables does not change with the scale of the problem, only that larger scale problems contain more variables so the chromosome would contain more bits). Thus, the binary GA scales relative well for larger scale problems; the remaining problem is to find a "good" set of GA parameters and procedures for mutation, crossovers, and selection rules. We focus on finding a good GA crossover method and a suitable mutation rate (for GA parameters, the general rule is that for larger scale problems, one should use a larger population size and a larger mutation rate if necessary). We did the testing of GA parameters and methods on the small scale Tennessee Eastman (TE) example and the larger fluid catalytic cracking (FCC) plant, whose size is 10 times bigger than the TE example. For obtaining benchmarking results of a candidate crossover method or a candidate mutation rate, two runs were made for each example (the TE and the FCC example). The best candidates for GA crossover method and mutation rate were determined using both criteria: optimality and computational time with focus on optimality.

The mutations and crossover procedures of the GA and the parameter values are chosen in accordance with the scale of the problem using the guidelines provided in the literature.[29] Aside from uniform crossover, we tried several "simple" crossover methods such as the two-point crossover. The uniform crossover method performs better than other methods (the computational times are comparable but the uniform crossover method generally finds better solution), and it scales relatively well for large scale problems (it still maintains good performance when the size of the problem become larger). Once the "right" GA crossover method was found, the mutation rate is then chosen. We tried only two values for mutation rate (0.25 and 0.3) and chose the 0.3 value. For population size, we intuitively choose the value 40 for small size problems like the TE example and the value 60 for bigger size problems like the FCC example. Following Haupt and Haupt,[29] we chose

- Selection: roulette wheel ranking
- Crossover: uniform crossover method
- Population size: 40 or 60
- Fraction of population to keep: 0.5
- Mutation rate: 0.3.

Obviously, the proper way to find the optimal set of GA parameters and methods is to employ experimental design techniques. However because there are so many crossover methods (both simple and advanced methods) and so many possible values for GA parameters, this task would take a long computational time, without the guarantee of success. We leave this for future work.

To reduce computation time, we stored all the previously evaluated solutions together with their objective values in a list; a new generated solution (new individual) is evaluated only if it is confirmed to be lexically "new" by checking this solution against all the solutions stored in the list.

10. Examples

Two examples are considered: one small scale example (TE process) and one large scale example (FCC unit). The maintenance model and GA optimization are implemented in Fortran running on a 2.8 GHz Intel CPU, 1028 MB RAM PC. We only show a sample of the full data for space reasons. More detailed information on the TE process example can be found in the work of Nguyen et al.[1] The complete set of data for the two examples can be obtained by contacting the authors.

10.1. Tennessee Eastman Problem. This example (Figure 3) was used in our previous paper.[1] The description of the TE process can be found in the literature, e.g. in Ricker and Lee.[30] The list of equipment in the process is given in Table 2. We include this example in this paper to test the performance of the GA by comparing the results with the results obtained by inspection by Nguyen et al.[1] The same maintenance model with the associated assumptions and the simulation procedure described in our previous work was used (our new proposed

