Development of a real-time, near-optimal control process for water-distribution networks

Zhengfu Rao and Elad Salomons

ABSTRACT

This paper presents a new approach for the real-time, near-optimal control of water-distribution networks, which forms an integral part of the POWADIMA research project. The process is based on the combined use of an artificial neural network for predicting the consequences of different control settings and a genetic algorithm for selecting the best combination. By this means, it is possible to find the optimal, or at least near-optimal, pump and valve settings for the present time-step as well as those up to a selected operating horizon, taking account of the short-term demand fluctuations, the electricity tariff structure and operational constraints such as minimum delivery pressures, etc. Thereafter, the near-optimal control settings for the present time-step are implemented. Having grounded any discrepancies between the previously predicted and measured storage levels at the next update of the monitoring facilities, the whole process is repeated on a rolling basis and a new operating strategy is computed. Contingency measures for dealing with pump failures, pipe bursts, etc., have also been included. The novelty of this approach is illustrated by the application to a small, hypothetical network. Its relevance to real networks is discussed in the subsequent papers on case studies.

Key words | artificial neural networks, genetic algorithms, optimal control, POWADIMA, water distribution

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INTRODUCTION

Aims and aspirations

Every water-distribution network comprises a unique configuration of interconnected pipes, storage tanks, pumping stations and valve chambers, which is subjected to highly variable demands that cannot be forecast with a great degree of certainty. Moreover, it has to be operated in a way so as not to violate any standards-of-service constraints relating to the continuity of supply, maintenance of a minimum delivery pressure, etc., as well as physical constraints such as the overtopping of storage tanks. In addition, operational staff are also expected to minimize the energy cost incurred by pumping, taking account of a tariff structure which can change with the hour of the day, day of the week and month of the year. To assist with the operational decisions, staff may have access to monitoring information from SCADA (Supervisory Control And Data Acquisition) facilities, which defines the current state of the network in terms of control settings, water levels in storage tanks, flow rates in a limited number of pipes, hydrostatic pressures at selected locations, etc. Either way, considerable reliance is placed on the experience and judgement of the skilled staff in deciding which pumps/valves to operate and when, in order to ensure compliance with the constraints and minimize energy costs.

During the past 30 years or so, there have been a number of attempts to develop optimal-control algorithms to assist in the operation of water-distribution networks. Most have been oriented towards determining least-cost, pump-scheduling strategies, based on the use of linear programming (Jowitt & Germanopoulos 1992; Burnell *et al.* 1993), non-linear programming (Chase & Ormsbee 1993;

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Yu *et al.* 1994), dynamic programming (Sterling & Coulbeck 1975; Lansey & Awumah 1994), decomposition-coordination techniques (Fallside & Perry 1975), fuzzy logic (Angel *et al.* 1999) and general heuristics (Ormsbee & Reddy 1995; Leon *et al.* 2000). However, the uptake of these procedures in practice has been somewhat disappointing, with relatively few having actually been applied to real water-distribution networks. This limited acceptance of these models by the water industry is partly due to:

- the techniques are confined to minimizing energy costs and largely ignore network performance;
- they are generally complex, involving a considerable amount of mathematical sophistication (e.g. requiring extensive expertise in problem formulation and fine tuning of parameters);
- their complexity is generally dependent upon the size of the network, which limits their applicability;
- they are usually subject to over-simplification of the network representation as well as assumptions to accommodate the non-linear network hydraulics;
- run times have tended to be excessive; and
- there is the possibility of being easily trapped at local optima and not achieving the global optimal solution.

Another important reason for their general lack of use is the scarcity of suitable, user-friendly pump-optimization packages. As a result, most of the models that have been developed so far have remained in academia.

The concept underpinning the POWADIMA (Potable Water Distribution Management) research project (Jamieson *et al.* 2007), of which this work-package forms a crucial part, provides an alternative approach to the traditional way in which water-distribution networks have hitherto been operated. Whilst initially the methodology would be restricted to providing operational advice to skilled staff, that does not negate the possibility of some form of closed-loop control in the future, thereby reducing the need for operator intervention. To achieve that end, it is necessary to consider the entire operational-control process rather than just energy cost reduction. At the present time, pump scheduling, which remains the current state-of-the-art, is limited to providing guidance for the pump-control settings in the form of 'set points' (targets) to minimize energy costs by transferring as much of the pumping as possible to the low-cost energy tariff period. In order to do so, an averaged demand profile is normally assumed for the following 24-h period. If for any reason there is subsequently a significant divergence between the assumed demand profile and reality, the pump-scheduling program is usually re-run with the amended demand profile: otherwise, the pump schedule is not updated until the end of the current 24-h operating period. No consideration is given to optimizing the performance of the distribution network *per se*. Ensuring demands are met within the operational constraints prevailing is left to the judgement of the operational staff, as previously. Given the uncertainty surrounding the whole process, there is an inevitable tendency for the operators to maintain a higher pressure than would otherwise be necessary with a better understanding of future demands and network hydraulics. If the aim is to improve the overall operational control of water-distribution networks, then clearly energy cost reduction and network performance have to be optimized together rather than separately or not at all.

