Power Plant Maintenance Scheduling Using Ant Colony Optimization – An Improved Formulation

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ABSTRACT
It is common practice in the hydropower industry to either shorten the maintenance duration or to postpone maintenance tasks in a hydropower system when there is expected unserved energy based on current water storage levels and forecast storage inflows. Therefore, it is essential that a maintenance scheduling optimizer can incorporate the options of shortening maintenance duration and/or deferring maintenance tasks in the search for practical maintenance schedules. In this paper, an improved Ant Colony Optimization - Power Plant Maintenance Scheduling Optimization (ACO-PPMSO) formulation that considers such options in the optimization process is introduced. As a result, not only the optimum commencement time, but also the optimum outage duration, is determined for each of the maintenance tasks that needs to be scheduled. In addition, a local search strategy is developed to boost the robustness of the algorithm. When tested on a 5-station hydropower system problem, the improved formulation is shown to be capable of allowing shortening of maintenance duration in the event of expected demand shortfalls. In addition, the new local search strategy is also shown to have significantly improved the optimization ability of the ACO-PPMSO algorithm.

1. INTRODUCTION

Maintenance of power plants is generally aimed at extending the life and reducing the risk of sudden breakdown of power generating units. Traditionally, power generating units have been scheduled for maintenance to ensure the demand of the system is fully met and the reliability of the system is maximized. However, in a deregulated power industry, the pressure of maintaining generating units is also driven by the potential revenue received by participating in the electricity market. Ideally, hydropower generating units are required to operate during periods when electricity prices are high and to be able to be taken offline for maintenance when the price is low. Therefore, determination of the optimum time periods for maintenance of generating units in a power system has become an important task from both system reliability and economic points of view.

The development of methods for optimizing the maintenance scheduling of power plants has been studied over the past two decades. Traditionally, mathematical programming approaches have been used, including dynamic programming [1], integer programming [2], mixed-integer programming [3] and the implicit enumeration algorithm [4]. Metaheuristics have been applied, including genetic algorithms (GAs) [5], simulated annealing (SA) [6] and tabu search (TS) [7]. These methods have generally been shown to outperform mathematical programming methods and other conventional approaches in terms of the quality of the solutions found, as well as computational efficiency [5, 6].

Inspired by the foraging behavior of ant colonies, Ant Colony Optimization is a relatively new metaheuristic for combinatorial optimization [8]. Compared to other optimization methods, such as

GAs, ACO has been found to produce better solutions in terms of computational efficiency and quality when applied to a number of combinatorial optimization problems, such as the Traveling Salesman Problem (TSP) [9] and De Jong's test functions [10]. In addition, the application of ACO has provided encouraging results when applied to scheduling, including the job-shop, flow-shop, machine tardiness and resource-constrained project scheduling problems [11-14].

Recently, a formulation has been developed by [15] to enable the application of ACO to power plant maintenance scheduling optimization (PPMSO). The ACO-PPMSO formulation was tested on a problem instance and found to outperform various metaheuristics adopted for the same problem instance in other studies [15]. The formulation was later used to solve a 5-station hydropower maintenance scheduling optimization problem [16], which demonstrated the capabilities of the ACO-PPMSO formulation when compared with traditional methods based on engineering judgement.

Despite the encouraging performance found for the original ACO-PPMSO formulation, it has shortcomings when applied to realistic maintenance scheduling problems. In real power systems, in particular those relying on the availability of renewable resources for power generation, there are times when the capacity of generating units is limited by the availability of the associated natural resources (e.g. water stored in dams in the case of hydropower). Under such circumstances, speeding up maintenance and postponing certain maintenance tasks is inevitable if demand shortfalls are expected due to the maintenance of certain generating units. The objective of this paper is to introduce an improved ACO-PPMSO formulation, which takes into account options for reducing the duration of maintenance periods (duration shortening) and postponing maintenance tasks (deferral). In addition, a new local search strategy that is capable of improving the solutions obtained by the ACO metaheuristic is introduced. In order to examine the utility of the improved ACO-PPMSO formulation and the usefulness of the new local search strategy, the 5-station hydropower case study investigated by [16] is adopted.

In section 2, the general PPMSO problem is defined in mathematical terms, while the improved ACO-PPMSO formulation is introduced in section 3. Details of the 5-station case system investigated, along with a description of the analyses conducted as part of this research, are described in section 4. In section 5, the results obtained are discussed. A summary and recommendations are given in section 6.

2. POWER PLANT MAINTENANCE SCHEDULING OPTIMIZATION (PPMSO)

The power plant maintenance scheduling optimization (PPMSO) problem has been defined previously as an optimization problem that involves the determination of the optimum timing of the maintenance periods of each of the generating machines (units) used for power generation, assuming maintenance durations are fixed [15]. In this paper, the PPMSO problem definition is refined to include the options of 'maintenance duration shortening' and 'deferral of maintenance tasks'. As a result, not only the optimum commencement time, but also the optimum duration is sought for each maintenance tasks to be scheduled within a planning horizon. The aim of the optimization procedure is to obtain maintenance schedules that minimize/maximize the objective function, subject to a number of constraints. In this section, the mathematical definition of the PPMSO problem, as well as the objectives and constraints generally encountered, are discussed.

PPMSO is generally considered as a minimization problem (S, f, Ω), where S is the set of all maintenance schedules, f is the objective function which assigns an objective function value $f(s)$ to each trial maintenance schedule $s \in S$, and Ω is a set of constraints. Mathematically, PPMSO can be defined as the determination of a set of globally optimal maintenance schedules $S^* \subset S$, such that the objective function is minimized $f(s^* \in S^*) \le f(s \in S)$ (for a minimization problem) subject to a set of constraints Ω. Specifically, PPMSO has the following characteristics:

- It consists of a finite set of decision points $D = \{d_1, d_{2,\ldots,} d_N\}$ comprised of N maintenance tasks to be scheduled;
- Each maintenance task $d_n \in D$ has a normal (default) duration $NormDur_n$ and is carried out during a planning horizon T_{plan}.
- Two decision variables v_1 and v_2 need to be defined for each task $d_n \in D$, including:
  - Start time for the maintenance task, $start_n$, with the associated set of options: $T_{n,chdur_n} = \{d_n \in D,\ i_{n,chdur_n} \in T_{plan};\ chdur_n \in K_n\text{: } ear_n \le i_{n,chdur_n} \le lat_n - chdur_n + 1\}$ where the terms in brackets denote the set of time periods when maintenance of unit d_n may start; ear_n is the earliest period for maintenance task d_n to begin; lat_n is the latest period for maintenance task d_n to end and $chdur_n$ is the chosen maintenance duration (to be defined) for task d_n.
  - Duration of the maintenance task, $chdur_n$, with the associated finite set of decision paths: $K_n = \{d_n \in D\text{: } 0, s_n, 2s_n, \ldots, NormDur_n\text{-}s_n, NormDur_n\}$, where the terms in brackets denote the set of optional maintenance durations for task d_n, and s_n is the timestep considered for maintenance duration shortening.
- A trial maintenance schedule, $s \in S = \langle d_n \in D,\ start_n \in T_n,\ chdur_n \in K_n\text{: } (start_1, chdur_1), (start_2, chdur_2), \ldots, (start_N, chdur_N)\rangle$ is comprised of maintenance commencement times, $start_n$, and durations, $chdur_n$, for all N maintenance tasks that are required to be scheduled.

Binary variables, which can take on values 0 or 1, are used to represent the state of a task in a given time period in the mathematical equations of the PPMSO problem formulation. $X_{n,t}$ is set to 1 to indicate that task $d_n \in D$ is scheduled to be carried out during period $t \in T_{plan}$. Otherwise, $X_{n,t}$ is set to a value of 0, as given by:

$$X_{n,t} = \begin{cases} 1 & \text{if task } d_n \text{ is being maintained in period } t \\ 0 & otherwise \end{cases} \tag{1}$$

In addition, the following sets of variables are defined:

- $S_{n,t} = \{d_n \in D,\ k \in T_{n,chdur_n},\ chdur_n \in K_n\text{: } t - chdur_n + 1 \le k \le t\}$ is the set of start time periods k, such that if maintenance task d_n starts at period k for a duration of $chdur_n$, that task will be in progress during period t;
- $D_t = \{d_n\text{: } t \in T_n\}$ is the set of maintenance tasks which is considered for period t.

Objectives and constraints

Traditionally, cost minimization and maximization of reliability have been the two objectives commonly used when optimizing power plant maintenance schedules. These objectives can take on many different forms, and are usually case study specific. Two examples of reliability objectives are evening out the system reserve capacity throughout the planning horizon, and maximizing the total storage volumes at the end of the planning horizon, in the case of a hydropower system. An additional objective associated with the refined definition of PPMSO presented in this paper is the minimization of the total maintenance duration shortened/deferred. The rationale behind this objective is that shortening of maintenance duration (i.e. speeding up the completion of maintenance tasks) requires additional personnel and equipment, whereas deferral of maintenance tasks might result in unexpected breakdown of generating units, and in both events, additional costs are incurred by the power utility operator.

Constraints specified in PPMSO problems are generally power plant specific. The formulation of some common constraints, including the allowable maintenance window, availability of resources, load, continuity, completion, precedence and reliability are presented in [16], and repeated in this paper (Equations (2) to (6)) for the sake of completeness. In addition, a minimum maintenance duration constraint (Equation (7)) is specified as a result of the incorporation of the 'maintenance duration shortening' and 'deferral of tasks' options in the refined definition of the PPMSO problem presented here.