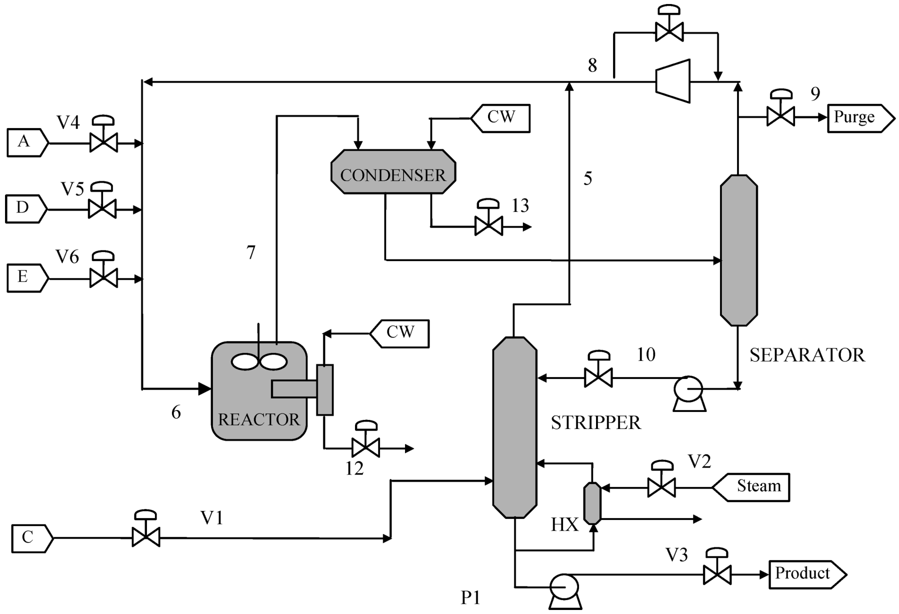

Figure 3. Tennessee Eastman process.

Table 2. List of Equipment of the TE Process

equipment	quantity	MTBF (days)	time for CM (hrs)	time for PM (hrs)	priority	PM interferes with production
valves	11	1000	2−5	2	3	
compressors	1	381	12−18	6	1	
pumps	2	381	4−12	4	4	
heat exchanger	2	1193	12−14	8	2	×
flash drum	1	2208	24−72	12	1	×
stripper	1	2582	48−96	12	1	×
reactor	1	1660	12−72	12	1	×

modifications were not used). The planning time horizon is 730 days, and the number of simulations is 1000. However, in this work, the PM starting time (P_{ini}) is also optimized together with the PM frequency, the spare part inventory policy (whether to keep spare parts necessary to repair a specific equipment or not), and the labor workforce size, while in our previous work the P_{ini} was fixed to some reasonable values (1, 3, and 6 months) and the decision variables were optimized by inspection.

The MTBFs for all equipment are obtained from the publication of the Center for Chemical Process Safety,[31] and the maintenance time is obtained from the work of Bloch and Geitner[32] (for pumps, compressors, and valves) or estimated if the information is not available. It is assumed that preventive maintenance of valves, compressors, and pumps does not interfere with production (called noninterfering units) while preventive maintenance of the main process instruments, which are heat exchangers, flash drum, stripper, and reactor, does interfere with production (called interfering units).

The results are shown in Tables 3−5 (in these tables, run 1 and run 2 are two different attempts to solve the proposed maintenance optimization problem using GA; because GA is a stochastic search method, each running attempt should give a different result).

One of the GA runs (run 1) gave a result somewhat similar to the one obtained by inspection (shown in the work of Nguyen et al.[1]) but with a better objective value as can be seen in column 3 of Tables 3−5 (It uses frequent PM for valves, pumps, and compressors while it does not use PM for the main process equipment). The result obtained by the second GA run (run 2 shown in column 4 of Tables 3−5) is the best one among the three. The best result has one fewer labor, more spare parts inventory is kept, and PM is not used for the valves, which leads to the following:

(i) Smaller labor cost and PM cost

(ii) Two opposite effects on economic loss: loss increases due to fewer labor and loss decreases thanks to greater level of spare parts inventory

(iii) Larger inventory cost.

Table 3. Optimal PM Time Frequency (Fraction of MTBF) for Example 1

equipment	by inspection	by GA optimization run 1	by GA optimization run 2
11 valves	0.1	0.1 (6 valves) and 0.2 (5 valves)	PM not used (scheduled PM time outside the time horizon)
1 compressor	0.1	0.4	0.1
2 pumps	0.1	0.1	0.15
2 heat exchanger	0.9	PM not used (scheduled PM time outside the time horizon)	PM not used (scheduled PM time outside the time horizon)
1 flash drum	0.9		
1 stripper	0.9		
1 reactor	0.9		

Table 4. Optimal Spare Parts Inventory Policy for Example 1

equipment	by inspection	by GA optimization run 1	by GA optimization run 2
	keep inventory?		
11 valves	yes	inventory for 5 out of 11 valves	inventory for 5 out of 11 valves
1 compressors	yes	yes	yes
2 pumps	yes	yes	no
2 heat exchanger	no	yes	yes
1 flash drum	no	no	no
1 stripper	no	no	no
1 reactor	no	no	no

Table 5. Optimal Number of Labor and Objective Value for Example 1

	by inspection	by GA optimization run 1	by GA optimization run 2
no. of labor	3	3	2
objective value (millions)	0.971	0.856	0.823

