Multi-Objective Genetic Algorithm for Optimal Scheduling of Chlorine Dosing in Water Distribution Systems

C.J. Rouhiainen & M.O. Tade
Department of Chemical Engineering, Curtin University of Technology, Perth, Australia

G. West
Department of Computing, Curtin University of Technology, Perth, Australia

ABSTRACT: This paper presents two new multi-objective genetic algorithm models using a Pareto-based selection technique for determining the optimal schedule of chlorine dosing within a water distribution system with multiple, competing objectives: primarily disinfection control and aesthetic control. Formulating the optimal dosing problem using a Pareto-based multi-objective genetic algorithm offers water utilities an innovative solution technique, with each optimisation simulation returning a Pareto-optimal set of candidate solutions. An overview of the object-oriented application architecture, encapsulating each model, is also given, including the independent linked design with the water network simulation program. Both models were applied to a hypothetical distribution system, including comparison with existing non-Pareto techniques. Results are discussed, including the advantages of using the new Pareto-based multi-objective models.

1 INTRODUCTION

Chlorine is a common disinfectant used in drinking water distribution systems to ensure customers receive safe, pathogen free drinking water. However, the disinfection potential of chlorine is reduced as water travels through the distribution system interacting with the physical, chemical and biological environment (Powell et al. 2000). To ensure satisfactory chlorine levels at the extremities of the distribution system, dosing of chlorine at the start of the system may need to be high. However, research has shown that high chlorine levels can result in taste and odour problems (Tansley and Brammer 1993) or possible health problems (Chlorine Chemistry Council 1997), caused by excessive disinfection by-products. Therefore, monitoring and controlling the levels of chlorine within the distribution system is an important area for the water industry. To achieve the necessary disinfection control as the water flows from the outlet of the water treatment plant (usual location for post-treatment chlorine dosing) to the customer taps, whilst also satisfying aesthetic control and minimising disinfection by-products, advanced techniques are necessary in order to predict, monitor and control the chlorine levels within the distribution system. One such technique consists of using optimal scheduling models.

Several studies clearly demonstrate the need for optimal scheduling models to help maintain chlorine residuals within the distribution system within prescribed limits (Levi and Mallevialle, 1995 & Uber et al., 1996). This problem has been partially addressed by developing optimal chlorine booster disinfection scheduling models (Tryby et al., 1997, Boccelli et al., 1998, Tryby et al., 1999 & Nace et al., 2001). However, these scheduling models assume 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. To overcome this limitation Rouhiainen & Tade (2003) developed an optimal scheduling model using a single objective genetic algorithm. This model

is capable of handling improved nonlinear chlorine decay algorithms by separating the genetic algorithm code from the network simulation code.

Existing optimal scheduling models solve the problem of disinfection control and aesthetic control by essentially combining these two competing objectives to create a "quasi" single objective problem, for solution using single objective optimization techniques. For example, the most recent scheduling model (Rouhiainen & Tade 2003) uses the classic weighted-sum method, where each objective is assigned a weight (the sum of weights equals one). However, the disadvantages of this approach and other "quasi" single objective formulations are that the trade-off relationships between the two objectives (in this case disinfection control and aesthetic control) are often unknown *a priori* and in the case of the weighted-sum method the model is often sensitive to the weighting factors used.

To address these limitations, this paper presents two new optimal scheduling models using a Pareto-based multi-objective genetic algorithm. The models do not require prior knowledge of objective priorities and each aims to produce a Pareto-optimal set of candidate solutions, where a decision maker, typically a water utility operator or manager, can select the best solution (from the Pareto-optimal set) given new knowledge (post optimisation) of the trade-off relationship between each objective. The models are also capable of handling improved non-linear chlorine decay algorithms by separating the multi-objective genetic algorithm code from the network simulation code, EPANET (Rossman 2000). An overview of the application architecture encapsulating each model is given. Both models were applied to a hypothetical distribution system, including comparison with existing non-Pareto techniques.

2 MULTI-OBJECTIVE OPTIMISATION

Most real-world optimisation problems involve multiple and conflicting objectives that need to be tackled separately while respecting various constraints, leading to an overwhelming problem complexity. If there is more than one objective function and it is preferred that they be treated separately, such as maximising disinfection control whilst minimising aesthetic concerns, the problem is defined as a multi-objective optimisation problem. The general (minimisation) form of a multi-objective optimisation problem given Z objective functions and n decision variables follows:

$$\left.\begin{array}{lll} \text{Minimise} & f_Z(\mathbf{x}), & z = 1,2,...,Z \\ \text{subject to} & \mathrm{g}_J(\mathbf{x}) \geq 0, & j = 1,2,...,J \\ & h_K(\mathbf{x}) = 0, & k = 1,2,...,K \\ & x_i^L \leq x_i \leq x_i^U, & i = 1,2,...,n \end{array}\right\} \quad (1)$$

Equation 1 can also be stated as a maximisation problem by multiplying all Z objective functions by -1. A solution $\mathbf{x}$ is defined as a vector of n decision variables with lower and upper bounds x^L and x^U respectively. The problem can also be subject to J inequality and K equality constraints.