Approach adopted

In the preceding paper, Rao & Alvarruiz (2007) described the methodology adopted for rapidly predicting the consequences of different control settings on the performance of the network, which is based on replicating a detailed hydraulic simulation model by means of an artificial neural network (ANN). This paper focuses on selecting the best combination of control settings not only for the present situation but also the expected conditions up to a given operating horizon in order to minimize the overall pumping costs. The objective is to meet the current and forecast demands on the network at minimal operating cost, without violating any of the physical or standards-of-service constraints. Following the next update of the SCADA facilities, which defines the current state of the network, the whole process is repeated to accommodate any amendments to the demand forecasts. Rolling the process forward at short, regular time intervals gives an approximation to real-time control.

As previously explained (Jamieson *et al.* 2007), the use of a conventional hydraulic simulation model to predict the effects of different control settings is not particularly suited to real-time control because of the excessive computer time required when used in association with optimization. Therefore, the domain knowledge of the hydraulic simulation model has been captured in a far more computationally-efficient form by means of an ANN. In this context, the ANN is used as a universal mapping function, which relates various input values (or 'neurons') to specified output values via a 'hidden' layer. Whereas the number of neurons in the input and output layers are determined by the nature of the physical network, as represented by the hydraulic simulation model, the number in the hidden layer is largely based on experience, augmented by experimentation where necessary. In order to train the ANN, the hydraulic simulation model must first be run in steady-state mode to generate the required training/testing sets of corresponding input/output vector pairs. For this particular application, the input layer consists of different spatial demand patterns, starting conditions and control settings, whilst the output layer comprises the energy consumption, changes in storage-tank water levels, in addition to any hydrostatic pressures and flow rates at critical points throughout the network. Having trained the ANN with a large number of vector pairs and verified its performance with the testing sets, the ANN predictor is embedded in the optimization process to assist in the search for the optimal-control settings for the current time and each time-step up to the operating horizon.

In most operational optimization methods, the problem specification is simplified by means of assumptions, discretization or heuristic rules. These simplifications make it easier for a specific optimization technique to determine the 'optimal' solution, but may introduce bias by excluding a large number of potentially good solutions. Genetic algorithms (GAs), which have been used in this project, do not require such measures, giving them a significant advantage in finding the global optimal (or at least a near-optimal) solution, over most other optimization methods. GAs are able to search multi-modal decision space and can deal efficiently with non-convexities that cause difficulties for traditional optimization techniques. The methodology is based on the Darwinian theory of natural selection, which relates survival of the fittest to genetic operators such as reproduction, crossover and mutation (Holland 1975; Goldberg 1989). In progressing towards the optimal solution, a new set of artificial offspring is created with each successive generation, using the genetic material from the fittest of the old, with an occasional mutation that might result in an improvement.

Amongst many other types of applications, GAs have been used for water-distribution networks, primarily for design purposes (see Dandy *et al.* 1996). They have also been used for pump scheduling (Mackle *et al.* 1995; Savic *et al.* 1997; Boulos *et al.* 2001; Rao & O'Connell 2002). In both instances, computational efficiency is not particularly important since there is generally no computational time limit for design problems and pump-scheduling programs are normally run only once every 24 h. However, for real-time, near-optimal control, where it is necessary to update the control strategy at short, regular time intervals, in order to accommodate the highly variable demands, computational efficiency is essential. Hence the reason for including an ANN predictor in the control process rather than a conventional hydraulic simulation model. The combination of a GA optimizer and an ANN predictor has been used previously for water-related, computationally-demanding design problems (for example, Rogers & Dowla 1994; Rao & Jamieson 1997; Wang & Jamieson 2002) but this application is believed to be the first case where a GA-ANN has been used for operational control.

USE OF A GENETIC ALGORITHM FOR OPERATIONAL CONTROL

Overview of a GA

As mentioned previously, a GA is a stochastic optimization procedure inspired by the process of biological evolution which, based on probability, allows the fitter solutions to survive and propagate. A GA deals with an initial 'population' of individual solutions, normally generated at random, which are subject to changes caused by the genetic operators of selection, crossover and mutation. Each new solution (or 'offspring') is evaluated and ranked according to its fitness in relation to the objective function, the fitter offspring being more likely to be selected for producing the next 'generation'. After selection, 'parent' offspring are paired and share their 'genetic' characteristics (crossover) to form two new offspring. In order to keep a stable population, the parents tend to be removed and replaced by their offspring, which generally have a better fitness. Occasionally, a mutation is introduced into the population, which may lead to an unexplored area of the decision space, containing fitter offspring. Thereafter, the whole process is repeated. The greater the number of generations, the more likely that the global optimum will be found. However, since the convexity of the objective function cannot be proven, this is not guaranteed. Therefore, in this project, the 'best' solution found after a finite number of generations is referred to as 'near-optimal'

GA structure

As stated by Goldberg (1989), the structure of a GA differs from the more traditional optimization techniques in four major ways:

- a GA typically uses a coding of the decision variables, not the single variables themselves;
- a GA searches within a population of decision-variable sets, not a single decision-variable set;
- a GA uses the objective function itself, not derivative information; and
- a GA uses probabilistic, not deterministic, search rules.

A flowchart depicting a simple GA is given in Figure 1.