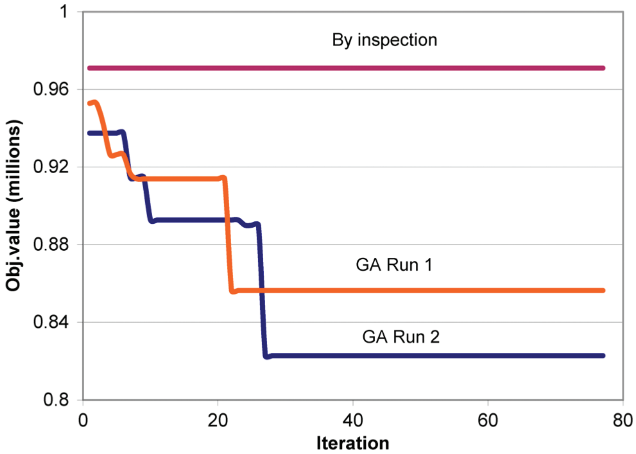

Figure 4. GA convergence, example 1.

Table 6. Effect of Imperfectness of PM, Optimal PM Policy Obtained by Inspection

	perfect PM	imperfect PM
economic loss (millions, $)	0.617	0.649
objective value (millions, $)	0.971	1.009
increase in obj value by imperfectness of PM (%)		3.9%
computational time (10000 simulations), s	56	59

Overall, the economic loss and the objective value decrease. The convergence of the GA is shown in Figure 4. The computation time in each GA run is about 2 h, 5 min.

To investigate the effect of the assumption of perfect/imperfect PM, the objective value corresponding to the optimal PM policy obtained by inspection is evaluated under the assumption of imperfect PM (with improvement factor $\gamma = 0.5$). The results are shown in Table 6.

As expected, the assumption of imperfect PM leads to higher number of failures; hence, higher economic loss and objective value than the case perfect PM is assumed. The computational time in the former case is longer than in the latter case because more failures are sampled and more maintenance requests are processed, but the difference in computational time is small (around 5%).

10.2. Example 2: An FCC Plant. A larger scale problem, the fluid catalytic cracker (FCC) unit in a refinery, is considered. A large west coast refinery volunteered equipment and volume specifications for its FCC unit. This unit, which processes roughly 50 000 barrels a day (bbl/day) of feed, is comprised of 61 pumps (31 primary, 30 spare), 2 compressors, 4 heaters, 87 heat exchangers, 15 vessels, 1 catalytic reactor and its associated catalyst regenerator, and 12 columns and strippers. The valves are not considered in this study. The main process equipment (process vessels and the catalytic reactor and its associated catalyst regenerator, columns, and strippers) are not included in this study. The reasons for this are the following:

(i) The failure of main process equipment is very rare; the failure rate is in the magnitude of $10^{-4}-10^{-2}$ (failures/year) (from data listed in the work of Mannan[33]).

(ii) Practically, the main pieces of process equipment are preventively maintained only at turnaround (i.e., when an entire processing unit or the refinery is shut down for overhaul). Thus, only rotating equipment (pumps and compressors) and heaters and exchangers are included in this study. These types of equipment are indeed the ones subjected to preventive maintenance program in refineries.

Table 7. List of Equipment of the FCC Unit

units	quantity	MTBF (days)	time needed for CM (h)	time needed for PM (h)	priority
pumps	61	694	6−8	4	1, 4, 5
compressors	2	381	30	8	1
heaters	4	1344	25−36	8	2
heat exchangers	87	1344	25−36	8	1, 2, 3, 4

The MTBFs and the mean time to repair of the equipment considered in this studied are listed in Table 7. These values are estimated (corresponding to the operating condition in a refinery) based on the values provided in the work of Mannan.[33] The mean time to perform preventive maintenance is estimated.

The following assumptions were made in estimating the economic losses:

- Economic loss of product is assumed to be $10/bbl. This results in an economic loss of $500 000/day if the process unit is fully shut down.
- For the pumps in the process
  1. Spare pumps always work. If a pump fails, the spare instantaneously comes online,
  2. If a spare is insufficient to maintain a stream at its normal operating rate, economic loss is proportional to the loss in throughput.

With these assumptions, the economic loss corresponding to failure of pumps with spares is essentially zero (it takes the nominal value of $10/day in the model).

