OPERATIONAL OPTIMIZATION OF WATER DISTRIBUTION SYSTEMS USING A HYBRID GENETIC ALGORITHM

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Abstract: Genetic algorithm (GA) optimization is well suited for optimizing the operation of water distribution systems, especially on large and complex systems. GAs have good initial convergence characteristics, but slow down considerably once the region of the optimal solution has been identified. In this study the efficiency of GA operational optimization was improved through a hybrid method which combines the GA method with a hillclimber search strategy. Hillclimber strategies complement GAs by being efficient in finding a local optimum. Two hillclimber strategies, the Hooke & Jeeves and the Fibonacci methods were investigated. The hybrid method proved to be superior to the pure GA in finding a good solution quickly, both when applied to a test problem and to a large existing water distribution system.

INTRODUCTION

Pumping energy costs form an important part of the operational cost of water distribution systems world-wide. In England and Wales, for instance, the total operational electricity costs exceeded £120 million in the 1998/99 financial year (OFWAT 1999). Even a small overall increase in operational efficiency would thus result in significant cost savings to the industry. Other benefits of operational optimization include improved water preservation and quality, ensuring compliance with water industry regulations, improved system management and benefits for future expansions such as automation (Jarrige et al 1991).

The problem of finding the optimal operating strategy is far from simple: both electricity tariff and consumer demand can vary greatly through a typical operating cycle; minimum water levels have to be maintained in tanks to ensure reliability of supply; and the number of pump switches in an operating cycle has to be limited to avoid excessive pump maintenance costs. Added to these factors is the fact that the hydraulic behavior of water distribution systems is highly nonlinear, making computer modeling a complex and time-consuming process. Finally, the number of possible operating strategies becomes vast for systems with more than a few pumps and tanks.

Various optimization techniques have been applied to the operational optimization problem, including linear programming (Burnell et al 1993, Jowitt and Germanopolous 1992), nonlinear programming (Yu et al 1994, Chase and Ormsbee 1993), dynamic programming (Nittivattanonnon et al 1996, Lansey and Awumah 1994), fuzzy logic (Angel et al 1999), nonlinear heuristic optimization (Ormsbee and Reddy 1995, Leon et al 2000), flexible constraint satisfaction (Likeman 1993) and genetic algorithms (Mackle et al 1995; Savic et al 1997, Boulos et al 2001).

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In most operational optimization methods, the optimization problem is simplified through assumptions, discretization or heuristic rules. Such simplification makes it easier for specific optimization methods to determine the optimal solution, but introduces bias into the solution by excluding a large number of potentially good solutions. Genetic algorithms (GAs) do not require such simplification measures, giving them a significant advantage in finding a near global optimal solution over most other optimization methods.

Genetic algorithms belong to a class of non-deterministic algorithms that draws on Darwinian evolution theory. The GA methodology is based on the mechanics of natural selection, combining survival of the fittest with a randomized information interchange between the members of a 'population' of possible solutions. GAs were originally conceived by John Holland in the 1970s, and have since been further developed by De Jong (1975), Goldberg (1989) and subsequently by many others (Miettinen et al 1999). GAs are best suited to solving combinatorial optimization problems with very large solution spaces which cannot be solved by using more conventional optimization methods.

One of the greatest drawbacks of GAs is that they require a high number of function evaluations to achieve convergence. Each function evaluation entails a full extended-period simulation of the system, which is a computationally expensive process. The net result is that GA optimization is time-consuming. For a large distribution system a GA optimization run can take up to a few days on a modern personal computer. Various reasons may be stated why long running times may be problematic. Operational planning often has to be performed at regular intervals, making lengthy simulation times undesirable. Short simulation times will also make it possible to utilize the optimization model in emergency situations where the operational plan of the system has to be adjusted in a limited period of time. Finally, faster optimization runs will bring engineers closer to the goal of online operational control, where the system is continually monitored and adjusted to ensure that the operational optimality is maintained at all times.

In this study, the efficiency of GA operational optimization of water distribution systems was improved by developing a hybrid optimization method which combines GAs with a hillclimber search strategy. It was found that even with the optimal parameter values, the GA's initially fast convergence rate slows down to a relatively inefficient rate after a number of iterations. In practical terms this means that the GA is able to identify the region of the optimal solution efficiently, but is much less efficient in finding the optimal point inside this region.

To improve the search efficiency in the region of the optimal point, a direct hillclimber method was employed. A hillclimber method seeks a minimum or maximum by exploring the vicinity of a solution for improvements using a specific search strategy. Direct search methods are characterized by the fact that only function values, and thus no derivatives of the objective function, are used in the search. The process is repeated until no further improvements can be found in the function value. Hillclimber strategies are efficient in finding a local optimum, but are not able to escape the attraction basin of the local optimum to explore other regions of the solution space. Hillclimber methods are thus strong where GAs are weak, and vice versa. Two hillclimber methods were applied to the problem of operational optimization, namely the Fibonacci and Hooke & Jeeves methods.

To exploit the advantages of both the GA and hillclimber methods, a hybrid method was developed. The hybrid method uses the GA to find the region of the optimal solution, and then a combination of GA and hillclimber methods to find the optimal point. The hybrid method showed significant improvements over the GA alone in converging on a near global optimal solution in terms of both time and reliability.

The operational optimization problem addressed in this study is discussed in the next section. This is followed by the development of the hybrid method with the help of a test problem. The GA parameters, selection of a hybrid method, combination of the GA and hillclimber methods into a hybrid method and the performance of the hybrid method compared to the pure GA are addressed. This is followed by a case study in which the operation of the Richmond water distribution system in the UK was optimized. Finally, the main conclusions of the study are presented.

PROBLEM DEFINITION

The main objective of operational optimization is to provide an acceptable level of service to the customer within the system constraints and legal regulations, while minimizing the operational cost (Brdys and Ulanicki 1994, Likeman 1993). These goals are in conflict with each other to a large extent. Attempts to minimize operational cost will generally place the system in a more vulnerable state and less able to handle abnormalities such as pipe bursts, thus reducing the level of service (Jowitt et al 1988).

It is important to set appropriate optimization objectives. Not only does this determine the potential benefits of the analysis, it also influences the speed and complexity of the calculations, and thus of the computer resources required. It is important to produce the simplest possible meaningful statement for expressing the optimization objectives and physical operational limitations of the system (Quevedo et al 1999).

A balance has to be struck between costs and risk. Cost will play a dominant role in most operational optimization problems, but it is also important to take level of service factors into account. In most water distribution systems, the greatest potential reductions in operational cost can be made by scheduling the pumps in the system to minimize electrical energy costs (Ormsbee and Reddy 1995). For this reason the term pump scheduling is often used as substitute for operational optimization. Other possibilities for reducing the operational cost include using the cheapest water source, minimizing water losses, minimizing the number of pump switches and minimizing the maximum power demand over a given period.

In this study, the optimization variables were defined in terms of tank level controls. Tank level controls trigger control actions in the distribution system when tank water levels reach certain pre-determined values and are widely used in practice, due to their simplicity and proven robustness. Tank level controls are normally used in pairs, with the one control triggering an action (such as switching a pump on) and the other control triggering an opposing action (switching the pump off).

In this study, different pairs of tank level controls were used for peak and off-peak electricity tariff periods. This means that each controlled element added four variables to the optimization problem: one pair of high-low tank level controls for the peak electricity tariff period, and another pair for the off-peak period.