With multi-objective optimisation problems there does not necessarily exist a solution that is best with respect to all objectives. A solution may be best for one objective but worst for another. However, there usually exists a set of solutions, called *non-dominated* solutions, where no improvement is possible in any objective function without sacrificing at least one of the other objective functions (refer to Fig. 1 for an example). This non-dominated set is also referred to as the Pareto optimal set, the admissible set, the efficient points, the non-dominated frontier, or the *Pareto Front* (PF_{TRUE}). Refer to Deb 2001 & Coello Coello et al. 2002 for definitions of domination, non-domination and Pareto-optimal.

Multi-objective optimisation problems have received increased interest from researchers with various backgrounds since early 1960 (Gen and Cheng 2000). In the past few years, there has been an increase in applying genetic algorithms (due to their success) to solving multi-objective optimisation problems, also referred to as evolutionary multi-objective optimisation. The genetic algorithm is a highly suitable technique for solving multi-objective optimisation problems, which solves the optimisation problem in parallel, using a 'population' of potential candidate solutions.

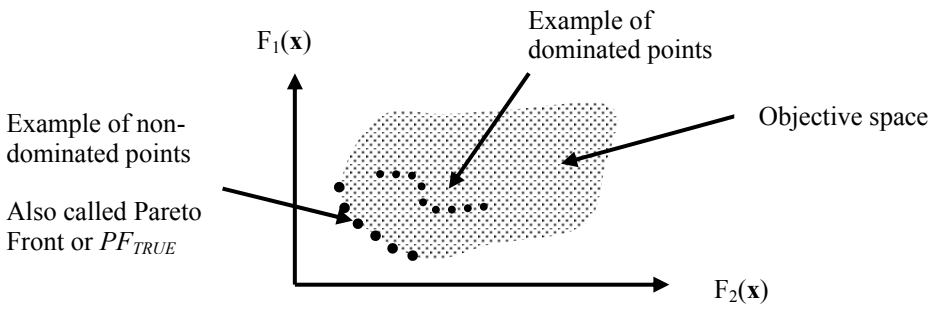

Figure 1. Example of PF_{TRUE} for two-objective (minimisation) problem

3 PROBLEM FORMULATION

The problem presented in this paper has two primary competing objectives: (1) disinfection control and (2) aesthetic control.

Disinfection control is achieved by ensuring adequate chlorine residual, nominally greater than 0.1mg/L, is maintained at all customer demand points within the distribution system. This is formulated as a minimisation problem as shown in Equation 2.

$$\text{Minimise } F_d(\mathbf{x}) = \sum_{m=1}^{M}\left(C_{dr} \sum_{t=TS_S}^{TS_e} \left(\left| \min\left[(u - u_{\min}), 0 \right] \right| \right) S_m f_T \right) \tag{2}$$

where: m=monitor node, M=number of nodes monitored for disinfection control, C_{dr}=cost rate ($ per consumer service per day), t=time interval (nominally 60 minutes), TS_s=start time for monitor node m, TS_e=end time for monitor node m, S_m=number of consumer services at node m, u=model predicted chlorine residual (mg/L) at node m at time interval t, u_{min}=minimum chlorine residual (mg/L) to achieve maximum disinfection control (nominally 0.1mg/L), f_T=fraction of day (nominally 1/24). The cost rate per service per day C_{dr} reflects the cost to the community associated with the risk of drinking water containing pathogens. The start time interval TS_s is the time of the first non-zero chlorine residual at monitoring node m calculated by running the network simulator with a short pulse of chlorine at t=0 at the chlorine dosing station. The end time interval TS_e is calculated as the sum of the start time interval plus the duration of chlorine dosing (nominally 24 hours).

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 as shown in Equation 3.

$$\text{Minimise } F_a(\mathbf{x}) = \sum_{n=1}^{N}\left(C_{ar} \sum_{t=TS_S}^{TS_e} \left(\max\left[(u - u_{\max}), 0 \right] \right) S_n f_T \right) \tag{3}$$

where: n=monitor node, N=number of nodes monitored for aesthetic control, C_{ar}=cost rate ($ per consumer service per day), t=time interval (nominally 60 minutes), TS_s=start time for monitor node n, TS_e=end time for monitor node n, S_n=number of consumer services at node n, u=model predicted chlorine residual (mg/L) at node n at time interval t, u_{max}=maximum chlorine residual (mg/L) for aesthetic control (nominally 0.6mg/L). The cost rate per service per day C_{ar} reflects the cost to the community associated with complaints for drinking water with taste and odour problems. TS_s, TS_e, and f_T are calculated as per Equation 2.

To solve the above multi-objective problem, to produce an optimal 24 hour dosing schedule, a solution **x** represents 24 decision variables, where each decision variable represents a dose rate for each one hour time interval.

