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Genetic Algorithms for Optimal Scheduling of Chlorine Dosing in Water Distribution Systems

Carl Rouhiainen, Curtin University, rouhiacj@ses.curtin.edu.au
Moses O. Tade, Curtin University, tadem@che.curtin.edu.au

EXECUTIVE SUMMARY

This paper presents a new model using a genetic algorithm optimisation technique for determining the optimal schedule of chlorine dosing within a water distribution system considering multiple, competing objectives: disinfection control and aesthetic control. The characteristics of genetic algorithms which solves the optimisation problem in parallel, using a 'population' of potential candidate solutions, makes the genetic algorithm a highly suitable technique for solving multi-objective optimisation problems, in particular for generating a set of Pareto-optimal solutions (a generating-based method). A logical process for multi-objective genetic algorithm development using generating-based methods is to first comprehend the single-objective genetic algorithm problem. To address this, the model formulation is based on the classic weighted-sum approached (a preference-based method) to convert the multi-objective problem into a single-objective problem, by weighting and summing the individual objective functions, to create a "quasi"-single objective function, for solving using a single-objective genetic algorithm. The model is also capable of handling improved nonlinear chlorine decay algorithms by separating the genetic algorithm code from the network simulation code used to calculate the hydraulic and water quality system dynamics.

Six different genetic algorithm models were developed and tested against a hypothetical water distribution system using a single monitoring node, to determine the best model configuration prior to application on a system consisting of 10 monitoring nodes. This was achieved by means of six different scenarios: a simple genetic algorithm (SGA), an elitist genetic algorithm (EGA), and a hybrid (with local search) genetic algorithm (HEGA); each tested using either binary-parameter or gray-parameter representations. Each scenario consisted of four simulations with population sizes 4, 8, 16 and 32 respectively. Of the 24 model configurations evaluated, the best model was determined as the hybrid elitist genetic algorithm using gray-parameter representation, with a population size of 16 ($HEGA_{GP16}$). Overall the hybrid technique was found to produce better results, with 83% of these making up the top 6 model configurations. Gray-parameter representation proved to produce better results than binary-parameter representation, with 67% of these making up the top 12 model configurations.

The best model configuration ($HEGA_{GP16}$) was applied to the hypothetical distribution system, with 10 demand nodes used as monitoring points. Three scenarios were modelled using weighting factors for disinfection control and aesthetic control as 0.25:0.75, 0.50:0.50, and 0.75:0.25 respectively. The results showed that the model was capable of producing the optimal dosing schedule considering the varying weighting factors used. However, the model is sensitive to the weighting factors applied to the two primary objectives and the best dosing schedule depends on some prior knowledge of the priorities

of each of the two primary objective functions. Solving the multi-objective problem using the weighted-sum approach (a preference-based method) has the disadvantage of requiring new runs of the model every time priorities or "preferences" change. To address this limitation, the development of a new multi-objective genetic algorithm model, using a Pareto-based approach (a generating-based method), is in progress.

INTRODUCTION

Controlling the levels of chlorine within the distribution system is an important area for the water industry. Chlorine dosing set points at post-treatment booster stations are typically constant with adjustments only being made on a weekly or seasonal basis, if at all. Due to the diurnal nature of system demand, opportunities exist to optimise the scheduling of chlorine dosing on an hourly basis, via feed-forward predictive optimisation models, to maximise disinfection control and minimise aesthetic concerns within water distribution systems. Existing research clearly demonstrate the need for optimal chlorine scheduling models to help maintain chlorine residuals within the distribution system within prescribed limits (Levi and Mallevialle, 1995 & Uber et al., 1996). Several studies have addressed this problem by developing optimal chlorine booster disinfection scheduling models (Tryby et al., 1997, Boccelli et al., 1998, Tryby et al., 1999 & Nace et al., 2001). Results from this research conclude that there are benefits for industry of using such models.

Existing models have treated the requirements for disinfection control and aesthetic control as constraints, by applying lower and upper chlorine bounds, to maintain chlorine residuals within the distribution system within prescribed limits. By formulating the requirements for disinfection control and aesthetic control as two distinct objective functions, the genetic algorithm (GA) model presented in this paper enables system operators to predefine priorities (preferences) for disinfection and aesthetic control, in the form of disinfection and aesthetic weighting factors.

Existing models have also assumed a first-order chlorine decay algorithm, simplifying the complex nonlinear optimisation problem. Studies have shown that first-order chlorine decay algorithms do not adequately represent the system, due to the complex physical, chemical and biological reactions that occur in water as it travels from treatment plant to customer taps. The model presented in this paper is capable of handling improved nonlinear chlorine decay algorithms by separating the genetic algorithm code from the network simulation.

MODEL FORMULATION

The model formulation is based on a hypothetical water supply scheme. The distribution system (Figure 1) is supplied from a ground water source, with the water being treated at a ground water treatment plant before being pumped to a high-level excavated service reservoir. Long detention times within the service reservoir require the addition of post-treatment disinfection, via a chlorine dosing station (node “CD”) at the outlet of the reservoir. The ‘chlorine-refreshed’ water gravity feeds to services (nodes “1” to “10”) within the distribution system. The service reservoir, dosing station (node “CD”), and distribution system are modelled using the EPANET network hydraulic and water quality simulation package (Rossman 2000). The hydraulic and chlorine decay models are assumed calibrated. For ease of presentation all network details, such as pipe sizes and chlorine decay coefficients, are omitted. System demand is assumed as a periodic 24-hour demand pattern (10-minute timesteps) for the predefined time horizon (72 hours for this hypothetical distribution system). The model is not limited to a periodic demand pattern,

however for ease of presentation the diurnal system demand (Figure 2) is assumed to repeat every 24 hours. The dosing schedule is also assumed as a periodic 24-hour pattern, with each one-hour dose rate (1 to 24) representing a decision variable for the optimisation problem. Curve fitting is used to convert the one-hour timesteps into 10-minute timesteps, for solving using EPANET.