To ensure the viability of solutions in the optimization process, constraints were imposed on the variables and the operational behavior of the system. Each optimization variable was constrained in the values that it could assume. The maximum value was determined by the tank's full water level, and the minimum value by the tank's emergency storage requirement.

The operational cost, or total pump energy cost, of each set of variables was calculated by doing an extended period simulation of the system. To ensure convergence on a viable solution, two operational constraints were applied. The first constraint is that the tank water levels have to balance over the run. In other words, the levels at the end of the run should not be lower than the levels at the start of the run. The second constraint is a limit on the number of pump switches in a 24-hour run, to avoid increased maintenance costs due to excessive wear-and-tear on the pumps. These constraints were implemented by adding penalty costs to the objective function. The tank level penalty cost was based on the total deficit volume at the end of the run. The deficit volume of tank *i*, *Di*, was calculated using the expression:

$$D_i = \begin{cases} A_i\left(H_{Si} - H_{Ei}\right); & H_{Ei} < H_{Si} \\ 0 \quad ; & H_{Ei} \geq H_{Si} \end{cases} \tag{1}$$

with H_{Si} and H_{Ei} the heads of tank i at the start and end of the simulation respectively, and A_i the cross sectional area of tank i.

The tank level penalty cost was calculated as the sum of the deficit volume of all the tanks in the system times a unit volume penalty cost. The pump penalty cost was calculated by multiplying the total number of pump switches in a simulation by a unit switch penalty value. To be effective, the penalty unit costs had to be high enough to assist convergence on a viable solution, but not so high that they eliminate potentially good solutions. Appropriate penalty unit costs were found using a trial-and-error approach.

The objective function was calculated as the weighed sum of the energy and penalty costs:

$$\min\left(C_O = C_E + C_{PP} + C_{RP}\right) \tag{2}$$

with C_O the objective function value, C_E the energy cost, C_{PP} the pump penalty cost and C_{RP} the tank end level penalty cost.

It was found that the GA sometimes traded off the pump penalty cost for the tank end level penalty costs. This is undesirable since balancing the tank volumes over a 24-hour period is more important for a sustainable solution than reducing the number of pump switches. To avoid this problem, an additional penalty term, $\sqrt{C_{PP} \cdot C_{RP}}$, was added to the objective function. This term is zero when either of the two penalty functions is zero. Since the number of pump switches can normally not be zero, the effect of the added penalty term is to increase the pressure on the GA to reduce the tank level penalty cost to zero, and thus balance the tank volumes over a day.

HYBRID METHOD DEVELOPMENT

A hybrid optimization strategy was developed by combining genetic algorithm search with a hillclimber search method. GAs have very good initial convergence rates, but are less efficient once the GA has found a near-optimal solution. Local search methods, on the other hand, are good at converging on the local optimum from a nearby starting point, but are not able to jump to other, possibly better, areas of the solution space. By combining the GA strategy with a local search strategy, the advantages of both methods are exploited to produce an optimization method which is both reliable and fast.

The ideal optimization method is one which is both reliable in finding a near global optimal solution, and fast in converging on that solution. However, these goals are often in conflict with each other, forcing a trade-off approach in selecting the parameters for the optimization method. When applied to water distribution systems, for instance in an emergency situation, it is often more important to find a good solution speedily than it is to find the global optimum solution. For this reason the hybrid method was developed with the main emphasis on convergence speed rather than reliability.

To determine the parameters of the different search strategies, it was necessary to base them on a test problem which represents the complexities associated with operational optimization of water distribution systems.

Test problem

The test problem used to determine parameters for the hybrid operational optimization method is shown in Figure 1. The system has a simple layout, but was designed to have a great number of viable operational strategies. It consists of a source, from which two tanks at different elevations are fed through a main and booster pump stations. The pump station at the source has two identical pumps (1A and 2B) in parallel. Pump 1A is controlled by the level in tank A, while pump 2B is controlled by the level in tank B. The efficiency curves of the parallel pumps were selected to produce similar unit pumping costs for the pumps operating alone and in parallel.

A booster pump (3B) is installed on the pipe feeding the higher of the two tanks (tank B) and is controlled by the level in tank B. When one or both of the two pumps in the pump station are running, the booster pump increases the flow to tank B. However, when neither pump 1A nor 2B is running, the booster pump conveys water from tank A to tank B.

The two tanks are also connected with a gravity line. All the demands in the system are taken from nodes on the gravity line. The demands vary according to a typical residential demand pattern with a peak (with a peak factor of 1.7) at 7:00 and a secondary peak (with a peak factor of 1.5) at 18:00. When the demands are high, water is extracted from both tanks to supply the demand. However, under low demand conditions water is conveyed under gravity from tank B to tank A. The network layout and the many valid pump configurations make this problem well suited for the refinement and testing of the hybrid operational optimization method. A standard Epanet text description (Rossman 2000) of the test system's input file is given in Appendix III.

Genetic Algorithms

Genetic algorithms (GAs) belong to a class of non-deterministic algorithms that draws on Darwinian evolution theory. This search strategy allows GAs to converge rapidly on an optimal or near-optimal solution while only analyzing a fraction of the number of possible solutions (Goldberg 1989). GAs only require that the objective function be calculated. This eliminates problems often encountered in optimization methods with a mixed-integer nature, or where partial derivatives of the objective function are required. In addition, GAs search from a number of starting points rather than a single point and use probabilistic transition rules which reduce the possibility of being trapped in a local optimum. The above properties make GAs ideally suited to address problems such as operational optimization of water distribution systems (Goldberg and Kuo 1987). Esat and Hall (1994), in particular, showed that in problems with more than four tanks, GAs show considerable economy in both memory requirements and execution time over more conventional optimization techniques. A number of other studies have also demonstrated the effectiveness of GAs in operational optimization of water distribution systems (De Schaetzen et al. 1998, Engelbrecht and Haarhoff 1996, Goldberg and Kuo 1987, Mackle et al. 1995, Savic et al 1997, Schwab et al 1996).

A GA evolves optimal solutions by sampling from all the possible solutions. The best of these solutions are then combined, using the genetic operators of crossover and mutation, to form new solutions. This process continues until some termination condition is fulfilled.

The object-oriented, multithreaded genetic algorithm class library of the Centre for Water Systems at the University of Exeter (Atkinson et al. 1998) was used to implement the genetic algorithm process. Pump switch level variables were encoded in a real-bounded gene with size four times the number of pumps, allowing trigger-on and trigger-off levels for both peak and off-peak electricity tariff periods to be included.

Steady-state GAs, in which individuals are added and removed from an otherwise steady population, were used rather than generational GAs, in which the whole population is replaced by a new generation of child solutions, since steady-state GAs are known to converge faster than generational GAs (Savic and Walters 1997). The parameters of the steady-state GA were determined by doing a sensitivity analysis on the standard problem. The sensitivity analysis was started from a basic parameter set obtained from the literature (Goldberg 1989) and some initial experimentation on the system. The resulting GA parameters are roulette wheel parent selection (biased proportional to the fitness of individuals in the population), simple one-point crossover, replacing of the weakest member in the population and crossover and mutation rates of 90 %. Crossover rate refers to the probability that the crossover operator will be applied to a selected pair of parent solutions. Mutation rate refers to the probability that a randomly selected gene on a newly created child solution will be adjusted.

