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ENTROPY BASED DESIGN OF 'ANYTOWN' WATER DISTRIBUTION NETWORK

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Abstract

Design optimization of looped water distribution networks has been a thoroughly researched problem for the last four decades. However, very few works have been published dealing with the optimal design of complex water distribution networks containing various network elements, such as the "Anytown" water distribution network. The central theme of the present work is to develop a design model satisfying the following requirements: (i) GAs are developed for unconstrained optimization problems. That is, they have difficulty in handling constraints in a constrained optimization problem, so the solution strategy should reduce the number of constraints that must be handled by GA and (ii) existing/new tanks should utilize their full operational capacity and exhibit good recirculation capabilities such that water quality problems are reduced. Keeping these two aspects in mind a new optimization model including a tank design procedure, which requires complete description of a tank's parameters, is proposed. Minimization of Network cost and maximization of flow entropy are considered as the two objectives. A multi-objective genetic algorithm, namely NSGA-II, is used and the efficacy of the proposed model is demonstrated. It will be shown that the flow entropy could be used as a surrogate reliability measure and that it alleviates drawbacks of some of the other surrogate measures such as resilience index. New results obtained for the "Anytown" network show that the model manages to find better solutions and satisfy all the constraints including pressure constraints in EPS.

1. INTRODUCTION

Most real-world Water Distribution Networks (WDNs) comprise of components such as reservoirs, tanks, pipes, pumps and valves. Pipes are used to convey water, pumps are used to add energy to water to overcome gravity and friction, valves are provided to control flows and pressures, and tanks are used for energy head (pressure) regulation and emergency storage. Deterioration of these components may lead to increase in leaks and breaks, inadequate supply, and poor water quality. The above problems have become more significant in the recent past due to stricter controls by the regulating authorities. This led to costly infrastructure improvement programmes by water companies. However, due to budgetary constraints many water companies are looking for the cost effective way of implementing various rehabilitation alternatives. The complexity of rehabilitation problem along with the enormous number of rehabilitation alternatives making it impossible to evaluate these alternatives manually. This is where optimization techniques will be of immense help as they can identify a small set of alternatives that are cheaper and satisfies the specified design criteria.

Formulation of a design model for gravity-fed networks without tanks is straight forward, as they can be designed using peak loading and doesn't require performance check using Extended Period Simulation (EPS). However, inclusion of tanks and pumps in the rehabilitation model require evaluation of their performance using not only peak loading but also normal day loading. The designs must be thoroughly checked and ensured that tanks are properly operated. Although, the cost of tanks may be a small component compared to the overall rehabilitation costs, nevertheless, their impact on overall network performance is significant. An improperly designed tank may significantly increase the costs of pipes, pumps and valves. At the same time, it may reduce the reliability of WDN and supply poor quality of water to consumers due to increased water age.

Relatively, very few works have been published dealing with the optimal design of complex water distribution networks containing various network elements, such as "Anytown" water distribution network. The "Anytown" problem was originally tackled by participants in the Battle of the Network Models workshop. All participants in the original workshop used optimization models to size the piping system while manually choosing the location and size of tanks. The difference between various methods originally used lies essentially in the pipe optimization models. Murphy et al. (1994), later obtained a better solution to this problem using a standard genetic algorithm (SGA). Walters et al. (1999) introduced the structured messy genetic algorithm (SMGA) for solving the "Anytown" water system. Farmani et al. (2005) used a multi-criterion optimisation to tackle this problem and Vamvakeridou-Lyroudia et al. (2005) developed a fuzzy multi-criterion optimization model to solve "Anytown" problem. More recently, Prasad (2007) has developed a sigle objective model, with improved tank design methodology, to tackle "Anytown" network. Although this network does not contain all the features of real systems, it serves as a challenging benchmark for optimization models that are able to consider many real system features, such as pump and tank sizing and location.