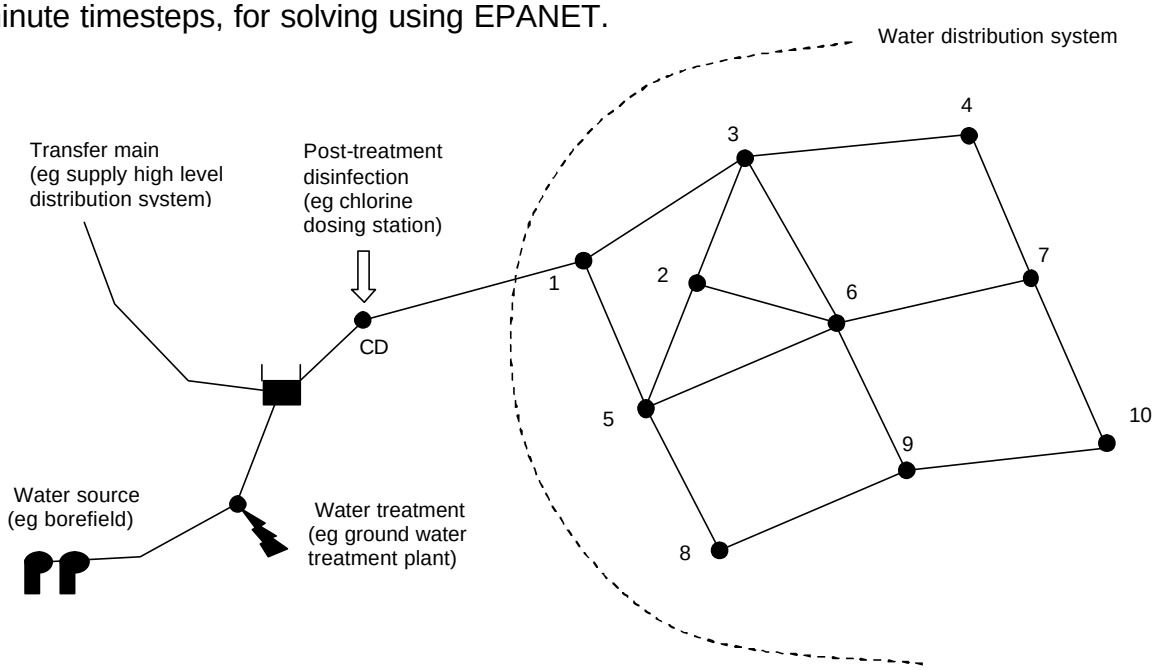

Figure 1 Hypothetical water supply scheme

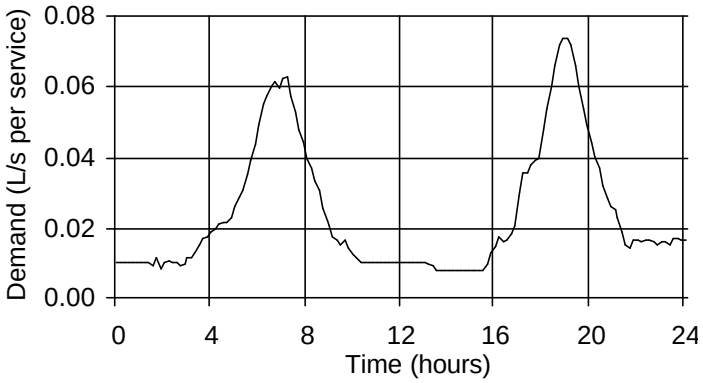

Figure 2 Diurnal demand curve (applied to single equivalent service)

Disinfection Control

Disinfection control is achieved by ensuring an adequate chlorine residual, nominally greater than 0.1mg/L, is maintained at a demand node. This is formulated as a minimisation problem (1).

$$\text{Minimise } F_d = \sum_{m=1}^{M} C_{dc}^m C_{dr}^m \sum_{t=TS_s}^{TS_e} U_d^m N_v^m f_T \qquad (1)$$

where:

m = node m

M = number of nodes monitored for disinfection control

C_{dc}^m = cost coefficient (user defined)

C_{dr}^m = cost rate ($) per service per day (user defined)

t = timestep (nominally 10 minutes)

TS_s = start timestep for monitoring node m

TS_e = end timestep for monitoring node m

N_v^m = number of services at node m

$U_d^m = \left|\min\left[(u - u_{\min}), 0\right]\right|$

u = model predicted chlorine residual (mg/L) at node m at timestep t

$u_{\min}$ = minimimum chlorine residual (mg/L) desired (user defined, nominally 0.1)

f_T = fraction of day (nominally 10/1440)

The cost coefficient is nominally 1.0, whilst the cost rate per service per day reflects the cost to the community associated with the risk of drinking water containing pathogens. The start timestep TS_s, calculated by running EPANET with a short pulse of chlorine at t=0 for chlorine dosing station "CD", is the time of the first non-zero chlorine residual (plus 12 hours) at monitoring node m. The end timestep TS_e is calculated as the sum of the start timestep plus the duration of chlorine dosing (nominally 24 hours). The 12 hour delay is an artificial fix and should be zero, as it was found that EPANET did not initialise immediately and took several hours (after the first non zero value) to stabilise.

Aesthetic Control

The goal of aesthetic control is to minimise taste and odour problems associated with high chlorine residuals, nominally greater than 0.6mg/L. This is formulated as a minimisation problem (2).

$$\text{Minimise } F_a = \sum_{n=1}^{N} C_{ac}^n C_{ar}^n \sum_{t=TS_s}^{TS_e} U_a^n N_v^n f_T \qquad (2)$$

where:

n = node n

N = number of nodes monitored for aesthetic control

C_{ac}^n = cost coefficient (user defined)

C_{ar}^n = cost rate ($) per service per day (user defined)

t = timestep (nominally 10 minutes)

TS_s = start timestep for monitoring node n

TS_e = end timestep for monitoring node n

$U_a^n = \left|\max\left[(u - u_{\max}), 0\right]\right|$

u = model predicted chlorine residual (mg/L) at node n at timestep t

$u_{\max}$ = maximum chlorine residual (mg/L) desired (user defined, nominally 0.6)

N_v^n = number of services at node n

f_T = fraction of day (nominally 10/1440)

The cost coefficient is nominally 1.0, whilst the cost rate per service per day reflects the cost to the community associated with complaints for drinking water with taste and odour problems.

Minimising Volume of Chlorine Used

The model also considers costs associated with operating the chlorine dosing station "CD", such as minimising the total volume of chlorine used. Limiting the total volume of chlorine used is formulated as a minimisation problem (3).

$$\text{Minimise } F_c = \sum_{s=1}^{S}\left(C_{cc}^{s} C_{cr}^{s} \sum_{t=1}^{T} \frac{U_t^s Q_t^s t60}{1000000} \right) \tag{3}$$

where:

s = chlorine dosing node s

S = number of chlorine dosing nodes

t = timestep (nominally 10 minutes)

T = maximum timestep (nominally 144)

C_{cc}^{s} = cost coefficient, for node s (user defined, nominally 1.0)

C_{cr}^{s} = cost rate ($) per kg chlorine used, for node s (user defined)

Q_t^s = flow of water (L/s) at dosing station node s, at time t

U_t^s = chlorine dosing rate (mg/L) for node s, at time t

Minimising Large Variations in Chlorine Dose Rates

Another cost associated with operating the chlorine dosing station "CD" would be to minimising large changes in dosing rates over short time intervals, which may affect the dosing equipment. This is formulated as a minimisation problem (4).

$$\text{Minimise } F_p = \sum_{s=1}^{S}\left(C_{pc}^{s} C_{pr}^{s} \sum_{t=1}^{T-1} U_t^s \right) \tag{4}$$

where:

s = chlorine dosing node s

S = number of chlorine dosing nodes

C_{pc}^{s} = cost coefficient for node s (user defined)

C_{pr}^{s} = cost rate ($) for exceeding maximum range $r_{\max}^{s}$, for node s (user defined)

t = timestep (nominally 10 minutes)

T = maximum timestep (nominally 144)

$U_t^s = \left| \max\left[\left(u_{t+1}^s - u_t^s \right), r_{\max}^s \right] \right|$

u_{t+1}^s = chlorine dose (mg/L) for node s, at timestep $t+1$

u_t^s = chlorine dose (mg/L) for node s, at timestep t

$r_{\max}^s$ = maximum change (mg/L) for node s (defined by user)

The cost coefficient is nominally 1.0, whilst the cost rate for exceeding the maximum range depends on local preferences and operating costs.

Weighted-Sum Approach

The weighted-sum approach is the simplest and most widely used classical approach for solving multi-objective optimisation problems, which (as its name suggests) involves weighting and summing the individual objectives to create a "quasi" single-objective function. If the objectives vary significantly in their order of magnitude, it may be appropriate to scale them (also referred to as normalisation) so that each objective has an equal order of magnitude. It is also the usual practice to choose weights such that their sum is equal to one.

