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EVOLUTIONARY COMPUTING TECHNIQUES FOR OPTIMAL PRESSURE REGULATION IN WATER DISTRIBUTION NETWORKS

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This paper addresses the problem of appropriate electrical motor valves setting for the pressure regulation of a water distribution networks for specified nodal demands by using both genetic algorithm (GA) and a relatively new concept known as Shuffled Complex Evolution-University of Arizona (SCE-UA). To demonstrate the performance of both techniques, a simple illustrative example of a controlled water distribution networks is presented showing the effectiveness of both algorithms to regulate the pressure at all the network nodes, between upper and lower values and as near as possible to the target values. Regardless the final mathematical solutions of both algorithms which are approximately the same, results show the superiority of SCE-UA technique to reach the optimal solution using less number of function evaluations than GAs. This paper concludes that the SCE-UA algorithm is well suited to deal with water supply networks problems, which provides a rich field for future research.

Key Words: *Water distribution, Genetic Algorithm, SCE-UA and Pressure regulation.*

1. INTRODUCTION

The purpose of a water supply network is to convey water to consumers in the required quantity at appropriate pressure, of acceptable quality, as economically as possible. In a supervisory system of water distribution network, sensor information from pressure gauges, flow meters, and electrically control valves are continuously sent to a control center where valve openings are adjusted depending on the situation in the network given by the sensor information. The purpose of the control is to minimize leakage and to maintain appropriate hydraulic pressures for the consumers. By controlling the distribution of hydraulic pressures in the network, pipe breaking could be lessened and water could be conserved. However to achieve this kind of control, it is necessary to accurately estimate the distribution of hydraulic pressures in the network and to properly control the valves.

It is well known that the amount of water leakage from a distribution network is directly related to the system service pressure[1)]. Germanopoulos and Jowitt[2)] dealt with the problem of leakage reduction by excessive pressure minimization and their study could be applied in conjunction with other problems like the detection and repairs of leaks, Jowitt and Xu[3)] extended this work, defining the total leakage as the objective function to be minimized and they illustrate their application through a moderate network contains 3 flow-control valves and 37 pipes. Reis *et al.*[4)] identified the optimal location of valves for leakage minimization using the genetic algorithm technique. The determination of valve settings to reduce network pressures has been studied by Miyaoka and Funabashi[5)] using the network flow theory without using evolutionary programming, they apply two-level of control. In the first level they used a nonlinear optimization method derived from network flow theory while the second level is a feedback control which absorb the estimated error and the variations in consumption.

Obtaining an optimal control of the distribution of system service pressures in a municipal water distribution networks has always faced combinatorial problems due to its complexity, scale of the problem, variation of water demand and the difficulty in estimating the roughness coefficient of old pipes. Referring to the previous difficulties, the application of linear, non-linear, dynamic programming, simulated annealing and genetic algorithm have been investigated by many authors and used in recent years for the optimization programs of water distribution networks design, replacement and leakage minimization. Particularly, the application of genetic algorithm (GA) in water distribution networks optimization models has been known as the most successful method in this field. It works with a coding of the parameter set, direct the search to the improved solutions by probabilistic rules and working directly with the objective function requiring no additional knowledge.

Recently, with the ever-increasing complexity of a city-wide distribution pipe network, motor valve operations to regulate pressure and flow came to depend more and more on the experience and technique of skills operators. Therefore, this paper presents the application of evolutionary computing for regulating the pressure in all the network nodes between upper and lower value and as near as possible to a target value. The implementation of this study is applied to calculate the reduction of water leakage volume.

2. FORMULATION OF THE MODEL

For a network has n_l links, n_n junction nodes, n_f fixed-grade nodes (constant water level), and l independent closed loops, the following mathematical statement of the pressure regulation is used as an objective function to be minimized using both GAs and SCE-UA Algorithms

$$J = \left[\frac{1}{n_n} \sum_{j=1}^{n_n} \left(H_j - H_j^T \right)^2 \right]^{1/2} \rightarrow \min \tag{1}$$

where H_j = head at node j, H_j^T = required target head at the same node. In Eq. 1 the number of junction nodes n_n could be reduced by the number of fixed-grade nodes n_f according that the head at the fixed-grade nodes is unchanged.

The foregoing function is to be minimized under the following constraints.

For each junction node of the water supply network, the mass continuity equation should be satisfied.

$$\sum_j \left(Q_{in} - Q_{out} \right) = C_j \tag{2}$$

where C_j is the consumption or demand at junction j, positive for outflow and negative for inflow, Q_{in} and Q_{out} are the flow entering and leaving the junction node j, respectively.