4 SOLUTION PROCEDURE

The multi-objective optimisation problem is solved using a new application OGAT (Object-oriented Genetic Algorithm Toolkit), incorporating two new Pareto-based multi-objective genetic algorithm models: (1) a multi-object genetic algorithm ($MOGA_{2o}$) and (2) an elitist multi-object genetic algorithm ($EMOGA_{2o}$). Program flows for each of these models are shown in Figure 2. The structure of OGAT, including an example (using $EMOGA_{2o}$) with typical program flow, is shown in Figure 3.

4.1 *Model Development*

Although $MOGA_{2o}$ and $EMOGA_{2o}$ were designed and developed using all new object-oriented programming code, the fitness assignment algorithm within each model is based on the fitness assignment procedure from the existing Pareto-based multi-objective genetic algorithm (called MOGA) developed by Fonseca and Fleming (1993). Future reference to the MOGA model, within this paper, will be referred to as Fonseca and Fleming's MOGA model. All other citing of the abbreviation MOGA will be short for "multi-objective genetic algorithm".

Coello Coello et al. (2002), presents a comprehensive review of all known multi-objective "evolutionary" algorithms (MOEAs) and specifically suggests using algorithms, such as Fonseca and Fleming's MOGA model, which use known MOEA theory, including Pareto-based selection, niching and fitness sharing.

The main difference between $MOGA_{2o}$ and $EMOGA_{2o}$ is that the latter incorporates elitism. In this case a secondary population is used to store the current non-dominated solutions (NDS) from the set of solutions found so far. In summary this secondary population is combined with the current population of the next generation and better NDS are updated in both populations. This elitism mechanism is initially only a simple algorithm (still under development) and does not include all the necessary features to prevent premature convergence or guarantee diversity along the Pareto Front. However, as will be shown later, preliminary results show the addition of this simple elitism component still proved beneficial.

Both models support binary-parameter or gray-parameter representation, use proportionate fitness selection (stochastic universal sampling), multi-point crossover and bit-wise mutation.

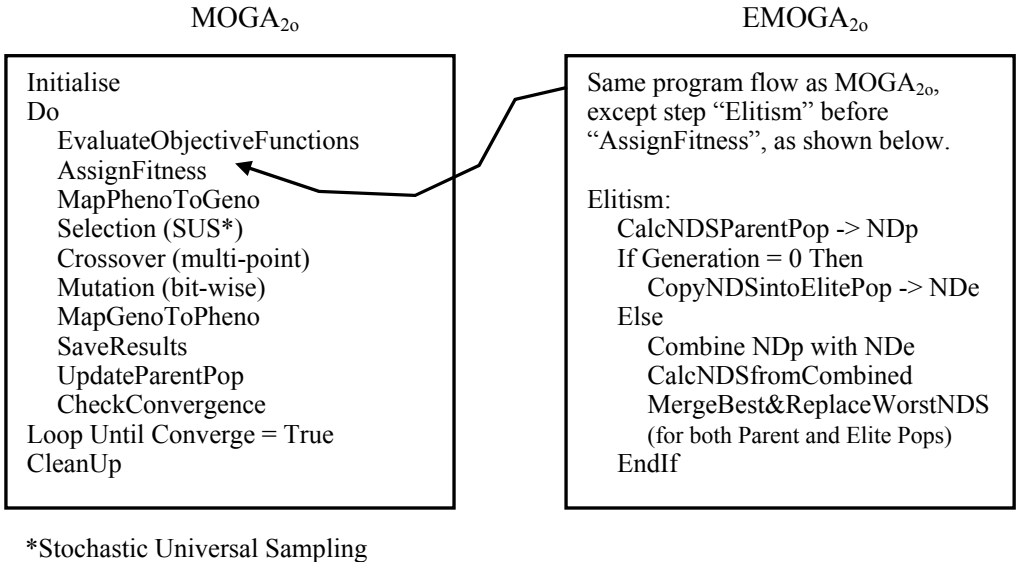

Figure 2. Program flow diagrams for $MOGA_{2o}$ and $EMOGA_{2o}$

4.2 *Software Architecture for Model Implementation*

The new application (OGAT) was designed and developed using several new object-oriented code components linked to an existing network simulation code EPANET (Rossman 2000). New components were written using the Microsoft Visual Basic (VB) programming language and are compiled as either stand-alone executables (VB EXE) or dynamic link libraries (VB DLL). All VB objects support Microsoft's Component Object Model (COM) architecture. EPANET, a free open source Windows™ based application, is used to calculate the hydraulic and water quality system dynamics for the water distribution system. The core network analysis algorithms for EPANET were designed and developed using the C programming language and are packaged as a dynamic linked library (C DLL). EPANET is dynamically linked to OGAT objects using the EPANET Programmer's Toolkit (Rossman 1999).

The overall object-oriented design ensures each major piece of program code is encapsulated from other code and provides a stable framework for future improvements. For example, changes to program code within $MOGA_{2o}$ will not cause unnecessary changes (e.g. errors) to program code within other model components. This ensures the progressive development of a robust genetic algorithm optimisation toolkit.

