Ant Colony Optimization for Power Plant Maintenance Scheduling Optimization

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ABSTRACT

In this paper, a formulation that enables ant colony optimization (ACO) algorithms to be applied to the power plant maintenance scheduling optimization (PPMSO) problem is developed and tested on a 21-unit case study. A heuristic formulation is introduced and its effectiveness in solving the problem is investigated. The results obtained indicate that the performance of ACO algorithms is significantly better than that of a number of other metaheuristics, such as genetic algorithms and simulated annealing, which have been applied to the same case study previously.

Categories and Subject Descriptors

1.2.8 [**Artificial Intelligence**]: Problem Solving, Control methods, and Search – *heuristics methods, scheduling.*

1.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence – *intelligent agents, multiagent systems.*

General Terms

Algorithms; Management; Performance; Experimentation.

Keywords

Ant Colony Optimization; power plant maintenance scheduling; heuristics; Max-Min Ant System; Genetic Algorithm; Simulated Annealing.

1. APPLICATION OF ACO TO POWER PLANT MAINTENANCE SCHEDULING OPTIMIZATION

The objective of this study is to introduce a formulation that enables ACO to be applied to the power plant maintenance scheduling optimization (PPMSO) problem, including the development of a formulation for heuristic information, which is used as part of the decision policy at each decision point. In the PPMSO problem, decisions have to be made with regard to the timing of the maintenance periods of each of the machines (units) used for power generation. Generally, the duration of the maintenance period for each machine is fixed, and the decision variable is the maintenance start time. The aim of the optimization procedure is to obtain a maintenance schedule that minimizes the objective function subject to a number of constraints. The objectives generally include cost minimization, system reliability maximization, or both [7]. The most commonly used constraints are load constraints, resources constraints and the window of time during which maintenance can be carried out.

Before the PPMSO problem can be optimized using ACO, it has to be expressed in terms of a set of points at which decisions have to be made ($\mathbf{D} = \{d_n$, where $n=1,2,\ldots N\}$) and the set of options that is available at each decision point ($\mathbf{F} = \{l_{n,j}$, where $d_n \in \mathbf{D}$, $j=1,2,\ldots, k_n\}$) [5]. The decision points consist of the N units at which maintenance needs to be carried out and the corresponding decisions are the k_n potential commencement times for maintenance (Figure 1.1).

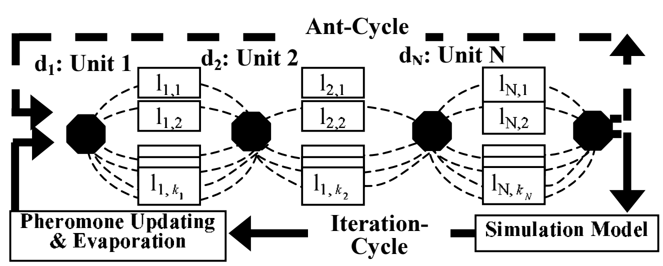

Figure 1.1: ACO algorithm applied to the PPMSO problem

As part of the ACO algorithm, ants generate trial maintenance schedules by choosing a maintenance commencement date for each of the units to be maintained. The probability that a particular commencement date will be chosen from the set of available options at a particular decision point is a function of the pheromone and the local desirability of that option based on heuristic information (generally referred to as the heuristic), as shown in Eq. 1.1.

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$$p_{n,j}(t) = \frac{[\tau_{n,j}(t)]^{\alpha} \cdot [\eta_{n,j}]^{\beta}}{\sum_{j=1}^{k_n} [\tau_{n,j}(t)]^{\alpha} \cdot [\eta_{n,j}]^{\beta}} \qquad \text{(Eq. 1.1)}$$

where $p_{n,j}(t)$ is the probability that start time $l_{n,j}$ is chosen for maintenance of unit d_n in iteration t; $\tau_{n,j}(t)$ is the pheromone intensity deposited on start time $l_{n,j}$ for unit d_n in iteration t; $\eta_{n,j}$ is the heuristic for start time $l_{n,j}$ for unit d_n; k_n is the total number of start time periods available for unit d_n; α is the relative importance of pheromone intensity; β is the relative importance of the heuristic.