The sum of the head losses and gains around a closed loop must be equal to zero since $\Delta H = 0$

$$\sum_k h = \Delta H \; ; \; k = 1, 2, \ldots, l + n_f - 1 \tag{3}$$

The minimum and maximum head constraint for each node in the network is given in the form

$$H_j^{\max} \geq H_j \geq H_j^{\min} ; \quad j = 1, \ldots\ldots, n_n \tag{4}$$

where H_j^{max} = maximum required head at node j; and H_j^{min} = minimum required head at the same node.

The hydraulic analysis of the network is performed using the Hazen-Williams empirical equation which is often applied in pipe network analysis.

$$H_i - H_j = r_{ij}^{-1/\alpha} \left| Q_{ij} \right|^{1/\alpha - 1} Q_{ij} + \frac{8 f_{vij}}{g \pi^2 d_{ij}^4} \left| Q_{ij} \right| Q_{ij} \tag{5}$$

where

$$r_{ij} = 0.27853 C_{ij} d^{2.63} l_{ij}^{-0.54} \tag{6}$$

The second term in Eq. 5 is required only if there is a valve between nodes. Here Q_{ij} (m^3/sec) is pipe discharge from node i to j, and $Q_{ij} = -Q_{ji}$; $|\quad|$ means absolute value, H_i (m) and H_j (m) are hydraulic pressures at nodes i and j; $\alpha = 0.54$ is a numerical constant, f_{vij} is valve loss coefficient; g is acceleration of gravity; C_{ij} Hazen-Williams coefficient, d_{ij} (m) is diameter of the pipe, and l_{ij} (m) is pipe length.

The coefficient of valve loss, f_{vij} is calculated using the following equation

$$f_{vij}(\theta) = \begin{cases} 165226 \times 10^{-0.180} & (0 \leq \theta < 13) \\ 3696 \times 10^{-0.060} & (13 \leq \theta < 40) \\ 221 \times 10^{-0.030} & (40 \leq \theta \leq 100) \end{cases} \tag{7}$$

where θ (%) is the valve openings. Eq. 7 is taken for the typical type of electrically motor valves used in Fukuoka City water distribution network[6].

The previous studies of water distribution network, which used GAs as optimization tool used a constant penalty multiplier for handling the different constraints[7]. This penalty multiplier is difficult to determine according that it is changed from problem to another[8]. Therefore, the method used in this study for not allowing any infeasible solution to be better than any feasible solution is to compute a failure index suggested by Todini[9] as

$$I_f = \sum_{j=1}^{n_n} e_j \tag{8}$$

$$\text{where} \begin{cases} e_j = Q_j \left(H_j - H_j^{max} \right) when\ H_j > H_j^{max} \\ e_j = Q_j \left(H_j^{min} - H_j \right) when\ H_j^{min} > H_j \\ e_j = 0.0 \qquad otherwise \end{cases} \tag{9}$$

According to the previous two equations, solution X is dominating a solution Y if any of the following are true:

- Solution X is feasible and solution Y is infeasible.
- Solution X and Y both are infeasible, but solution X has a smaller failure index than solution Y.

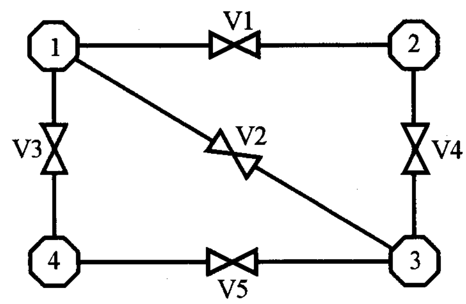

Fig.1 Example network

Table 1 Links data set for the example network

Pipe	1-2	1-3	1-4	2-3	3-4
Length (m)	100	300	500	200	400
Diameter (mm)	100	200	300	100	200

Table 2 Links data set for the example network

Node	1	2	3	4
Demand (m^3/hour)	75	100	100	50
Outflow (m^3/hour)	-325	0	0	0
H^{max} (m)	-	32	32	32
H^T (m)	-	30	30	30
H^{min} (m)	-	21	21	21

- Solution X and Y are feasible and solution X dominates solution Y.

The network hydraulic analysis used in the above model is performed using Newton-Raphson type of iteration by utilizing a good initial vector for fast convergence.

3. STANDARD GENETIC ALGORITHMS

Genetic Algorithms are a set of evolutionary computing techniques that have been used to find the optimal or near optimal solution of many engineering problems. Good description of GAs was given by Holland[10] and Goldberg[11] who discussed several applications of GAs in optimization problems.