OGAT has six major components as shown in Figure 3: (1) Main Program, (2), GA Manager, (3) SOGA Manager, (4) MMGA Manager, (5) MOGA Manager, and (6) MO Solution.

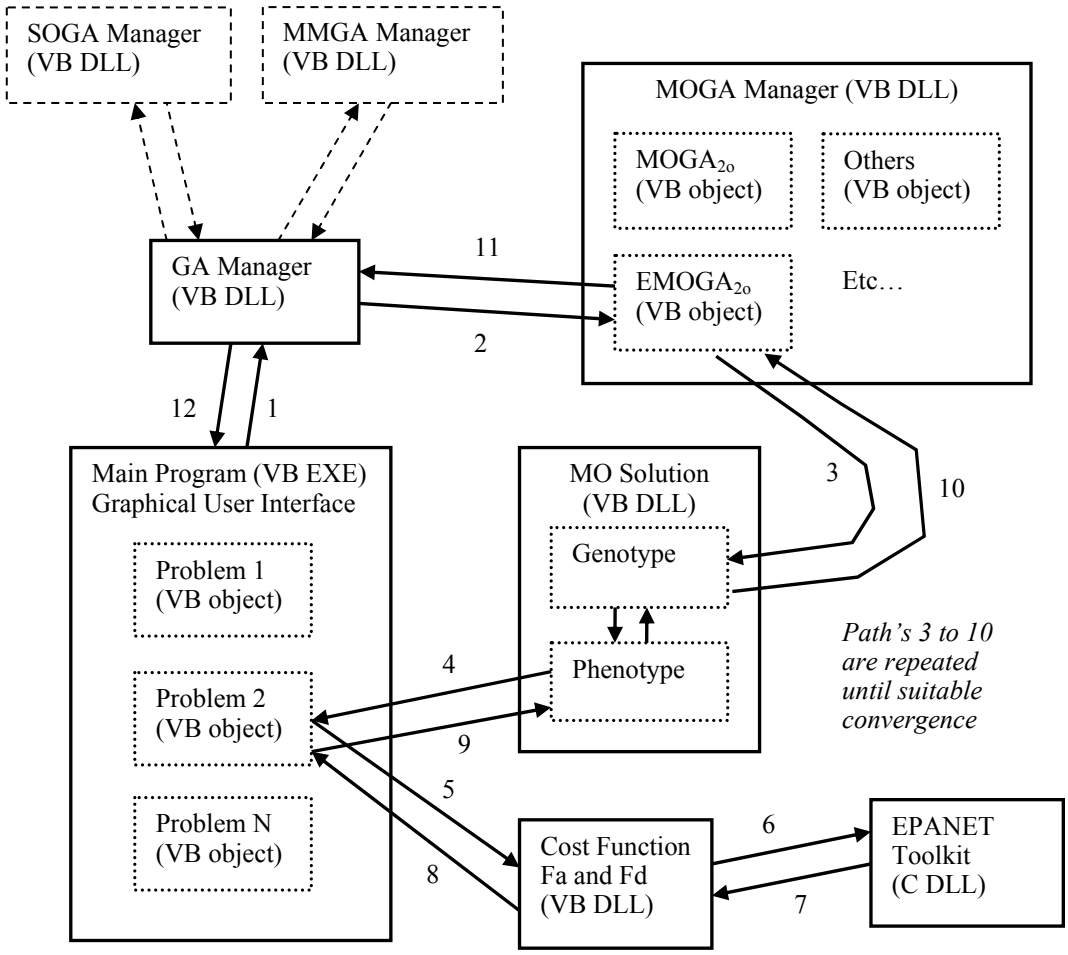

Figure 3. Program flow diagram for OGAT (with example showing program flow for $EMOGA_{2o}$)

The main program provides the graphical user interface and can host multiple single objective (SO), multi-modal (MM) or multi-objective (MO) problems and their associated data. For example, Figure 3 shows the flow paths for a particular multi-objective optimisation problem (called Problem 2) where the Problem 2 "object" contains all relevant (problem specific) optimisation details, such as the number of objective functions (including pointers to any custom function solver) and their definitions, the number of decision variables including minimum precision and lower and upper bounds, and custom load data and save data functions.

The GA Manager hosts three main genetic algorithm model managers, SOGA Manager, MMGA Manager, and MOGA Manager. Due to space limitations, the details of SOGA and MMGA models are not discussed in this paper. The MOGA Manager currently hosts two object models: $MOGA_{2o}$ and $EMOGA_{2o}$. The last major component, MO Solution, contains the code for each solutions phenotype (e.g. decision variables) and genotype (e.g. binary string) structure, including objective function values and associate fitness values. MO Solution also contains the mapping code between the phenotype and genotype structures.