- For the heat exchangers and heaters in the process
  1. Failed exchangers transfer heat, but at a reduced rate (20−30% heat transfer loss).
  2. Any exchanger located in series with other exchangers may be bypassed while being serviced without interrupting the process.
  3. Economic loss is proportional to the portion of heat-duty lost due to the failure.
- For the compressors
  1. If the compressor fails, the process goes offline.
  2. The result is a maximum economic loss per day ($500 000/day).

A sample of economic data is given in Table 8, which shows the cost of corrective maintenance (CM cost), the economic loss due to unrepaired failure of equipment (type 1), the economic loss due to unavailability of equipment during repair time (type 2), and the probability of occurrence for each type of failure modes for some equipment. Full data for all the equipment, which also include other types of data such as waiting time for an emergent purchasing order to arrive, can be obtained by contacting the authors.

To save computational time, only 100 simulation runs are used to evaluate the total cost plus loss of a candidate PM policy (i.e., a chromosome). The objective value is the total costs plus losses for a 10-year span. The solutions (optimal and near-optimal) obtained by GA are reevaluated by using a higher number of simulations (1000) to confirm the optimality of the solutions (it is the difference in objective values of the obtained solutions that matters, not their absolute values). Note that, since GA does not guarantee global optimality, the term “optimal” is meant to be the best possible obtained by GA. The computational time is 6 h, 20 min. Figure 5 depicts the convergence of the GA.

Table 9 depicts the results. The inventory level for a group of equipment is calculated as the average inventory level of all types of spare parts serving that group of equipment. The

Table 8. Sample of Economic Data in the FCC Example

equipment	failure mode	failure mode description	prob. of occurrence	CM cost ($/CM action)	econ. loss, type 1 ($/day)	econ loss, type 2 ($/day)	invent. cost ($/part/year)
pump	1	seals failure	0.4	6900	10	10	98
	2	leak	0.05	6900	10	10	88
	3	motor failure	0.05	6900	10	10	79
	4	couplings	0.05	6900	10	10	101
	5	bearings	0.05	6900	10	10	91
	6	corrosion	0.2	6900	10	10	0
	7	wear/tear	0.2	6900	10	10	0
compressor	1	lubrication breakdown	0.15	37400	200000	500000	1927
	2	seal failure	0.2	37400	200000	500000	1730
	3	excessive vibration	0.15	37400	200000	500000	1554
	4	fatigue/rupture	0.2	37400	200000	500000	1927
	5	corrosion	0.15	37400	200000	500000	1730
	6	erosion/wear	0.15	37400	200000	500000	1554
heater	1	fouling	0.5	69000	50000	100000	930
	2	fatigue/crack	0.1	69000	50000	100000	831
	3	tube rupture	0.1	69000	50000	100000	747
	4	corrosion	0.2	69000	50000	100000	1002
	5	others	0.1	69000	50000	100000	897
process heat exchanger	1	fouling	0.5	12600	14940	49800	465
	2	fatigue/crack	0.1	12600	14940	49800	416
	3	tube rupture	0.1	12600	14940	49800	374
	4	corrosion	0.2	12600	14940	49800	501
	5	others	0.1	12600	14940	49800	449
heat exchanger	1	fouling	0.5	6700	1500	3000	310
	2	fatigue/crack	0.1	6700	1500	3000	277
	3	tube rupture	0.1	6700	1500	3000	249
	4	corrosion	0.2	6700	1500	3000	334
	5	others	0.1	6700	1500	3000	299

inventory level for a specific spare part is in turn calculated as the number of stored items divided by the number of equipment it services (assuming a one spare−one equipment relationship). For a specific group of equipment, the inventory levels for each type of spare part are optimized separately (they are generally different from one another but the difference is small) but only the average inventory level is reported. The result shows that, in general, a reasonable inventory level of 50% is recommended.