The pheromone level associated with a particular option (i.e. maintenance commencement date for a particular unit) is a reflection of the quality of the maintenance schedules that have been generated that contain this particular option. The heuristic associated with a particular option is related to the likely quality of a solution that contains this option based on some heuristic information. It can be seen from Eq. 1.1 that during the early stages of an ACO run, before pheromone trails are significantly distinct, heuristic information is the dominant factor affecting the selection of decision paths. In other words, the heuristic plays a crucial role in defining the region in a solution search space in which the ACO algorithm commences its search. As the way in which heuristic information is represented mathematically is problem specific [4], the transformation of any heuristic information into a formulation to be used in the ACO algorithm is an important task.

As ACO has not been previously applied to the PPMSO problem, a heuristic formulation (Eq. 1.2) is introduced for a typical PPMSO problem in this paper. Furthermore, the following variables are defined:

- $J_{n,j} = \{ l_{n,j} \le k \le l_{n,j} + dur_n - 1\}$ is the set of time periods k such that if the maintenance of unit d_n starts at period $l_{n,j}$, that unit will be in maintenance during period k.
- $Y_{ManV(k)=0}$ is switched to 1 if there is no personpower violation in time period k. Otherwise it is switched to 0.
- $Y_{LoadV(k)=0}$ is switched to 1 if there is no load violation in time period k. Otherwise it is switched to 0.

$$\eta_{n,j} = (\eta_{n,j}^{M})^{w1} \cdot (\eta_{n,j}^{C})^{w2} \qquad \text{(Eq. 1.2)}$$

$$\eta_{n,j}^{M} = \frac{\sum_{k \in J_{n,j}} Y_{ManV(k)=0} \cdot M_{n,j}(k)}{\sum_{k \in J_{n,j}} (1 - Y_{ManV(k)=0}) \cdot M_{n,j}(k)}$$

$$\eta_{n,j}^{C} = \frac{\sum_{k \in J_{n,j}} Y_{LoadV(k)=0} \cdot C_{n,j}(k)}{\sum_{k \in J_{n,j}} (1 - Y_{LoadV(k)=0}) \cdot C_{n,j}(k)}$$

where $\eta_{n,j}$ is the heuristic value of unit d_n to start maintenance at time period $l_{n,j}$; dur_n is the outage duration required for unit d_n; $M_{n,j}(k)$ is the prospective personpower available in reserve in time period k if unit d_n is maintained starting at period $l_{n,j}$; $C_{n,j}(k)$ is the prospective generation capacity available in reserve in time period k if unit d_n is maintained starting at period $l_{n,j}$.

It can be seen from Eq. 1.2 that the heuristic formulation comprises personpower-related heuristics, $\eta_{n,j}^{M}$ and load-related heuristics, $\eta_{n,j}^{C}$. $\eta_{n,j}^{M}$ is designed to direct the optimization algorithm to regions in the search space where there are fewer personpower constraint violations. This is achieved mathematically by making the probability of a start time being chosen for any machine unit directly proportional to the prospective personpower available in reserve and inversely proportional to the amount of personpower shortfall. The same applies to $\eta_{n,j}^{C}$, where start times at which no tasks are scheduled are preferred to avoid violation of load constraints. It should be noted that where personpower and load constraints are easily satisfied inherently in a problem, the two heuristics are expected to evenly distribute maintenance tasks over the entire planning horizon, which potentially maximizes the overall reliability of a power system. In order to implement the heuristic, each ant is provided with a memory matrix on personpower reserve and another matrix on generation capacity reserve prior to construction of a trial solution, which is updated every time a unit maintenance commencement time is added to the partially completed schedule.

Once a trial maintenance schedule has been constructed by choosing a maintenance commencement time at each decision point (i.e. for each machine to be maintained), taking into account pheromone levels and the heuristic information introduced above, one ant-cycle has been completed (Figure 1.1). After r ant-cycles, where r equals the number of ants used, the ACO algorithm enters the iteration-cycle (Figure 1.1). During this stage, the quality of the r trial solutions is evaluated using a simulation model, as part of which the objective function values, such as maintenance cost and power system reliability, are calculated and violations of any constraints are identified. The objective function values (OFVs) of these trial solutions are then determined by an evaluation function, which is the weighted sum of the objective function values and penalty costs associated with constraint violations. It should be noted that some constraint violations can only be identified once a complete trial solution has been constructed, and hence these constraints cannot be accounted for explicitly, necessitating the use of penalty functions.