5 MODEL APPLICATION

Both $MOGA_{2o}$ and $EMOGA_{2o}$ models were applied to a hypothetic distribution system (Figure 4). For ease of presentation all network details are omitted. The goal was to produce the Pareto-optimal set of solutions (PF_{TRUE}) by solving Equations 2 and 3. The decision variable bounds, shown in Figure 5, were calculated using the previously developed hybrid elitist (single-objective) genetic algorithm model HEGA (Rouhiainen & Tade 2003). HEGA uses the weighted-sum method to convert the two objective functions (Equations 2 and 3) into a "quasi" single objective problem, for solution using a single-objective genetic algorithm. The lower bound curve was produced using a weighting factor of 1 for 100% aesthetic control (all monitoring nodes below 0.6 mg/L). The upper bound curve was produced using a weighting factor of 1 for 100% disinfection control (all monitoring nodes have a chlorine residuals greater or equal to 0.1 mg/L).

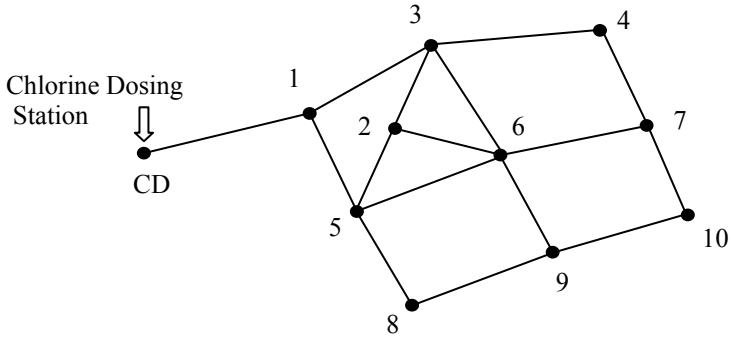

Figure 4. Hypothetical distribution system (showing dosing at node CD and demand nodes 1 to 10)

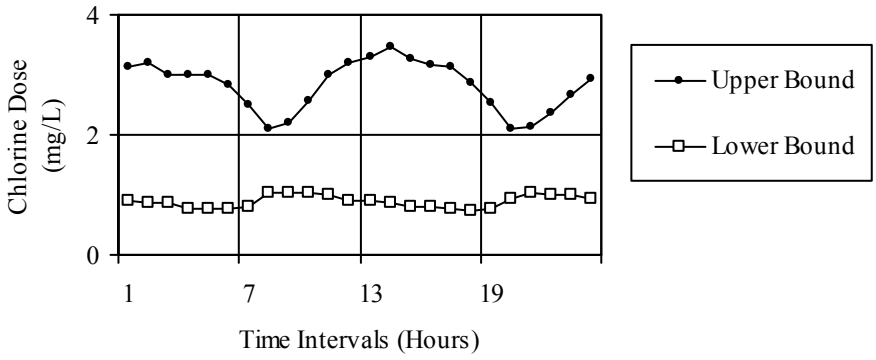

Figure 5. Decision variable bounds calculated using HEGA

5.1 *Finding PF_{TRUE} Using Non-Pareto Model (HEGA)*

To evaluate the effectiveness of the two new models ($MOGA_{2o}$ and $EMOGA_{2o}$) it is often beneficial to know the true Pareto-optimal front (PF_{TRUE}). One way of doing this was by using HEGA (a non-Pareto model), previously developed by Rouhiainen & Tade (2003), which is based on the weighted-sum method. Using a set of seven uniformly spaced weighting factors for aesthetic control, ranging from 0 to 1, seven solutions (which may represent PF_{TRUE}) are compared. As can be seen by Figure 6, uniformly spaced weighting factors do not always equate to uniformly spaced solutions. Five additional solution points had to be found using trial and error weighting factors, between 0.01 and 0.1245, to determine the approximate curve for PF_{TRUE}.

