An Optimal Scheduling for Medical Equipment

Preventive Maintenance Over a Finite Planning

Horizon Using Ant Colony Algorithm

Neven Saleh, PhD, Samanta Rosati, PhD, Amr Sharawi, PhD, Manal Abdel Wahed, PhD, and Gabriella Balestra, PhD

**Corresponding author:** Neven Saleh, PhD, is an assistant professor at the Faculty of Engineering, Systems and Biomedical Department, Cairo University, Oula, Giza, Egypt, and Electronics and Telecommunication Department, Duca degli Abruzzi, 24, 10129, Politecnico di Torino, Italy. She can be reached at nevensaleh76@gmail.com.

Samanta Rosati, PhD, is a researcher at the Electronics and Telecommunication Department, Politecnico di Torino, Italy.

AmrSharawi,PhD, is an associate professor at the Faculty of Engineering, Systems and BiomedicalDepartment,Cairo University,Oula, Giza, Egypt.

Manal Abdel Wahed, PhD, is a professor at the Faculty of Engineering, Systems and BiomedicalDepartment,Cairo University,Oula, Giza, Egypt.

Gabriella Balestra, PhD, is an associate professor at the Electronics and Telecommunication Department, Politecnico di Torino, Italy.

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**ABSTRACT**

The importance of preventive maintenance management has been gradually recognized specially with the great attention to the role of health technology management. Finding the optimal schedule to perform preventive maintenance for medical equipment is rarely considered in the literature. This research suggests using ant colony optimization method to solve the problem of finding the optimal preventive maintenance schedule. We developed 2 versions of the algorithm, both starting from a prioritized medical equipment list and differing in the heuristic function. The experimental results indicate the effectiveness of the ant colony optimization algorithm for this kind of problems.

**INTRODUCTION**

Preventive maintenance (PM) is a core function of clinical engineering, having as objectives the assurance of ongoing safety and performance of medical devices and the preservation of the investment in the equipment through improved longevity.1

Preventive maintenance consists of a set of activities that aims at improving the overall reliability and availability of a system.2 The main goal is to keep equipment in a specified condition such as safety and quality.

Because PM is expensive, it is important to decide when it should be performed. One of the most used concept is periodical PM,3,4 which specifies the interventions following to be performed at equal time. Another approach is the so-called sequential PM, characterized by search of optimal number of maintenance actions to be performed during a given period.3 Although the first concept is more convenient, sequential PM results are more realistic because it usually complies better with budget constraints.

Optimizing PM is an old problem, which is very important in different fields, so it has been discussed extensively in the literature. In general, PM sequence can be classified into single-unit and multiunit systems.5

The literature is rich of different optimization techniques for PM scheduling for single-unit and multiunit systems. Examples in the studies by Khan and Haddara,6 Kim and Ozturkoglu,7 and Leou8 present different techniques for optimum single-unit PM interval, whereas the studies of Joo,9 Saleh and Balestra,10 and Sitayeb et al11 show different cases for multiunit systems.

In case of medical equipment (ME), several models were developed to optimize maintenance interval, considering both costs and reliability. An adaptive PM protocol based on inspections database was designed in Arslan and Ulgen.12 It uses a risk-based approach to determine the optimal PM interval. In the study of Joseph and Madhukumar,13 a PM index was developed for every device in the inventory to assign an optimal PM interval based on a risk level coefficient of the device. Risk level coefficient was calculated through 5 different classified factors related to the ME electrical risk. A mathematical model is developed in Khalaf et al’s study14 using a mixed

Integer-based approach for maintenance operation schedules for ME. Field data are used to get the parameters of the model by nonlinear least square regression. A greedy algorithm is proposed to give an initial solution for the model.

To reduce costs, it is important to optimize the intervention sequence decreasing the time spent in going through the departments. Even if there are different models that deal with optimal PM policy or strategy for ME, the literature review has shown that no empirical approach has been presented to find the optimum sequential list of ME to perform PM in an efficient sequence. In other words, if

we have a set of equipment that should undergo PM, what is the best sequence of devices that minimizes time, labor, and, consequently, costs?