A GA requires that the decision variables describing the different combinations of pump and valve settings be represented by a unique coded string of finite length. This coded string is the equivalent of a chromosome in biological evolution. On the basis of Goldberg's recommendation, a binary code has been adopted for this application. Coding and decoding a string is relatively straightforward. Each fixed-rate pump can be represented by 1 bit at each time-step up to the operating horizon. If the pumps were variable speed, several bits would need to be used to represent the different flow rates of each pump: for example, 4 bits would be required to represent 16 flow rates. Similarly, had it been necessary, each valve could be represented by several bits depending on the number of valve settings required, again for each time-step up to the operating horizon. Figure 2 shows a simple example of a coded string for one fixed-rate pump and one valve, assuming a T-h operating horizon.

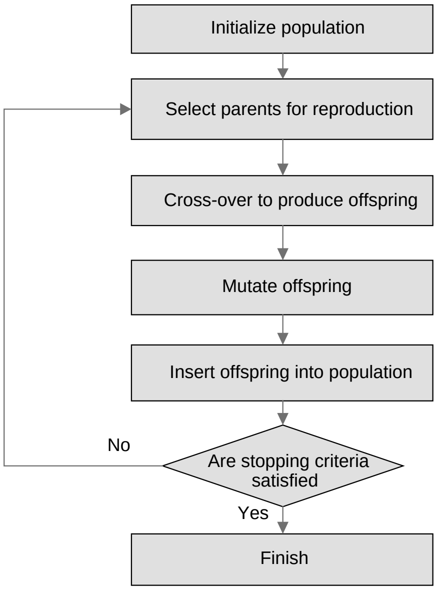
Initialize population
Select parents for reproduction
Cross-over to produce offspring
Mutate offspring
Insert offspring into population
No
Are stopping criteria satisfied
Yes
Finish

Figure 1 | Structure of a simple genetic algorithm.

Given a population consisting of individuals identified by their strings, selecting two strings as parents to produce offspring is guided by a probability rule based on the higher the fitness value an individual has, the more likely that individual would be selected. There are, of course, many different methods of selection available, including weighted roulette wheel, sorting schemes, tournament selection and proportionate reproduction. In this particular instance, tournament selection has been used. Additionally, the so-called 'elitist' principle has been included to improve the rate and consistency of convergence towards the optimal solution. This automatically guarantees the selection of the fittest string in a generation rather than simply having a high probability of selection.

Having selected the parents, the next phase of the reproductive cycle is crossover in which their strings are cut and spliced, one with the other, as if chromosomes were being combined. Since the fitter individuals have a higher probability of producing offspring, the new population will, on average, have a higher fitness value. The basic operator is the one-point crossover where the two selected strings create two offspring by exchanging partial strings, which have been cut at one randomly sampled breakpoint, as shown in Figure 3. Although not practised here, a one-point crossover can easily be extended to a multi-point crossover

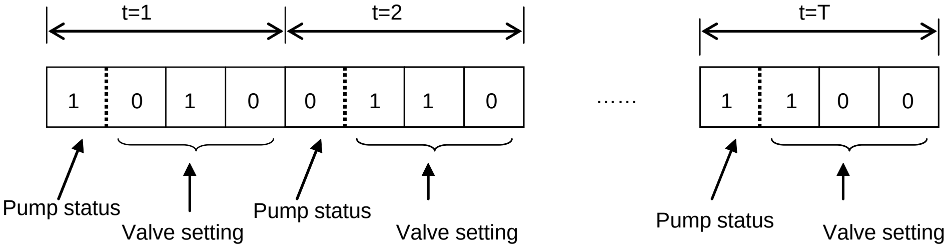

Figure 2 | Coded string for one fixed-rate pump and one valve, assuming 24-h operating horizon.

by having several breakpoints and then exchanging every second corresponding segment of each parent's string.

The remaining genetic operator, mutation, is introduced with a small probability of occurrence at a bit level by randomly altering a bit value from 1 to 0 or vice versa. Again this is in imitation of biological evolution where a small change in the genetic code may lead to a fitter offspring. Its purpose is to ensure that the search process does not converge prematurely at a local optimum rather than continuing to explore other areas of the decision space, which may contain a fitter solution.

Constraint handling

In general, a constrained optimization problem takes the form of

$$\min f(\boldsymbol{x})$$

$$\text{subject to}\, g_m(\boldsymbol{x}) \leq b_m,\ m = 1, \ldots, M$$

$$\boldsymbol{x} = (x_1, x_2, \ldots, x_n),\ x_i > 0,\ i = 1, \ldots N$$

where $f(\boldsymbol{x})$ represents objective function; $\boldsymbol{x} = (x_1, x_2, \ldots, x_n)$ is a set of decision variables; $g_m(\boldsymbol{x})$ is the mth constraint; b_m is the mth constant constraint upper bound; and M is the total number of constraints.

If the problem is continuous and convex, then there is a rich body of constrained optimization theories on which to build a solution algorithm. Although GAs can readily deal with these conditions, a normal GA does not explicitly incorporate constraints into the formulation. Instead, as with many other optimization techniques, the constrained optimization problem is reformulated as an unconstrained optimization problem by incorporating the constraints in the objective function. Any infeasible solutions are penalized.

