Optimal Pump Scheduling: Representation and Multiple Objectives

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Abstract

This paper considers the pump scheduling problem using a multi-objective approach and several alternative representations to a candidate solution. Despite the practical importance of the optimisation of pump scheduling for water distribution networks (WDN), most of the published algorithms restrict themselves to a single objective, i.e., minimise the cost of pumping. Multiple objectives and alternative representations will be the key factors when deciding to apply optimisation algorithms for the real-world operation of WDN. The present work considers a bi-objective problem, where the objectives are: minimise the cost of pumping and maximise the minimum stop time. Solutions to pump scheduling problem are, usually, encoded using a binary string showing the state (on/off) of each pump during each time interval. In this paper a new representation to pump scheduling, based on time controlled triggers, is presented. This representation is capable of restricting the number of pump switches to a specified maximum. Different representations are compared by examining advantages and disadvantages of these methods through empirical experimentation.

Keywords
Pump Scheduling, multi-objective optimisation, water distribution networks.

1. INTRODUCTION

In Water Distribution Networks (WDNs), the main savings are obtained by carefully scheduling the operation of pumps to reduce electrical and maintenance costs. Contrary to the estimation of electrical cost, where the computation is straightforward, maintenance costs are assumed to increase with the number of *pump switches*, i.e., turning on a pump that was previously off. Therefore, minimisation of the total number of pump switches is a natural surrogate objective for pump maintenance cost.

Many techniques have been applied to optimise the scheduling of pumps in terms of a single objective. Among them is linear, non-linear, integer, dynamic and mixed programming formulations [4]. Inherent limitations of these techniques restrict their usefulness when applied to complex WDN. This fact has generated an important interest on techniques without such limitations. In particular, Evolutionary Algorithms have been widely used, [8] to minimise the electricity cost, while other objectives such as maintenance costs were incorporated as penalties. In contrast, very few works have considered a multi-objective approach [6], [7]. Since these works were published, advances in the field have led to better Multi-Objective Evolutionary Algorithms (MOEAs).

An important issue with the evolutionary algorithms is representation of candidate solutions. Operational schedules of pumps in a network can be defined in terms of properties of other elements in that network, called *implicit pump scheduling*. For example, water levels in tanks are often used to trigger the operation of the pumps [8]. On the other hand, pumps may also be controlled directly by specifying the time during which a pump is on/off, called herein *explicit pump scheduling*. Most of the works on explicit pump scheduling [6] have encoded pump schedules using a binary string. In this study, we propose a new representation, which was not investigated by earlier researchers, based on explicit pump scheduling and using time controlled triggers. These different approaches are tested on a network instance already considered in the literature, so we compare their performance with a state-of-the-art single objective hybrid genetic algorithm [8]. The second version of Strength Pareto Evolutionary Algorithm (SPEA2) [9] is used to optimise pump schedules with respect to both electrical cost and a surrogate parameter to represent maintenance cost. Each schedule is evaluated by conducting an extended period hydraulic simulation using EPANET [5]. Furthermore, unlike earlier studies, performance assessment of Pareto-optimal solutions is carried out by means of the attainment function [3].

2. PUMP SCHEDULING PROBLEM

The main goal of the Pump Scheduling Problem is to schedule the operation of N pumps over a time period, typically 24 hours, in such a way that system constraints and boundary conditions are satisfied, while the operational cost is minimised. The most important costs associated with the operation of pumps are *electrical* and *maintenance* costs.
The electrical cost is composed of the *consumption charge* (£/kW·h), i.e., the cost of electrical energy consumed during a time period, and the *demand charge* (£/kW), i.e., the cost associated with the maximum amount of

power consumed (peak energy). The consumption charge usually varies depending on the time of the day, with peak and off-peak electricity tariffs. Maintenance costs cannot be easily estimated, however, the wear and tear of pumps is mainly caused by frequent switching them on and off. Formally, a *pump switch* is defined as turning on a pump which was previously off. Therefore, minimising the number of pump switches will result in minimisation of maintenance costs. Nevertheless, in order to minimise the wear and tear of pumps and protect the network from frequent pressure fluctuations, it may be desirable to increase the time elapsed between two operation intervals, that is, to maximise the minimum time interval that a pump is off (*minimum stop time*). Therefore, we study an alternative approach which replaces the minimisation of the total number of pump switches with the maximisation of average minimum stop time as an objective (in addition to the electrical cost).