A genetic algorithm is a local search algorithm, which works starting from an initial collection of strings (a population) representing possible solutions of the problem. Each string of the population is called a *chromosome*, and has associated a value called *fitness function* that contributes in the generation of new populations by means of genetic operators (denoted *reproduction, crossover* and *mutation*, respectively). Every position in a chromosome is called a *gene* and its value is called *allelic* value. This value may vary on an assigned *allelic alphabet*; most commonly the allelic alphabet is {0, 1}. At each generation, the algorithm uses the fitness function values to evaluate the survival capacity of each string i of the population using simple operators in order to create a new set of artificial creatures (a new population) which try to improve on the current *fitness function* values by using pieces of the oldest ones.

In recent times, a variety of applications has shown that GAs reach better solutions when applied to water distribution network problems than other optimization strategies. The Following represent a brief summary of some successful applications in the field of pipe network problems: (i) Pipe replacement[12], (ii) Optimal design of water supply networks[7], (iii) Optimal location of valves[4], (iv) Developing operating schedules[13),14] and (v) Water network rehabilitation[15].

4. SCE-UA ALGORITHM

The Shuffled Complex Evolution – University of Arizona (SCE-UA) method is a general purpose global optimization evolutionary programming technique which combines the strengths of the simplex procedure[16] with the concepts of controlled random search[17], competitive evolution[10] and the concepts of complex shuffling[18].

The synthesis of these concepts makes the SCE-UA algorithm not only effective and robust, but also flexible and efficient. The use of deterministic strategies permits the SCE-UA algorithm to make effective use of the response surface information to guide the search. Robustness and flexibility is taken care of by the use of random elements. The implicit clustering strategy guides to the most promising region of the search space. The use of the systematic complex strategy helps to ensure a relatively robust search that is guided by the structure of the objective function. [Readers not familiar with SCE-UA strategy may refer to the details of this algorithm[18),19]] .

The SCE-UA technique has been successfully used in the calibration of conceptual rainfall-runoff models and the identification of aquifer formation parameters in the area of surface and subsurface hydrology, respectively. However, this algorithm has never been used in the field of management and planning of water distribution networks and this paper is our first attempt in this direction.

5. APPLICATION OF THE MODEL

(1) Network specifications

The applications of GAs and SCE-UA technique to the valve operation problem are illustrated considering the simple and typical network shown in **Fig. 1**. The system configurations are given in **Tables 1** and **2**. In this network, there are 4 nodes

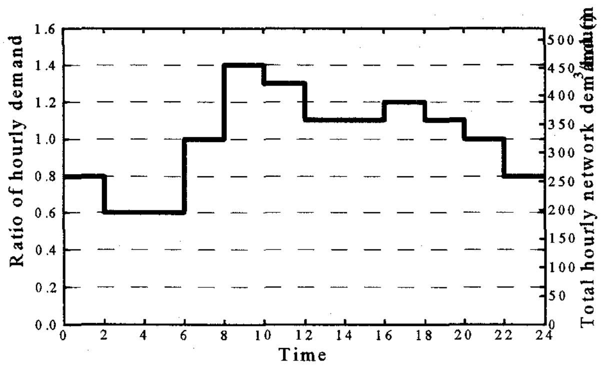

Fig.2 Variation of daily demand

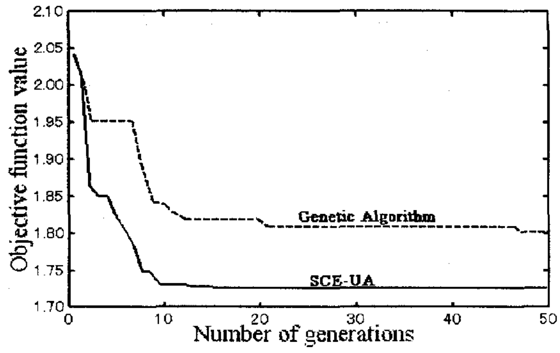

Fig.3 Course of evolution of SCE-UA and GAs

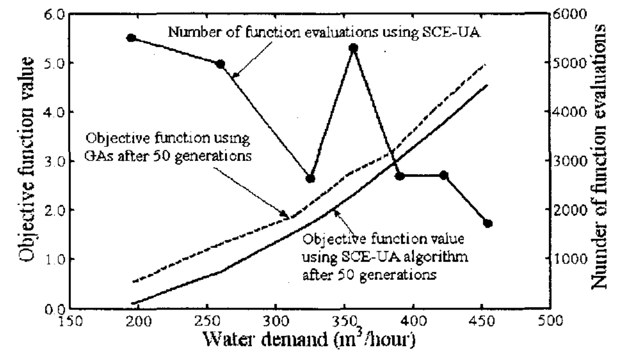

Fig.4 SCE-UA and GAs performances

and 5 pipes. All nodes are considered in the same horizontal level, the assumed Hazan-Williams coefficient is 130 and node (1) is considered as a fixed grade node with a constant pressure head = 35.00 m (given condition).