For this particular application, the multiplicative penalty method (MPM) has been used, in which the objective function is multiplied by a factor proportional to the total amount of violation. The cost multiplier, $\mu(x)$, that penalizes an infeasible string is given by the linear function

$$\mu(x) = 1.0 + \sum \omega_m v_m, \quad m = 1, \ldots, M$$

where ϖ_m are the constraint weights and the constraint violation is measured by

$$v_m = [\max(0, g_m(x) - b_m)], \quad m = 1, \ldots, M.$$

The new objective function is then determined by

$$\mu(\boldsymbol{x}) f(\boldsymbol{x}).$$

If a solution results in no violations for any of the constraints, then $\mu(\boldsymbol{x})$ is 1.0, and the objective function or fitness of the solution remains equal to the original objective function evaluation. The constraint weights, ϖ_m, can be constant or varied with each generation and may be the same or varied for all M constraints. A detailed description of the MPM method and others can be found in the paper by Hilton & Culver (2000).

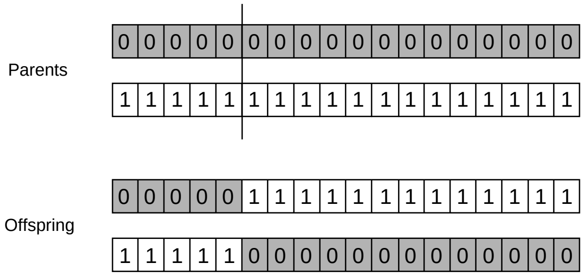

Figure 3 | Single-point crossover between parent strings.

MODEL FORMULATION

Decision variables

In the case of water distribution, the decision variables are the operational control settings of the pumps $\boldsymbol{x}_t = (x_{1t}, x_{2t}, \ldots, x_{Nt})$, $t = 1, \ldots, T$ and valves $\mathbf{y}_t = (y_{1t}, y_{2t}, \ldots, y_{Kt})$, $t = 1, \ldots, T$, for the current time and each time-step up to the operating horizon, where N is the number of pumps, K is the number of valves and T is the number of time-steps up to the operating horizon. For fixed-rate pumps, the decision variable is confined to pump status which can be either off or on, whereas for variable-speed pumps, the decision relates to the actual pump settings controlling the hydrostatic pressures in the network. Operating valves are similar to variable-speed pumps although here the setting is the valve opening controlling the rate of flow. Moreover, whilst the valve settings affect the network hydraulics, they have no associated operating cost and therefore do not feature in the objective function.

Objective function

For water-distribution networks, optimal control has been formulated as an implicit, non-linear optimization problem, subject to both implicit and explicit constraints. The objective function is to minimize the energy costs of meeting the current and future demands up to the operating horizon, whilst at the same time satisfying the physical and standards-of-service constraints, which collectively are referred to as the operational constraints. In mathematical terms, the objective function can be expressed as

$$\text{Minimize} \sum_{n=1}^{N} \sum_{t=1}^{T} C_{nt} E_{nt}(x_{nt})$$

where N represents the number of pumps; T is the number of time steps to the operating horizon; C_{nt} is the unit energy cost of pump n at schedule time of t; E_{nt} (x_{nt}) is the energy consumption of pump n during the schedule time interval from t to $t + 1$ with a specified pump control setting x_{nt}.

In those instances where the distribution network has more than one source of supply and each of those sources has a different unit production cost as a consequence of raw water and treatment costs, then the objective function becomes

$$\text{Minimize} \sum_{n=1}^{N} \sum_{t=1}^{T} C_{nt} E_{nt}(x_{nt}) + \sum_{r=1}^{R} \sum_{t=1}^{T} W_{rt} Q_{rt}(x_{nt})$$

where R represents the number of water sources; W_{rt} is the unit cost of water at source r at schedule time t; $Q_{rt}(x_{nt})$ is the amount of water pumped from source r during the schedule time interval from t to $t + 1$ with a specified pump control setting x_{nt}.

Implicit constraints

The implicit constraints on the network system are the equality constraints defining the equilibrium state of the network, which correspond to the conservation of mass at each junction node and conservation of energy around each loop in the network. These are represented by a set of quasi-linear hydraulic equations that are implicitly solved using a conventional hydraulic simulation model on which the artificial neural network (ANN) is trained. Each function call to the ANN with a set of pump and valve settings returns the simulated steady-state hydraulic equilibrium solution for pipe flow velocities, pipe hydraulic gradients, node pressures and tank water levels as well as power consumption for each pump.

Explicit constraints

The explicit bound constraints on the optimization problem comprise the required network-performance criteria and may include constraints on junction node pressure (P), flow velocity (V), storage tank water level (S) and installed power capacity (IPC).

Pressure constraints

For each operational time interval, the pressure at any junction node j may be bound between a maximum value and a minimum value. This can be expressed as

$$P_{\min j} \le P_{jt} \le P_{\max j} \quad \forall j, \forall t$$

where P_{jt} represents the pressure at node j at time t; $P_{\min j}$ is the minimum pressure required at node j and $P_{\max j}$ is the maximum pressure allowed at node j.

Flow constraints

The velocity (or flow rate) associated with any pipe k during time interval t may be constrained between a minimum and a maximum value expressed as

$$V_{\min k} \leq V_{kt} \leq V_{\max k} \quad \forall k, \forall t$$

where V_{kt} is the flow velocity of pipe k at time t; $V_{\min k}$ is the minimum velocity required at node k and $V_{\max k}$ represents the maximum allowable flow velocity for pipe k.