Cost minimization alone tend to reduce the diameter of pipes to the possible minimum, thus leading the system vulnerable to hydraulic and mechanical failures. The best way to tackle such a scenario is to include reliability into optimization. However, there is no universally acceptable method for reliability estimation and the available methods require enormous computational resources. To overcome this problem, some researchers (Todini, 2000; Prasad and Park, 2004; Farmani et al., 2005; and Jayaraman and Srinivasan, 2008) have used surrogate reliability measures and the others have used simplified reliability estimates (Tolsen et al., 2004). Reliability can be included in optimization either as an additional constraint or as a second objective. Handling more than one objective has become easier with the introduction of multiobjective genetic algorithms (MOGAs). Many MOGAs are available in the literature such as PESA, SPEA2, NSGA2 and others (Deb et al., 2000).

In this study, a multiobjective model is formulated to solve complex water distribution network rehabilitation problem. Infrastructure cost including present worth of operating cost, and a surrogate reliability measure that used entropy concept are considered as the objectives. The formulated model satisfies not only pressure constraints but also other operational constraints such as recovery of water levels in tanks, and utilization of full capacity of existing and new tanks. Flow entropy, a statistical entropy measure for WDNs, is considered as a surrogate reliability measure. This measure can better represent multi-source networks and it was observed elsewhere that as the flow entropy increases, the network becomes more reliable. The main objectives of the study are: (i) to show that using the tank design methodology presented, many feasible solutions can be obtained along the Pareto front, and (ii) the surrogate reliability measure can be used effectively to improve reliability of multi-source networks. The developed rehabilitation model is applied to solve the benchmark network problem "Anytown" water distribution network. The results obtained indicate the better performance of tank sizing approach and also improved reliability of networks obtained along the Pareto front.

2. PROBLEM STATEMENT

The problem of water distribution network rehabilitation can be formulated as the minimization of cost of the network, including capital cost and operational cost, while meeting supply requirements. This single objective formulation could be modified to include reliability as the minimization of cost and the maximization of a surrogate reliability measure. Mathematically it can be stated as

$$\begin{aligned} &\textit{Minimize} \quad && C = C_i + C_e \\ \text{and } &\textit{Maximize} \quad && S \end{aligned} \tag{1}$$

subject to:

(i) variable bounds
(ii) physical constraints such as conservation of mass equations
and (iii) operational constraints

where C_i is the infrastructure cost; C_e is the operational cost; and S is a reliability measure. The infrastructure cost include the cost of new and rehabilitated pipes, new pump stations and/or expanding existing pump stations, new tanks, and new valves in the network. Operational cost, in general, include present value of pumping cost and pump maintenance cost estimated over the planning horizon. However, quantifying pump maintenance cost is very difficult, therefore, only pumping cost is considered as the operational cost in this study. In Addition, pipe repair costs may also be included in the operational costs.

To solve the above stated problem, it was decided to use a multiobjective genetic algorithm. The constraints on variable bounds are encoded into the GA string, whereas physical constraints such as conservation of mass and conservation of energy are implicitly satisfied by hydraulic simulator. The remaining constraints (operational constraints), must be explicitly handled in the GA model. GAs are originally developed for unconstrained optimization problems. Constrained optimization using GAs is carried out by penalizing infeasible solution. Therefore, constraints form a major part in evolving the GA search and moving the search towards the global optimum. Inclusion of extraneous constraints impedes its search capabilities and may lead to suboptimal solutions. Therefore, careful consideration must be given to the selection and handling of constraints under GA framework. Keeping the above aspects in mind, the following operational constraints were considered in the multiobjective model.

Water must be supplied to consumers at a minimum specified pressure. Accordingly, system pressure constraints are given by

$$H_{i,l} \geq H_{i,l}^{\min} \quad i = 1,\ldots,N_j \; and \; l = 1,\ldots,N_l \tag{2}$$

where $H_{i,l}$ is the pressure at node i under hydraulic loading l; $H_{i,l}^{\min}$ is the minimum required pressure at node i; N_j is the number of demand nodes; and N_l is the number of hydraulic loadings.