A sensitivity analysis was done by comparing the GA performance for different values of the parameters listed above. The performance of the GA for the different parameter values was then compared by plotting them on the same axes. An example of such a comparison is shown in Figure 2 for the replacement parameter, i.e. which member of the population should be replaced by a newly generated child solution (since two child solutions are generated in each iteration, this operator is applied twice in succession). The figure clearly shows that replacing the weakest member of the population resulted in the fastest convergence of the GA, compared to replacing the first weaker member of the population found, and replacing a random member of the population. Replacing the weakest member of the population did not find the best overall solution, although it came close to it. However, since the emphasis of the method was on convergence speed, replacing the weakest member of the population was selected as the most appropriate replacement method.

In Figure 2 the GA objective value of the fittest individual in the population is plotted against the number of function evaluations. The number of function evaluations was used instead of the number of GA iterations to allow comparisons between GA and hillclimber method performance. In each GA iteration two new solutions are generated and evaluated. One GA iteration is thus equivalent to two function evaluations. The number of function evaluations is considered to be a better measure of computational effort than computer time, due to the large variations in the performances of computers (even when using the same processor) and the high rate at which faster computers are introduced. The computational effort associated with the optimization methods themselves are also very small compared to that of the function evaluations, each of which require a full extended-period simulation of the system. A logarithmic scale was used on the X-axis of Figure 2 to show details of the initial convergence more clearly.

The sensitivity analysis resulted in the following GA parameters: Stochastic remainder selection without replacement (SRSWR) for parent selection, one point crossover, replacing the weakest organism in the population, crossover and mutation rates of 90 %, and a population size of 35 organisms. In SRSWR parent selection, the ratio of each organism's fitness to the average fitness of the population is calculated. For each organism where this ratio is above one, a number of clones equal to the whole number of the ratio are placed in the selection pool. The remaining organisms to make the size of the chosen set equal to that of the population are chosen from these remainder values using roulette wheel selection.

Hillclimber Methods

'Hillclimber strategies' is the name given to a group of numerical parameter optimization methods applied to unimodal, static, non-discrete, non-stochastic, mostly unconstrained functions. The name refers to the manner of searching for a maximum which corresponds to the way a blind climber might feel his way to the highest peak of a mountain (Schwefel 1981).

Due to the indirect nature of tank level controls and the discrete pump switch penalty function, the partial derivatives of the objective function could not be calculated for all variable values. For this reason only direct search methods, which only use the objective function and not gradients, were considered.

Direct search methods use heuristic schemes to systematically search the solution space from a given starting point. Changes are made to variables and the effect tested by evaluating the objective function. These attempts are called steps and are used in various ways to search the solution space. Steps in ‘wrong’ directions are inevitable. The attraction of direct search methods lies not in theoretical proofs of convergence, but in their simplicity and the fact that they have proved themselves in practice (Schwefel 1981). Two direct hillclimber strategies were investigated for possible inclusion in the hybrid method: the Fibonacci coordinate method and the Hooke & Jeeves pattern search method.

Fibonacci Coordinate Search

In a coordinate strategy a line search is done sequentially on each parameter. The line search entails three steps: determine the search direction, delimit the search interval and then search for the optimal parameter value. The Fibonacci method was chosen because it has been shown to be the best of all sequential interval division procedures (Schwefel 1981).

Since the gradient of the objective function is unknown, the search direction is determined by taking a small step in the positive and, if required, also in the negative direction. If the function value is improved, further steps are required in the successful direction until the optimal parameter value is overstepped (i.e. a reduction in the function value is found). This is known as ‘blocking the maximum’ and returns an interval which must contain the optimal parameter value. This interval is then searched by repeatedly subdividing the interval into four, and then eliminating one of the two outer intervals which cannot contain the optimal parameter value. A detailed description of the Fibonacci method may be found in books on hillclimber search strategies, such as the book by Schwefel (1981).

An advantage of the Fibonacci method is that each iteration requires only one new function evaluation. Blocking the maximum in using the Fibonacci method has the advantage that the blocked interval is immediately initialized and of the right size for a Fibonacci search.

Hooke & Jeeves Pattern Search

The Hooke & Jeeves method is based on two types of moves. At each iteration there is an exploratory move, which resembles a simplified coordinate search with one discrete step per coordinate direction. On the assumption that the line joining the first and last points of the exploratory move represents an especially favorable direction, a pattern move is made by extrapolating in the direction of this line. Another exploratory move is made from the extrapolated point before the new function value is compared to the function value before the pattern step. The length of the pattern step is hereby increased at each successive pattern move while the pattern search direction only changes gradually. This pays off to most advantage where there are narrow ridges (for maximization) or valleys (for minimization) in the solution space (Schwefel 1981). When no further improvements are made through exploration around the base point, the initial step size can be reduced and the process repeated if a higher accuracy is required.

Comparison

To compare the performance of the Fibonacci and Hooke & Jeeves hillclimber methods on the operational optimization problem, both methods were applied from a number of different starting points. Both methods benefited from starting their searches with a larger size step and then reducing the step size in one or more stages until a minimum step size is reached. Two stages were used in the Fibonacci method, starting from a 75 mm step size, and then reducing it to a minimum step size of 5 mm. Since the Hooke & Jeeves method uses extrapolation steps, a smaller starting step size of 20 mm was used, which was halved in two successive stages to reach the 5 mm minimum step size. The direct search methods were run from the same starting solutions, obtained at points in a randomly selected GA run. The results are shown in Figure 3.

Although the Fibonacci method showed better initial convergence rates, the Hooke & Jeeves method was able to sustain its convergence longer to find considerably better final solutions. For this reason, the Hooke & Jeeves method was selected for inclusion in the hybrid method.

Another important result from Figure 3 is that in two cases (with starting objective function values of 350.5 and 357.8) the Hooke & Jeeves converged on inferior solutions compared to the other Hooke & Jeeves runs. This occurred despite the fact that the first mentioned two runs started off from better objective function values than other two runs (with starting objective function values of 356.3 and 359.5) that did find near optimal solutions. The reasons for the variation in convergence behavior are not clear, but multiple local optima or discontinuities in the solution space may both play a role. What is clear, however, is that a simple switch from the GA to the direct search strategy will not always converge on a near optimal solution. This had to be taken into consideration when combining GA and hillclimber searches into a hybrid optimization strategy.

Hybrid method

GAs are often used in combination with a problem-specific or local search procedure, especially in commercial applications (Goldberg and Voessner 2000). The goal of using a problem specific search method is to improve the efficiency of the GA, either in terms of the time required to find a good solution, or the quality of the solution found. Early hybrid GAs were introduced in 1985 by Smith and Grefenstette et al, and are commonly used today in serious GA applications (Goldberg and Voessner 2000).

The respective strengths of GA and hillclimber search methods make it obvious that the GA should be used first to find the region of the global optimum solution. The local search method is then employed to find the optimum point to the required level of accuracy.

The problem of when first to switch from the GA to the Hooke & Jeeves method was addressed by calculating the convergence rate of the GA and switching to the Hooke & Jeeves method when the latter can be expected to provide a better convergence rate. Figure 3 shows similar convergence rates for all the Hooke & Jeeves runs. Calculating the moving average slope of the GA over the last 500 function evaluations, and first switching to the Hooke & Jeeves method when the moving average slope was better than the typical

Hooke & Jeeves method slope proved to be a reliable switching criteria for the test problem.

Another problem that had to be addressed was the unreliable convergence characteristics of hillclimber methods when applied to the operational optimization problem, as discussed earlier. This was done by re-introducing the Hooke & Jeeves solution back into the GA. The GA was then applied until a better solution was found, after which another switch was made to the Hooke & Jeeves method. This process was repeated until the termination criteria were met. A flow diagram of the hybrid method is given in Figure 4.