Water level constraints

A storage tank in a water distribution system must also be operated within a minimum and a maximum allowable water level. The bounds on the tank water levels can be expressed as

$$S_{\min it} \leq S_{it} \leq S_{\max it} \quad \forall i, \forall t$$

where $S_{\min it}$ represents the minimum water storage level allowed at tank i at time t; S_{it} is the water storage level of tank i at time t and $S_{\max it}$ denotes the maximum water storage level allowed at tank i at time t.

Pumping power capacity constraints

The total pumping power at a pumping station may be subject to the installed power capacity expressed as

$$PP_{mt} \leq IPC_m \quad \forall m, \forall t$$

where IPC_m represents the installed power capacity at pumping station m and PP_{mt} is the total pumping power consumption at station m at time t.

APPLICATION OF CONTROL PROCESS TO A HYPOTHETICAL NETWORK

Any Town (Modified) water-distribution network

The paper by Rao & Alverruiz (2007) also contains a brief description of the small, hypothetical water-distribution network that has been used for experimental purposes. This is based on an expanded version of the well-known Any Town network (Walski *et al.* 1987) and is referred to as the Any Town (Modified) or AT(M) network. Figure 4 is a diagrammatic representation of the AT(M) network, which has been modelled by means of the EPANET hydraulic simulation package (Rossman 2000). Subsequently, the knowledge base of the EPANET model was captured in a far more computationally efficient form using an ANN(5,20,7), representing 5 neurons in the input layer, 20 neurons in the hidden layer and 7 neurons in the output layer. The root mean squared error (*RMSE*) of replicating the EPANET model by the ANN was 1.65%. Since the ANN is both quick and accurate in predicting the consequences of different control settings on the performance of the network, this has been used in the near-optimal control process, in preference to the hydraulic simulation model.

Near-optimal control process

Figure 5 depicts the basic GA-ANN control process for given starting conditions, demand profile and energy tariff structure. Initialization of the control settings is random. Thereafter, the control settings are input to the ANN predictor, which estimates the resulting hydrostatic pressures and flow rates at critical points within the network, as well as the water levels in storage tanks and energy usage, at each time-step up to the operating horizon. The fitness value of the string is then evaluated based on the operating costs (energy cost plus production cost, if appropriate) to which the total penalty cost relating to any constraint violations is added. At the outset, this procedure is repeated until there is a sufficient population to engage the GA optimizer when parent strings are selected and subjected to crossover and mutation, thereby producing two new combinations of control settings. These new control settings are input to the ANN predictor and the whole process is repeated until the search is terminated by either some convergence criteria or, as in this instance, a fixed number of generations. The best combination of control settings found at the end of the search process is referred to as the near-optimal solution.

In the case of the AT(M) network, which has 1 source of supply, 3 fixed-rate pumps, 3 storage tanks and 3 critical pressure nodes, it has been assumed that the operating horizon is the usual 24 h and that the time-step is 1 h.

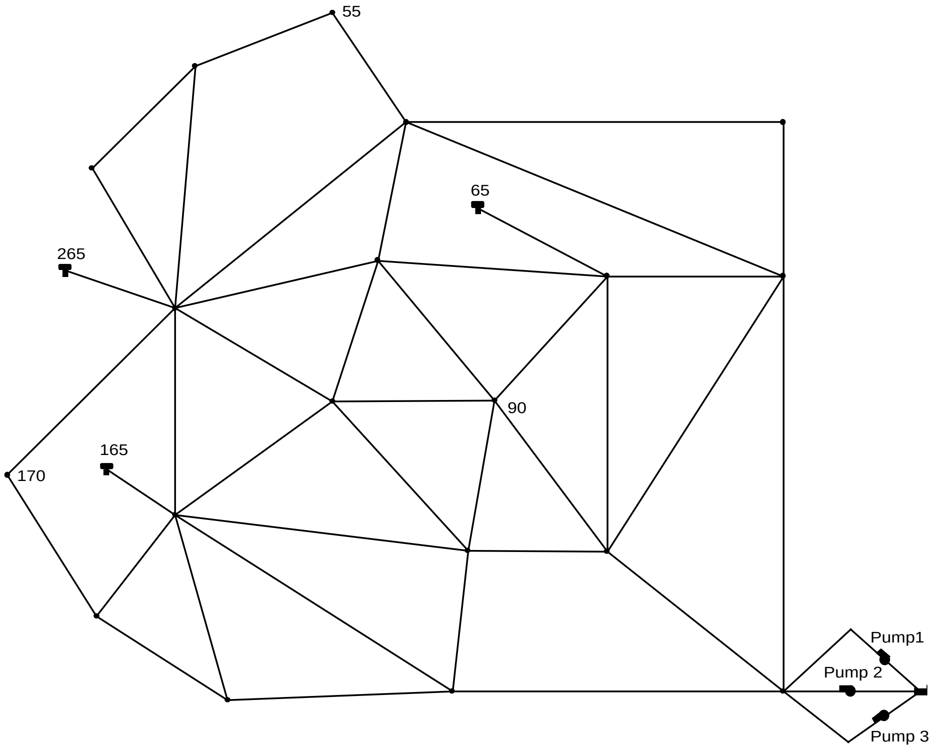

Figure 4 | The Any Town (Modified) water-distribution network.