The multi-objective problem defined in this paper consists of four different minimisation functions. However, the researchers are mainly interested in the two primary objectives, disinfection control and aesthetic control, defined in (1) and (2) respectively. The other two objectives, (3) and (4), are not weighted and are treated as constraints, similar to the "penalty method", a common technique for handling constrained genetic algorithm problems. Normalisation is not required in this case, as the researchers are interested in minimising the total cost. For example, it would not be practical to scale up the cost of the volume of chlorine used, as shown in (3), to give this equal priority to disinfection control. The composite function is defined in (5).

$$\text{Minimise } F_{SOGA} = W_d F_d + W_a F_a + F_c + F_p \qquad (5)$$

where:

W_d = weighting factor for disinfection control (between 0 and 1)

W_a = weighting factor for aesthetic control ($W_d - 1$)

SOLUTION PROCEDURE

The minimisation function (5) is solved using a new model, developed using a new genetic algorithm code linked to the existing EPANET network simulation code (EPANET ver 2, Rossman, 2000) used to calculate the hydraulic and water quality system dynamics. Rossman (1999) developed a programming toolkit for EPANET that allows model developers to simplify the tasks required to link the EPANET simulation code to other modelling code, such as a genetic algorithm optimisation model. The independent 'linked' design developed for the new model enables future, improved chlorine decay algorithms to be used without changing the genetic algorithm optimisation code. The structure of the model is shown in Figure 3.

The model was designed to support a population of *individuals*, where each individual has both a *phenotype* and *genotype* structure. Each individual represents one possible solution. The phenotype holds the decision variables, in this case 24 one-hour dose rates, whilst the genotype hold the genetic algorithm *genes* (a decision variable encoded into a series of 0 and 1 bits). The model supports either binary or gray-parameter representations, with adjustable user defined precision's for each dosing rate. The model supports 2-parent tournament selection, multi-point crossover and bit-wise mutation. Experimentation with the model indicated a population size ranging between 4 and 32 may lead to the best convergence rates, when considering the expensive (time consuming) objective function, solved using EPANET. The individuals of the first population are initialised randomly.

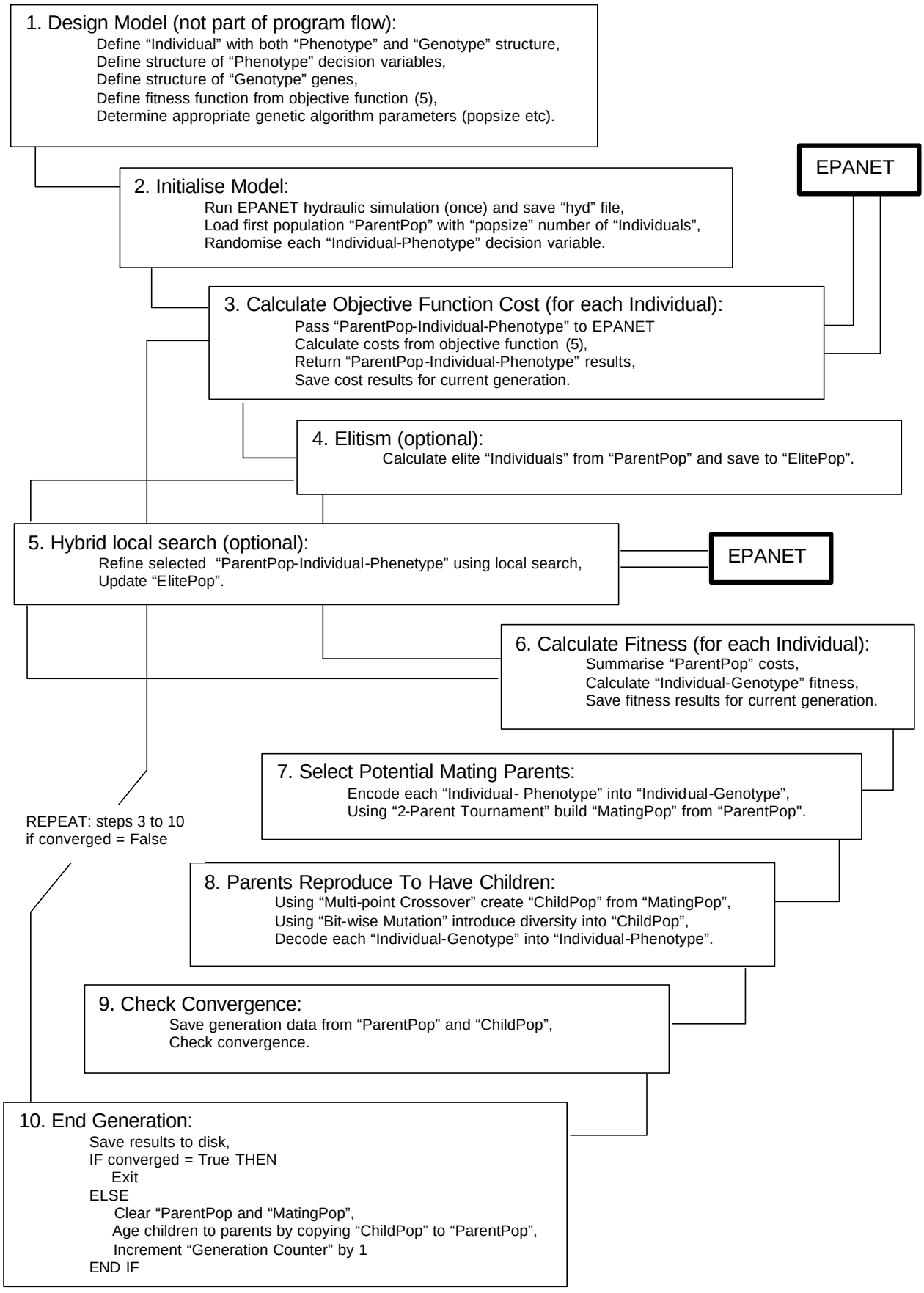

Figure 3 Model program flow diagram

Calculating Objective Function Cost

For each individual in the population, the phenotype representation, which consists of 24 one-hour dose rates, is passed to EPANET. Using the programmer's toolkit provided with EPANET, the chlorine dosing schedule is loaded into the EPANET input file, where each input file consists of distribution system hydraulic and water quality data. EPANET is run and the predicted chlorine residual data for each monitoring node is saved. Given the chlorine dosing schedule, costs for objective function (3) and (4) can be calculated. Using the results from each monitoring node the costs for objective functions (1) and (2) can be calculated. The total cost for each genetic algorithm individual, which represents a potential optimal solution, is finally calculated using (5).

Calculating Fitness

In the simplest terms the genetic algorithm simulates the evolution process of life, whereby the fittest individuals (in this case an individual represents a mathematical solution) are brought together for mating. The concept is that these fit individuals, using the genetic algorithm reproduction process, will pass on "good" parts of themselves to their children, whilst unfit individuals die off. The measure of fitness for each individual can simply be the cost of the objective function (5), where a lower cost represents a fitter individual. However, this can cause confusion for some, where a high fitness has a low cost value. To overcome this, the model uses (6) to calculate the fitness of each individual, using population costs statistics, where the lowest cost individual has a fitness value of 100 and the highest cost individual has a fitness value of zero.

$$\text{Fitness} = 100 * \frac{(C_{\max} - C)}{(C_{\max} - C_{\min})} \tag{6}$$

where:

C = Cost of individual

$C_{\min}$ = Minumum cost of all individuals within population

$C_{\max}$ = Maximum cost of all individuals within population

Convergence Criteria

The end of the first genetic algorithm reproduction process is referred to as the first generation. Future generations are evolved from this first generation, using steps 2 through 8 of Figure 3, until a suitable (ideally optimal) solution is found. To stop the generation process from continuing infinitum a convergence check is required. The model supports three levels of convergence checking. The model stops running when one of the following three criteria (7) is met, whichever comes first.