The timeframes within which individual tasks in the system are required to start and finish maintenance form maintenance window constraints, which can be formulated as:

$$T_{n,chdur_n} = \{t \in T_{plan},\ chdur_n \in K_n\text{: } ear_n \le t \le lat_n - chdur_n + 1\},\ \text{for all } d_n \in D. \tag{2}$$

Load constraints (Equation (3)) are usually rigid / hard constraints in PPMSO, which ensure feasible maintenance schedules that do not cause demand shortfalls throughout the whole planning horizon are obtained:

$$\sum_{d_n \in D} P_{n,t} - \sum_{d_n \in D_t} \sum_{k \in S_{n,t}} X_{n,k} P_n \ge L_t \ \text{for all } t \in T_{plan}. \tag{3}$$

where L_t is the anticipated load for period t and P_n is the loss of generating capacity associated with maintenance task d_n.

Resource constraints are specified in the case where the availability of certain resources, such as highly-skilled technicians, are limited. In general, resources of all types assigned to maintenance tasks should not exceed the associated resource capacity at any time period, as given by:

$$\sum_{d_n \in D_t} \sum_{k \in S_{n,t}} X_{n,k} Res^r_{n,k} \le ResAvai^r_t\ ,\ \text{for all } t \in T_{plan} \text{ and } r \in R. \tag{4}$$

where $Res^r_{n,k}$ is the amount of resource of type r available that is required by task d_n at period k; $ResAvai^r_t$ is the associated capacity of resource of type r available at period k and R is the set of all resource types.

Precedence constraints that reflect the relationships between generating units in a power system are usually specified in PPMSO problems. An example of such constraints is a case where task 2 should not commence before task 1 is completed, as given by:

$$T_{2,chdur_2} = \{t \in T_{plan}, chdur_2 \in K_2\colon\ lat_2 - chdur_2 + 1 > t > start_1 + chdur_1 - 1\}. \tag{5}$$

where $start_n$ is the start time chosen for task d_n.

Depending on particular system characteristics and requirements, reliability constraints can be formulated in various ways, including provision of reserve generation capacity of a portion of demand throughout the planning horizon. This is given by:

$$\sum_{d_n \in D} P_{n,t} - \sum_{d_n \in D_t} \sum_{k \in S_{n,t}} X_{n,k} P_n \geq L_t + f \cdot L_t \text{ for all } t \in T_{plan}. \tag{6}$$

where L_t is the anticipated load for period t; P_n is the loss of generating capacity associated with maintenance task d_n and f is the factor of load demand for reserve.

In the case of maintenance duration shortening, there is a limit to how much the duration can be shortened by. Due to the different characteristics of maintenance tasks, minimum maintenance durations may vary with individual tasks:

$$NormDur_n \geq chdur_n \geq MinDur_n, \text{ for all } d_n \in D. \tag{7}$$

where $chdur_n$ is the maintenance duration of task d_n; $MinDur_n$ is the minimum shortened outage duration for task d_n; $NormDur_n$ is the normal duration of maintenance task d_n.

3. IMPROVED ACO FORMULATION FOR POWER PLANT MAINTENANCE SCHEDULING OPTIMIZATION

Inspired by the foraging behavior of ant colonies [8], Ant Colony Optimization (ACO) is a metaheuristic that has recently gained popularity as a result of encouraging findings obtained for benchmark combinatorial optimization problems, such as the traveling salesman problem [9] and resource-constrained project scheduling problems [14]. By marking the paths they have followed with pheromone trails, ants are able to communicate indirectly and find the shortest distance between their nest and a food source when foraging for food. When adapting this search metaphor of ants to solve discrete combinatorial optimization problems, artificial ants are considered to explore the search space of all possible solutions. The ACO search begins with a random solution (possibly biased by a heuristic) within the decision space of the problem. As the search progresses over discrete time intervals, ants deposit pheromone on the components of promising solutions. In this way, the environment of a decision space is iteratively modified and the ACO search is gradually biased towards more desirable regions of the search space, where optimal or near-optimal solutions can be found. Interested readers are referred to [8] for a detailed discussion of ACO metaheuristics and the benchmark combinatorial optimization problems to which ACO has been applied.

Recently, a formulation has been developed by [15] to apply the ACO metaheuristic to power plant maintenance scheduling optimization (PPMSO) problems. When the ACO-PPMSO formulation was tested on two benchmark case studies, new best-known solutions were found for both [15]. The same formulation was also successfully applied to a 5-station subset of the Hydro Tasmania hydropower system in Australia. However, this formulation is unable to cater for some of the decisions that are commonly made with regard to maintenance scheduling, including: shortening of maintenance duration and deferral of maintenance tasks. In this paper, an improved ACO-PPMSO formulation is presented, which is capable of taking into account these two options effectively.

3.1 ACO-PPMSO graph

In order to cater for the options of duration shortening and deferral of maintenance tasks, the following ACO-PPMSO graph (Figure 1) is proposed, which is expressed in terms of a set of decision points consisting of the N maintenance tasks that need to be scheduled $D = \{d_1, d_2, d_3, \ldots, d_N\}$. For each maintenance task, there are three variables that need to be defined $V = \{v_1, v_2, v_3\}$:

Variable 1, v_1: the overall state of the maintenance task under consideration (i.e. if maintenance currently being carried out or not),

Variable 2, v_2: a duration of the maintenance task, and

Variable 3, v_3: a commencement time for the maintenance task.

For maintenance task d_n, a set of decision paths $DP_{c,n}$ is associated with decision variable $v_{c,n}$ (where subscript c = 1, 2 or 3) (shown as dashed lines in Figure 1). For decision variable $v_{1,n}$, these correspond to the options of carrying out the maintenance tasks d_n at normal duration, shortening the maintenance duration and the deferring maintenance tasks . For decision variable $v_{2,n}$, these correspond to the optional shortened durations available for the maintenance tasks. For decision variable $v_{3,n}$, these correspond to the optional start times for maintenance tasks d_n. It should be noted that, as the latest finishing time of maintenance tasks is usually fixed, there are different sets of start time decision paths, each corresponding to a maintenance duration decision path (Figure 1).

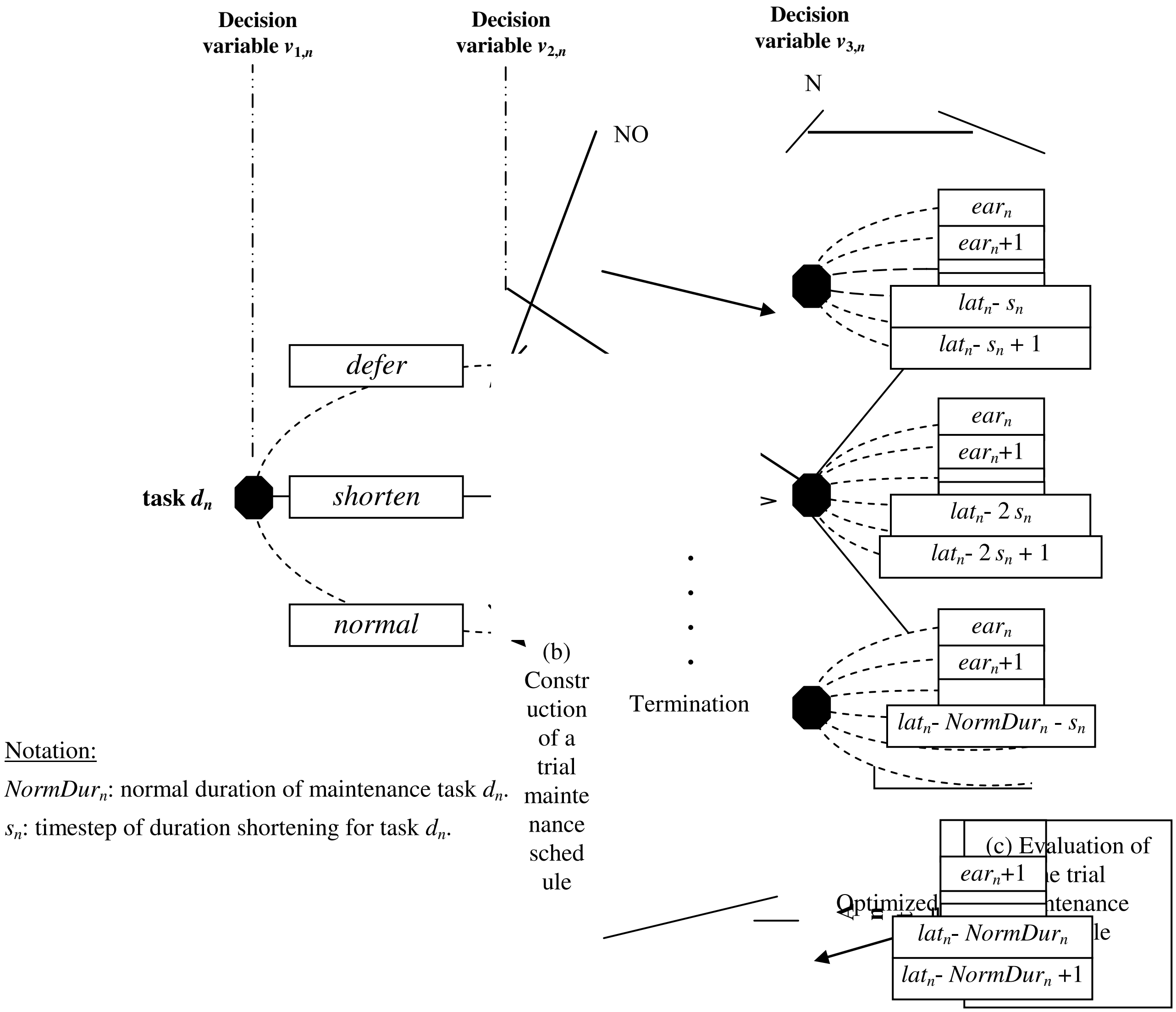

Figure 1: Proposed ACO-PPMSO graph

3.2 ACO-PPMSO algorithm

The ACO-PPMSO algorithm [15] can be represented by the flowchart given in Figure 2. Details of each procedure in the optimization process (a) – (e) are explained below.