To ensure convergence of GA to a viable design, the tank water levels have to recover over the normal operating cycle. That is, tank water volume at the end of the normal operating cycle must be greater than or equal to the volume of water at the beginning of the cycle.

$$V_{k,E} \geq V_{k,\mathrm{S}} \quad k = 1,\ldots,N_t \tag{3}$$

where $V_{k,S}$ is the volume of water in tank k at the beginning of operating cycle; $V_{k,E}$ is the volume of water in tank k at the end of operating cycle; and N_t is the number of tanks in the network.

This constraint ensures that volume of water at the end of a normal operating cycle is not lower than that at the beginning. The normal operating cycle begins with all tanks completely full, typically, at the beginning of morning peak demand period and ends 24 hours later with the same condition. It is assumed that, although questionable, the same cycle repeats every day so that present value of operational cost over a planning horizon could be estimated based on results from a single operating cycle.

The above constraints are sufficient for obtaining a feasible design using the proposed model. However, it is not guaranteed that the solutions obtained using such a model fully utilize existing/provided tank operational volumes and that stagnation of water can be avoided. Therefore, the following two constraints are incorporated into the model to achieve these targets.

$$\sum_{k=1}^{N_t} F_{k,L} = 0 \qquad 4)$$

and $$\sum_{k=1}^{N_t} \Delta t_k = 0 \qquad 5)$$

where $F_{k,L}$ is the fraction of operational volume not used during a normal operating cycle; and Δt is the time for which net flow of tank k is zero. Eq.4 stipulates that complete draining of a tank must take place at least once during a normal day loading. Whereas Eq.5 enforces that duration for which a tank's riser is closed to zero. This way it can be ensured that water in the tank is not stagnated. Although, other constraints such as water quality constraints, budgetary limits, velocity limits, etc., can be considered in the model, they have not been considered in this study.

Tank Sizing Methodology

The tank sizing methodology used in this study requires complete description of a tank before conducting simulation. That is, a tank's parameters: diameter, top elevation, maximum operational level, minimum operational level and bottom elevation must be completely defined. This can be achieved in a number of ways, for example, by encoding these parameters in a GA string explicitly or implicitly in terms of parameter ratios such as diameter to height ratio. For simplicity, the new tanks are assumed to be cylindrical with a free volume of 10% of the total tank volume. Since, elevations must be in an increasing order it is better to encode them implicitly such that this increasing order is always preserved. In this study, a tank's location, volume, diameter to height ratio, minimum operational elevation, and fraction of minimum volume are treated as the decision variables. By knowing these parameters, all tank levels can easily be calculated and assigned to the respective tanks. Variables representing tank riser(s) will be included in the group of pipe variables. If a new tank is located at a junction, then that tank's riser costs will be added to the infrastructure cost. The set of variable bounds used in this work are given in Table 1.

Hydraulic modelling of tanks is carried out using the following procedure.

1. Add a new tank to the network at a specified location
2. from known values of volume, diameter to height ratio, minimum operational elevation, and fraction of minimum volume, calculate various tank levels (top, maximum, minimum, and elevation) and tank diameter.
3. Assign these parameters to the new tank added in step (1)
4. assuming tanks are full at the beginning of morning peak demand period, set the initial water level in the tank equal to maximum water level.
5. repeat the above procedure for all new tanks and complete the extended period simulation.

The above approach to tank sizing eliminates the need of considering tank water level constraints explicitly. That is, hydraulic simulator implicitly ensures that tank water levels are always within the maximum and minimum operational levels during EPS. When a tank's water level reaches its minimum, corresponding tank riser will be temporarily closed and simulation will be continued. If there is a deficiency in supply due to a tank closure, it will be reflected in the form of pressure drop at demand nodes and/or increased pumping costs.