Next, pheromone is updated in a way that reinforces good solutions. The general form of the pheromone update equation is given by:

$$\tau_{n,j}(t+1) = \rho \cdot \tau_{n,j}(t) + \Delta\tau_{n,j}(t) \qquad \text{(Eq. 1.3)}$$

where $\tau_{n,j}(t+1)$ is the pheromone intensity of decision path $l_{n,j}$ in iteration (t+1); (1-ρ) is the pheromone evaporation rate; $\Delta\tau_{n,j}(t)$ is the pheromone awarded to decision path $l_{n,j}$ in iteration t.

The way the change in pheromone, $\Delta\tau_{n,j}(t)$, is calculated can vary depending on the particular ACO algorithm used. In this study, the MMAS algorithm is adopted due to its superior performance in [6]. MMAS uses information from the best performing ant in the pheromone updating process (Eq. 1.4), but imposes upper and lower bounds (τ_{max} and τ_{min}) on the pheromone intensities in order to prevent premature convergence and greater exploration of the solution surface.

$$\Delta\tau^*_{n,j}(t) = \begin{cases} \dfrac{Q}{OFV_{n,j}(t)} & \text{if } n, j \in \text{best ant} \\ 0 & \text{otherwise} \end{cases} \qquad \text{(Eq. 1.4)}$$

where Q is the reward factor.

The τ_{max} and τ_{min} values are given by:

$$\tau_{max}(t+1) = \frac{1}{1-\rho} \cdot \frac{Q}{OFV_{best\,ant}(t)} \quad \text{(Eq. 1.5)}$$

$$\tau_{min}(t+1) = \frac{\tau_{max}(t+1)(1-\sqrt[n]{p_{best}})}{(avg-1)\sqrt[n]{p_{best}}} \quad \text{(Eq. 1.6)}$$

where p_{best} is the probability that the paths of the current iteration-best-solution, $OFV_{best\ ant}(t)$, will be selected, given that non-iteration best-options have a pheromone level of $\tau_{min}(t)$ and all iteration-best options have a pheromone level of $\tau_{max}(t)$.

The algorithm terminates when either the number of iterations specified is met or a stagnation of the evaluation function value is encountered.

2. CASE STUDY

The case study considered in this research is the 21-unit power plant maintenance problem investigated by [1], [2] and [3] using a number of metaheuristics. This case study is a modified version of the 21-unit problem introduced by [7], and consists of 21 generating facilities, of which 20 units are thermal and one is hydropower. The system details can be obtained from [2]. The objective of the problem is to even out reserve generation capacity over the planning horizon, which can be achieved by minimizing the sum of squares of the reserve (SSR) generation capacity in each week. A single peak load, 4739 MW, and a limit of 20 maintenance staff are used as demand and manpower constraints, respectively.

2.1 Mathematical Formulation

The specification of this maintenance scheduling optimization problem can be represented by mathematical equations using binary (1-0) variables, which indicate the state of a unit in a given time period. In the case study under consideration, a time period of one week has been adopted. $X_{n,t}$ can be switched to 1 to indicate that unit d_n is scheduled to be maintained during period t. Otherwise, $X_{n,t}$ is switched to a value of 0. Furthermore, the following sets of variables need to be defined:

- $T_n = \{t \in T: ear_n \leq t \leq lat_n - dur_n + 1\}$ for each unit d_n, which is the set of periods when maintenance of unit d_n may start.
- $S_{n,t} = \{k \in T: t - dur_n + 1 \leq k \leq t\}$ is the set of start time periods k, such that if the maintenance of unit d_n starts at period k, that unit will be in maintenance during period t.
- $D_t = \{n: t \in T_n\}$ is the set of units which is considered for maintenance in period t.

where t is the index of periods; T is the set of indices of periods in the planning horizon; d_n is the index of generating units; ear_n is the earliest period for maintenance of unit d_n to begin; lat_n is the latest period for maintenance of unit d_n to end; dur_n is the duration of maintenance for unit d_n.