Therefore, the GA string length is 72 (3 pumps × 24-h operating horizon × 1-h time-step = 72) decision variables. The population size used was 50, with crossover and mutation probabilities of 0.86 and 0.015 respectively. The tournament size for selection was 4 and the maximum number of generations was 20,000. With these parameters and a prescribed operational storage range of between 71.53 m (maximum) and 66.53 m (minimum), the near-optimal control process was run with a series of independent but representative demand profiles. For all three storage tanks, the requirement was that the finishing water level must be the same or above the starting level which was 66.93 m. In essence, these discrete 24-h operating strategies correspond to pump schedules that could have been derived using a pump-scheduling package. However, there is an additional advantage inasmuch that they take account of the operational constraints imposed on the distribution network and could have included valve scheduling, had there been a need.

By way of results, Figure 6 depicts the near-optimal control strategy for a typical 24-h operating period in terms of the number of pumps used at different times, whilst Figure 7 shows the corresponding water levels in the three storage tanks, confirming that each ended the period at or above the original starting level. Moreover, throughout the whole period, hydrostatic pressures can be maintained at or slightly above the designated values of 51 m (node 90), 42 m (node 55) and 30 m (node 170), as evidenced by Figure 8. In computing this control strategy, Figure 9 indicates that the objective function rapidly converges to the near-optimal solution in less than 1000 GA generations.

Dynamic, real-time control process

Having demonstrated that it is possible to derive a near-optimal control strategy for a given 24-h demand profile, the next stage was to develop a *dynamic* version, which was capable of being rolled forward with each update of the SCADA measurements which, in this instance, has been assumed to be 1 h: that is to say, the time-step adopted is 1 h. The way in which this was achieved was first to 'ground'

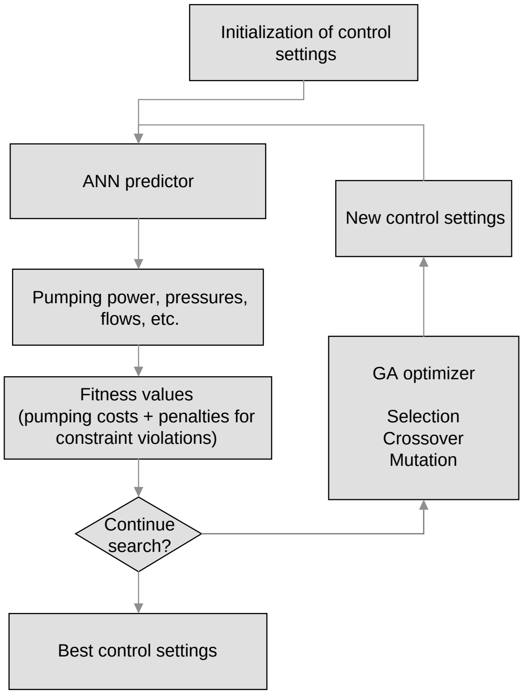
Initialization of control settings
ANN predictor
New control settings
Pumping power, pressures, flows, etc.
GA optimizer
Selection
Crossover
Mutation
Fitness values (pumping costs + penalties for constraint violations)
Continue search?
Best control settings

Figure 5 | The Genetic Algorithm – Artificial Neural Network control process.

any discrepancies between what had been predicted at the previous time step for the current storage-tank water levels and the observed values from the SCADA facilities, since setting the new starting conditions to the actual levels help reduce error accumulation over the period up to the operating horizon which again has been taken to be 24 h. It should also be noted that grounding the errors in the demand forecasts is not required as these errors are automatically compensated in the forecasting methodology developed by Alvisi *et al.* (2007), which comprises the next paper in this special edition.

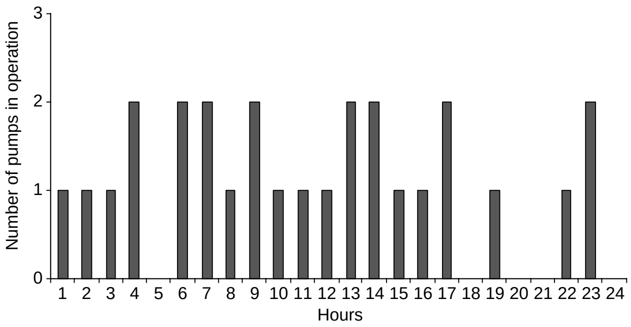

Figure 6 | Near-optimal control pumping strategy for a typical 24-h operating period.

Normally, initialization of the decision variables is random. However, the repetitive nature of *real-time* control offers the prospect of reducing the number of generations necessary to find the new control settings for the next update of the operating strategy which occurs each hour. Since the existing operating strategy for the current time-step is not expected to be radically different from the next, rather than randomly initializing the decision variables at the next update, the contemporaneous portion of the current operating strategy can be used instead. As a result, the number of generations required to find the next operating strategy can be reduced significantly. However, rolling the control process forward leaves a 'loose end' as there are no previous settings to initialize the control settings for time-step 24. Therefore, the control settings for the current time-step are used to initialize those for 24 h later. A loose end can also cause problems for large storage tanks with comparatively small pumping capacities which take a disproportionate amount of time to refill, or if the operating horizon is reduced to less than 24 h for any reason. In these instances, it may compromise the common operational requirement to refill each storage tank to a prescribed level at a given time each morning, since the tendency of the control process is to draw on storage wherever possible, as that is the cheapest option. To avoid this possibility, the storage-tank levels for the current time-step are used to temporarily anchor the loose end 24 h later, as detailed in the later paper by Salomons *et al.* (2007).