Application of Hybrid Method

To determine the efficiency of the hybrid method compared to the pure GA or hillclimber methods, these methods were applied to optimize the operation of the test problem. Seven optimization runs were performed from randomly selected starting points. At first, the pure GA was applied to the problem and allowed to run for 100 000 function evaluations to ensure that convergence had been achieved. The pure Hooke & Jeeves, and the hybrid methods were then applied from the same starting points and the performance of the different methods compared. Typical convergence of the three methods are shown graphically in Figure 5 for the first 6 000 function evaluations.

Although the figure does not demonstrate a great difference between the solutions found by the pure GA and the hybrid methods, the hybrid solution achieved full convergence in less than 700 function evaluations, while the pure GA in, this case, took more than 30 000 function evaluations to achieve full convergence. The pure Hooke & Jeeves method showed initial convergence rates matching those of the GA, but was unable to sustain these and invariably ended up with inferior solutions.

The performance the hybrid method is compared to that of the pure GA in Table 1. In the first two columns of Table 1, the GA results after 100 000 function evaluations is compared to the hybrid method results after 6 000 function evaluations. The pure GA solutions varied between £344.19 and £364.94 with an average of £350.36. The hybrid method was not able to improve on the best pure GA solution, but managed to get very close at £344.43. However, when all seven runs are considered, the hybrid method performed significantly better than the pure GA. This is reflected in the worst and average solutions found by the hybrid method (£354.79 and £348.58 respectively), both of which are significantly better than the pure GA. Considering the individual runs, the hybrid method was able to match (within 0.2 %) or improve on all the solutions found by the GA. The best improvement was made in run 6 where the hybrid method was able to improve by 2.8 % on the GA solution.

The improvement in convergence rates of the hybrid method over the pure GA is clearly illustrated by comparing the number of function evaluations required to converge on a good solution. A good solution was arbitrarily defined as a solution within 0.5 % of the best solution found. The number of function evaluations varied between 307 and 14 197 for the pure GA, and between 307 and 2 212 for the hybrid method. The average number of function evaluations required by the hybrid method is less than one third of that required by the pure GA.

Comparison of optimization runs

To understand the complexity of the operational optimization problem better, the results of the seven hybrid method optimization runs were analyzed in more detail. Figures 6 and 7 show the tank profiles for the seven runs and the running times of the pumps linked to the respective tanks. The runs are shown in order of increasing operational cost.

The figures illustrates two diverging strategies identified by the hybrid method to minimize the operational cost. In the first operational strategy, the level of the lower tank A is maintained as high as possible during central part of the peak tariff period. The higher level reduces the head difference between the two tanks, thus minimizing flow from tank B to tank A and increasing the fraction of the demand supplied from tank A. Subsequently less water is pumped to the higher, and thus more expensive, tank B. The four best runs (runs 5,4,7 and 1) applied this strategy.

The second operational strategy minimized cost by letting both tanks' levels drop as much as possible during the peak tariff period and then filling them up during the off-peak period. The fifth best run (run 2) applied this strategy. The worst two runs (runs 3 and 6) used combinations of the two strategies to minimize the operational cost.

CASE STUDY

The hybrid method was subsequently applied to the Richmond water distribution system, which is part of the Yorkshire Water supply area in the UK. The calibrated hydraulic model of the system used in the optimization study consisted of 948 links and 836 nodes.

Problem Description

The Richmond water distribution system consists of a set of six cascading tanks supplying different pressure zones, with the primary source of water coming from boreholes within the lowest zone. Water is raised from the lower to the higher tanks by pump stations containing one or more level controlled pumps.

A schematic diagram of the Richmond system is shown in Figure 8. The main source of water into the system is based at the Catterick Bridge boreholes. From the Catterick Bridge boreholes, water is pumped by the Catterick Bridge pump station and the St. Trinians booster pump station up to the Low Zone tank. In addition to its own supply zone, the Low Zone tank supplies:

- The High Zone tank via the High Zone booster pump station.
- The Gallow Gate tank via the Gallowfields booster pump station.
- The Hudswell tank via the Holly Hill booster pump station.

In addition to its own demand area, the Gallow Gate tank supplies Marske tank by gravity, which, in turn, supplies the Skelton tank via the Skelton booster pump station.

Objectives and constraints

The primary objective of the optimization was to determine the optimum trigger levels that would minimize the annual pumping costs over the whole system. Two pairs of trigger-on and trigger-off levels were used for each level control pump, one for off-peak, and the other for peak electricity tariff periods.

Trigger level variables were constrained by the full water level and minimum emergency storage levels in the service tanks. Two further constraints were applied through penalty functions: The first penalty function was applied to the deficit volume if the tanks in the system did not balance over a 24-hour period. The second penalty function was applied as a unit penalty cost for each pump switch in a 24-hour period to limit pump maintenance cost resulting from excessive switching. Initial tank levels were set to 95 % full at 7:00, the start of the peak tariff period.

Optimization

The operation of the Richmond water distribution system was optimized previously using GAs in a study by Atkinson et al (2000). Before this study, the operational policy of the Richmond system was based on operator experience. A hydraulic simulation of the existing operational policy resulted in an estimated annual operating cost of £47 500 for the system.

Atkinson et al (2000) applied GAs to the problem and were able to reduce the annual operational cost by almost 20 % to £38 300 through better utilization of the off-peak electricity tariff periods for pumping. Hydraulic simulation in this study was done via a commercial geographical information system (GIS), resulting in a high level of computational overheads and thus making the optimization runs time-consuming. A typical GA optimization run using approximately 150 000 function evaluations, took 69 hours of computer time on a Pentium 400 MHz personal computer.

In this study, improvements in both the optimization results and running times were achieved through innovations in a number of areas. At first, the problem definition was slightly altered to be more realistic. Atkinson et al (2000) assumed that all tanks were 95 % full at 5:00, the start of the morning peak water demand period. Changing the 95 % full requirement to 7:00, the start of the peak electricity tariff period, more off-peak time could be utilized for pumping. This allowed a further reduction in the operational cost to £35 300.

The second improvement was made by linking Epanet directly to the GA software library of the Centre for Water Systems at the University of Exeter. This significantly reduced the computational overheads imposed by the GIS and thus reduced the running time for 150 000 function evaluations from 69 hours to 21 hours.

Ten different optimization runs were performed from different, randomly selected, starting points. To ensure that convergence was achieved, the GA runs were continued for 200 000 function evaluations. The best solution was found in Run 4 with an annual operating cost of £35 296. Four other runs found solutions within one percent of this value.

Finally, the hybrid method was applied to the same ten starting points used for the GA runs. The hybrid method significantly improved the convergence rate of the GAs, allowing a good solution to be found in considerably less time than the GA. Figure 9 shows the results of the hybrid method after 8 000 function evaluations compared to that of the GA method after 200 000 function evaluations.

In three of the ten runs the hybrid method was able to improve on the GA solution and in seven of the ten runs the hybrid method was able to get within 1 % of the GA solution. In only two cases, runs 2 and 3, did the hybrid method find solutions that were considerably worse than the GA solutions. This is probably due to premature switching from the GA to the local search strategy. Using the hybrid method, the running time for an optimization run was further reduced to only 1.1 hours.