The results show that PM is used for all types of equipment under consideration in this FCC unit but too frequent PM is not recommended (the PM frequency is generally in the magnitude of 1.0 × MTBF). There are two explanations for this:

- For equipment with a spare online such as pumps, their PM does not interfere with production (favorable condition to perform PM), but the economic loss incurred by their failures is also small (the reduction in loss, which is the benefit or the incentive to perform PM, is small). Moderate PM frequencies (0.9, 0.1, and 0.35) are used for this type of equipment.
- For equipment without a spare such as heat exchangers and compressors, it is assumed that their PM interferes with production (the extent of interference is quantified by the economic loss incurred during the maintenance time of the equipment). As Nguyen et al.[1] pointed out, there are two competing effects of PM on economic loss for this type of equipment: as PM frequency increases (doing PM more often), the economic loss may decrease because PM reduces failure-induced downtime but the economic loss may also increase because PM increases PM-induced downtime. It may be beneficial to apply PM for this kind of equipment, but the PM should not be done so frequently. The result shows that, for exchangers with a minor impact of PM activities on production (groups 6, 7, 10, 11, 12, 14), PM is used with moderate frequencies (from 0.7 to 1.2). For the main process equipment (compressors, heaters, and exchangers group 8, 9, and 13) whose PM activities cause significant PM-induced downtime and economic loss, PM is generally not recommended (PM frequency ranges from 1.05 to 1.6) because the gain (reducing failures-related cost and lost) is shadowed by the undesirable side effect of PM (economic loss increases).

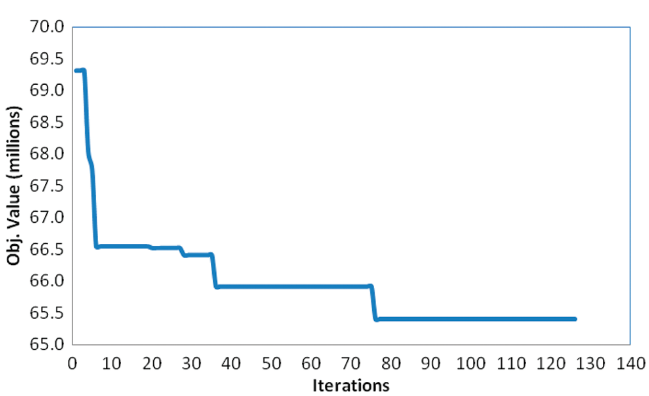

Figure 5. Optimal objective value by GA, FCC unit.

The optimal labor workforce size is shown in Table 10. Contribution of different terms in the objective value for some solutions found by GA (the top chromosomes in the final population) is given in Table 11.

The reported average inventory level is the mean value of inventory levels for all groups of equipment. The inventory cost of the top five solutions ranges from 500 000 to 610 000 (the optimal inventory cost is 558 000). The economic loss ranges from 58.25 million (best solution) to 61.62 million (fifth best solution). It can be seen from Table 11 that the total economic loss accounts for a large part (roughly 90%) in the objective function. Thus, to reduce the total costs plus losses, it is necessary to reduce economic losses by maintaining sufficient resources (labor and spare parts) for punctuality of maintenance actions. The obtained optimal number of employees (7) is greater than the actual number in the actual FCC plant used in this example (5), and the optimal inventory level may also be greater

Table 9. Optimal Maintenance Policy by GA Optimization for the FCC Unit

group	description	group size	PM starting time	PM frequency	inventory level	range of economic loss type 2 (thousands/day)
1	pumps	14	1.3	0.9	0.29	0.01
2	pumps	14	0.5	0.1	0.43	0.01
3	pumps	3	1	0.35	0.8	10−73
4	compressors	2	1.3	1.6	0.63	500
5	heaters	4	1.3	1.05	0.5	100
6	heat exchangers	13	1.1	0.85	0.54	7−9
7	heat exchangers	12	0.5	0.9	0.47	15−33
8	heat exchangers	6	0.7	1.05	0.39	45−58
9	heat exchangers	6	1	1.3	0.33	115−450
10	heat exchangers	13	0.6	1.2	0.56	5−7
11	heat exchangers	9	0.8	0.7	0.3	8−15
12	heat exchangers	10	0.7	0.9	0.47	3
13	heat exchangers	9	0.7	1.6	0.56	22
14	heat exchangers	9	1	1.2	0.37	3

Table 10. Optimal Labor Workforce Size

labor group	equipment covered	number of employees
1	rotating equipment (pumps, compressors)	2
2	heaters, heat exchangers	5
total		7

than the standard level in industrial practice where minimal inventory level is desired. The PM policy (PM frequency) and the size of resources of the optimal solution are comparable to those of the next two top solutions, but the optimal solution either better allocates labor resources (as compared to the second best solution whose sizes of the two labor groups are four and three) or has a larger spare parts inventory (as compared to the third best).