Reliability Measures

Design optimization without reliability constraints is unsatisfactory: cost minimization by its very nature removes redundancy, which therefore leaves the system potentially vulnerable during some critical operating conditions. Many researchers have tried to incorporate reliability and uncertainty into the design process (Xu and Goulter, 1999). In general, Monte-Carlo simulation (MCS) is regarded as the best method for estimating reliability. However, the number of hydraulic simulations required for reliability analysis – reliability analysis is NP-hard – often prohibits the inclusion of reliability constraints in design optimisation procedures. To overcome this difficulty some researchers have used approximate first-order reliability methods (Tolson et al., 2004) for reliability estimation and others have used surrogate reliability measures such as Resilience Index and Network Resilience (Prasad and Park, 2004, and Farmani et al., 2005). The following reliability measures were investigated in this study.

Resilience index(I_r)

The concept of resilience index was introduced by Todini (2000) to increase the reliability and availability during stressed conditions. Due to mechanical and hydraulic failures, internal loss of energy increases causing deficient supply at network nodes. Increased internal losses could be met, if sufficient excess power is available for internal dissipation. This excess power has been used by Todini to characterise the resilience index. The total power input (P_{inp}) into a network is equal to the power lost internally (P_{int}) to overcome friction plus the power delivered (P_{out}) at demand nodes.

$$P_{inp} = P_{\text{int}} + P_{out} \tag{6}$$

The resilience index of a network is then defined as

$$I_r = 1 - \left(\frac{P_{\text{int}}}{P_{\text{int}}^{\max}} \right) \tag{7}$$

where P_{int} , is the amount of power dissipated in a network; and $P_{\text{int}}^{\max}$, is the maximum power that would be dissipated internally in order to satisfy design demand Q and design head $H^{\min}$ at junction nodes. Substitution of appropriate quantities in the above equation gives

$$I_r = \frac{\sum_{j=1}^{nn} Q_j \left(H_j - H_j^{\min} \right)}{\left(\sum_{k=1}^{nr} Q_k H_k + \sum_{i=1}^{npu} P_i / \gamma \right) - \sum_{j=1}^{nn} Q_j H_j^l} \tag{8}$$

It is expected that maximization of resilience index will lead to improved network reliability, although it does not involve statistical consideration of failures. It was clearly demonstrated by Prasad and park (2004) that increase in resilience index does not necessarily improve the network reliability. More recently, Jayaram and Srinivasan (2008) have demonstrated the inability of resilience index to handle multiple source networks. Due to these drawbacks of resilience index, it was decided to use another surrogate reliability measure called flow entropy to study the network reliability.

Flow entropy (S)

Shanon (1948) derived the informational entropy function as a statistical measure of the amount of uncertainty that a probability distribution represents. Tanyimboh and Templeman (1993) developed the flow entropy concept, based on Shannon's entropy function, that enabled pipe flow rates to be interpreted in a probabilistic way. For a network with known pipe flows and flow directions, the flow entropy can be calculated as

$$S = S_0 + \sum_{i=1}^{N_j} P_i S_i \tag{9}$$

where S_0 is the entropy of source supplies; S_i is the entropy of demand node i; and P_i is the fraction of the total flow through the network that reaches node i or the probability that a particle of water entering the network will reach node i. The probability P_i is calculated as

$$P_i = {}^{T_i}\!/\!_{T} \tag{10}$$

where T_i is the total flow reaching node i; and T is the sum of the nodal demands. The entropy of the source supplies is given by

$$S_0 = -\sum_{k=1}^{N_s} \frac{Q_k}{T} \ln\left(\frac{Q_k}{T}\right) \tag{11}$$

where Q_k is the inflow at source node k; and N_s is the number of source nodes. Similarly the entropy of demand nodes is given by

$$S_i = -\frac{Q_i}{T_i} \ln\left(\frac{Q_i}{T_i}\right) - \sum_{ij \in ND_i} \frac{Q_{ij}}{T_i} \ln\left(\frac{Q_{ij}}{T_i}\right) \tag{12}$$

where Q_i is the demand at node i; Q_{ij} is the pipe flow from node i to node j; and ND_i is the set of all pipe flows emanating from node i. The flow entropy is a measure of the uniformity of the pipe flow rates. It is shown elsewhere that maximization of entropy leads to increase the ability of network to supply water under stressed conditions. This aspect will be further investigated in this work.