This kind of problem can be easily reformulated as an optimization problem. The goal of the optimization is to find the solution of a specific problem that maximizes or minimizes (generally that optimizes) a given objective function. Two different strategies can be followed to find optimal solutions: the global search, which explores the complete space of feasible solutions and selects the overall best solution, and the metaheuristic approach that avoids the analysis of the complete set of possible solutions, assuring to reach a sufficiently good solution with less computational effort. In the last category, different algorithms are included, such as genetic algorithm and ant colony optimization (ACO) algorithm, that were extensively used for various optimization problems15 in different fields.

The aim of this article is to propose a new approach for finding a good PM scheduling. It starts from a list of ME that must be maintained and finds the sequence that is a good compromise between the priority of each ME that must be maximized and the time spent by technicians to go from the actual device and the next that must undergo maintenance, which must be minimized. Our method is based on an ACO algorithm because it provides an efficient answer in finding solutions of combinatorial problems as demonstrated by its application to traveling salesman and similar problems in addition to giving positive feedback accounts for rapid discovery of good solutions16 and inherent parallelism. Because the proposed algorithm requires a list of prioritized ME, we used the method proposed by Saleh et al17 for the calculation of a priority index of ME for PM based on quality function deployment technique. The output of this model is a weighted priority list of ME, which reflects the priority level for every device.

The rest of the article is organized as follows: section 2 explains the methodology based on ACO algorithm. The formulation of the algorithm for the specific PM problem is described in section 3. Section 4 illustrates the results of algorithm applications to a real case. Section 5 discusses the results, and section 6 presents the conclusions.

**METHODOLOGY**

Ant colony optimization algorithm was recently proposed in the field of computational intelligence. It has strong robustness, as well as good distributed calculative mechanism, and it is easy to combine with other methods. It has been shown to have good performances on resolving complex optimization problems.18 It is based on the observation that ants leave a substance called pheromone on their way to look for food. The more ants take 1 same way, the more substance will be left on this way. As a result, there will be a larger probability for the following ants to take the same path.

Ant colony algorithm simulates the cooperation process of a real ant colony. In ACO, a number of artificial ants build solutions to an optimization problem and exchange information on their quality via a communication scheme that is reminiscent of the one adopted by real ants.19 The original ACO algorithm is known as ant system and was proposed in the early 1990s. Since then, a number

of other ACO algorithms were introduced.19 All ACO algorithms share the same idea of representing the problem as a graph made by nodes and edge among nodes. A solution is built by adding to the current partial path a new node, moving along the link connecting the nodes and leaving on each traversed link a given amount of pheromone. Their main characteristic is that the pheromone values are updated by all the ants that have completed the route.

The main steps of a generic ACO algorithm are presented in Figure 1 and described as the following:

1. Pheromone initialization with a small random value for each link
2. Solution construction for each ant: The construction for each ant starts with an empty partial solution and proceeds iteratively by adding to the current path a newnode, until the destination node (complete solution) is reached. To choose the new edge to travel, each ant takes a decision based on a transition probability. This parameter takes into account the pheromone trails, memorizing the solutions already visited, and the heuristic probability of edges, which is a measure of the improvements due to the choice of a certain node.
3. Pheromone update: The evaporation phenomenon allows ants to explore a wider solution region, avoiding the achievement of the same solution too fast.
4. Reinforcement of pheromone amount according to the solution quality
5. Stopping criterion verification: The algorithm restarts from step 2 (all ants returned to the starting nodes) until the stopping criterion is satisfied. Generally, the evolution stops when a fixed number of iteration is reached or when a satisfactory solution is found.

In general, an ACO algorithm can be applied to any combinatorial problem20 as long as it is possible to define: (1) appropriate problem representation, (2) heuristic desirability of edges, (3) construction of feasible solutions, (4) pheromone updating rule, and (5) probabilistic transition

rule.

During the process of constructing its solution, each ant calculates the state transition probability in accord with the amount of pheromone, as well as the heuristic information of each path.18

The transition probability of the *k*th ant moving from node *i* to node *j* is given by



Fig.1 Flow chart of the ACO algorithm used to identify the optimal PM schedule.