The improvement in GA convergence is further illustrated by looking at the number of GA simulations needed to match the hybrid solution after 8 000 function evaluations. In three runs the GA was not able to match the hybrid method solution even after 200 000 function evaluations. The other runs needed an average of 17 935 function evaluations, more than double the number required by the hybrid method to achieve the same level of convergence.

CONCLUSIONS

GAs have been shown to be efficient in optimizing the operation of water distribution systems. A drawback of GAs is that, while they are efficient in finding the region of an optimal solution, they are much less efficient in identifying the optimal point inside this region. In this study, a hybrid optimization method was developed by combing a GA method with the Hooke & Jeeves hillclimber method. Hillclimber strategies complement GAs by being efficient in finding a local optimum from a given starting point. The hybrid method was tested by applying it to a hypothetical water distribution system and a large existing water distribution system in the UK. It was shown that the hybrid method was able to perform significantly better than the pure GA method, both in convergence speed and in the quality of the solutions found.

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APPENDIX II. NOTATION

The following symbols are used in this paper:

A_i = cross-sectional area of tank i;
C_E = energy cost;
C_O = objective function value;
C_{PP} = pump penalty cost;
C_{RP} = tank end level penalty cost;
D_i = deficit volume in tank i;
H_{Ei} = head of tank i at the end of a simulation;
H_{Si} = head of tank i at the start of a simulation;
i = counter variable;

APPENDIX III. TEST PROBLEM INPUT DATA

```
[JUNCTIONS]
;ID       Elev    Demand  Pattern
 n1       10      0
 n2       10      0
 n3       75      0
 n6       30      100     pattern24
 n5       30      50      pattern24
 n12      100     0
 n13      100     0
 n10      100     0
 n11      100     0
 n361     100     0
 n365     100     0
 n362     100     0
 n364     100     0

[RESERVOIRS]
;ID    Head
 r1    20

[TANKS]
;ID   Elev  InitLev MinLev MaxLev Diam
 t5   80    4.5     0      5      25
 t6   85    9.5     0      10     20

[PIPES]
;ID     Node1  Node2   Length  Diam   Rough   Status
 p1     r1     n1      1       1000   100     Open
 p2     n2     n3      2600    450    100     Open
 p3     n3     t5      1000    350    100     Open
 p4     n365   t6      2000    350    100     Open
 p6     t6     n6      1100    300    100     Open
 p5     t5     n5      500     300    100     Open
 p7     n6     n5      1       200    100     Open
 p12    n1     n12     1       1000   100     Open
 p10    n1     n10     1       1000   100     Open
 p11    n11    n2      1       1000   100     Open
 p13    n13    n2      1       1000   100     Open
 p361   n361   n362    1       1000   100     Open
 p364   n364   n365    1       1000   100     Open
 p18    n3     n361    1       1000   100     Open
 p19    n361   n365    1       1000   100     CV

[PUMPS]
;ID      Node1  Node2  Curve
 pmp1    n10    n11    HEAD 1
 pmp2    n12    n13    HEAD 1
 pmp6    n362   n364   HEAD 6
```

```
[PATTERNS]
;ID          Multipliers
 pattern24   0.62  0.62  0.67  0.76  0.91  1.1
 pattern24   1.48  1.71  1.48  1.02  0.73  0.55
 pattern24   0.49  0.55  0.73  1.02  1.36  1.53
 pattern24   1.53  1.36  1.1   0.91  0.76  0.67
 pumptariff  0.0244  0.0244  0.0244  0.0244  0.0244  0.0244
 pumptariff  0.0244  0.1194  0.1194  0.1194  0.1194  0.1194
 pumptariff  0.1194  0.1194  0.1194  0.1194  0.1194  0.1194
 pumptariff  0.1194  0.1194  0.1194  0.1194  0.1194  0.1194

[CURVES]
;ID      X      Y
 1      0      100
 1      120    90
 1      150    83
 6      0      120
 6      90     75
 6      150    0
 1eff   50     78
 1eff   107    80
 1eff   151    68
 1eff   200    60

[ENERGY]
 Global Efficiency       85
 Global Price            0
 Demand Charge           0
 Pump  pmp1   Efficiency  1eff
 Pump  pmp1   Price       1
 Pump  pmp1   Pattern     pumptariff
 Pump  pmp2   Efficiency  1eff
 Pump  pmp2   Price       1
 Pump  pmp2   Pattern     pumptariff
 Pump  pmp6   Price       1
 Pump  pmp6   Pattern     pumptariff

[TIMES]
 Duration            24:00
 Hydraulic Timestep  1:00
 Pattern Timestep    1:00
 Pattern Start       7:00
 Start ClockTime     7 am

[OPTIONS]
 Units              LPS
 Headloss           H-W
 Accuracy           0.00001

[END]
```

TABLES

Table 1 Comparison of the pure GA and hybrid method performances on the test problem

Run no	**Best Solution Found (£/day)**		**No of Function Evaluations to get within 0.5 % of the GA Solution**	
	Pure GA after 100 000 function evaluations	**Hybrid after 6 000 function evaluations**	**Pure GA**	**Hybrid**
1	347.71	347.10	2 451	616
2	354.20	352.06	1957	1 621
3	352.08	352.15	307	307
4	344.71	344.43	3 695	1 516
5	344.67	344.81	2 045	785
6	364.94	354.79	2 413	1 345
7	344.19	344.74	14 197	2 212
Ave	**350.36**	**348.58**	**3866**	**1200**

FIGURE CAPTIONS

FIG. 1. A test water distribution system

FIG. 2. Comparison of GA performance for different types of replacement

FIG. 3. Comparison of the performance of the Fibonacci and Hooke & Jeeves hillclimber search methods from different starting points

FIG. 4. Flow diagram of the hybrid optimization method

FIG. 5. Typical convergence patterns of the GA, Hooke & Jeeves and hybrid optimization strategies

FIG. 6. Behavior of tank A and pump 1A of the test problem for seven optimization runs

FIG. 7. Behavior of tank B and pumps 2B and 3B of the test problem for seven optimization runs

FIG. 8. Schematic layout of the Richmond Water Distribution System

FIG. 9. Comparison of the GA results after 200 000 function evaluations and the hybrid method after 8 000 function evaluations