$$\begin{aligned} &\text{Check 1:} && \text{If } C_{\min} \le C_{stop} \\ &\text{Check 2} && \text{If } r_c \ge r_{stop} \\ &\text{Check 3:} && \text{If } G_c \ge G_{stop} \end{aligned} \tag{7}$$

where:

G_c = Current generation count

G_{stop} = User defined maximum generation count

$C_{\min}$ = Minimum cost of all individuals within parent population

C_{stop} = User defined cost

r_{stop} = User defined check ratio (typically 0.98)

X = User defined (typically 10)

Y = User defined (typically 100)

r_c = Check ratio for current generation $= \left(\sum_{i=G}^{G-X} C_{\min} \Big/ X \right) \Big/ \left(\sum_{i=G}^{G-Y} C_{\min} \Big/ Y \right)$

The Elitist Genetic Algorithm

The genetic algorithm reproduction process may not always lead to better individuals. For example, it is possible that the lowest cost of all individuals within the parent population of generation X is greater than the lowest cost of all individuals within the parent population of generation X-1. To prevent the loss of good solutions an elitist strategy was implemented. The genetic algorithm elitism process saves a set number (*e*%**popsize*) of the best (lowest cost) individuals from each generation into an elite population of size *e*%**popsize*. The elite population of generation X is compared with the elite population of generation X-1 and the best *e*%**popsize* number of individuals of both elite populations replace the individuals within the elite population of generation X.

The Hybrid Genetic Algorithm

The combination of a local search technique is sometimes referred to as a *hybrid* genetic algorithm. The model was developed to support the option of including a local search, the objective being to take the best *h*%**popsize* of the parent population and apply a local search on each individual until a better (if possible) cost is achieved. This is done by randomly picking a decision variable (a one-hour dose rate) and incrementing the value by a small amount, in a random direction (up or down). The modified chlorine dosing schedule is then solved and the cost function (5) calculated. If the cost is lower the process repeats, moving in the same direction until there is no more improvement in cost. If the cost is higher (or the same) the direction of change is reversed and the process repeated in the new direction.

MODEL CONFIGURATION

Prior to applying the model to a hypothetical distribution system (Figure 1) consisting of 10 demand nodes, the model was first tested against a single demand node, to determine the best model configuration. This was achieved by means of six different scenarios: a simple genetic algorithm (SGA), an elitist genetic algorithm (EGA), and a hybrid (with local search) elitist genetic algorithm (HEGA); each tested with either binary or gray-parameter representation. Each scenario consists of four simulations, with each simulation consisting of 5 separate randomly initialised runs. Demand node "10" was chosen as the test node. The schedule for chlorine dosing at node “CD” was defined as 24 one-hour decision variables with lower and upper bounds of 0.2 and 6.0mg/L respectively and a minimum precision of 0.1mg/L. All model configurations used 2-parent tournament for selection and 2-point crossover (probability of 0.8) with bit-wise mutation (probability of 0.02) for reproduction. The convergence check data, as per (7), was defined as: C_{stop} = \$50, r_{stop} = 0.98 (X=10, Y=600), and G_{stop} =3000. The weighting factors for disinfection control and aesthetic control were 0.5 and 0.5 respectively. Data for each scenario are listed in Table 1 through Table 4. Optional parameters were *e*= 20 and *h*= 20.

Table 1 Data for disinfection control, objective function (1)

Scenarios	m	M	C_{dc}^{m}	C_{dr}^{m}	t	TS_s	TS_e	N_v^m	$u_{\min}$
1-6	10	1	1	5000	10	224	368	200	0.097

Table 2 Data for aesthetic control, objective function (2)

Scenarios	n	N	C_{ac}^{n}	C_{ar}^{n}	t	TS_s	TS_e	N_v^n	$u_{\max}$
1-6	10	1	1	5000	10	0	144	200	0.103

Table 3 Data for chlorine volume control, objective function (3)

Scenarios	s	S	C_{cc}^{s}	C_{cr}^{s}	t	T
1-6	CD	1	1	2000	10	144

Table 4 Data for dose change rate control, objective function (4)

Scenarios	s	S	C_{pc}^{s}	C_{pr}^{s}	t	T	$r_{\max}^{s}$
1-6	CD	1	1	3000	10	144	0.5

Scenario 1: Simple GA using Binary Representation (SGA_B)

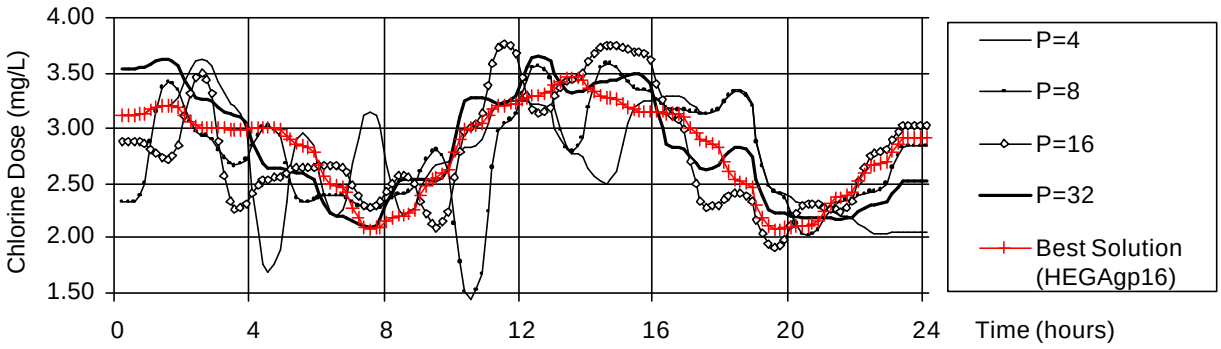

Figure 4 SGA_B - dosing at node "CD" for monitor node "10"

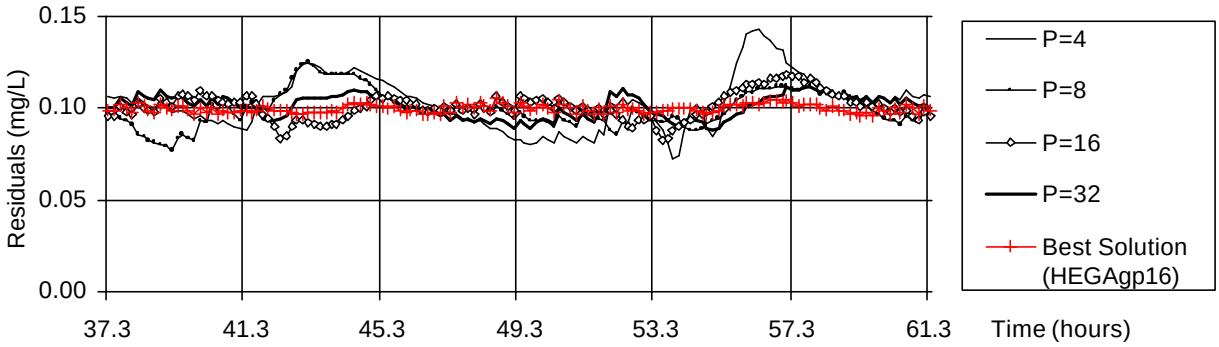

Figure 5 SGA_B - residuals at monitor node "10" (target 0.1mg/L) for dosing at node "CD"