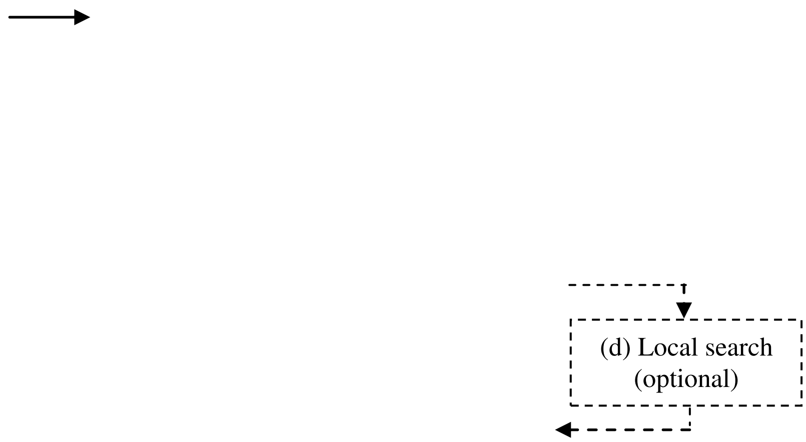

Figure 2. ACO-PPMSO algorithm

(a) **Initialization**: The optimization process starts by reading details of the power system under consideration (eg. generating capacity of each unit, daily system demands, time step for duration shortening etc.). In addition, various ACO parameters (eg. initial pheromone trails, number of ants used, pheromone evaporation rate etc.) need to be defined.

(b) **Construction of a trial maintenance schedule**: A trial maintenance schedule is constructed using the ACO-PPMSO graph shown in Figure 1. In order to generate one trial maintenance schedule, an ant travels to one of the decision points (maintenance tasks) at a time. At each decision point, d_n, a 3-stage selection process that corresponds to the 3 decision variables, $v_{1,n}$, $v_{2,n}$ and $v_{3,n}$, is performed.

At each stage, the probability that decision path *opt* is chosen for maintenance of task d_n in iteration t is given by:

$$p_{n,opt}(t) = \frac{[\tau_{n,opt}(t)]^{\alpha} \cdot [\eta_{n,opt}]^{\beta}}{\sum_{y \in DP_{c,n}} [\tau_{n,y}(t)]^{\alpha} \cdot [\eta_{n,y}]^{\beta}}. \tag{8}$$

subscript c = 1, 2 and 3 refers to the three decision variables, $v_{1,n}$, $v_{2,n}$ and $v_{3,n}$; $\tau_{n,opt}(t)$ is the pheromone intensity deposited on the decision path opt for task d_n in iteration t; $\eta_{n,opt}$ is the heuristic value of decision path opt for task d_n; α and β are the relative importance of pheromone intensity and the heuristic, respectively.

It should be noted that the term opt in Equation (8) represents the decision path under consideration, of all decision paths contained in set $DP_{c,n}$. When used for stages 1, 2 and 3, respectively, the terms opt and $DP_{c,n}$ are substituted by those associated with the decision variable considered at the corresponding stage (Table 1). The pheromone level associated with a particular decision path (e.g. deferral of a particular maintenance task) is a reflection of the quality of the maintenance schedules that have been generated previously that contain this particular option. The heuristic associated with a particular decision path is related to the likely quality of a solution that contains this option, based on user-defined heuristic information. The following paragraphs detail the 3-stage selection process for decision point (maintenance task) d_n, including the adaptations required when using Equation (8) for each stage.

Table 1: Adaptations for Equation (8) in stages 1, 2 and 3 of selection process

	Stage 1	Stage 2	Stage 3
c	1	2	3
opt	$stat \in DP_{1,n}$	$dur \in DP_{2,n}$	$day \in DP_{3,n,chdur_n}$
$DP_{c,n}$	$DP_{1,n}$={$normal, shorten, defer$}	$DP_{2,n} = \{d_n \in \mathrm{D}: 0, s_n, 2s_n, \ldots, NormDur_n\}$	$DP_{3,n,chdur_n} = \{d_n \in D, chdur_n \in DP_{2,n}: ear_n, ear_n+1, \ldots, lat_n - chdur_n + 1\}$
$\tau_{n,opt}$	$\tau_{n,stat}$	$\tau_{n,dur}$	$\tau_{n,chdur_n,day}$
$\eta_{n,opt}$	$\eta_{n,defer} < \eta_{n,shorten} < \eta_{n,normal}$	$\eta_{n,dur_n} \propto dur$	$\eta_{n,chdur_n,day} = \left(\eta^{Res}_{n,chdur_n,day}\right)^w \cdot \eta^{Load}_{n,chdur_n,day}$

In stage 1, a decision needs to be made whether to perform the maintenance task under consideration at normal or shortened duration, or to defer it (decision variable $v_{1,n}$ in Figure 1). In this case, c = 1 and $opt = stat \in DP_{1,n}$={$normal, shorten, defer$} is the set of decision paths associated with decision variable $v_{1,n}$ for task d_n. The probability of each of these options being chosen is a function of the strength of the pheromone trails and heuristic value associated with the option (Equation (8)). For the PPMSO problem, the heuristic formulation should generally be defined such that normal maintenance durations are preferred over duration shortening, and deferral is the least favored option (Equation (9)).

However, real costs associated with duration shortening and deferral options can be used if the extra costs incurred associated with these options are quantifiable and available. The adaptations required for Equation (8) to be used in the stage 1 selection process are summarized in Table 1.

$$\eta_{n,defer} < \eta_{n,shorten} < \eta_{n,normal} \tag{9}$$

Once a decision has been made at stage 1, the selection process proceeds to stage 2 (decision variable $v_{2,n}$ in Figure 1), where the duration of the maintenance task under consideration, d_n, is required to be selected from a set of available decision paths $DP_{2,n} = \{d_n \in \mathrm{D}: 0, s_n, 2s_n, \ldots, NormDur_n\}$. The symbols s_n and $NormDur_n$ denote the time step for maintenance duration shortening, and the normal maintenance duration, respectively. For Equation (8) to be used at stage 2, the terms c and opt in the equation are substituted by the value of 2 and $dur \in DP_{2,n}$, respectively. It should be noted that if the 'normal' or 'defer' options were chosen at stage 1, the normal duration of the maintenance task, or a duration of 0, respectively, are automatically chosen for the task. In the case of duration shortening, a constraint is normally specified where each maintenance task has a minimum duration at which the completion of the task cannot be further accelerated due to limitations such as the availability of highly specialized technicians. This constraint can be addressed at this stage such that only feasible trial maintenance schedules (with regard to this constraint) are constructed (see section 4.3 for details). The pheromone trails and heuristic values associated with optional durations are used to determine the probability that these durations are chosen. In order to favor longer maintenance durations (i.e. the smallest amount of shortening compared with the normal maintenance duration), the heuristic value associated with a decision path should be directly proportional to the maintenance duration (Equation (10)).

$$\eta_{n,dur_n} \propto dur \tag{10}$$

The substitutions for the various terms in Equation (8) when used in stage 2 are summarized in Table 1.

Once a maintenance duration has been selected, the solution construction process enters stage 3 (decision variable $v_{3,n}$ in Figure 1), where a start time for the maintenance task is selected from the set of optional start times available $DP_{3,n,chdur_n} = \{d_n \in D,\ chdur_n \in DP_{2,n}\text{: } ear_n, ear_n+1, \ldots, lat_n - chdur_n + 1\}$, given a chosen duration of $chdur_n$. In order to utilize Equation (8) at stage 3, adjustments are made such that $c = 3$ and $opt = day \in DP_{3,n,chdur_n}$. It should be noted that this stage is skipped if the 'defer' option is chosen at stage 1. The probability that a particular start day is chosen is a function of the associated pheromone trail and heuristic value. The heuristic formulation for selection of the maintenance start day is given by Equations (11) to (16).

$$\eta_{n,chdur_n,day} = \left(\eta^{Res}_{n,chdur_n,day}\right)^{w} \cdot \eta^{Load}_{n,chdur_n,day} \tag{11}$$

$$\eta^{Res}_{n,chdur_n,day} = \frac{\sum\limits_{k \in J_{n,chdur_n,day}} Y_{Res\,V(k)=0} \cdot R_{n,chdur_n,day}(k)}{\sum\limits_{k \in J_{n,chdur_n,day}} (Y_{Res\,V(k)=0} - 1) \cdot R_{n,chdur_n,day}(k)} \tag{12}$$

$$\eta^{Load}_{n,chdur_n,day} = \frac{\sum\limits_{k \in J_{n,chdur_n,day}} Y_{Load\,V(k)=0} \cdot C_{n,chdur_n,day}(k)}{\sum\limits_{k \in J_{n,chdur_n,day}} (Y_{Load\,V(k)=0} - 1) \cdot C_{n,chdur_n,day}(k)} \tag{13}$$

$$Y_{Res\,V(k)=0} = \begin{cases} 1 & \text{if no violation of resource constraints in time period } k \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

$$Y_{Load\,V(k)=0} = \begin{cases} 1 & \text{if no violation of load constraints in time period } k \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

$$w = \begin{cases} 1 \text{ if resource constraints are considered} \\ 0 \quad\quad\quad\quad\quad \text{otherwise} \end{cases} \tag{16}$$

where $\eta_{n,chdur_n,day}(t)$ is the heuristic for start time $day \in DP_{3,n,chdur_n}$ for task d_n, given a chosen duration $chdur_n$,; $R_{n,chdur_n,day}(k)$ represents the prospective resources available in reserve in time period k if task d_n is to commence at start time day and takes $chdur_n$ to complete (less than 0 in the case of resource deficits); $C_{n,chdur_n,day}(k)$ is the prospective power generation capacity available in reserve in time period k if task d_n is to commence at start time day and takes $chdur_n$ to complete (less than 0 in the case of power generation reserve deficits); $J_{n,chdur_n,day}$=$\{d_n \in D,\ day \in DP_{3,n,chdur_n}: day \le k \le day + chdur_n - 1\}$ is the set of time periods k such that if task d_n starts at start time day, that task will be in maintenance during period k.