Five controlled valves are connected to each pipe of the network, each valve has a varied percentage of opening varies between 0.0 (completely closed) to 100 (fully opened). Coefficient of valve head-loss is estimated according to Eq. (7).

Unrealistic configurations of this network are due to find the optimal valve settings even under the difficult conditions. (Biggest pipe 1-4 feeds the lowest demand at node 4).

(2) SCE-UA and GAs parameters

In both algorithms, the number of variable to be optimized $(n_{opt} = 5)$, which is the total number of valves in the network.

In the SCE-UA the followings are the used parameter values; number of complex $(p = 10)$, number of complex population $(m = 2n_{opt} + 1 = 11)$, number of sub-complex population $(q = n_{opt} + 1 = 6)$, the user defined parameter which determines how many offspring should be generated $(\beta = m = 11)$ and the user defined parameter which determine the number of generation inside the extermination room $(\alpha = 1)$. All these previous values except the first one are the suggested ones[19].

For GAs runs, a population size containing 60 individuals is used, a simple crossover is used, the probability of crossover is set to $p_c = 1.0$ and the mutation rate is equal to $p_m = 0.05$. Previous values are the recommended values from the literature[7][11].

(3) Computational details

GAs and SCE-UA are applied to minimize the objective function of Eq. 1 according to the different cases of typical daily demand variation prescribed in **Fig. 2**[3]. In GAs runs the total number of function evaluations used in each generation is equal to the population size since the probability of crossover is set to 1.0. While in SCE-UA the number of function evaluations is not fixed during all generations according to some internal tests. Therefore, the number of function evaluations corresponding to the best solution obtained from any generation in either algorithm is recorded. This will aid in comparing the efficiency of both algorithms.

The overall procedure outlined before which contains SCE-UA algorithm, GAs and the program of network hydraulic analysis has been coded in Matlab language (Release12) and applied on PC computer.

6. RESULTS AND DISCUSION

Both SCE-UA and GAs methods are applied for the above-mentioned problem. **Fig. 3** shows the best value of objective function in each generation up to 50 generations using SCE-UA algorithm for the case of relative hourly demand equal 1.0. In this case, the number of function evaluations in these generations varied between 9500 and 10500 function evaluations according to the studied case of demand pattern.

For purposes of comparison, the results of GAs are also plotted for the same number of generations which correspond to 6000 function evaluations. The SCE-UA is more efficient than simple genetic algorithm according to the improved searching

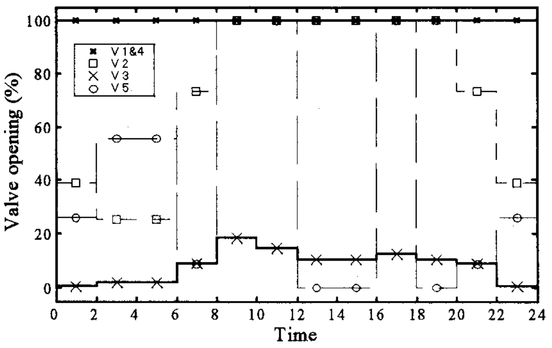

Fig.5 Valves setting for optimal control

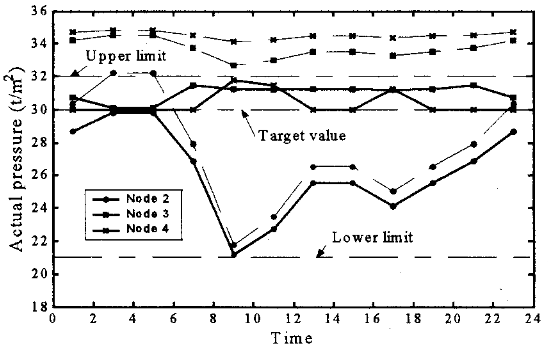

Fig.6 Pressure in the different network nodes

ability of SCE-UA. The same trend of both algorithms is recorded in the other cases of demand pattern.

Fig. 4 shows a typical plot of the final minimized values of objective function with the different cases of water consumption. From this figure, the results obtained by using SCE-UA are more accurate than that of GAs. The number of function evaluations to obtain the optimal solution using SCE-UA algorithm is plotted in **Fig. 4**, considering that the objective function values of GAs are plotted for a number of 50 generations (6000 function evaluations) which is the same number required to obtain the optimal solution using SCE-UA algorithm. This indicates the superiority of SCE-UA to reach the optimal solutions in a less number of generations than GAs.