System constraints define the hydraulic state of the system, e.g., conservation of mass at each junction node and conservation of energy around each loop in a network. These constraints are handled by the network simulator EPANET. Bound constraints represent system performance criteria, usually constraints on maximum and minimum tank water levels, and pressures at demand nodes. In addition, we must ensure that the volume of water in the tanks at the end of the simulation period is not lower than the volume at the start of the simulation period in order to achieve periodicity between supply and demand. We will refer this as *volume deficit* of a tank and it is the difference in percentage between the initial volume and the final volume of water in a tank. For all tanks if the volume deficit of the tank is positive, this value is added to the *total volume deficit* of the particular schedule. When the total volume deficit is not zero, the supply and demand are not balanced and the resulting deficit will have to be recovered in the next scheduling period, increasing operational costs. Therefore, our constraint handling procedure will give preference to solutions with zero total volume deficit. A rather different situation arises if for a given pump schedule, the system cannot supply required volume of water at specified minimum pressure at demand nodes. This schedule cannot be implemented. Therefore, we would consider such schedules as *infeasible* and EPANET will generate warnings during the simulation.

3. MULTI-OBJECTIVE PUMP SCHEDULING

Single objective approaches to pump scheduling usually restrict to the minimisation of *electrical cost,* while other desirable objectives, such as minimisation of *pump switches,* are incorporated as penalties to the objective function. However, this approach prevents system operators from trading-off maintenance costs for electrical costs using their expertise. A multi-objective approach in terms of Pareto optimality provides system operators with a Pareto set of solutions to choose a particular solution. As an alternative to the number of pump switches, we explore the average *minimum stop time* to be the second objective of the multi-objective approach to the Pump Scheduling problem. The maximisation of the average minimum stop time interval will prevent very short time intervals between operating periods, which are generally produced when considering implicit scheduling through tank level-based controllers [8]. Certainly, system operators may trade-off longer minimum stop time for small increments of electrical costs. In addition, the minimum stop time defines an upper bound to the number of pump switches, and therefore, the maximisation of the average minimum stop time interval per pump imposes an upper bound to the average number of pump switches, although it does not directly imply the minimisation of the number of switches. In our experiments we will test the minimisation of electrical cost and the maximisation of the average minimum stop time as the two objectives.

4. REPRESENTATION OF THE PUMP SCHEDULING PROBLEM

Most approaches to the Pump Scheduling problem using Evolutionary Algorithms considered only a binary representation [6], [7]. In this work we propose a new representation which restricts the maximum number of pump switches while allowing pumps to start and stop operating at any time.

4.1 Binary representation

An explicit schedule can be represented by a binary string: if the bit's value is one then the pump is operating during that time interval, otherwise the pump is off. Then, the number of pump switches is the number of 01 sequences, plus one if the scheduling starts with 1 and ends with 0. Also, the minimum stop time is the minimum number of consecutive of zeros. Given N pumps and T time intervals, the number of possible solutions is $2^{N\cdot T}$ and the maximum number of switches per pump is T/2. Typically, 24 time intervals of 1 hour are considered. The binary representation has some disadvantages. First, it allows schedules with 12 switches per pump, which are more than the desirable number of switches, and thus, the number of pump switches must be constrained by other means. Also, it requires pumps to start or stop at fixed times separated by one hour, what prevents the algorithms to obtain more fine-grained schedules where the pumps can start or stop at any time moment as occurs when using level-based controllers.