As mentioned above, the heuristic formulation in Equation (11) includes a resource-related term, $\eta^{Res}_{n,chdur_n,day}$, and a load-related term, $\eta^{Load}_{n,chdur_n day}$. These two terms are expected to evenly distribute maintenance tasks over the entire planning horizon, which potentially maximizes the overall reliability of a power system. For PPMSO problem instances that do not consider resource constraints, the value of w in Equation (11) can be set to 0 (Equation (16)). In order to implement the heuristic, each ant is provided with a memory matrix on resource reserves and another matrix on generation capacity reserves prior to construction of a trial solution. This is updated every time a unit maintenance commencement time is added to the partially completed schedule. Foong et al. [15] found that inclusion of the heuristic resulted in significant improvements in algorithm performance for the 21-unit case study investigated.

The 3-stage selection process is then repeated for another maintenance task (decision point). A complete maintenance schedule is obtained once all maintenance tasks have been considered.

(c) **Evaluation of trial maintenance schedule**: Once a complete trial maintenance schedule, $s \in S$, has been constructed by choosing a maintenance commencement time and duration at each decision point (i.e. for each maintenance task to be scheduled), an ant-cycle has been completed. The trial schedule's objective function cost (*OFC*) can then be determined by an evaluation function, which is the weighted sum of the values of objectives and penalty costs associated with constraint violations:

$$OFC(s) = \sum_{z=1}^{Z_T} \left[w_z \cdot obj_z(s) \right] + \sum_{c=1}^{C_T} \left[w_c . vio_c(s) \right] \tag{17}$$

where $OFC(s)$ is the objective function cost associated with a trial maintenance schedule, s; $obj_z(s)$ is the value of the z^{th} objective; $vio_c(s)$ is the degree of violation of the c^{th} constraint; Z_T and C_T are the total number of objectives and constraints, respectively; w_z and w_c are the relative weights of the z^{th} objective and the c^{th} constraint violations in the objective function, respectively. In general, the trial schedule has to be run through a simulation model in order to calculate some elements of the objective function and whether certain constraints have been violated. This is the reason why only some constraints can be satisfied during the construction of trial maintenance schedules, while others have to be incorporated via penalty functions.

After m ants have performed procedures (b) and (c), where m is predefined in procedure (a), an iteration cycle has been completed. At this stage, a total of m maintenance schedules have been generated for this iteration. It should be noted that all ants in an iteration can generate their trial solutions concurrently, as they are working on the same set of pheromone trail distributions in decision space.

(d) **Local search**: Recently, local search has been utilized to improve the optimization ability of ACO. While it has been found to result in significant improvements in some applications [17, 18], little success has been obtained in others [14]. Local search has also been found useful for some problems where the formulation of heuristics is difficult [8]. Traditionally, the application of local search to ACO requires the choice of a number of user-defined parameters, such as the size and location of the local neighborhood and the number of ants to perform local search. In this research, a new local search strategy is developed to overcome these problems and to increase the robustness of the ACO metaheuristic by dealing directly with the optimization objectives. In particular, the proposed local search looks for a reduced number of solutions that have shortened durations or have been deferred, which in turn, results in better *OFC*s. The details of the new local search algorithm are presented as a flowchart in Figure 3.

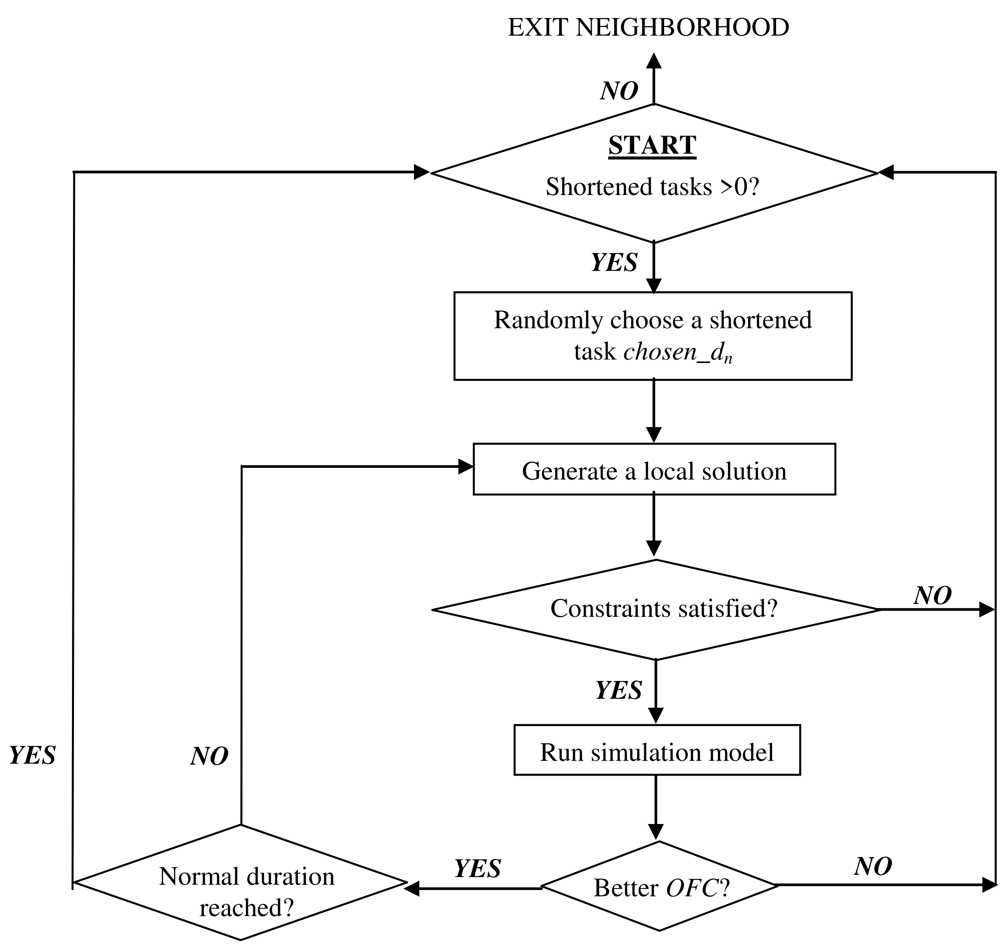

Figure 3: Proposed local search algorithm

The local search algorithm is called upon after all m ants in an iteration have finished constructing trial maintenance schedules. If the least-OFC schedule found in the iteration, $Sol_{iter\text{-}best}(t)$, does not include any shortening or deferral decisions, the local search is not required. However, if this is not the case, local search is applied, as part of which a shortened/deferred task is randomly selected. For the selected shortened/deferred task, $chosen\_d_n$, local search will be performed in the following two neighborhoods: **(i)** The maintenance duration of the chosen task, $chosen\_d_n$, is extended by s_n time periods, where s_n is the maintenance duration time step of task d_n. As a result, a local solution $Sol_{local}(t)$ is obtained. Satisfaction of constraints, such as the allowable maintenance window and precedence constraints, are checked and the simulation model is used to assess the quality of the local solution. If the local solution, $Sol_{local}(t)$, results in a better objective function cost (OFC), the original iteration-best solution $Sol_{iter\text{-}best}(t)$ is replaced. As part of the local search process, the maintenance duration of $chosen\_d_n$ will be extended by s_n until either no better local solution is returned or the normal duration of that task is reached. The search in this neighborhood is terminated when all shortened/deferred task(s) in $Sol_{iter\text{-}best}(t)$ is/are considered. **(ii)** The maintenance duration of the chosen shortened/deferred task, $chosen\_d_n$, is rescheduled by s_n periods earlier and s_n time periods are added to its maintenance duration. The procedures carried out for (i) are repeated for the second neighborhood. By the end of the local search, the best-found local solution, or the original iteration-best solution in the case where no better local solution can be found, is adopted to proceed to the next step of the ACO-PPMSO algorithm.