It is important to notice that results obtained from both algorithms are approximately the same when we increase the number of generations in GAs to 500 (30,000 function evaluations). **Fig. 5** shows the final optimal settings of the different five valves attached to the network and **Fig. 6** is plotted for the different network nodes in order to compare the pressure distribution before and after applying the regulation model, considering the solid line for the regulated case and the broken line for the unregulated case; pressure in all nodes has been brought down.

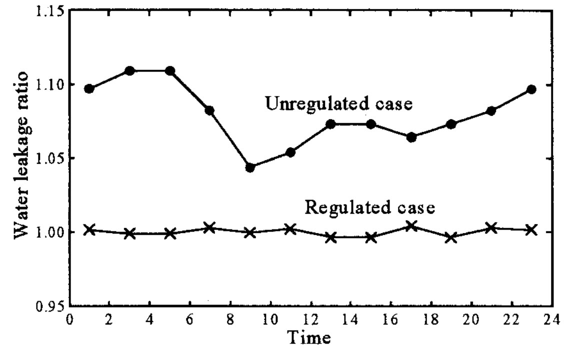

Fig.7 Reduction of leakage

Referring to **Fig. 6**, it is worthwhile noting that pressure reduction during the peak demand period is smaller than during nighttime in which the pressure reduction is maximized. In the minimization process of the objective function (Eq.1) using the two algorithms of this study, the number of function evaluations could be lessened if an approximately optimum point is acceptable as operating point.

7. LEAKAGE MANAGEMENT

As an effect of applying the pressure regulation to the simple network shown in **Fig.1**, in this part an estimation of the total amount of leakage is calculated for both cases of controlled and uncontrolled pressure.

The following empirical equation is used to determine the total leakage volume from a pipe connecting node i with node j.

$$A_{ij} = K_{ij} l_{ij} p_{ij}^{1.15} \tag{10}$$

where A_{ij} is the total leakage volume from the pipe, K_{ij} is an unknown experimental coefficient depends on the value of service pressure, age of the pipe, deterioration of the pipe and the soil properties, p_{ij} average service pressure of the studied pipe[5].

It might be noted that the exponent 1.15 used in Eq. 8 is approximately same to the exponent 1.18 used in other studies[3]. This exponent is quite different from the value of 0.5 which characterizes the relationship between flow through an orifice and head difference according that this it is based on field data and it incorporates any openings or cracks caused in the pipe[3].

To overcome the difficulties of determining the coefficient K_{ij}, water leakage calculations in this study is computed as a ratio to the average leakage volume of the controlled case. By applying Eq. (10) to the actual pressure values obtained as a result from the variations of water demands during the day. **Fig. 7** shows the reduction of leakage obtained by applying the two algorithms used in this study.

The average daily rate of leakage reduction is about 8 percent, maximum rate of saving is during the nighttime (12%) while the minimum rate of reduction is during the rush-hours (8.00 a.m. to 10.00 a.m.) is about 6%.

8. CONCLUSIONS

The paper presents the applicability of both simple genetic algorithm and Shuffled Complex Evolution-University of Arizona algorithm to the problem of optimal valve settings for pressure regulation in water supply networks. The objective function used in this study which represent the root mean square error (RMSE), consider to control the pressure between upper and lower limits and as near as possible to a target values.

For the simple and typical network presented in this paper which is often used in demonstrations, significant savings of water leakage volume may be achieved by using the evolutionary computing techniques to a typical daily water demand pattern.

Comparing both algorithms used in this study, SCE-UA strategy has the preference over the GAs for the following reasons:

1) SCE-UA performed less number of function evaluations than GAs for obtaining the optimal solution.
2) The size of executable program of SCE-UA is less than that of GAs.
3) GAs needs to convert the optimization variables to binary representation, while SCE-UA deals with these variables with its true values.
4) The memory used during SCE-UA runs is less than that of GAs runs by 52%.
5) Results obtained by using SCE-UA are slightly accurate than that of Gas.
6) Dealing with the parameter of SCE-UA like α, β is simpler than determining the optimal values of the probability of crossover and mutation rate in GAs.

Even though it has been demonstrated in this paper that SCE-UA have been able to process good solutions for the studied case, but in water distribution network problems, it is still at the research level and we think that the above results could be obtained for the practical size. To ensure these conclusions we are now trying to apply this algorithm for the actual Fukuoka City water supply network.

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