FIGURES

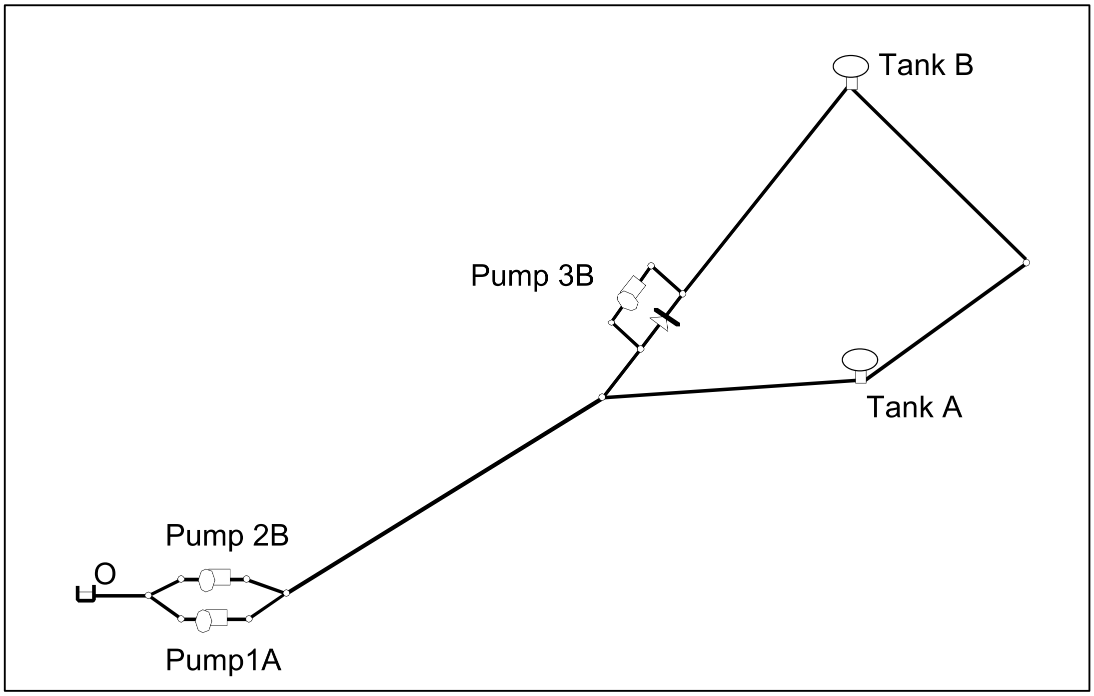

FIG. 1. A test water distribution system

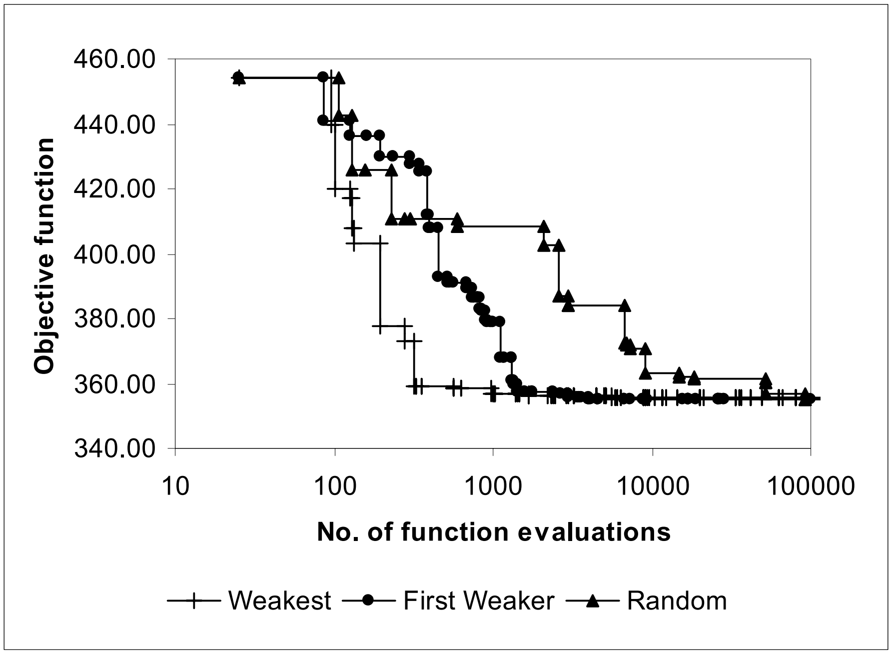

FIG. 2. Comparison of GA performance for different types of replacement

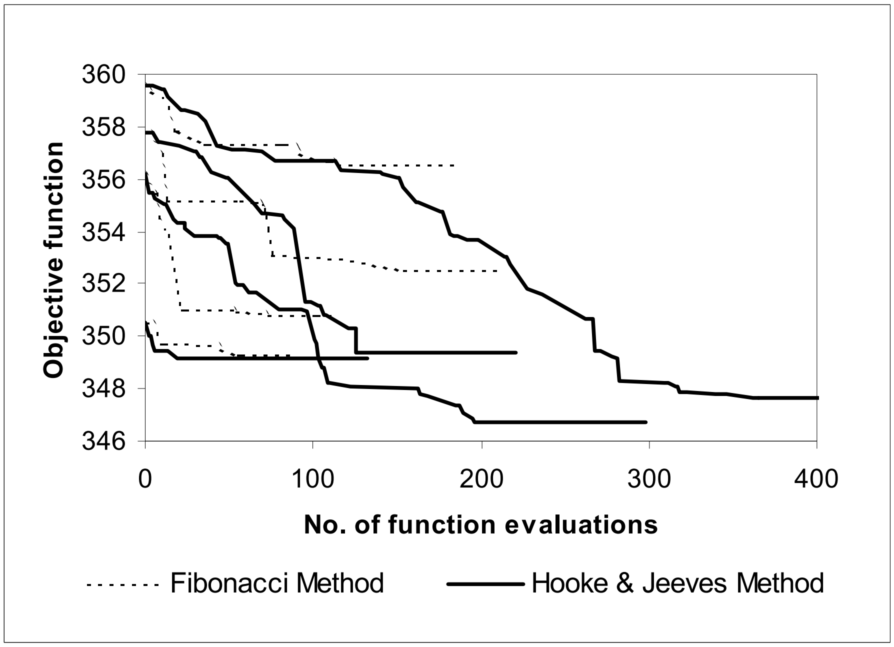

FIG. 3. Comparison of the performance of the Fibonacci and Hooke & Jeeves hillclimber search methods from different starting points