(e) **Pheromone updating**: Two mechanisms, namely pheromone evaporation and pheromone rewarding, are involved in the pheromone updating process. Pheromone evaporation reduces all pheromone trails by a factor. In this way, exploration of the search space is encouraged by preventing a rapid increase in pheromone on frequently-chosen paths. Pheromone rewarding is performed in a way that reinforces good solutions. In the formulation presented in this paper, the best trial solution found in every iteration, $Sol_{best\text{-}iter}(t)$, is rewarded (Equation (18)) by an amount of pheromone that is a function of the solution's OFC (Equation (19)). It should be noted that the decision paths being rewarded include those associated with decisions made with regard to decision variables $v_{1,n}$, $v_{2,n}$ and $v_{3,n}$.

$$\tau_{n,opt}(t+1) = \begin{cases} \rho \cdot \tau_{n,opt}(t) + \Delta\tau(t), \mathit{if}\ \ n,opt \in Sol_{best-iter}(t) \\ \rho \cdot \tau_{n,opt}(t) \quad otherwise \end{cases}; \quad opt \in DP_{c,n} \quad for \quad c = 1, 2, 3 \tag{18}$$

where the amount of pheromone rewarded is given by:

$$\Delta\tau(t) = \frac{Q}{OFC_{best-iter}(t)} \tag{19}$$

where reward factor Q is user-defined arbitrary number.

In the formulation presented here, Max-Min Ant System (MMAS) [19], which only rewards the iteration-best solutions, is adopted. As part of this algorithm, additional upper and lower bounds (τ_{max} and $\tau_{c,min}$) are imposed on the pheromone trails in order to prevent premature convergence and greater exploration of the solution surface. These bounds are given by:

$$\tau_{\max}(t+1) = \frac{1}{1-\rho} \cdot \frac{Q}{OFC_{best-ant}(t)}. \tag{20}$$

$$\tau_{c,\min}(t+1) = \frac{\tau_{\max}(t+1)(1-\sqrt[n_c]{p_{best}})}{(avg_c - 1)\sqrt[n_c]{p_{best}}} \tag{21}$$

where n_c is the number of decision points for decision variable $v_{c,n}$; avg_c is the average number of decision paths available at each decision point for decision variable v_c; p_{best} is the probability that the paths of the current iteration-best-solution, $Sol_{best\text{-}iter}(t)$, will be selected, given that non-iteration best-options have a pheromone level of $\tau_{c,min}(t)$ and all iteration-best options have a pheromone level of $\tau_{max}(t)$.

The lower and upper bound of pheromone are applied to the pheromone sets in Equation (8) such that:

$$\tau_{c,\min}(t) \le \tau_{n,opt}(t) \le \tau_{\max}(t) \quad \text{for all } t, n, opt \in DP_{c,n}. \tag{22}$$

Procedures (b) to (e) are repeated until the termination criterion of an ACO run is met, e.g. either the maximum number of evaluations allowed has been reached or stagnation of the objective function cost has occurred. A set of maintenance schedules resulting in the minimum *OFC* is the final outcome of the optimization run.

4. Case Study: A 5-Station Hydropower System

4.1 Background

Located to the south of the south-east corner of the Australian mainland (Figure 4), Tasmania is the smallest and the only island state of Australia. It has a total area of 68,331 km^2 and a total population of 485,000. Tasmania has abundant water resources for renewable energy production, attributed to its high rainfall and mountainous terrain. Having harnessed Tasmania's water for energy production for over 80 years, Hydro Tasmania is Australia's largest renewable energy generator with 28 small- to medium-sized hydroelectric power stations. With an installed generating capacity of 2,260 MW, the Hydro Tasmania system produces over 10,000 GWh of renewable energy on an annual basis, which is approximately 60% of Australia's total renewable energy production.

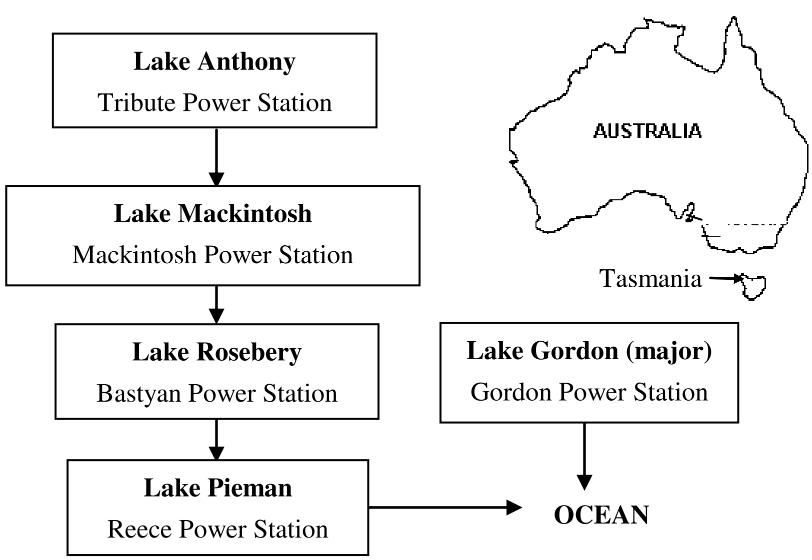

Figure 4. Schematic diagram of the 5-station hydropower case study system

A subset of the Hydro Tasmania power system is investigated in this study, which includes two catchment areas (Pieman-Anthony and Gordon-Pedder) and five power stations.

4.2 System specification

A total of eight generating units with a total generating capacity of 893 MW (Figure 4) are installed at the five power stations considered in this study. Of the five storages where water is drawn for power generation, three are run-of-the-river (Lakes Anthony, Rosebery and Pieman), while the other two are major storages (Lakes Mackintosh and Gordon). Given their limited storage capacity, run-of-river storages are usually given priority to operate, especially during high-inflow periods. On the other hand, major storages can store large volumes of water, and are normally relied upon for power generation during low inflow periods. Details of the five storages and the associated power stations are given in Table 2.

Table 2. Power station and headwater data

Power station	Tribute	Mackintosh	Bastyan	Reece	Gordon
Number of generators	1	1	1	2	3
Generating capacity of each generator (MW)	83	80	80	115	140
Maximum discharge (cumec)	34	145	145	144	86
Average efficiency factor (MW/cumec)	2.42	0.55	0.55	0.8	1.62
Headwater storage	Lake Anthony	Lake Mackintosh	Lake Rosebery	Lake Pieman	Lake Gordon
Storage capacity (10^6 m^3)	22	336	51	100	10,990

4.3 Formulation of the maintenance scheduling optimization problem

This case study system requires a total of 14 maintenance tasks to be scheduled once over a planning horizon of 365 days from Jan 1, 2006 (Table 3). The task IDs denoted by "Inv" are investigative tasks, during which the condition of generators is examined prior to the actual maintenance (task IDs denoted by "Act"). Among all maintenance tasks, the biggest loss of generation capacity occurs during the upgrade of the Gordon power station, when all three generating units of the station are inoperable.

Table 3. Details of maintenance tasks

Power Station	**Machine number**	**Maintenance type**	**Task ID**	**Normal maintenance duration (days)**	**Loss of generating capacity (MW)**
Tribute	1	Investigative	Tri_Inv	5	83
	1	Actual	Tri_Act	12	83
Mackintosh	1	Investigative	Mac_Inv	5	80
	1	Actual	Mac_Act	19	80
Bastyan	1	Investigative	Bst_Inv	5	80
	1	Actual	Bst_Act	12	80

Reece	1	Investigative	Rce#1_Inv	5	115
	1	Actual	Rce#1_Act	19	115
	2	Investigative	Rce#2_Inv	5	115
	2	Actual	Rce#2_Act	19	115
Gordon	1	Actual	Gor#1_Act	19	140
	2	Actual	Gor#2_Act	19	140
	3	Actual	Gor#3_Act	19	140
	Station upgrade	Actual	Gor_stn	42	420

The aim of this optimization problem is to determine a commencement time and duration for each maintenance task in the case study system, such that the system reliability is maximized (Equation (23)) and the total duration shortened/deferred is minimized (Equation (24)), subject to a number of constraints. It should be noted that, the maximization of system reliability is achieved by maximizing the total expected energy in storage of the two major storages at the end of the planning horizon:

$$\textbf{Objective 1}: Max\ \{ETFEIS = EFEIS_{Mackintosh} + EFEIS_{Gordon}\} \tag{23}$$

where *ETFEIS* is the expected total energy in storage of Lakes Mackintosh and Gordon, at the end of the planning horizon; $EFEIS_{Mackintosh}$ and $EFEIS_{Gordon}$ are the expected energy in storage of Lakes Mackintosh and Gordon, respectively, at the end of the planning horizon (GWh).

$$\textbf{Objective 2}: Min\{totalcutdur\} \tag{24}$$

where

$$totalcutdur = \sum_{n=1}^{14}(NormDur_n - chdur_n) \tag{25}$$

where *totalcutdur* is the total maintenance period duration reduction associated with a maintenance schedule due to shortening and deferral; n is the index of maintenance task d_n, n = 1, 2, 3, . . ., 14 in this case system; $NormDur_n$ is the normal maintenance duration of task d_n; $chdur_n$ is the chosen outage duration for maintenance task d_n.

The constraints to be satisfied are:

1. The earliest time a maintenance task can start is January 1 and all tasks should finish by December 31.
2. An investigative task has to finish between 4 to 6 weeks prior to the commencement of the actual maintenance task.
3. There is no maintenance during the Easter, Christmas and New Year public holidays.
4. The maintenance duration of all tasks can be shortened by a time step of 2 days, up to a maximum of 50% of individual normal durations. (i.e. the minimum duration of a maintenance task is 50% of its normal duration).