As previously, the re-initialized control settings for the next time-step are input to the ANN predictor and GA optimizer, with a view to *adapting* the existing operating strategy to meet the revised demand forecast an hour later. Having computed the new operating strategy, the control settings for the current time are implemented via the SCADA facilities, whilst the remaining portion is retained for re-initializing the control variables, after the update of the SCADA data at the following time-step. This control system is referred to as DRAGA-ANN (Dynamic Real-time Adaptive Genetic Algorithm – Artificial Neural Network), a flow diagram of which is given in Figure 10.

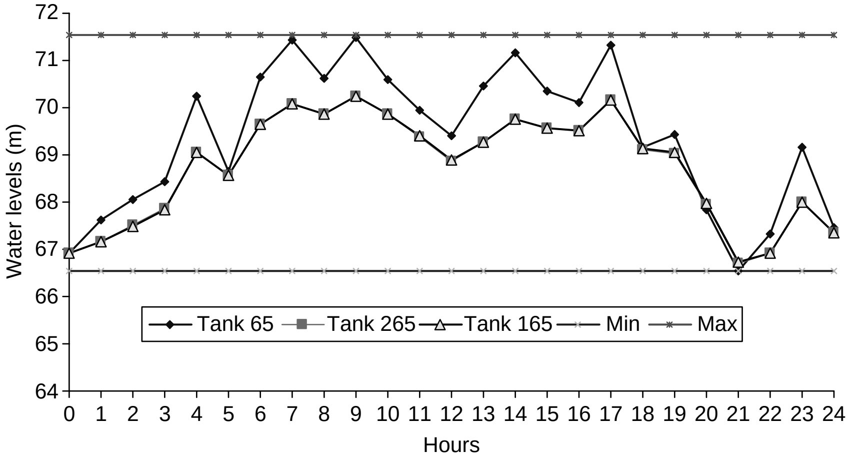

Figure 7 | Corresponding water-level profiles for storage tanks.

Contingency measures

Since water-distribution networks are not 100% reliable, some provision is required for operating the network in the event of a major emergency such as a power outage, pump failure, jammed valve or pipe burst. One option would be to revert to manual control, using the tried and tested contingency plans. However, the question arises as to whether the DRAGA-ANN control system could be used and, if so, under what conditions. Ideally, the aim should be to automatically isolate the failure, re-adjust the control settings and continue to supply as much of the network as possible whilst the fault is repaired. However, from the outset, it was felt that achieving this end was too ambitious with the prevailing state of knowledge. Therefore, a more pragmatic approach was envisaged, which involved operator intervention.

In practice, it is generally found that water-distribution networks have a considerable degree of redundancy, enabling water to be routed around the problem area, albeit with less efficiency than usual. Moreover, if a pump fails, there is usually a standby that can be substituted. If, however, a pump fails and there is no standby, then it is still possible to use the GA-ANN by manually setting the pump capacity to zero and allow the control system to find the best feasible solution with that as an additional operating constraint. Similarly, a jammed valve can be manually set to a fixed position. The only proviso is that all of these possibilities have

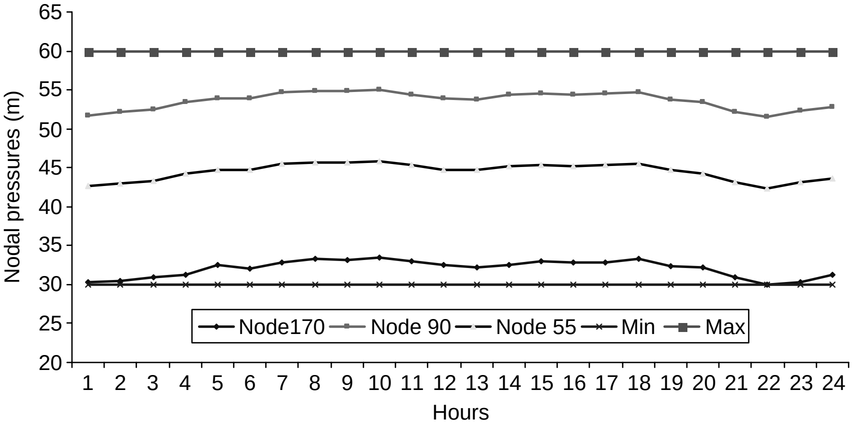

Figure 8 | Corresponding hydrostatic-pressure profiles at critical points.

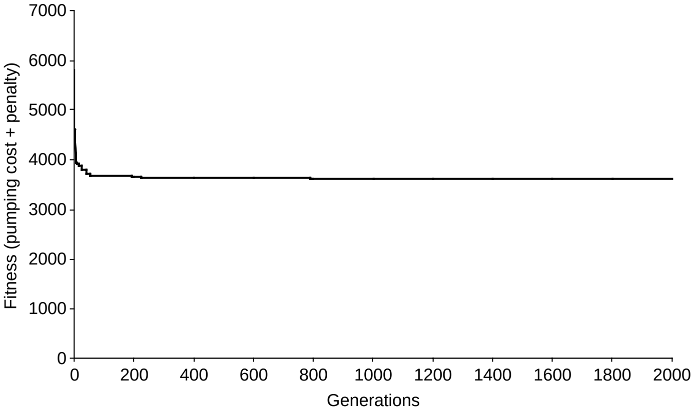

Figure 9 | Convergence of the fitness function in relation to the number of GA generations.

to be anticipated so that they can be included in the ANN predictor. This implies the full range of each pump from zero to maximum capacity and each valve from closed to fully open have to be included within the training sets (see Rao & Alverruiz 2007). The same applies to the installed power capacity at each pumping station, where zero should be included to cater for power outages.