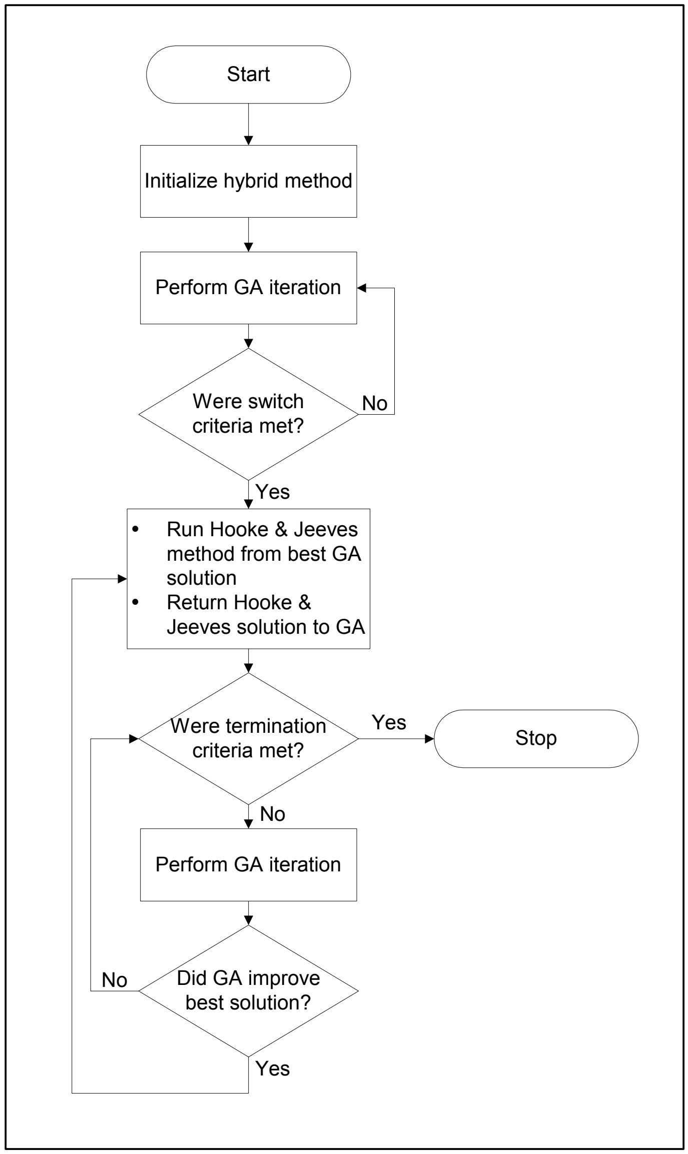

FIG. 4. Flow diagram of the hybrid optimization method

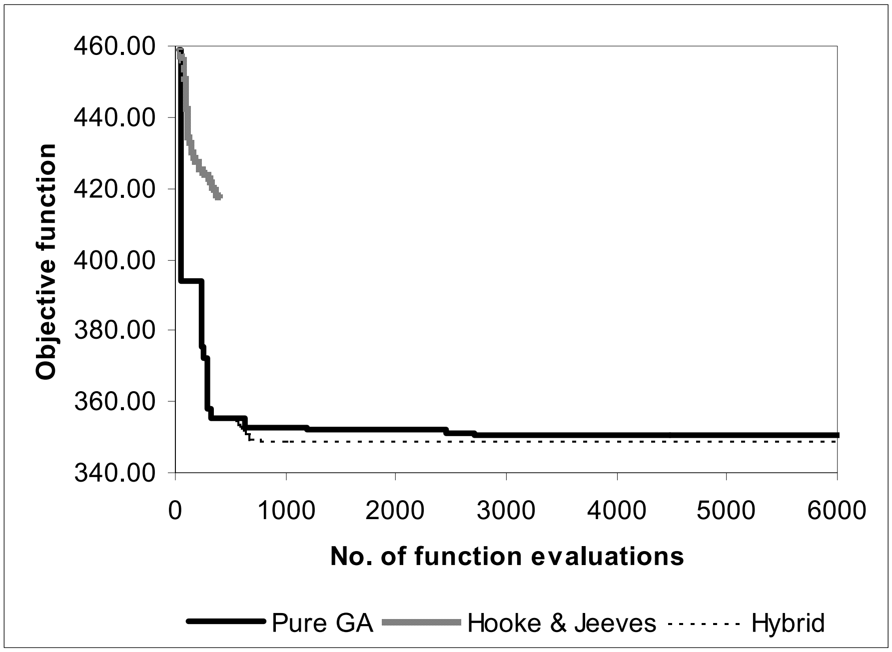

FIG. 5. Typical convergence patterns of the GA, Hooke & Jeeves and hybrid optimization strategies

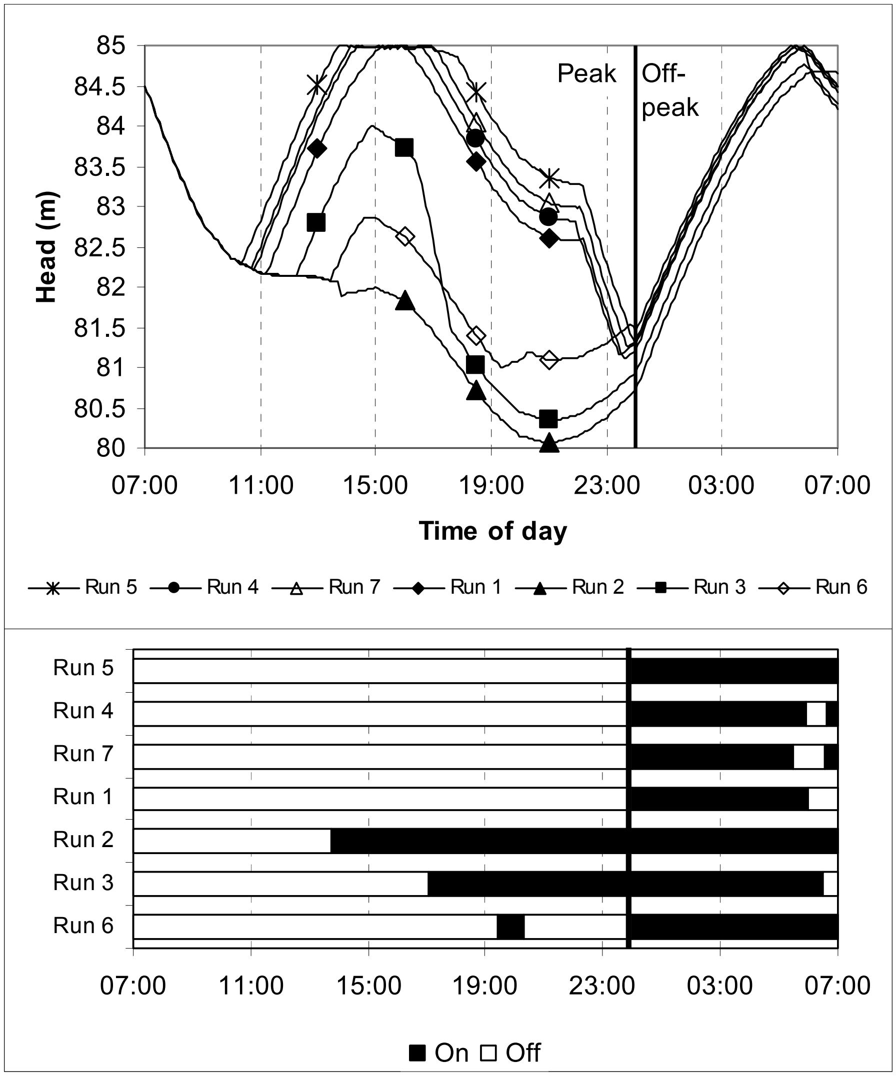

FIG. 6. Behavior of tank A and pump 1A of the test problem for seven optimization runs