In the case study considered, the number of units to be maintained, N is 21. Consequently, the set of decision points is given by $\mathbf{D} = \{d_1, d_2, \ldots, d_{21}\}$. In addition, set $\mathbf{F}$ can be defined such that $\mathbf{F} = \{d_n \in \mathbf{D}, j \in T_n: l_{n,j}\}$. For example, unit 8 is allowed to undergo maintenance within the second half of the year, which must be completed by Week 52. Since a maintenance job for this unit takes 6 days, the earliest and latest date for Unit 8 to start its maintenance are Weeks 26 and 47, respectively. Hence, the decision paths associated with decision point d_8 are $\{l_{8,1}=26, l_{8,2}=27, \ldots, l_{8,22}=47\}$. Mathematically, this optimization problem can be defined as the determination of maintenance schedule(s) such that SSR, which is defined as the sum of square of reserve generation capacity within the planning horizon, is minimized (Eq. 2.1) without violating the personpower and load constraints (Eqs. 2.2 & 2.3).

$$\text{Min}\left\{ SSR = \sum_{t \in T}\left(\sum_{n=1}^{N} P_n - \sum_{n \in D_t}\sum_{k \in S_{n,t}} X_{n,k}P_n - L_t\right)^2 \right\} \quad \text{(Eq. 2.1)}$$

$$\sum_{n \in D_t}\sum_{k \in S_{n,t}} X_{n,k}M_{n,k} \leq 20 \quad \text{(Eq. 2.2)}$$

$$\sum_{n \in D_t}\sum_{k \in S_{n,t}} X_{n,k}P_n \leq 4739 \quad \text{(Eq. 2.3)}$$

where L_t is the anticipated load demand for period t; P_n is the generating capacity of unit d_n.; $M_{n,k}$ is the personpower needed by unit d_n at period k.

Upon completion of an ant-cycle, the maintenance schedule generated is assessed by a simulation model (Figure 1.1) that returns an overall quality of the schedule. The quality of a maintenance schedule in this problem is given by an objective function value (OFV), which is a function of the value of SSR and the total violation of both constraints (Eq. 2.4). The calculations of constraint violations are given in Eq. 2.5 to 2.8.

$$OFV = c_R \,.\, SSR + c_M \,.\, ManVio_{tot} + c_L \,.\, LoadVio_{tot} \quad \text{(Eq. 2.4)}$$

where SSR is the sum of squares of reserve generation capacity; c_R is the relative weight of SSR; $ManVio_{tot}$ is the total personpower violation; c_M is the relative weight of personpower violation; $LoadVio_{tot}$ is the total load violation; $c_L$is the relative weight of the load violation.

For a proposed maintenance schedule, the total personpower violation, $ManVio_{tot}$, is given by summation of the personpower shortage in all periods within the planning horizon, such that

$$ManVio_{tot} = \sum_{t \in T_{MV}}\left(\sum_{n \in D_t}\sum_{k \in S_{n,t}} X_{n,k}M_{n,k} - AM_t\right) \quad \text{(Eq. 2.5)}$$

where T_{MV} is the periods where personpower constraints are violated (Eq. 2.6).

$$T_{MV} = \left(t: \sum_{n \in D_t}\sum_{k \in S_{n,t}} X_{n,k}M_{n,k} > AM_t\right) \quad \text{(Eq. 2.6)}$$

where AM_t is the available personpower at period t.

The total load violation, $LoadVio_{tot}$ is the summation of load shortfall in all periods within the planning horizon. The calculation of this value may be represented by:

$$LoadVio_{tot} = \sum_{t \in T_{LV}}\left(\sum_{n} P_n - \sum_{n \in D_t}\sum_{k \in S_{n,t}} X_{n,k}P_n\right) \quad \text{(Eq. 2.7)}$$

where T_{LV} is the periods where load constraints are violated, and is given by:

$$T_{LV} = \left(t: \sum_{n} P_n - \sum_{n \in D_t}\sum_{k \in S_{n,t}} X_{n,k}P_n < L_t\right) \quad \text{(Eq. 2.8)}$$

2.2 Analysis Conducted

The ACO formulation introduced in Section 1 was used to solve the 21-unit case problem. For the heuristic information in Eq. 1.1, the heuristics given in Eq. 1.2 was used. Due to the probabilistic nature of ACO methods, 30 runs with different random starting conditions were conducted. A total of 150 iterations, which is equivalent to the construction of 30,000 trial solutions in each run, was chosen as the termination criterion of all runs to provide a basis for direct comparison between the performance of ACO and that of other metaheuristics used for the same case study. It should be noted that the values of the parameters controlling the behaviour of the ACO algorithms used (Table 2.1) were chosen based on preliminary sensitivity analysis.