4.2 Time-controlled triggers

We propose a new representation using time-controlled triggers, as shown in Fig. 1, where the time at which each pump starts and stops are defined explicitly by a pair of integers $\{t^{start}, t^{stop}\}$. Each integer is a number of seconds since the beginning of the simulation and each pair of integers is actually a pump switch, and thus, the number of pairs establishes an upper bound in the number of switches per pump. All integers corresponding to the same pump are ordered in increasing order $t^{start}_i < t^{stop}_i < t^{start}_{i+1} < t^{stop}_{i+1}$. We define also a ``null pair'' {–, –} in order to allow less pump switches than the maximum allowable switches for a pump. An example of this representation for a maximum number of pump switches of 4 is shown in Fig. 2, where for the sake of clarity integers represent hours instead of seconds.

P_i	t_1^{start}	t_1^{stop}	t_2^{start}	t_2^{stop}	$\cdots$	$\cdots$	t_K^{start}	t_K^{stop}

Figure 1: Representation based on time controlled triggers with K pump switches for each pump i.

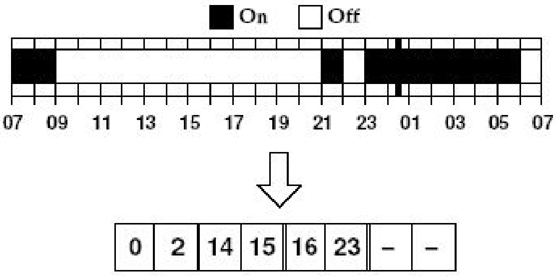

Figure 2: Binary representation and its equivalent time-controlled triggers.

5. APPLICATION OF MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM

The multi-objective evolutionary algorithm (MOEA) considered in this work is the second version of the Strength Pareto Evolutionary Algorithm (SPEA2) [9]. SPEA2 is a well-known and widely used MOEA which uses advanced techniques as elitism; fitness based on the number of solutions dominated; preservation of boundary solutions; nearest neighbour density estimation; and fixed size of the archive of non-dominated solutions (population size). More details on SPEA2 can be found in the original publication [9].

5.1 Feasibility and constraint handling

In the literature of the Pump Scheduling problem, constraints are usually handled by means of penalty functions. This approach requires the definition of appropriate penalty functions and, additionally, it requires fine-tuning of penalty costs since low penalty costs produces convergence to infeasible solutions, while high penalty costs prevents best solutions to be found. Instead of penalty functions, we use a methodology given by Deb et al., [2] where the usual dominance criterion is augmented with the following rules: (*i*) any infeasible solution is dominated by any feasible one; (*ii*) for two infeasible solutions, the one which produces lower number of pressure violations during the simulation dominates the other; (*iii*) for two feasible solutions, the one with the lower total volume deficit dominates the other (total volume deficit is zero if at the end of the simulation there is equal or more water in all tanks than at the start of the simulation); (*iv*) for two feasible solutions with equal volume deficit, the normal dominance criterion between their objective values is applied, i.e., one solution dominates the other if it is not worse in all objectives and better in at least one.

5.2 Genetic operators

For the binary representation, many operators can be found in the literature. In our experiments we used uniform crossover and flip mutation with a probability of $P_m/12$ for each pump. Custom recombination and mutation operators are required for time controlled triggers representation in order to maintain fixed number of pump switches. We adapt the uniform crossover for this representation in the following way. First, for each pump the integer values of both parents define a number of subintervals of the 24 hour simulation period. Then, each subinterval is assigned two values on/off corresponding to the state of that pump at that time in each parent. Next, for each subinterval one of the two values is randomly selected with probability 0.5. Finally, contiguous subintervals with the same on/off state are merged into larger time intervals and the boundaries of the intervals are used to construct the time-based triggers representation of the offspring solution. The resulting solution may contain more switches than its parents. To reduce the number of switches, the shortest ones are removed from the final offspring solution. The mutation operator used for this representation generates two random integers and inserts them in the proper order in the schedule, after excluding the repeated integers. Finally, if the number of pump switches is larger than the maximum allowed, the shortest switch is removed. This mutation operator is applied with a probability P_m to each pump of each solution generated after recombination.