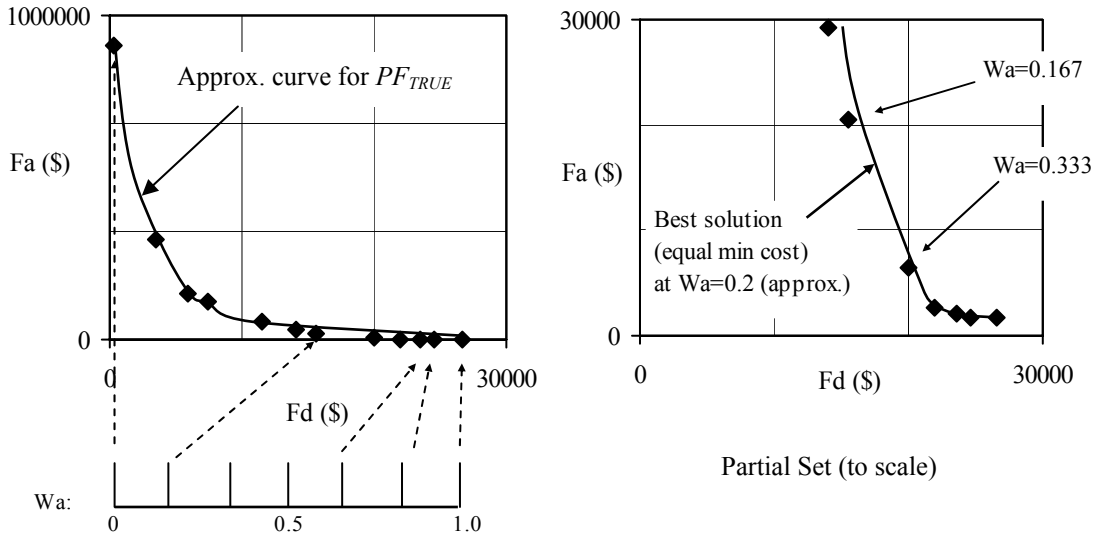

Figure 6. Approximate PF_{TRUE} using HEGA (single-objective weighted-sum method)

5.2 *Finding PF_{TRUE} Using Enumeration*

Another way to determine PF_{TRUE} is using enumeration. An attempt was made to find PF_{TRUE} by solving all possible solutions Fx_{ALL} and calculating the non-dominate set PF_{TRUE} from Fx_{ALL}.

Using the lower and upper bounds shown in Figure 5 and assuming a minimum desired precision of 0.1 mg/L per decision variable, the total search space equates to 2.02E+31 possible solutions. Considering each solution requires running the EPANET network simulation (to evaluate the objective functions defined in Equations 2 and 3) and estimating the simulation time as 0.05 seconds per solution, the total time to do full enumeration is estimated as 1.17E+25 days. Therefore, finding PF_{TRUE} using total enumeration is not feasible.

Although it was not possible to use enumeration to find PF_{TRUE}, enumeration can still provide valuable information about the density of the objective space and possibly the "landscape" of the search space. Using partial enumeration 10,000 random points were evaluated (from within the search space) and 10,000 solutions in objective space were plotted alongside the approximate curve for PF_{TRUE} found previously using HEGA. Figure 7 shows two examples graphing the density of objective space using two different decision variable precisions.

The left graph assumes a minimum decision variable precision of 0.1 mg/L. The total number of solutions plotted equates to only 4.95E-26% of the total possible search space. The right graph assumes a maximum possible precision, calculated by assuming two dose values per decision variable: the lower bound and the upper bound (see Fig. 5). The total number of solutions plotted equates to 5.96E-02% of the total search space. The results shown in Figure 7 indicate that the majority of solutions lie near the centroid defined by: Fa = $300,000 and Fd = $10,000. As will be shown later, the density of solutions within the object space hinders the ability of the new Pareto-based models to find all points within PF_{TRUE}.

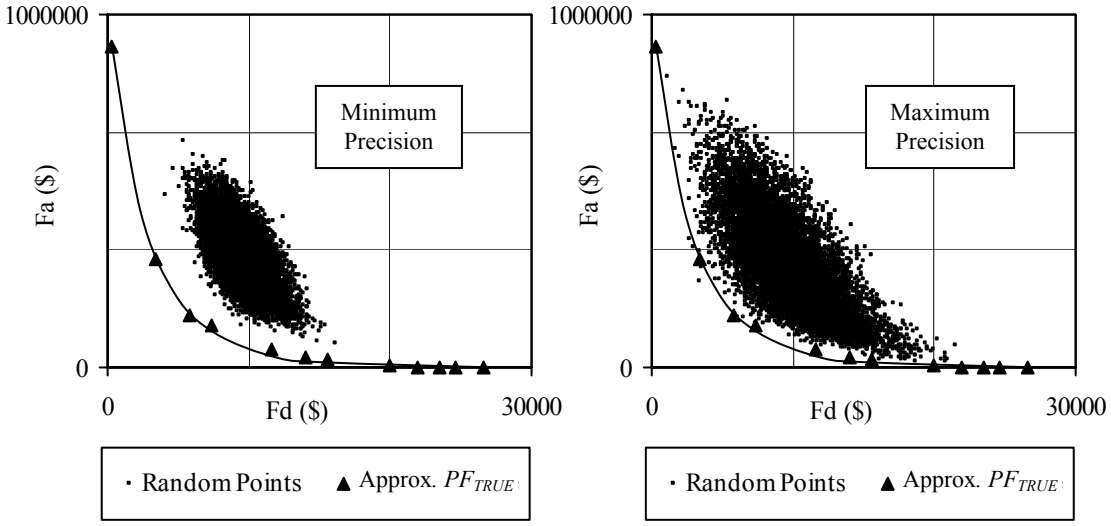

Figure 7. Density of objective space using partial enumeration (10,000 random points)

5.3 *Finding PF_{TRUE} using a Pareto-Based Model ($MOGA_{2o}$)*

A good Pareto-based MOGA model should find all points within PF_{TRUE} as well as maintain diversity along the Pareto-optimal front. As with single-objective genetic algorithm models most MOGA models also require "tuning" of parameters, such as population size (N), probability of crossover (Pc) and probability of mutation (Pm). Without prior knowledge of algorithm performance the following nominal starting parameters are commonly used: N=100, Pc=0.9, and Pm=0.01. Figure 8 shows the last generation of non-dominated solutions, using a population size N=100 (left graph) and N=500, for example, (right graph).