5. The total expected unserved energy (*EUE*) over the planning horizon should not be greater than 0.002% of total annual energy demand. The system power demands over the planning horizon are shown in Figure 5.

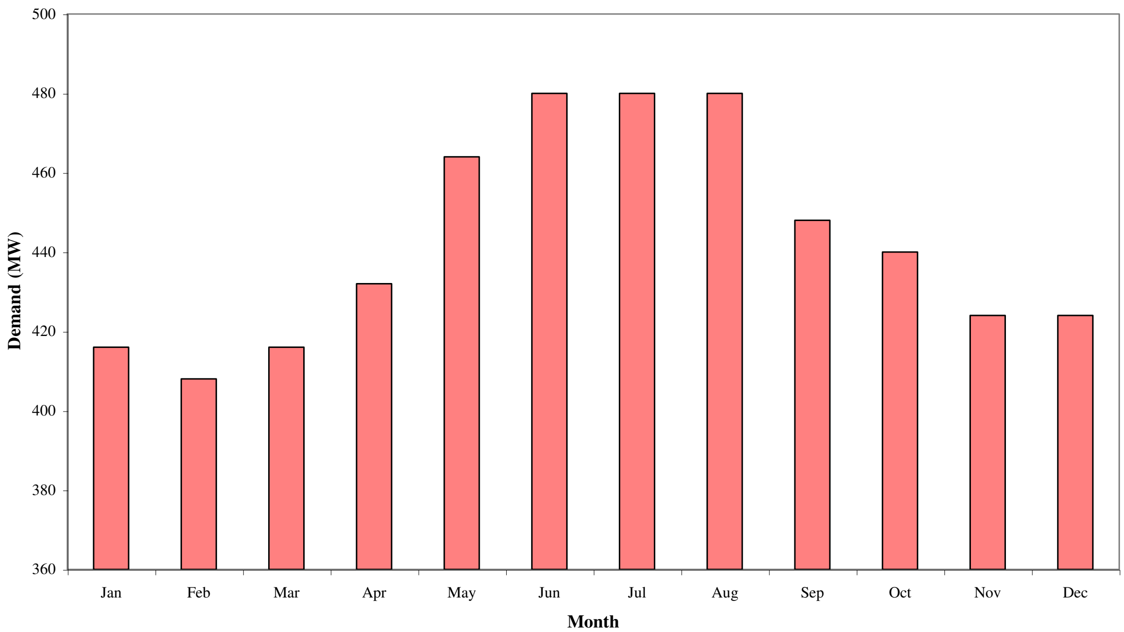

Figure 5: 5-station hydropower system demand

In the ACO-PPMSO formulation, constraints are incorporated at the earliest possible stage during the optimization process. In the 5-station case study system, constraints 1, 2 and 3 are related to the timeframe during which maintenance tasks are allowed to commence. Therefore, it is more computationally effective to take these constraints into account during the construction of trial solutions, so that the trial solutions generated are feasible with regard to these constraints. When handling such constraints during the construction of maintenance schedules, each decision point (maintenance task) is only assigned decision paths that would result in a feasible maintenance schedule with regard to the constraints. For example, in order to incorporate constraint 2, the decision paths associated with investigative and actual tasks are dynamically updated during construction of each trial maintenance schedule. In the construction of a trial maintenance schedule, if May 18 was chosen as the commencement date for the actual maintenance task of the unit at Tribute power station, the corresponding investigative task would be dynamically assigned optional start days from April 1 to April 15 (Figure 6). It should be noted that if the investigative task was assigned a start time first, the optional start days for the corresponding actual task would be updated dynamically in the same way [16].

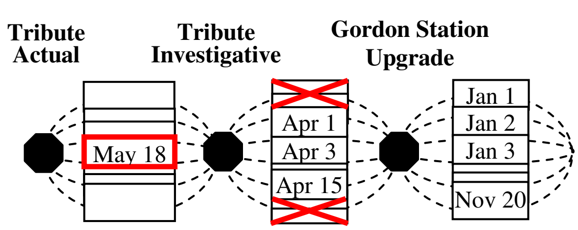

Figure 6: Handling of constraint 2

Similarly, constraint 4 is handled by allowing only durations that are greater than the minimum maintenance durations during the construction of trial maintenance schedules (Figure 7).

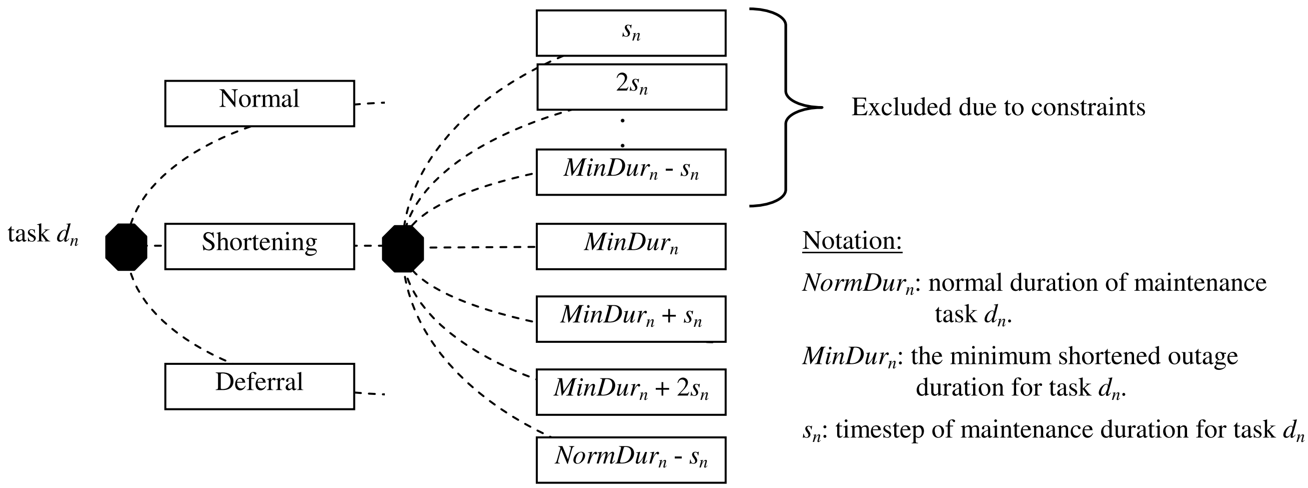

Figure 7: Handling of minimum maintenance duration constraints

Unlike constraints 1 to 4, whether or not constraint 5 (load) is satisfied by a trial maintenance schedule is not known until the complete schedule has been constructed and a simulation model has been run, necessitating the use of a penalty function in order to meet this constraint. A penalty function is used to transform a constrained optimization problem into an unconstrained problem by adding or subtracting a value to/from the objective function cost based on the degree of constraint violation [20]. Adapting Equation (26), the objective function used for this problem is comprised of the actual objective terms i.e. the expected total energy in storage (*ETFEIS*) and the total duration cut down (*totalcutdur*), as well as an additional term to address the violation of load constraints (*EUE*), and is given by:

$$OFC(s) = (c_{EUE} \cdot EUE(s) + \frac{c_{ETFEIS}}{ETFEIS(s)}) \cdot totalcutdur(s)^2 \tag{26}$$

where *OFC(s)* is the objective function cost ($) associated with a trial maintenance schedule, *s*; *EUE*(*s*) is the total annual expected unserved energy (GWh) associated with a trial maintenance schedule, *s*; *ETFEIS*(*s*) is the expected total energy in storage (GWh) associated with a trial maintenance schedule, *s*; c_{EUE} is the penalty cost per unit *EUE* ($/GWh); c_{ETFEIS} is the cost per unit of the inverse of *ETFEIS* ($GWh); *totalcutdur*(*s*) is the total reduction in maintenance duration due to shortening and deferral (day) associated with a trial maintenance schedule, *s*.

The *OFC* can be viewed as the virtual cost associated with a trial maintenance schedule. It should be noted that the values of c_{EUE} and c_{ETFEIS} in the objective function (Equation (26)) can be varied to reflect the relative importance of the objectives and constraints, as perceived by the decision maker. Hard constraints (load constraints in this case) are usually assigned relatively higher costs, such that trial solutions that violate these constraints are more heavily penalized. It can be also be seen that the greater the reduction in maintenance duration in a trial maintenance schedule, the higher the associated *OFC*.

The values of c_{EUE} and c_{ETFEIS} used in the optimization runs for this problem are arbitrarily chosen as 1000 and 10000, respectively.

The value of *totalcutdur* (Equation (26)) associated with a trial schedule can be calculated once the complete schedule has been obtained, or even during the construction of the schedule. However, the values of expected unserved energy (*EUE*) and expected total energy in storage (*ETFEIS*) associated with a trial maintenance schedule are calculated using a simplified version of the SYSOP (SYStems-OPeration) simulation model currently used by Hydro Tasmania for the assessment of proposed maintenance schedules for its full system. In SYSOP, dispatching rules that specify the order in which storages are used for power generation when meeting demands are employed. For example, run-of-river storages that have exceeded certain storage levels are given higher priority during dispatch to avoid spilling. During the ACO-PPMSO optimization process, the trial maintenance schedule generated by individual ants, along with the system load, storage inflows, and the initial level of storages at the start of the planning horizon are input into the simplified SYSOP model. The starting levels of Lake Gordon and other storages are assumed to be 60% and 75% full, respectively, in this problem. The outputs of the simplified SYSOP model, including the expected total final energy in storage of the major storages and the expected unserved energy over the planning horizon, are used to calculate the objective function cost (*OFC*) associated with a trial maintenance schedule using Equation (26).