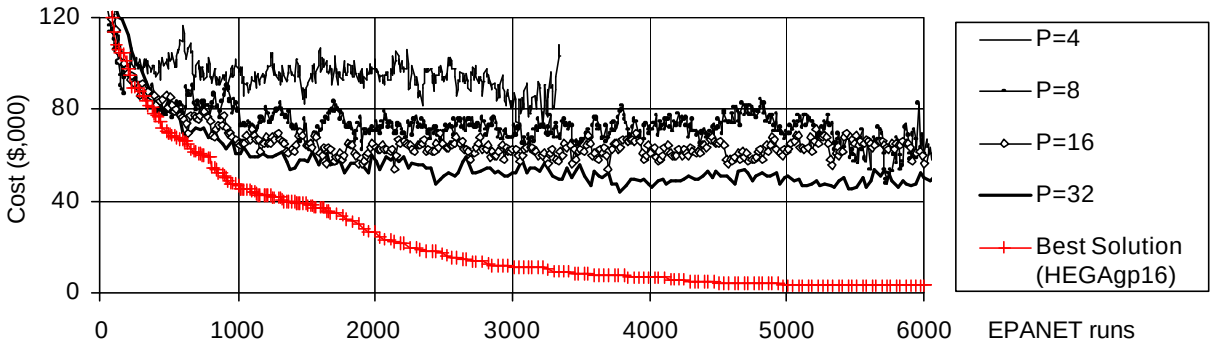

Figure 6 SGA_B - cost versus EPANET runs

Scenario 2: Simple GA using Gray Representation (SGA_G)

The results of the dosing schedule and monitor node residuals for SGA_G follow similar trends as Figure 4 and Figure 5 respectively.

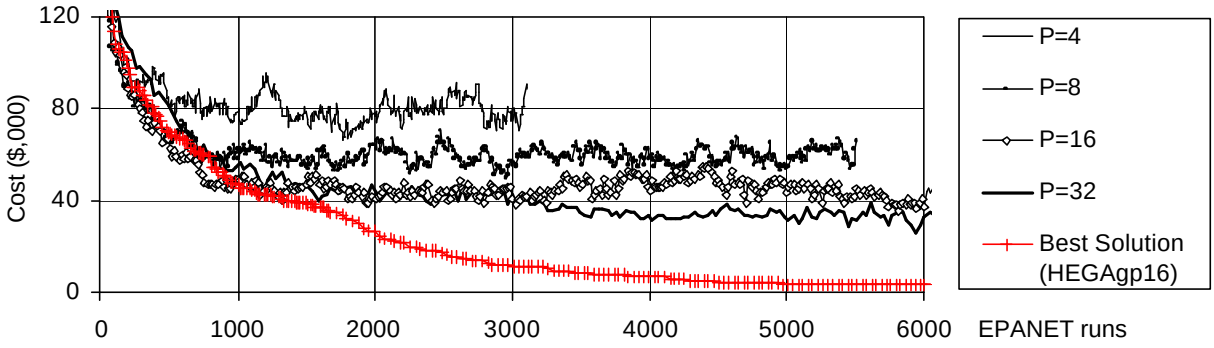

Figure 7 SGA_G - cost versus EPANET runs

Scenario 3: Elitist GA using Binary Representation (EGA_B)

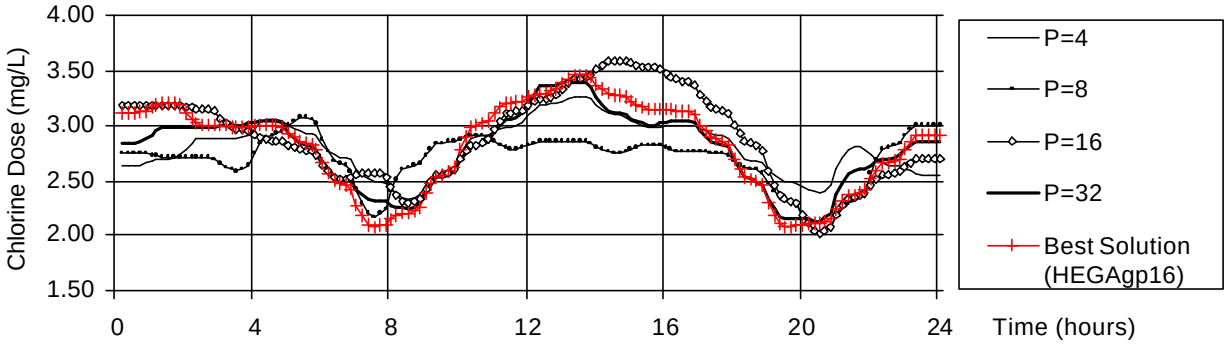

Figure 8 EGA_B - dosing at node "CD" for monitor node "10"

The results of the monitor node residuals for EGA_B follow similar trends as Figure 5, with slight improvement.

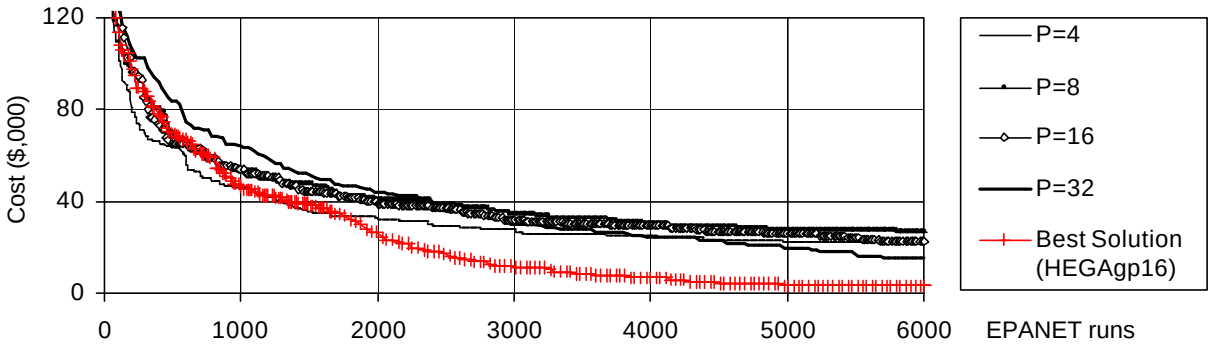

Figure 9 EGA_B - cost versus EPANET runs

Scenario 4: Elitist GA using Gray Representation (EGA_G)

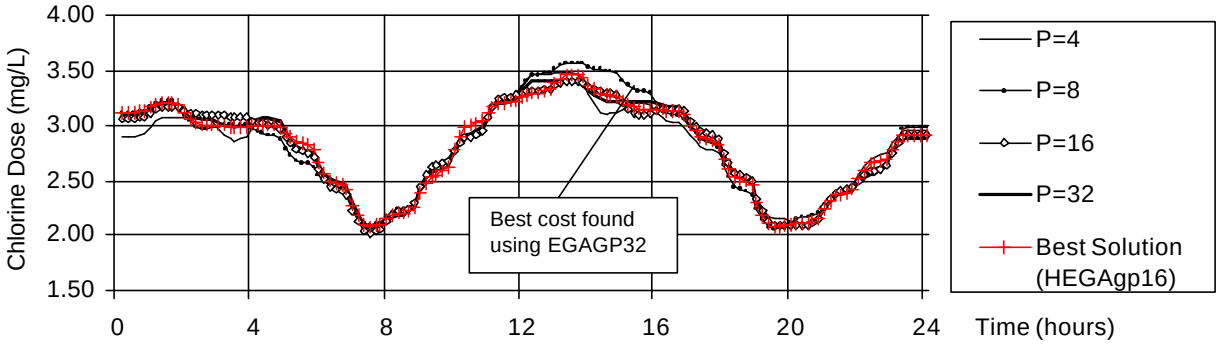

Figure 10 EGA_G - dosing at node "CD" for monitor node "10"