(1)

where *allowed k* is the list of nodes not yet visited by the *k*th ant, *τij*, represents the pheromone amount for edge joining nodes *i* and *j*, and *ηij* is the heuristic information that is the value of our object function and indicates the expectation degree of ant moving from element *i* to element *j*. *α* and *β* are the parameters that control the relative importance of these last 2 quantities. Specifically, *α* is the information heuristic factor that indicates the importance of path and reflects the role of cumulative amount of pheromone to the ant during its moving. The larger *α* is, the more the ant will tend to choose the path that other ants have passed and the stronger the cooperation among ants will be. The coefficient *β* represents the expectation heuristic factor that indicates the relative importance of visibility and reflects the stressing degree to heuristic information when the ant chooses the path.18

The pheromone update for *τij*, which is for edge joining nodes *i* and *j*, is calculated as follows:

 (1-ρ).+ (2)

where is the evaporation rate, *m* is the number of ants, and is the quantity of pheromone per unit length laid on edge (*i, j*) by the *k*th ant.

**Algorithm Formulation and Data Set Description**

In this research, we model the problem of finding the optimal sequence of ME for PM using ACO algorithm. In our application, each node represents a device to be included in the PM scheduling, and each solution, corresponding to the sequence of nodes visited by an ant, denotes a feasible

sequence of PM activities.

To increase the model complexity step by step, we implemented 2 versions of the algorithm that differ by the heuristic formulation. The first version of the algorithm is the simplest one. It generates the best sequential PM schedule (SPMS) taking into account only the equipment

priorities, and it was used for the tuning of the algorithm parameters. The second version of the algorithm is designed starting from the first one and adding the information about the location of equipment (in terms of hospital and department) to identify the best SPMS.

First, some assumptions are made for both systems:

1. Our model takes into account only those devices that must and can be maintained; for this reason, PM budgets are not included in our model.
2. There is only 1 technician for PM.
3. The working days are 5 days with an average of 6 hours per day.
4. The required maintenance durations for ME are proposed based on the complexity level of equipment.
5. The planning horizon is a finite time and calculated in hours.
6. Delay times are calculated in hours.

The notations for problem formulation are the following:

N number of equipment

*i* index of equipment

Wi priority weight of equipment *i*

D delay time

T total PM duration

S distance score index for the devices

F heuristic function

Both versions of the algorithm were tested on real data. The list of devices used as input for this optimization problem is the one described in Saleh et al’s study,17 in which 5 categories of devices are identified according to their need of PM. Specifically in this case, we consider only the equipment in first 4 classes (182 from 200 equipment) because the last category includes only the devices that do not require PM. Moreover, in our data set, we have 2 different hospitals with a total of 32 departments, 16 for each hospital.

**First Version of SPMS Algorithm**

The first version of the algorithm we developed to find the SPMS for ME was used to identify the optimal parameters for ACO implementation.

The number of ants is set equal to the number of equipment in the first class-in our application, 30- and with an ant starting from each of those devices.

The heuristic function is formulated as shown in equation (3) to maximize the total number of ME to perform PM, considering the priority weight *Wi* for every device. The priority list is the output of the PM prioritization model developed in Saleh et al’s study,17 and the priority weight associated to each device ranges from 0 to 1.

F (max) = (3)

The total PM duration (*T*) in this algorithm is considered 3 months as assumed in Saleh et al’s study,17 that is, 12 weeks. Because we assumed that the total working hours per week is 30 hours, accordingly, we have 360 maximum working hours in the PM duration. The delay *Di* is the time difference between the recommended maintenance time limit and the actual maintenance time limit for each device.

Actual maintenance time limit is calculated as the sum of the time spent for the maintenance of all devices included in the analyzed sequence before the actual one. The average PM time (APMT) for each ME is estimated according to the 3 complexity levels of equipment resulting from Saleh et al’s study17: high, medium, and low. In particular, we used higher values of APMT for high complexity

level devices. Moreover, we implemented different durations for different trials to understand the impact of APMT on the best solution. At the end, we decided to use 2 hours for high complex equipment, 1.5 hours for medium complex equipment, and 0.5 hour for low complex equipment.