4.4 Analyses conducted

The impact of including duration shortening and deferral options in the improved ACO-PPMSO formulation and the usefulness of the local search strategy proposed in this study are investigated in this paper. The experimental setup for this case problem was identical to that detailed in [16]. Firstly, the optimum maintenance schedules obtained as a result of different storage inflows were examined. The three storage inflow conditions tested were extracted from 80 years of historical inflow data at the 92nd percentile (wet year), 64th percentile (intermediate year) and 13th percentile (dry year). The monthly total system inflows for dry, intermediate and wet years are shown in Figure 8 (however, monthly average inflows of individual storages are used in the optimization process).

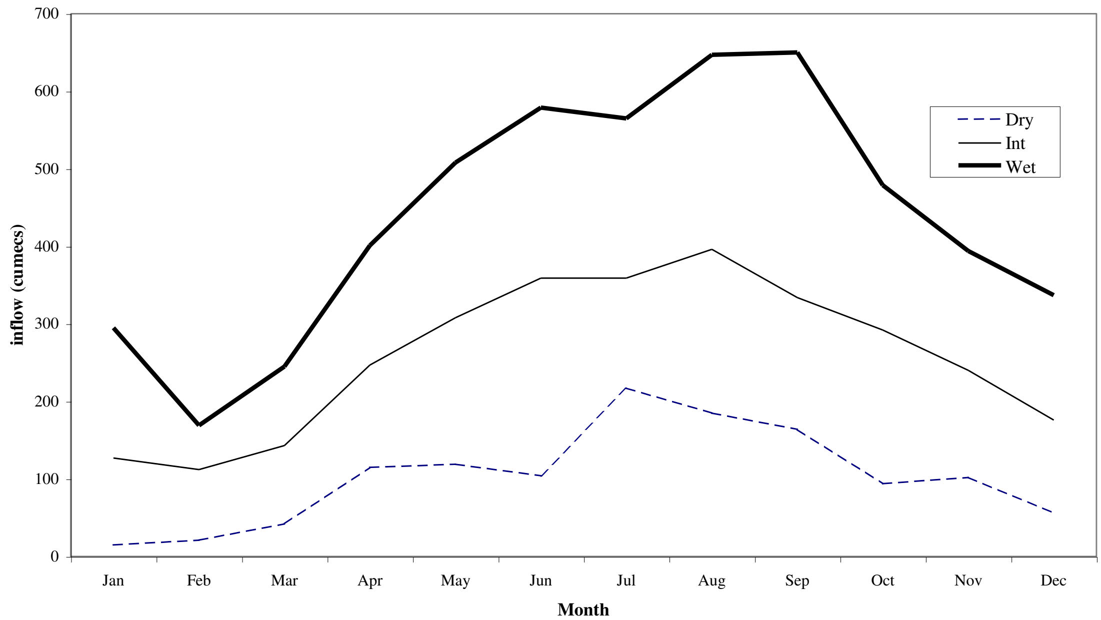

Figure 8: 5-station hydropower system storage inflows

As part of the sensitivity analysis, a wide range of values (Table 4) was tested for a number of ACO parameters, including the number of ants m, pheromone evaporation rate (1-ρ) and p_{best}. It should be noted that investigations into the effect of the reward factor Q (Equation (19)) and initial pheromone τ_0 (section 3.2 (a)) are not considered in this study, as they were found to have no impact on algorithm performance by [15]. The values of α and β are both set to 1.0.

Table 4. ACO algorithm parameters investigated

Parameter	**Reference in paper**	**Values investigated**
Number of ants, m	Figure 2	25, 50, 100, 250, 500, 800, 1000
Pheromone evaporation rate, (1-ρ)	Equations (18) and (20)	0.1, 0.3, 0.5, 0.7, 0.9, 0.95, 0.99
p_{best}	Equation (21)	0.01, 0.05, 0.1, 0.3, 0.5, 0.7, 0.9

In each ACO run, a maximum of 100,000 trial solutions were generated. In this paper, 'an ACO run' is defined as the use of a particular set of parameters (for example, m = 800; ρ = 0.9; p_{best} = 0.01) to solve the hydropower case study system maintenance scheduling problem, given a storage inflow condition (for example, wet year inflow), using a specified random number seed (for example, 8998). For each set of parameters and storage inflow conditions tested, 30 ACO runs were performed with different random number seeds in order to minimize the influence of random starting positions in solution space on the results obtained. The performance of a parameter setting is then gauged by the best OFC obtained in each run, averaged over 30 ACO runs with different random number seeds.

5. RESULTS AND DISCUSSION

The performance of the improved ACO-PPMSO algorithm for the three different inflow conditions investigated is shown in Table 5. The ACO parameter combinations that resulted in the best performance, as well as the impact of including the proposed local search algorithm on algorithm performance, are also shown. For dry and intermediate inflow conditions, it can be seen that all maintenance schedules obtained are feasible (Average *EUE* = 0) when the durations of some maintenance tasks are shortened (Average *totalcutdur* > 0) (first two rows of each inflow results in Table 5). In addition, the usefulness of the new local search strategy developed (section 3.2(d)) is shown to be statistically significant (p-value < 0.01) for both dry and intermediate inflow conditions when checked with an unpaired, 2-sided student's t-test. The improvement in Average *OFC* when local search is used is mainly attributed to the reduction of total duration shortened and deferred (second row of each inflow results in Table 5). However, it should be noted that, the local search strategy is only performed for iteration-best trial schedules that include duration shortening and deferral (section 3.2(d)). Therefore, the local search was of little use, if any, during the optimization for wet inflow conditions, as load constraints are well satisfied in that scenario without the need for duration shortening and deferral.

On the other hand, when shortening and deferral options were not allowed, as per of the original ACO-PPMSO formulation, no feasible solutions could be obtained for dry and intermediate inflows conditions (Average *EUE* > 0, third row for each inflow results in Table 5). In other words, the 5-station system seemed to be over-constrained in both dry and intermediate inflow conditions if all maintenance tasks were to be scheduled at normal durations. By allowing maintenance duration shortening and deferral of maintenance tasks, the improved ACO-PPMSO formulation was able to provide the decision makers with practical and feasible maintenance schedules.

Table 5. Results given by the improved ACO-PPMSO for different inflow conditions investigated

Inflow	Local search	Avg. *EUE* (GWh)	Avg. *ETFEIS* (GWh)	Avg. *totalcutdur* (day)	Avg. *OFC* ($)	Avg. evalua-tion	Std dev. of *OFC*	Best parameter setting $\{m; \rho; p_{best}\}$*
Dry	✗	0	542.35	34.1	22,679	84,987	546	{1000; 0.7; 0.01}
	✓	0	543.50	33.7	22,204	77,918	843	{50; 0.99; 0.3}
	✗	131.06^{+}	631.80	0	131,078	76,700	2,270	{800; 0.7; 0.3}
Int	✗	0	2527.77	29.9	3,525	83,614	336	{1000; 0.9; 0.05}
	✓	0	2531.65	27.1	3,115	51,784	213	{50; 0.7; 0.05}
	✗	32.45^{+}	2523.76	0	32,455	90,241	785	{500; 0.95; 0.3}
Wet	✗	0	4699.33	0	2.12	51,223	0.003	{100; 0.3; 0.5}
	✓	0	4713.45	0	2.12	65,935	0.001	{100; 0.3; 0.5}
	✗	0.00	4710.11	0	2.12	68,731	0.00	{500; 0.3; 0.3}

+ Expected unserved energy (*EUE*) > 0 i.e. load constraints violated

Notation: *EUE*: Expected unserved energy, *ETFEIS*: Expected total energy in storage at the end of planning horizon, *totalcutdur*: Total duration cut down due to duration shortening and deferral of maintenance tasks; *OFC*: Objective function cost.

* m: number of ants; (1-ρ): pheromone evaporation rate; p_{best}: see Equation (21).

The best-*OFC* schedules for wet, intermediate and dry inflow conditions are presented in Figures 9 to 11. The rationale behind these schedules was analysed, by taking into account storage inflows, system demand, as well as the rules implemented in the simulation model (SYSOP) with regard to the priorities of power stations being called for generation.