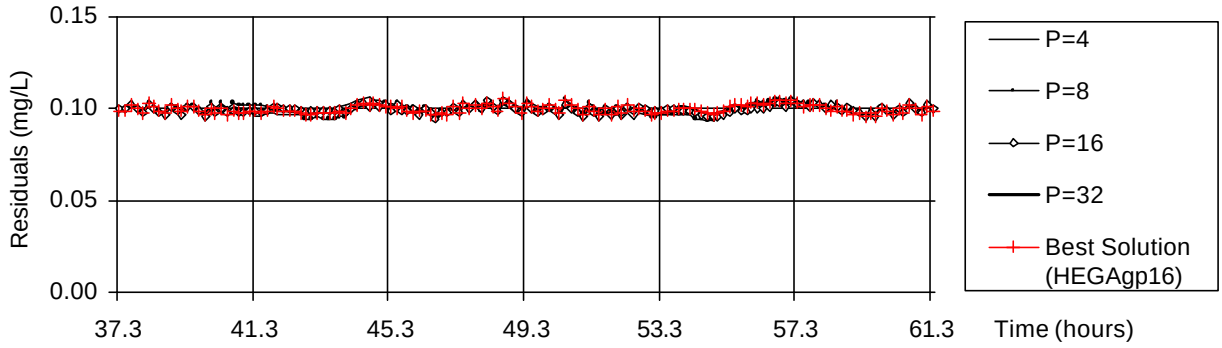

Figure 11 EGA_G - residuals at monitor node "10" (target 0.1mg/L) for dosing at node "CD"

The results for cost versus EPANET runs follow similar trends as Figure 9.

Scenario 5: Hybrid Elitist GA using Binary Representation ($HEGA_B$)

The results of the dosing schedule and monitor node residuals for $HEGA_B$ follow similar trends as Figure 10 and Figure 11 respectively.

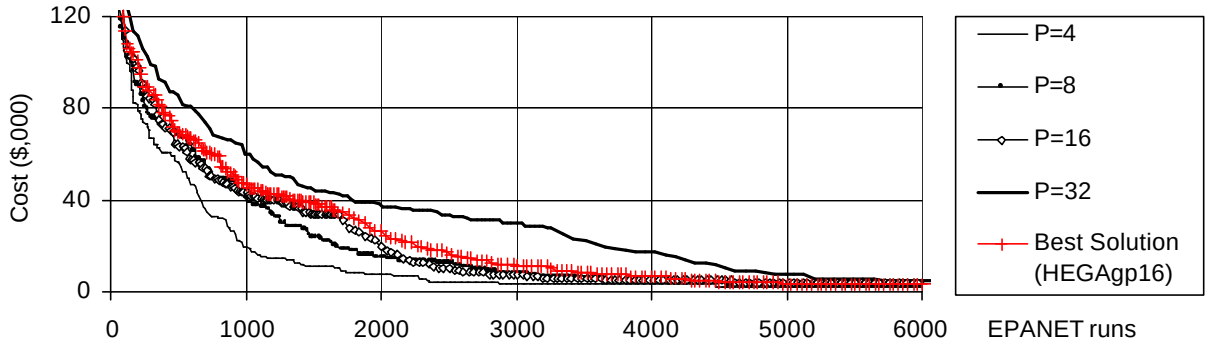

Figure 12 $HEGA_B$ - cost versus EPANET runs

Scenario 6: Hybrid Elitist GA using Gray Representation ($HEGA_G$)

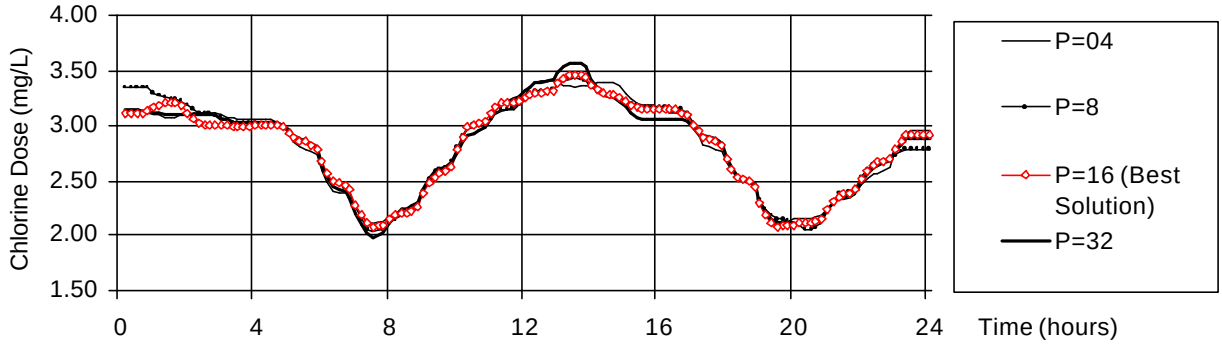

Figure 13 $HEGA_G$ - dosing at node "CD" for monitor node "10"

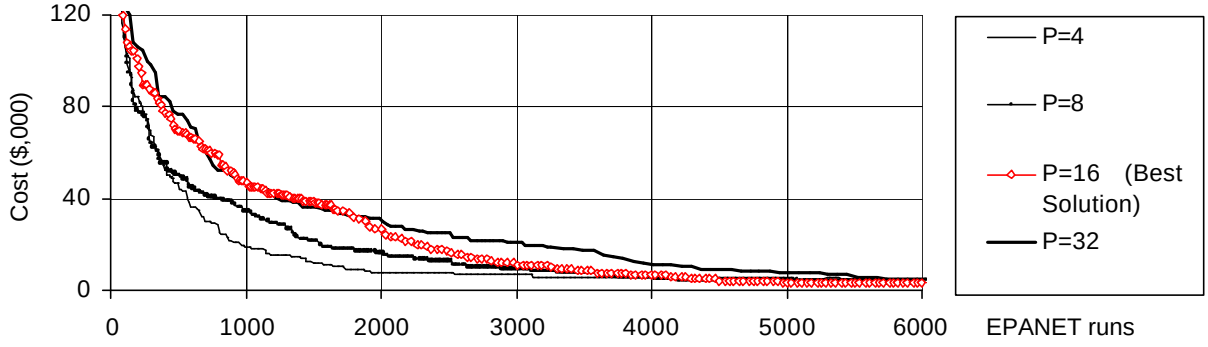

Figure 14 $HEGA_G$ - cost versus EPANET runs

The results of the monitor node residuals for $HEGA_G$ follow similar trends as Figure 11.

Summary of Model Configuration

The simple genetic algorithm (both binary and grey-parameter model configurations) performed fairly, as compared to the best solution provided by $HEGA_{GP16}$. The elitist genetic algorithm models performed better overall, as compared to the simple genetic algorithm models. EGA_{GP32} produced the lowest cost (refer Figure 16). However, when compared to the results obtained from $HEGA_{GP16}$, it was concluded that $HEGA_{GP16}$ was the best (out of 24) model configuration, when considering the computational expense, in terms of the number of EPANET runs. Overall it was observed that simulations with a larger population size were able to obtain a lower final cost. It was also noted that models using grey-parameter representation performed better overall, as compared to models using binary-parameter representation, with 67% of these making up the top12 (out of 24) model configurations. Overall the hybrid technique was found to produce better results, with 83% of these making up the top 6 model configurations. Figure 15 summarises all model configurations. The top 12 of 24 model configurations are shown in detail in Figure 16.