The recommended maintenance time limit represents the time limit for doing PM on each specific category of devices. In particular, we set a limit of 60 hours for the first class (2 weeks), 120 hours for the second class (4 weeks), 240 hours for the third class (8 weeks), and, finally, 360 hours for the fourth class (12 weeks).

We assumed that the evaporation rate ρ is a constant value equals 0.3 for both algorithms. Moreover, as shown in equation (1), we have to determine the optimal values for *α* and *β* to set pheromone update and the transition probability, keeping in mind that these parameters range from 0 to 1.19

The maximum number of iterations is set to100 for both versions, and each algorithm is repeated 10 times starting from the same initial conditions to test the solution stability.

**Second Version of SPMS Algorithm**

In the second algorithm, another parameter is added to the heuristic function to take into account also the location of the ME. In other words, if we consider the department location and the hospital location for PM performance, could this consideration be reflected positively or negatively on the optimal sequence path of PM?

In this case, we develop an algorithm that takes into account also the time spent from the technician to move in different departments of the same hospital and between the 2 hospitals. The heuristic function is then reformulated as shown in equation (4), where a penalty term that takes into account the distance between the hospitals and among the departments is added to the heuristic function of the first algorithm. The ant’s number of this algorithm is the same as in the first algorithms, 30 ants.

F (max) =] (4)

In equation (4), we modeled a distance index *Si* as 3 values: 10 if 2 consecutive devices in the list are in different hospitals, 5 if the 2 consecutive devices are in the same hospital but in different departments, and 0 when the devices are in the same department.

The second algorithm follows the same procedures that are described for the first one, using the optimal values for *α* and *β* that we determined in the first algorithm. As we mentioned before, *T* in equation (4) is equal to 360 hours, and the priority weights *Wi* range from 0 to 1 as indicated in Saleh et al’s study.17

**RESULTS**

**Results of the First Version of SPMS Algorithm**

First of all, we had to determine the optimal values fo *α* and *β*. Table 1 illustrates the trials we performed to identify the best combination of *α* and *β* to find the best solutions. The best solution is the one that leads to considering the whole set of prioritized ME in the optimal path over planning horizon and gives us the maximum value for the heuristic function.

Table 1 Results of first algorithm in terms of µ, σ, median, and mode of heuristic functions, for different values of *α*, and *β*.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| α | β | µ | σ | Median | Mode  |
| 0.5 | 0.5 | 119.94 | 0.12 | 119.95 | 120.03 |
| 0.6 | 0.4 | 120.07 | 0.31 | 120.125 | N/A |
| 0.8 | 0.2 | 120.01 | 0.25 | 120.05 | 120.19 |
| 0.4 | 0.6 | 119.97 | 0.27 | 119.96 | 119.96 |
| 0.2 | 0.8 | 120.01 | 0.27 | 119.95 | 119.82 |

As we have 10 best solutions for every *α* and *β* combination (one for each repetition), we compare the results by means of a set of statistical parameters calculated on the resultant heuristic functions, to check the variability among the 10 solutions for every trial.

The results in Table 1 are shown in terms of mean value (µ), standard deviation (σ), median, and mode of the heuristic functions of all solutions obtained for every combination of *α* and *β*. As shown in Table 1, there is no wide variability in the standard deviations of the last 3 combinations of *α* and *β*.

Moreover, all solutions include the whole set of equipment in the PM list. Regarding these aspects, we consider only the last 3 combinations for *α* and *β* for the second algorithm. The proposed values for *α* and *β* are ranging between 0.2 and 0.8.

The results obtained with the 3 optimal set of parameters are depicted in Figure 2 in terms of best sequences of ME. Figure 2A reports the optimal sequence for PM obtained with *α* = .8 and *β* = 0.2. Figure 2B points to this sequence in case of *α* = .4 and *β* = 0.6. Finally, Figure 2C presents the optimal sequence with *α* = .2 and *β* = 0.8.

For each graph in the figure, sequence is presented on the x-axis in terms of number of devices, whereas hospitals are reported on the y-axis of the graphs. The total number of movements between different departments of the same hospital (H1 -> H1 and H2 -> H2) and between the 2 hospitals (H1 -> H2 and H2 -> H1) is shown at the top of the figure.