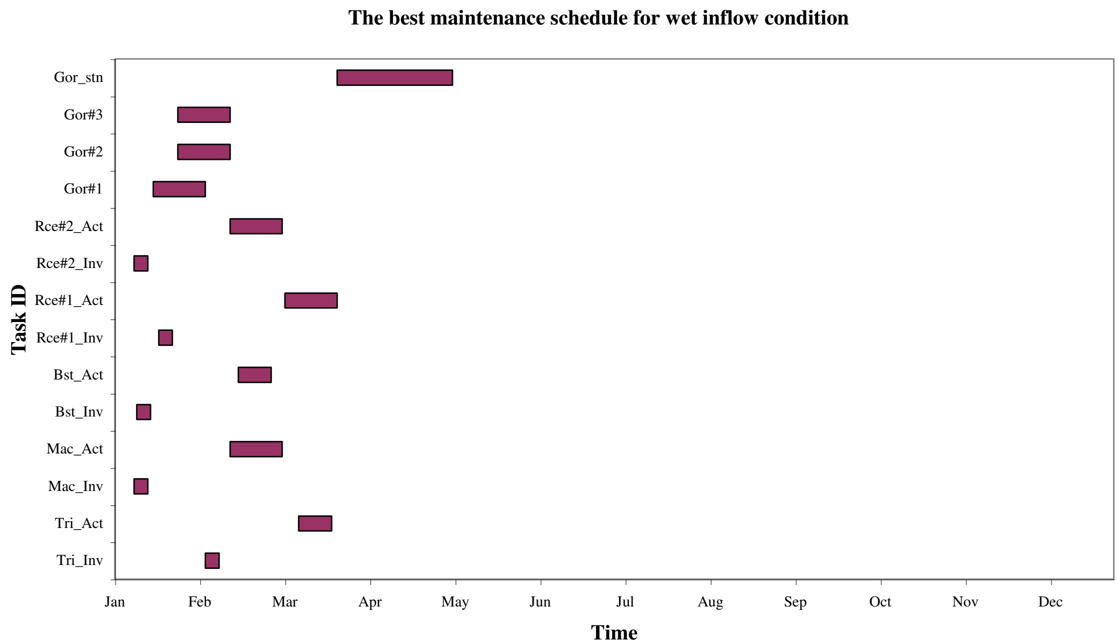

Figure 9: One of the best-*OFC* schedules for wet year
(*EUE* = 0 GWh; *ETFEIS* = 4718 GWh)

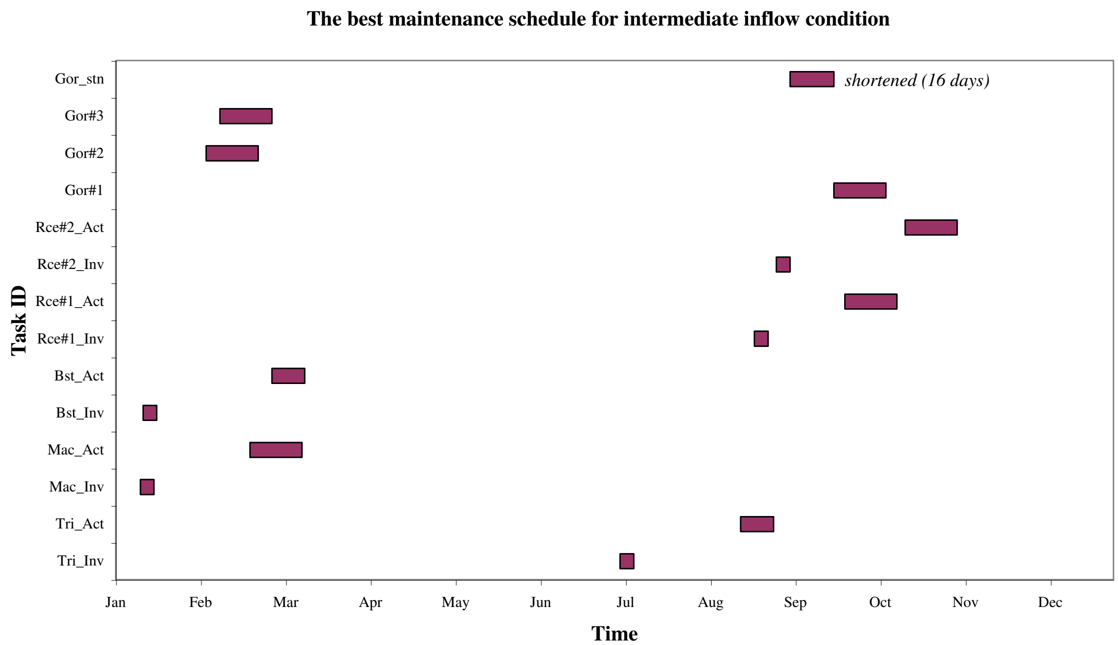

Figure 10: One of the best-*OFC* schedules for intermediate year (*EUE* = 0 GWh; *ETFEIS* = 2539 GWh)

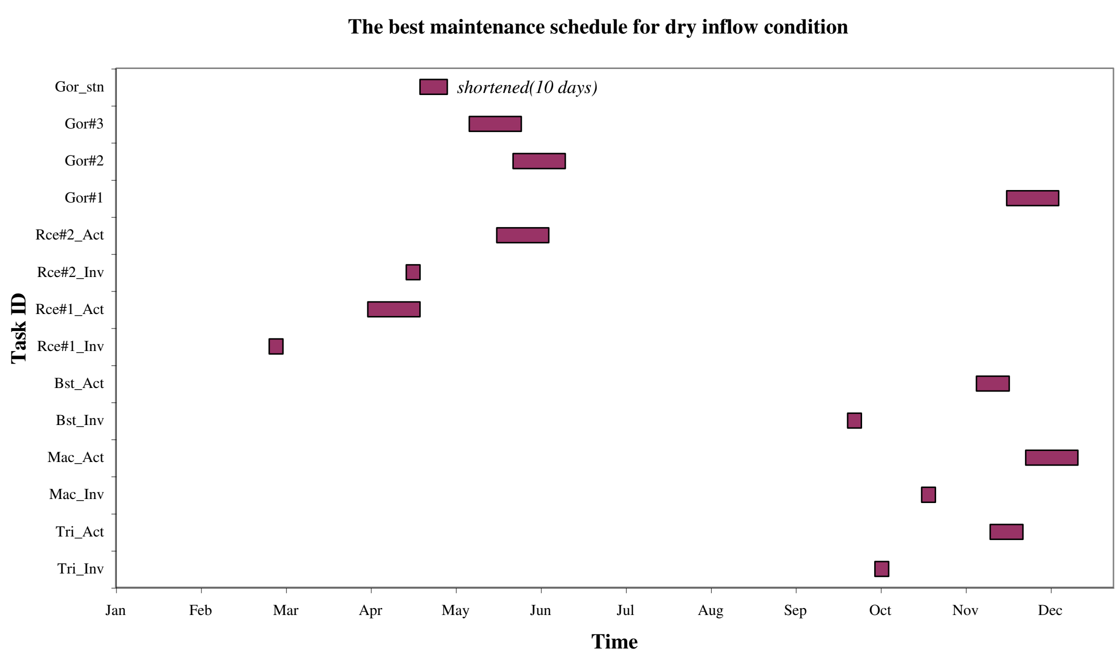

Figure 11: One of the best-OFC schedules for dry year (*EUE* = 0 GWh; *ETFEIS* = 544 GWh)

For the wet inflow condition (Figure 9), neither duration shortening nor deferral of maintenance tasks is required, as load constraints are easily satisfied. In addition, it can be seen that all maintenance tasks are scheduled in the first quarter of the planning horizon. All storages are about 75% full at the start of the planning horizon, and are still able to accommodate inflows during maintenance. By winter, when storage inflows are even higher, run-of-river storages are almost full, if not spilling, and are able to provide the relatively high demand in this period without having to draw down major storages (Lakes Mackintosh & Gordon). In this way, generation from major storages is minimized and the expected total energy-in-storage is maximized.

For the intermediate inflow condition (Figure 10), the Gordon station upgrade task, which normally takes 42 days to complete, had to be shortened by 66.7% in order to satisfy load constraints. In addition, most of the maintenance tasks are not scheduled in the period from April to August. This is because although the highest storage inflows take place in August, run-of-river storages are still incapable of meeting winter demands (May to August, Figure 5), therefore requiring the major storages for generation. Only when the demand is relatively lower in September and the storage inflows are still quite high, Gordon station is taken offline for maintenance. However, as the run-of-river storage levels are decreasing rapidly during the time when Gordon station was off-line, Gordon station had to be brought back on-line to avoid demand shortfalls. The schedules obtained also indicated that the maintenance tasks for Mackintosh, Gordon#2 and Gordon#3 machines are scheduled in a way such that Lake Mackintosh is emptied before its maintenance to reduce spilling.

Compared to the intermediate inflow condition, the duration of the Gordon station upgrade task is shortened even more (by 76%) for the dry inflow condition (Figure 11). This is anticipated, as the expected unserved energy during dry conditions is worse than that during intermediate inflows. Similar to the intermediate inflow condition, all maintenance tasks are not scheduled in winter (May-September, Figure 5) when demand is the highest in a low-inflow year. Specifically, as inflows are exceptionally low in the Jan-Mar period (Figure 8), all storages are used to meet demand. Only in April, when storage inflows start to increase, are run-of-river storages fully relied on for meeting demand while the shortened upgrade task of Gordon station is carried out. In addition, the last quarter of the planning horizon is deemed to be the best period for maintaining the run-of-river stations as these storages are already running quite low at that time.

6. SUMMARY AND CONCLUSIONS

The ultimate goal of any optimization tool is that it can be used to solve real-world problems. As part of this research, an improved ACO-PPMSO formulation has been developed to cater for the complications associated with real-world power plant maintenance scheduling optimization problems. In the new formulation, the options of shortening maintenance duration and deferring maintenance tasks are included. These options are essential when demand shortfalls are expected as a result of maintenance activities. A new local search strategy has also been proposed to further improve the proposed algorithm’s performance. The improved ACO-PPMSO formulation has been tested on a 5-station hydropower case study system and the results obtained indicate that shortening of maintenance periods, which is related to the anticipated expected unserved energy in this case study system, can be accommodated successfully. In addition, the new local search strategy has been shown to be useful in improving the performance of the proposed approach. In conclusion, the improved ACO-PPMSO formulation appears promising in offering a practical optimization tool for real-world power plant maintenance scheduling, but needs to be subjected to further testing. As part of the future work in this research, the formulation will be applied to a larger real hydropower maintenance scheduling problem.

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