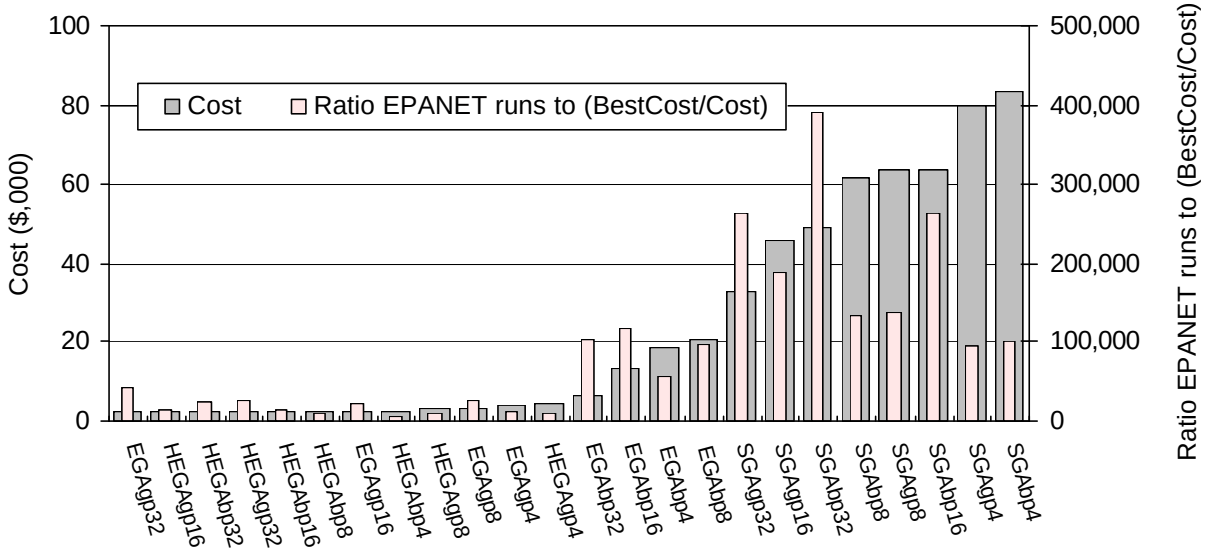

Figure 15 Summary of all model configurations (order of lowest cost)

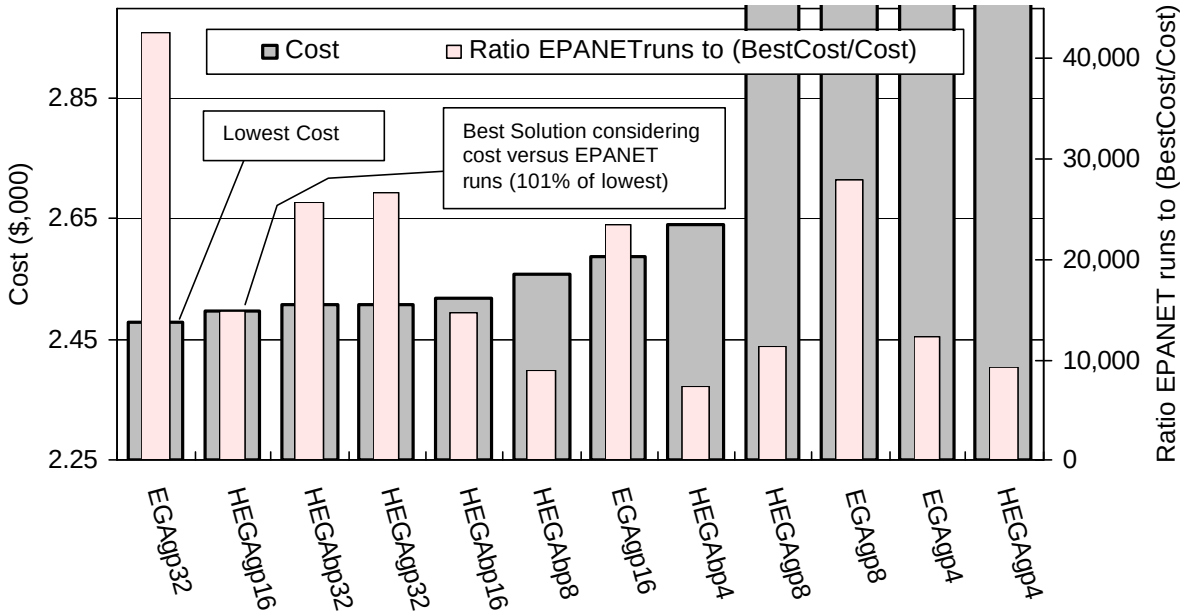

Figure 16 Detailed view of top 12 (of 24) model configurations

MODEL APPLICATION

The best model configuration ($HEGA_{GP16}$) was applied to the hypothetical distribution system, taking into consideration all nodes "1" to "10. Three scenarios were modelled using different weighting factors for disinfection control, to assess the impact this had on the optimal chlorine dosing schedule. Figure 17 shows the results for weighting factors W_d=0.25, 0.50, and 0.75.

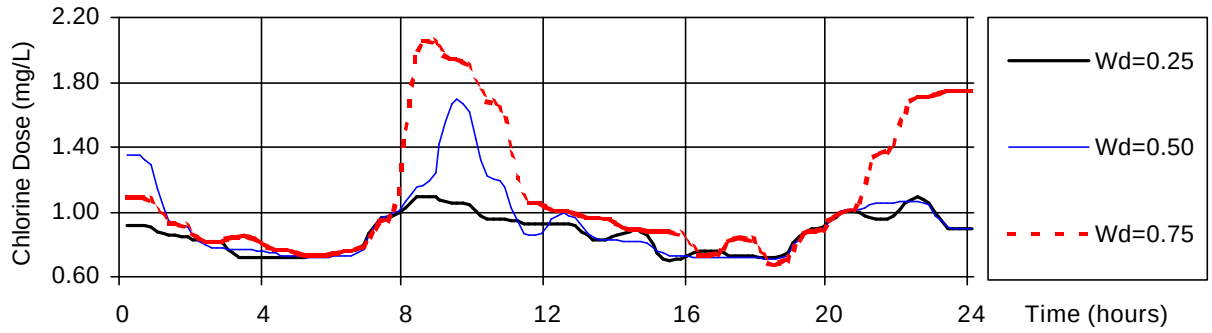

Figure 17 $HEGA_{GP16}$ - dosing at node "CD" for monitoring ALL nodes "1" to "10"

Each scenario converged after approximately 3000 EPANET runs (Figure 18). The time to run each simulation, using a Pentium4™ (2GHz) personal computer, was approximately 25 minutes for each scenario. This is within suitable time requirements for off-line scheduling, considering a scheduling period of 24 hours. It is anticipated that the time to converge to an optimal solution, considering a slightly modified demand pattern at some future time (say 2 hours past first model run), would be decreased dramatically if the model were initialised using results from a previous run.

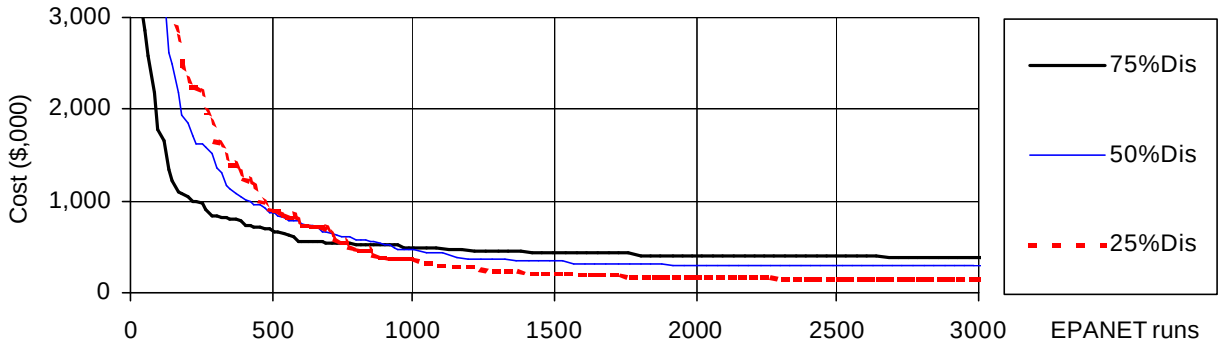

Figure 18 $HEGA_{GP16}$ - cost versus EPANET runs (varying W_d)

Figure 19 shows the results, using W_d=0.5, for three representative nodes within the distribution system, a node closest to the dosing station (node "1"), a node midway (node "6"), and a node furthest from the dosing station (node "10"). It was observed that node "1" had some rapid chlorine residual increases, at around 31 hours. Depending on the degree of change, this could pose a problem for customers as they may notice the changes. However, in the case above, the change is only 0.2mg/L and this would not be a great concern for the hypothetical distribution system. However, to avoid this change rate from becoming too excessive when applying the model to other distribution systems, an additional cost function could be added to (5). The additional cost function could be used to penalise large changes in chlorine residual over a short period, similar to cost function (4).