6. EXPERIMENTAL SETUP

The network instance shown in Figure 3 is used for studying the various alternatives proposed here. In this instance the demand charge is taken to be zero and the water available at the reservoir is assumed to be infinite. The electricity cost is divided into two periods with a peak electricity tariff period from 7 am to 12 am and a off-peak tariff from 12 am to 7 am. The demand pattern contains two peaks at 7 am and 6 pm. More details about the test instance are provided by Van Zyl et al., [8].

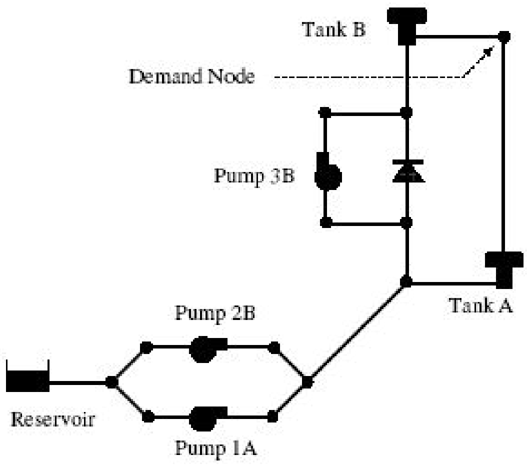

Figure 3: Network Test Instance

For SPEA2 the archive size and the number of initial solutions were 200; and the number of solutions selected as parents and the number of offspring solutions was 50. When mutation was used, the probability of mutation P_m was 0.4. We ran each experiment for 6000 and 20000 function evaluations, where each function evaluation implies a complete simulation run of EPANET. Finally, we performed 30 repetitions of each configuration. Our implementation of SPEA2 is based on source code from the PISA project [1] but with significant modifications.

7. ANALYSIS OF RESULTS

Results are analysed in terms of the empirical attainment function [3], which represents an estimation of the probability of attaining an arbitrary goal in the objective space during a single run of the particular algorithm. Here, attaining an objective vector means finding any objective vector which is equal or dominates it. The *median attainment surface* contains objective vectors with an empirical frequency of 50% of being attained. In a similar way, the *best attainment surface* contains objective vectors attained by at least one of the runs carried out, and the objective vectors in the *worst attainment surface* were attained in all the runs carried out. The single objective state-of-the-art algorithm for this instance [8] generates solutions with an average electricity cost of 348.58 and an average total number of pump switches of 4.29 within 6000 function evaluations. For reference, this objective vector is denoted by the symbol "×" in the plots.

Figure 4 shows attainment surfaces corresponding to the binary representation. The use of mutation (bottom plots) is harmful in order to achieve good results in only 6000 evaluations (left plots). Mutation is essential for the time-based triggers representation in order to achieve lower electricity cost, as shown by the differences between the top and bottom rows of Figure 5. The same conclusion as when considering the total number of pump switches holds here, that is, the binary representation allows to obtain the schedules with the lowest electricity cost at the expense of a short minimum stop time (and thus, a higher number of pump switches). On the other hand, the time-based triggers representation obtains always schedules with a long minimum stop time (and thus, keeps the number of pump switches low) and with an electricity cost still lower than the reference solution.