3. MULTIOBJECTIVE GENETIC ALGORITHM

Genetic Algorithms (GAs) are computationally simple yet powerful search algorithms. GAs mimic the adaptation of natural species and genetically evolve to suit their environment over many generations. Using this analogy, a mechanism involving selection, crossover, and mutation can be used to evolve a population of potential solutions towards improved solutions. In single objective optimization the goal is to find the best design solution, called the global optimum. However, many real world engineering design problems involve simultaneous optimization of multiple objectives. The presence of multiple objectives gives rise to a set of compromised solutions, largely known as the Pareto-optimal solutions. In the absence of any further evaluation criteria, no one solution in this set can be said to be better than the other. Therefore, the goal in a multi-criterion optimization is to find as many Pareto-optimal solutions as possible. Once such solutions are found, it usually requires a higher-level decision making with other considerations to choose one of them for implementation. It must be recognized that optimization can only assist the engineer and that engineering judgment and experience is still required to provide a practicable solution. The Pareto set gives an engineer more flexibility in the selection of a practicable solution.

Although many advanced multiobjective genetic algorithms are available in the literature, it was decided to use NSGA-II as it will enable a fairer comparison of the proposed model with those published. A complete description of NSGA-II can be found in Deb et al. (2000). The following paragraphs briefly describe various operations involved in NSGA-II. It differs from a simple genetic algorithm only in the way the selection operator in used. The idea behind NSGA-II is that, initially, a random parent population P_0 of size N is created. Before selection is performed, the population is first ranked on the basis of an individual's non-domination level, and then fitness is assigned to each population member based on its domination level. Binary tournament selection, SBX crossover, and Polynomial mutation operators are used in the creation of child population. Thereafter, the following algorithm is repeated in every generation until a convergence criterion is satisfied.

$R_t = P_t \cup C_t$
F = fast non-dominated sorting (R_t)
$P_{t+1} = \phi$ and i = 1
Until $|P_{t+1}| + |F_i| = N$
    Crowding-comparison assignment (F_i)
    $P_{t+1} = P_{t+1} \cup Fi$
    i = i + 1
Sort (F_i)
$P_{t+1} = P_{t+1} \cup F_i\ [1 : (N-|P_{t+1}|)]$
C_{t+1} = make new population (P_{t+1})
t = t + 1.

The parent and child populations are combined to form combined population $R_t = P_t \cup C_t$ of size 2N. This way elitism is maintained. The R_t is sorted using non-domination algorithm. The sorting procedure classifies the combined population into several non-dominated fronts, F_1, F_2, and so on. The new population, P_{t+1}, is formed by filling with solutions of different non-dominated fronts one at a time. The filling of P_{t+1} starts with the best non-dominated front (F_1) and continues with F_2, and so on until its size is N. The last accepted front may contain more solutions than the number of available slots for filling. Instead of arbitrarily discarding some members from the last front, the solutions that make diversity of the selected solutions are chosen. The above procedure is repeated until convergence is achieved.

4. ANYTOWN NETWORK

The above proposed model is applied to a well-known benchmark problem “Anytown” water distribution network (Walski et al. 1987). The general layout of the network is shown in Fig.1. The problem is to upgrade the system to meet future demands. Full details of the original problem are presented in Walski et al. 1987 and are summarised in the following paragraphs. The town is formed around an old central city, where pipes are marked with thick solid lines. Pipes in the residential area are marked with thin solid lines, while new pipes are marked with dashed lines in the layout (Fig.1). Excavations in the city centre area are difficult to undertake, hence more expensive. The objective of the problem is to find the least-cost design that satisfies performance criteria while meeting future demands. Both capital and pumping costs must be considered in evaluating total cost of the network. The proposed new design could include new pipes, cleaning and lining of existing pipes, duplication of existing pipes, construction of new pumping station(s), upgrading existing pumping station, and provision of new tanks.