In this example, increasing the population size improves the model's ability to find more points in PF_{TRUE}. However, it was observed that (without an elitism preserving strategy) some Pareto-optimal solutions found in previous generations were lost from the final generation. Hence, the motive for developing an elitist version of $MOGA_{2o}$, called $EMOGA_{2o}$.

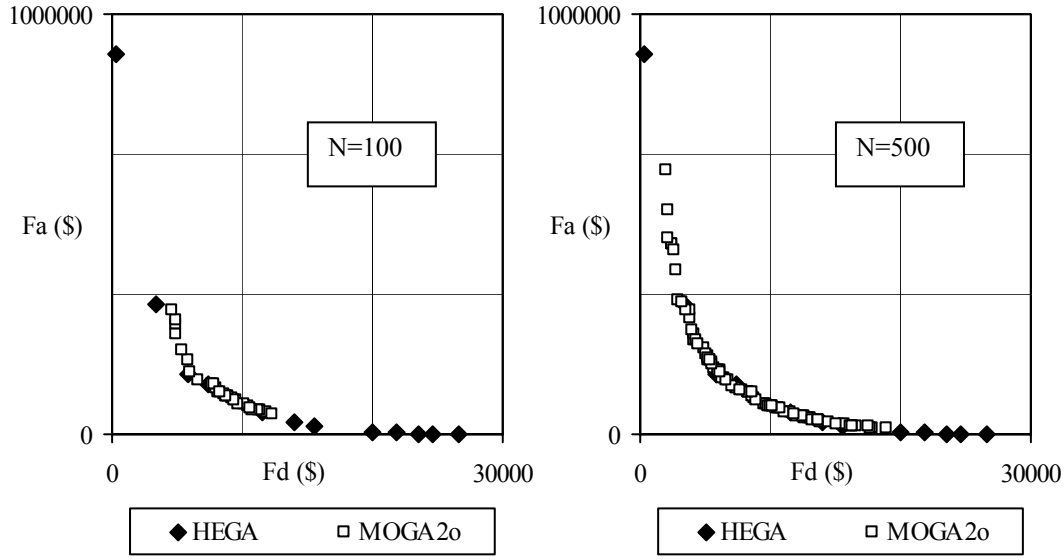

Figure 8. Non-dominated solutions (approximate PF_{TRUE}) using $MOGA_{2o}$ (N = 100 and 500)

5.4 *Finding PF_{TRUE} using an Elitist Pareto-Based Model ($EMOGA_{2o}$)*

The elitist version of $MOGA_{2o}$ ($EMOGA_{2o}$) can find more points along the Pareto-optimal (near optimal) front. We say near optimal as we do not know the true Pareto-optimal front (PF_{TRUE}). However, as can be shown by Figure 9, the current elitism technique is sensitive to the probability of mutation (*Pm*). To overcome this, the addition of a niching technique is required to preserve diversity along the Pareto-optimal front. Nonetheless, with a little tuning, $EMOGA_{2o}$ still provides significantly better results than $MOGA_{2o}$ or other non-Pareto methods.

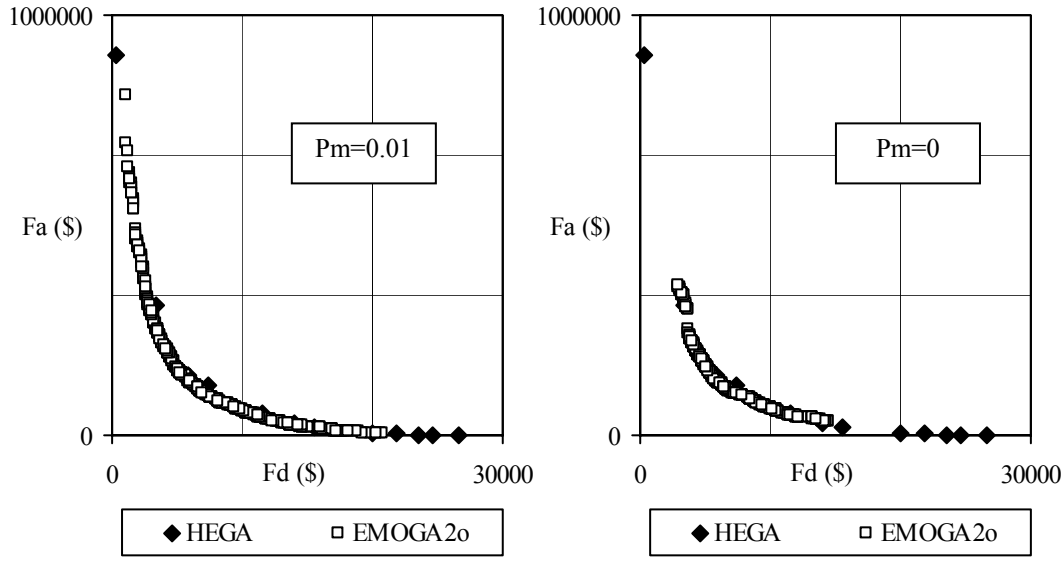

Figure 9. Non-dominated solutions (approximate PF_{TRUE}) using $EMOGA_{2o}$ (Pm = 0.01 and 0)