When sufficient resources are used, the economic loss due to postponement of equipment repair (economic loss type 1) is small: in the top three solutions, it accounts for only 2.5−6% of the total economic loss. The rest is economic loss of type 2, which is due to unavailability of equipment when the equipment is being repaired or preventively maintained. Further, the economic loss of type 1 accounts for not more than 9% of the total economic loss in the top ten solutions of the final population.

11. Future Work

As described above, a simple approach was used to find good crossover method and mutation rate. Thus, the performance of the genetic algorithm could be improved by using either or both of the followings: (i) expanding list of candidates for crossover methods (may including more complicated crossover methods), mutation rate, and population size, (ii) performing experimental design techniques to determine optimal set of GA methods and parameters. This improvement is not difficult to implement; however, it costs lots of time because each GA run takes several hours.

Other improvements that we considered but did not implemented in this work are shown below. The reason for this is the lack of available data or the considered improvement can be addressed in a simple way (hence eliminating the need of modifying the simulation procedure).

- Use of other types of failure distributions: Indeed, the exponential failure distribution was used in our model for all types of equipment because this type of distribution needs only one parameter (MTBF or failure rate, which is available in literature). If other types of failure distributions with time-dependent failure rates such as those given by the Weibull distribution are used, then (referring to the Monte Carlo simulation described above).
  - (i) Failure times are then generated using the new failure distributions instead of the exponential one (even though the failure rate is time-dependent, failure events are still random).
  - (ii) It makes more sense to use the age-dependent PM policy (described next) instead of the periodic one.
- Age-dependent and sequential preventive maintenance: These are more realistic than the standard periodic preventive maintenance. Due to external effects such as unfriendly operating conditions (e.g., dirty fluids being processed), harsh ambient conditions, or the operational characteristics of the equipment (e.g., the failure hazard of mechanical parts in rotating equipment usually increases with time because they are subjected to gradual degradation process during operation), the reliability measures of equipment may decrease with time (shorter MTBF or larger failure rate). In such a case, it is necessary to shorten the PM time interval (increase of PM frequency) with the age of the equipment; this is implemented in the age-dependent and sequential preventive maintenance policies. However, the applicability of these policies depends on the quantification of the time dependence of equipment reliability parameters, which is generally not available. A rigorous approach to implement age-dependent PM is to incorporate this type of PM into the Monte Carlo simulation procedure. This means that the PM schedule is generated according to the age-dependent policy (PM schedule varies with time because it depends on the age of the unit) instead of the periodic one. Alternatively, an approximate approach can be used instead. In our model, the PM time interval is expressed as a fraction of MTBF; thus if the MTBF is shortened as time passes (failure rate increases), then the PM time interval is automatically shortened. To consider

Table 11. Contribution of Different Terms in the Objective Function

solutions	PM cost (%)	CM cost (%)	labor cost (%)	inventory cost (%)	total econ loss (%)	objective value (millions)	average inventory level	labor size
best	0.26	5.54	4.28	0.85	89.07	65.39	0.47	7
second best	0.19	5.50	4.13	0.89	89.30	67.82	0.50	7
third best	0.16	5.65	4.65	0.74	88.79	68.74	0.44	8

the time dependence of reliability parameters and the PM time interval, a two step procedure is implemented:

(i) Every three months (or other user-selected time period), re-evaluate the MTBF/failure rate of equipment using updated historical data on failures of equipment or some kinds of simulation model.

(ii) Rerun the model with the updated MTBF data to get the new optimal PM time interval.

Rigorous treatment of other types of distributions and other types of preventive maintenance policies can be done by modifying the simulation procedure, which will be addressed in future work.

12. Conclusions

We presented a new Monte Carlo simulation-based maintenance model that improves on our previous one[1] by including imperfect maintenance as well as a more detailed spare parts policy. We also show that genetic algorithms can be used to obtain optimal allocation of resources and PM schedules. We showed that the genetic algorithm outperforms the exhaustive inspection method.

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