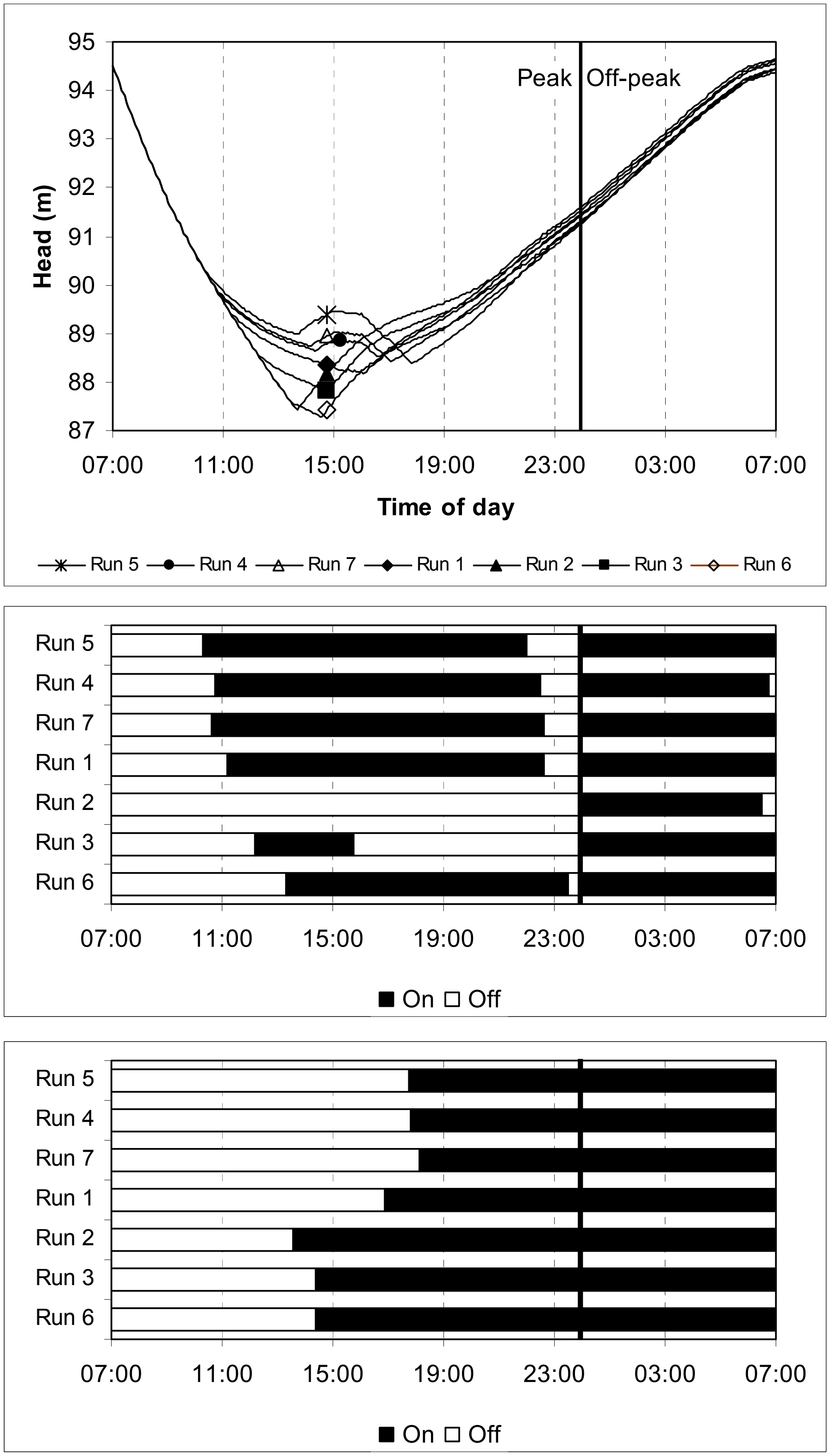

FIG. 7. Behavior of tank B and pumps 2B and 3B of the test problem for seven optimization runs

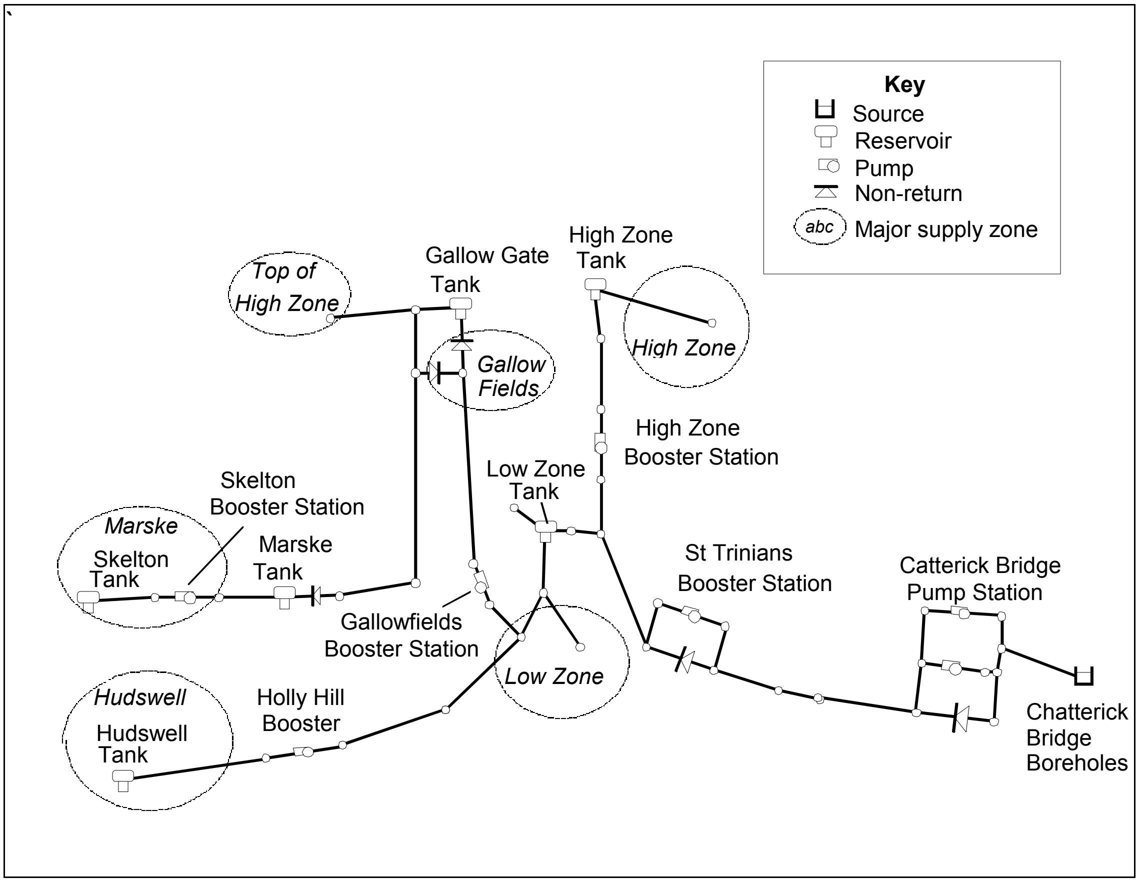

FIG. 8. Schematic layout of the Richmond Water Distribution System

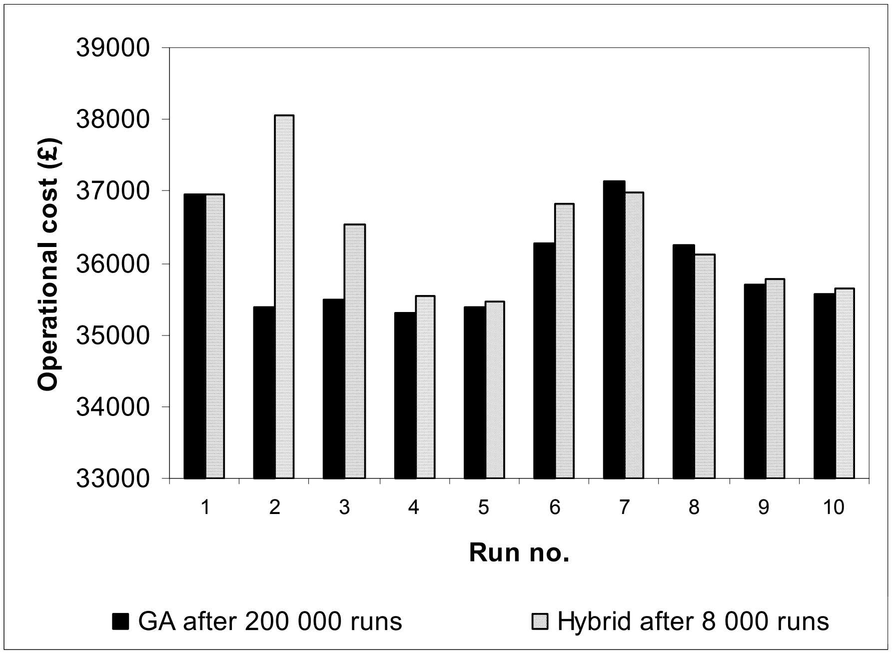

FIG. 9. Comparison of the GA results after 200 000 function evaluations and the hybrid method after 8 000 function evaluations

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