6 CONCLUSIONS

This paper presents two new multi-objective genetic algorithm models ($MOGA_{2o}$ and $EMOGA_{2o}$) which use a Pareto-based selection technique for determining the optimal schedule of chlorine dosing within a water distribution system considering multiple, competing objectives: primarily disinfection control and aesthetic control. An overview of the model structures were given, including the new object-oriented application framework.

To evaluate the effectiveness of each new model's ability to find the true Pareto-optimal front (PF_{TRUE}) existing non-Pareto based techniques were used in an attempt to find PF_{TRUE}. The first attempt used an existing weighted-sum model (HEGA). Although several points along the Pareto-optimal (near optimal) front are found, the weighted-sum method has the disadvantage of requiring prior knowledge from a decision maker about the trade-off relationships between the varying objective functions. In most real world optimisation problems this is not known *a priori*. Furthermore, although an approximate PF_{TRUE} can be found using several different weighting factors, this is a trial and error process and requires new model runs for every new weighting factor. It was concluded that, for the purpose of finding PF_{TRUE}, HEGA is not an effective model.

Given the enormous size of the search space it was concluded early in the investigation that enumeration was not a practical method of finding PF_{TRUE}. However, partial enumeration provides an insight into the "landscape" of the objective space, in particular the density of this space. It was concluded that the dense region within the objective space hindered both the $MOGA_{2o}$ and $EMOGA_{2o}$ model's ability to find certain points within PF_{TRUE} that lie towards the two extreme ends of the front, where the objective function space is sparse. Upon further review of literature it was found that the fitness assignment algorithm adopted from Fonseca and Fleming's (1993) MOGA model is sensitive to the density of the objective space (Deb 2001).

Therefore, it is recommended that both $MOGA_{2o}$ and $EMOGA_{2o}$ be evaluated using a modified fitness assignment method, based on other proven Pareto-based MOGA models, such as that used by Horn and Nafpliotis (1993) or Srinivas and Deb (1994), for example.

Finally, it is concluded that $EMOGA_{2o}$ performed better overall as compared to existing non-Pareto methods, including $EMOGA_{2o}$'s companion model $MOGA_{2o}$.

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.

Chlorine Chemistry Council, Ed. 1997. Drinking Water Chlorination White Paper: A Review of Disinfection Practices and Issues, Chlorine Chemistry Council.

Coello Coello, C.A., Van Veldhuizen D.A., & Lamont, G.B. 2002. *Evolutionary Algorithms for Solving Multi-Objective Problems*. New York: Kluwer Academic.

Deb, K. 2001. Multi-Objective Optimization Using Evolutionary Algorithms. John Wiley & Sons: Chichester

Fonseca, C.M. and Fleming, P.J. 1993. Genetic algorithms for multi-objective optimisation: formulation, discussion and generalisation. In S. Forrest (ed), *Proceedings of the 5th International Conference on Genetic Algorithms, Urbana, Illinois*. 416-423.

Gen, M. and Cheng, R. 2000. *Genetic Algorithms & Engineering Optimization*. New York: John Wiley & Sons, Ltd.

Horn, J. & Nafpliotis, N. 1993. *Multiobjective optimisation using the Niched Pareto Genetic Algorithm*. Technical Report IlliGAl Report 93005, University of Illinois at Urbana Champaign, Urbana, Illinois, USA.

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 1995*, Shanghai, China.

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, May 20-24, Orlando, Florida*. In D. Phelps and G. Sehlke (eds), Bridging the Gap: Meeting the World's Water and Environmental Resources Challenges.

Powell, J.C., Hallam, N.B., West, J.R., Forster, C.F. and Simms, J. 2000. Factors which control bulk chlorine decay rates. *Water Research*. 34(1): 117-126.

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*. Vol 4E: 1-10.

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

Rouhiainen C.J. & Tade M.O. 2003. Genetic Algorithms for Optimal Scheduling of Chlorine Dosing in Water Distribution Systems. *Proceedings of the 20th Convention of the Australian Water Association, 6-10 April 2003*. Perth, Australia. 1-16

Srinivas, N. & Deb, K. 1994. Multiobjective Optimization Using Nondominated Sorting in Genetic Algorithms, *Evolutionary Computation*. 2(3): 221-248.

Tansley, N.S. and Brammer, L.F. 1993. Chlorine residual modelling in distribution – the importance of taste and the maintenance of effective disinfection, In B. Coulbeck (ed), *Integrated Computer Applications in Water Supply - Applications and Implementations for Systems Operation and Management (vol 2)*. Research Studies Press Ltd: 111-126.

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.