This approach is not possible in the case of a burst pipe which isolates part of the network, as the hydraulic characteristics of the network would have changed which are not reflected in the ANN predictor. Therefore, in these circumstances, there is no alternative to employing GA-EPANET. Since the EPANET model can be easily re-configured to represent the reduced network, it is possible to use GA-EPANET regardless of the burst location, although obviously the computational time increases significantly. As a consequence, it may be necessary to reduce the operating horizon to, say, 12 h in order to complete the computation before the next SCADA update. This restriction adds weight to the argument that the loose end of the control strategy should be anchored as there might not be a prescribed tank storage water level constraint within the revised operating horizon.

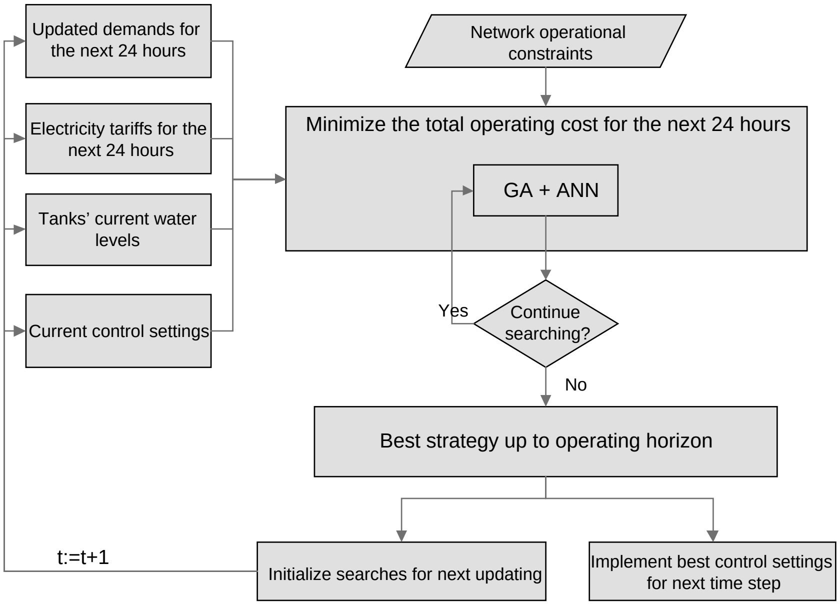
Updated demands for the next 24 hours
Electricity tariffs for the next 24 hours
Tanks' current water levels
Current control settings
Network operational constraints
Minimize the total operating cost for the next 24 hours
GA + ANN
Yes
Continue searching?
No
Best strategy up to operating horizon
t:=t+1
Initialize searches for next updating
Implement best control settings for next time step

Figure 10 | The DRAGA-ANN (Dynamic Real-time Adaptive Genetic Algorithm – Artificial Neural Network) control system.

CONCLUSION

Outcome of experimentation

Experimentation with a small, hypothetical network such as AT(M), was a convenient starting point since it avoided the idiosyncrasies of real water-distribution networks. Despite its simplicity, the AT(M) model has demonstrated that the concept of real-time, near-optimal control of water-distribution networks appears to be a practical proposition. Having replicated a conventional hydraulic simulation model of the network by means of an ANN which is then used to predict the consequences of different control settings, it would seem there are no insuperable difficulties in employing a GA to select the best combination of settings to meet the projected demands. Initially, this was undertaken for a series of separate 24-h runs in much the same way as a pump-scheduling program but with the added advantage of ensuring compliance with the operational constraints imposed on the network. Subsequently, a dynamic version, referred to as DRAGA-ANN, was developed, which automatically rolled the whole control process forward with each update of the SCADA data. By comparing the computational efficiency of the GA-ANN process with that relating to the direct use of the hydraulic simulation model, even for the AT(M) network it was found that run times for calculating the near-optimal control strategy could be reduced significantly: for large, complex networks, the computational gain is expected to be considerably more. With the benefit of hindsight, this implies that the time-step used (which in this case was 1 h) could have been smaller, thereby giving a better approximation to real-time control.

Limitations

Whilst the use of a small, hypothetical network in developing the control process may have been appropriate, it does have some drawbacks. For instance, the AT(M) network cannot be described as ‘representative’ since most real water-distribution networks have not been configured with similar logical forethought. Indeed, the majority have been extended in a haphazard way as a consequence of urban growth. It follows that these will present more of a challenge in deriving the near-optimal control strategy. Nor has it been possible to compare the resulting reduction in operating costs since they do not exist for a hypothetical network. It should also be noted that the AT(M) network does not have multiple sources of supply or operating valves, which are common features in real networks. While both were anticipated at the model formulation stage, the complexities they induced were not known until later. However, all of these issues have, of necessity, been addressed when applying the control system developed to the two case studies (see Salomons *et al.* 2007; Martinez *et al.* 2007).

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