Furthermore, because we have 4 categories for the priority list, we addressed it with a color code in which red color is given for the highest priority and blue color is given for the lowest priority. In addition, we represent the APMT separately for each device, modifying the dimension of the maintenance duration for everyone.

**Results of the Second Version of SPMS Algorithm**

The second algorithm has been implemented using the 3 optimal combinations for *α* and *β*. All the other parameters, such as number of ants, number of iterations and repetitions for each combination, and evaporation rate, are kept unchanged with respect to the first one. The statistical analysis results for the heuristic function are presented in Table 2 for each tested *α* and *β* combination.

Hence, it emerges from Table 2; the lowest standard deviation is obtained with *α* = .4 and *β* = 0.6. This reflects the low variability existence within the solutions. Because the algorithm considers the location of the equipment, accordingly, an improvement is expected to occur in the optimal sequence of PM by reducing the mobility frequency between hospitals, as shown in Figure 3.

A

B

C

**Fig. 2** The optimal PM solutions result using SPMS first algorithm with three different combinations of *α* and *β*: (a) *α* = 0.8 and *β* = 0.2, (b) *α* = 0.4 and *β* = 0.6, (c) *α* = 0.2 and *β* = 0.8 respectively.

Table 2 Results of the second algorithm in terms of µ, σ, median, and mode of heuristic functions, for different values of α, and β.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| α | β | µ | σ | Median | Mode  |
| 0.8 | 0.2 | 119.89 | 0.37 | 119.92 | 120.01 |
| 0.4 | **0.6** | 119.88 | 0.15 | 119.89 | 120.02 |
| 0.2 | 0.8 | 119.99 | 0.28 | 119.89 | 119.89 |

**DISCUSSION**

The optimization of PM schedule for ME is an important problem for clinical engineering departments that is rarely addressed in the literature. In this research, the authors developed 2 versions of SPMS algorithm to seek the optimum PM schedule using ACO algorithm. The results

of both SPMS versions are reported by Figures 2 and 3, respectively. The best solution is the one that maximizes the required list for PM and, at the same time, minimizes the mobility frequency between the hospitals.

By regarding these criteria between the resultant solutions of 2 SPMS versions, we can easily reveal the optimum sequence. In particular, by comparing Figure 3A versus Figure 2A, we found that the movements are reduced from 85 to 80; that is, there is a decrease of mobility frequency of approximately 6%. Comparing Figure 3B versus Figure 2B, the movements are reduced from 94 to 76; that is, there is an improvement of 20%. Finally, comparing Figure 3C versus Figure 2C shows

that the mobility frequency is decreased from 93 to 85, that is, 9%.

Although the first algorithm is used essentially to find the best parameters for the ACO implementation, the second algorithm implements a more complex and adequate model of the real problem.

A

B

C

Fig.3 The optimal PM solutions result using the SPMS second algorithm with three different combinations of *α* and *β*: (a) *α* = 0.8 and *β* = 0.2, (b) *α* = 0.4 and *β* = 0.6, (c) *α* = 0.2 and *β* = 0.8 respectively.

**CONCLUSIONS**

This work presents a first attempt to seek the optimal PM sequence of ME using ACO algorithm. The study highlights the importance of a prioritized ME list to perform PM, in addition to existence of a planned PM schedule that impacts on PM management.

Two versions of an SPMS algorithm that allows finding a solution containing all the ME that needs PM were developed. Both are based on a prioritized list. Moreover, the second version addresses the problem of the time spent by the technician. This is an important issue because reducing the time means also saving costs. The results showed the consistence of the second algorithm by decreasing the mobility frequency between the investigated hospitals.

The algorithm may be used either by clinical engineering departments or maintenance agencies to organize their activities. In fact, because maintenance agencies deal with several hospitals for different kinds of equipment, it is important for them to optimize the PM scheduling to reduce labor and costs.

This is a general algorithm that can handle different scenarios with good results. A future work could be to customize it modifying the objective function. A possible personalization is to add criteria to better represent the department or agency specificities. Another improvement is represented by the substitution of the weighted sum with the results of the simulation of the activities.

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