Water is pumped into the system from water treatment works using an existing pumping station containing three identical pumps connected in parallel. Link and node data as well as water consumption data are obtained from CWS 2004. Water level in clear well at water treatment works is maintained at a fixed level of 3.05 m (10 ft) and the two existing tanks have operational levels between elevations 68.58 m (225 ft) and 76.20 m (250 ft). The volume of water below minimum operational level (65.58 m) and above tank bottom (65.53 m) is retained for emergency needs. The existing network has a total operational storage of 591.47 m^3 (156,250 gal) and an emergency storage of 236.59 m^3 (62,500 gal). The proposed new design must satisfy, mainly, three loading conditions: (i) normal day flows at a minimum pressure of 276 kPa (40 psi); (ii) instantaneous peak flow, which is 1.8 times the average day flow, at a minimum pressure of 276 kPa (40 psi); and (iii) three fire flow scenarios at a minimum pressure of 138 kPa (20 psi). Full details about these loadings are available from CWS 2004. The fire flows must be supplied for a period of 2 hours, with tanks at their minimum operational levels and one pump out of service. The fire flows must be supplied while also supplying peak day flows, which are 1.3 time average day flow. During fire flow events, only the flow required for fires is supplied at the corresponding nodes. Full extended period simulation must be performed to satisfy normal day flows using a time step of 3 hours. It is assumed that tanks are full at 6 am, start of the morning peak demand period.

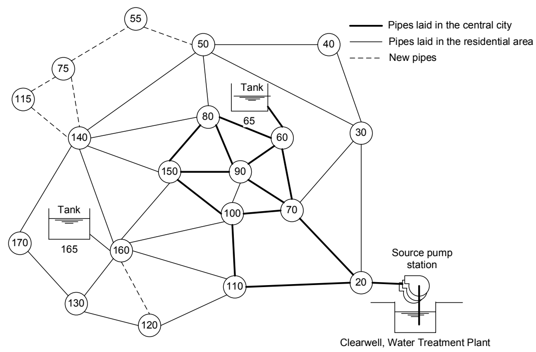

Fig.1 The “Anytown” water distribution network

Since both design and operational optimization are involved (due the presence of pumps in the network), the number of decision variables is rather large. There are a total of 40 pipes including 32 existing pipes, 6 new pipes, and 2 existing risers. In this study all existing pipes and risers are considered for duplication, or cleaning and lining. Up to a maximum of 3 new tanks can be added in the improved design. This makes the total number of pipe decision variables to 43, including three new risers. There are 10 tank decision variables with each new tank contributing five variables. New pumping stations are not considered in this study; however, the model could easily be extended to include new pumping stations. Upgrading the existing pumping station is allowed through the addition of a maximum of 2 new pumps with the same characteristics as the existing ones. Given 24 h operational cycle and 8 time steps (3 hrs each), for each pumping station, 8 operational decision variables are needed. That is each decision variable is representing the number of pumps operating during each pumping period. Since, "Anytown" network has only one existing pumping station comprising of three identical pumps this coding is possible. However, if there are pumps of different characteristics present in a pumping station, a different coding must be adopted. In total, there are 60 design variables: 42 for pipes; 8 for pumps; and 10 for tanks.