Table 2.1 Chosen values of ACO parameters

r	ρ	α	β	c_R	w1
200	0.7	1	1	1	7
p_{best}	Q	τ_0	c_L	c_M	w2
0.7	$5x10^5$	1,000	200	$1 x10^5$	1

2.3 Results & Discussion

The results obtained are presented in Table 2.2 in terms of best, average and worst objective function values (referred to as OFVs hereafter) as well as the standard deviation of the OFVs. It should be noted that the various statistics were calculated for results with the same ('standard') ACO parameters, but with 30 different random starting positions in objective function space, as described previously. It can be seen that the optimization outcome has been improved greatly by the inclusion of the heuristic formulation introduced in this paper, and the improvement is highly significant when tested with a two-tailed, unmatched t-test. It can also be seen from Figure 2.1 that the results obtained by MMAS are better than those obtained using the algorithms that have been applied to this case study previously. However, the information provided about these studies in the literature is insufficient for statistical analysis.

Table 2.2: Results given by Max-Min Ant System (MMAS)
[% deviation from best-found OFV]

	Best OFV ($x10^5$)	**Average OFV ($x10^5$)**	**Worst OFV ($x10^5$)**	**Std dev. ($x10^5$)**
No heuristics	138.81 [1.58]	145.79 [6.69]	154.44 [13.01]	3.76
With heuristics	136.65 [0]	136.88 [0.17]	137.26 [0.45]	0.14

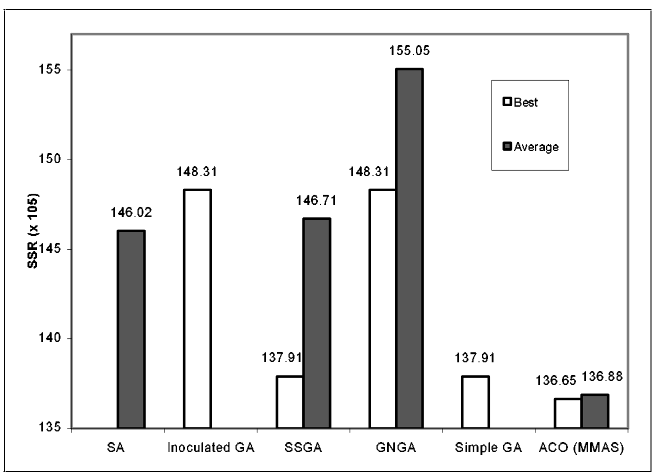

Figure 2.1 Comparison between the best result given by other optimization methods and MMAS

3. SUMMARY & CONCLUSION

In this paper, a formulation for applying Ant Colony Optimization (ACO) to power plant maintenance scheduling optimization (PPMSO) has been developed and successfully tested on a 21-unit power plant case study to which other metaheuristics had been applied previously. The results obtained indicate that ACO can be applied successfully to the PPMSO problem, as it performed better than any of the other optimization algorithms that had been applied to the case study considered previously.

4. FUTURE WORKS

Encouraged by the results, we are currently working on a similar ACO formulation for solving multi-objective power plant maintenance optimization problems. The 21-unit case problem is slightly modified by converting the manpower constraint into an objective. The relative importance of total manpower violation in the objective function, as well as the relative importance of the two terms in heuristic formulation are varied throughout an optimization run. The outcome of the multi-objective optimization run is a best-TMV SSR curve, which consists of the best sum of square reserve (SSR)-values obtained for different levels of total manpower violation (TMV). In addition, the option of coupling local search with the current ACO formulation will be investigated.

The proposed formulation is also currently being applied to a cut-down hydropower system, which is a part of the Hydro Tasmania hydropower system. Options of shortening outage duration and deferring maintenance tasks are added into the formulation. Ultimately, all proposed formulations would be applied to the optimization of maintenance scheduling of the real Hydro Tasmania system, which consists of 68 generating units.

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