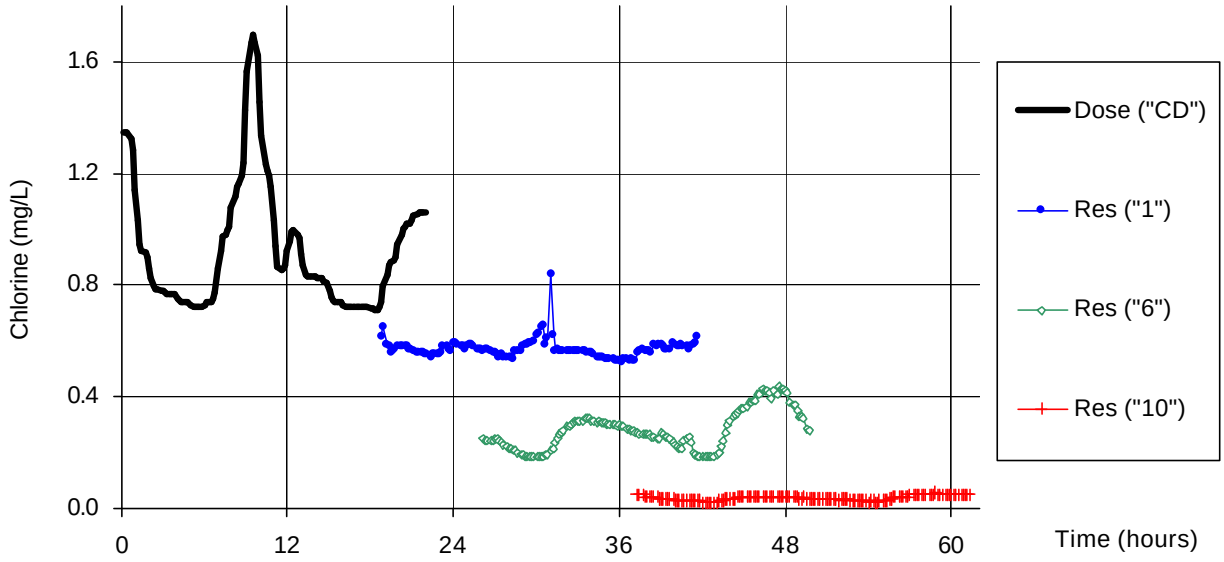

Figure 19 HEGA$_{GP16}$ - Dosing at "CD" with Wd=0.5, showing nodes "1", "6", and "10"

CONCLUSIONS

This paper presented a new model using a genetic algorithm optimisation technique for determining the optimal schedule of chlorine dosing within a water distribution system considering multiple, competing objectives: disinfection control and aesthetic control. The design of the model enables future, improved chlorine decay algorithms to be used with the optimisation model without changing the genetic algorithm optimisation code. The model was developed to support either binary or gray-parameter representations. Six different model configurations were developed and each configuration was tested using a scenario with four different population sizes, applied to a single demand node within a hypothetical distribution system. The first two model configurations were developed based on the "classic" simple genetic algorithm, but slightly modified to include 2-parent tournament for selection and multi-point crossover with bit-wise mutation for reproduction. The next two model configurations were developed to include elitism, which was found to increased the performance of the model, in attaining an optimal chlorine dosing schedule. The last two model configurations were developed as a hybrid genetic algorithm. The hybrid design included a local search technique and was found to outperform all other model configurations. Of the 24 model configurations evaluated, the best model was determined as the hybrid elitist genetic algorithm using-gray parameter representation. Overall gray-parameter representation was found to produce better results, as compared to model configurations using binary-parameter representation. Hybrid model configurations, including the local search technique, performed the best overall, with 83% of these making up the best 6 configurations.

The best model configuration (HEGA$_{GP16}$) was applied to the hypothetical distribution system with 10 demand nodes used as monitoring points. Three scenarios were modelled using weighting factors for disinfection control and aesthetic control as 0.25:0.75, 0.50:0.50, and 0.75:0.25 respectively. The results showed that the model was capable of producing the optimal dosing schedule considering the varying weighting factors used. However, the model is sensitive to the weighting factors applied to the two primary objectives and the best dosing schedule depends on some prior knowledge of the priorities of each of the two primary objective functions. Solving the multi-objective problem using the weighted-sum approach (a preference-based method) has the disadvantage of requiring new runs of the model every time priorities or "preferences" change. To address

this limitation, the development of a new multi-objective genetic algorithm model, using a Pareto-based approach (a generating-based method), is in progress.

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REFERENCES

Boccelli, D.L., Tryby, M.E., Uber, J.G., Rossman, L.A., Zierolf, M.L. and Polycarpou, M.M. (1998) *"Optimal scheduling of booster disinfection in water distribution systems", Journal of Water Resources Planning and Management,* 124(2), 99-111.

Levi, Y. and Mallevialle, J. (1995) *"Global strategy and new tools for maintaining water quality in distribution system", Proceedings of the China Water Supply Association - Safety of Water Supply in Transmission and Distribution Systems,* November, Shanghai, China, 100-108.

Nace, A., Harmant, P. and Villon, P. (2001) *"Optimization of location and chlorine dosage of the booster chlorination in water distribution network", Proceedings of the World Water & Environmental Resource Congress, Bridging the Gap: Meeting the World's Water and Environmental Resources Challenges, eds. Don Phelps and Gerald Sehlke,* May 20-24, Orlando, Florida, pre-conference copy, 11pp.

Rossman, L.A. (1999) *"The EPANET programmer's toolkit for analysis of water distribution systems", Proceedings of the 26th Annual Water Resources Planning and Management Conference,* June 6-9, Tempe, Arizona, 4E, 1-10.

Rossman, L.A. (2000) *"EPANET Users Manual, EPA/600/R-00/057",* United Stated Environmental Protection Agency, Ver 2.

Tryby, M.E., Boccelli, D.L., Uber, J.G., Rossman, L.A., Zierolf, M.L. and Polycarpou, M.M. (1997) *"Optimal scheduling of booster disinfection", Proceedings of the AWWA Annual Conference,* June, Atlanta, GA, Vol C, 375-384.

Tryby, M.E., Boccelli, D.C., Koechling, M.T., Uber, J.G., Summers, R.S. and Rossman, L.A. (1999) *"Booster disinfection for managing disinfectant residuals", Journal of American Water Works Association,* 91(1), 95-108.

Uber, J.G., Summers, R.S., Boccelli, D.C., Koechling, M.T., Tryby, M.E. and Rossman, L.A. (1996) *"Booster Chlorination", Proceedings of the AWWA Annual Conference,* June 23-27, Toronto, Ontario, Canada, Vol D, 197-202.