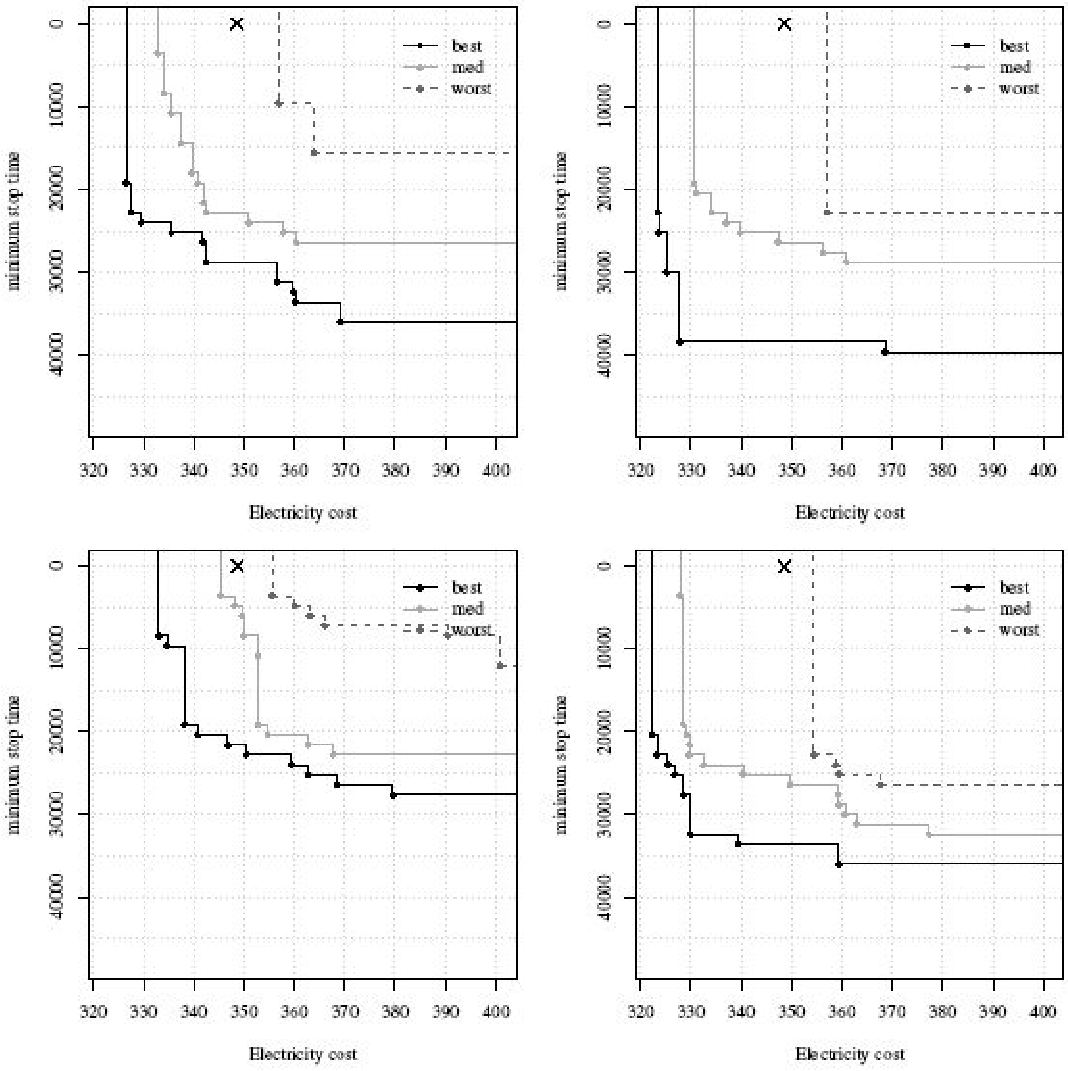

Figure 4: Binary representation. Uniform recombination without mutation (top) and with mutation (bottom) for 6000 (left) and 20000 (right) evaluations.

8. CONCLUSION

We have shown that a multi-objective approach allows taking into account electrical and a surrogate measure for maintenance costs. In addition, we have proposed the maximisation of the minimum stop time, which also imposes an upper bound on the number of pump switches per pump, as the surrogate objective for maintenance cost. We also studied a new representation based on time-controlled triggers for the Pump Scheduling problem and compared it with the well-known binary representation. The results showed that in the test network instance, the binary representation is able to obtain schedules with the lowest electrical cost at the expense of a higher maintenance cost; however, the time-based triggers representation keeps both maintenance and electrical costs lower than the state-of-the-art algorithm for this network instance. From the results we can conclude that the proposed representation will hold on different network instances and offers a better direction for further research. Also, since the algorithms and evolutionary operators considered here are rather straightforward, other advanced techniques such as customised genetic operators and hybrid methods may improve our current results.

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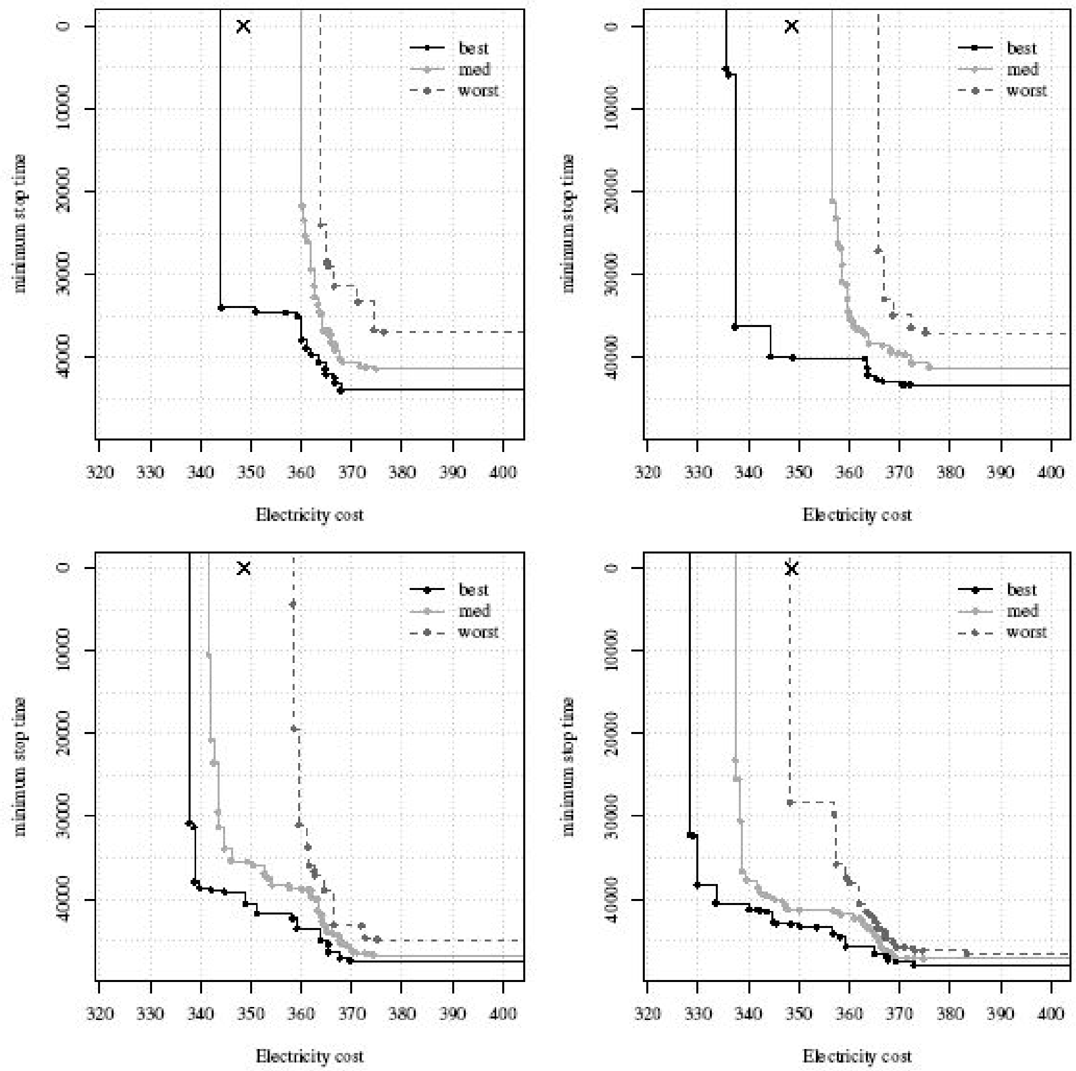

Figure 5: Time-based triggers representation. Uniform recombination without mutation (top) and with mutation (bottom) for 6000 (left) and 20000 (right) evaluations.