The ranges of various variables are given in Table 1. Pipe options include (i) 0: do nothing; (ii) 1: cleaning and lining of existing pipes; (iii) 2 – 11: duplicate existing pipes with one of the 10 available discrete diameters; and (iv) 12 – 21: select a diameter for new pipe from among 10 available discrete diameters. A pipe that has been cleaned and lined, has a Hazen-Williams roughness coefficient of C=125, and for new pipes C=130. The existing pumping station has three identical pumps connected in parallel and up to a maximum of 2 new pumps could be added to the existing pumping station. The number of pumps in operation during each time period is represented by integer values 0, 1, 2, …, NPMP, where NPMP is equal to 5 (3 existing pumps plus 2 new pumps). All junctions in the network, except those already connected directly to existing tanks, are considered as possible locations for new tanks, and therefore, there are 16 possible locations. Tank volumes could be any value between minimum and maximum possible volumes of 189.27 m^3 (50,000 gal) and 3785.41 m^3 (1,000,000 gal) respectively. It should be noted that if a tank's trial volume is less than the minimum possible volume, that tank will be removed (made offline) and corresponding riser costs will not be added to the capital cost. Variables representing tank minimum operating level is allowed to vary between 54.86 m (180 ft) and 76.15 m (240 ft). The ratio of diameter to height of tank is varied between 0.75 to 2.5, and the ration of emergency volume to total volume is allowed to vary between 0.25 and 0.6. These ratios can be specified by the user according to the requirements.

Table 1. Problem variables and their bounds

Variable	Lower bound	Upper bound
Existing pipe (Do nothing/clean & line/ duplicate)	0	11
New pipe	12	21
Number of pumps in each period (8 time steps)	0	5
Tank location	1	16
Tank Diameter to height ratio	0.75	2.5
Minimum normal day elevation	54.86 m	73.15 m
Volume	189.27 m^3	3785.41 m^3
Minimum volume to total volume ratio	0.25	0.6

5. APPLICATION OF MODEL

The proposed GA model was applied to the "Anytown" water distribution network problem. The above presented model was solved using NSGA-II. Several runs with different random seeds and GA parameters were conducted. The GA parameters used in the study are: population size (100--300), probability of crossover (0.7--1.0), probability of mutation (0.01--0.05), and number of generations (2000–5000). The termination criterion was set as the maximum number of function evaluations of 500,000. Initially, the model was solved using resilience index as the surrogate reliability measure. Thereafter, flow entropy was used as the surrogate reliability measure. Finally a comparison of the results obtained was made. During GA runs it was found that obtaining feasible solutions by including Eq.5 (i.e., time of rise closure is zero) as constraint was near impossible. Therefore, it was decided to treat it as a soft constraint instead of a hard constraint.

The performance of each candidate design solution was evaluated through simulation of the network flows. An extended period hydraulic network solver EPANET2, (Rossman 2000) was used to determine the constraint violations. The cost of a trial solution includes the capital costs of pipes, pumps, and tanks, as well as the present value of the energy cost. The energy cost was computed based on a unit cost for energy equal to \$0.12 / kWh. The present value of energy cost is based on an interest rate of 12% and an amortization period of 20 years. Tank costs are a function of volume and are taken from CWS 2004. For intermediate tank sizes capital costs were obtained by interpolating linearly from given standard sizes and costs.

Initially, the model was solved with the aim of minimising the network cost and maximizing resilience index as the objectives subject to constraint Eqs. 2 – 4. Fig. 2 gives the payoff characteristic between the total cost and the resilience index as a surrogate measure for reliability for the Anytown network. The search results indicate that NSGAII has the potential to find Pareto optimal solutions for water distribution networks. As it can be observed from Fig.2, there are a number of solutions along the Pareto front, indicating that the proposed model along with the proposed tank design methodology is capable of conducting search in an efficient manner. The water level variation during normal operating cycle for the least cost solution is shown in Fig.3. It can be observed from Fig.3 that all the tanks have utilised their operating volume completely. This indicates that constraint Eq.4 is effective in finding solutions that utilize the available operating volume completely. It can also be observed that except one tank all other tanks exhibit good water circulation characteristics.

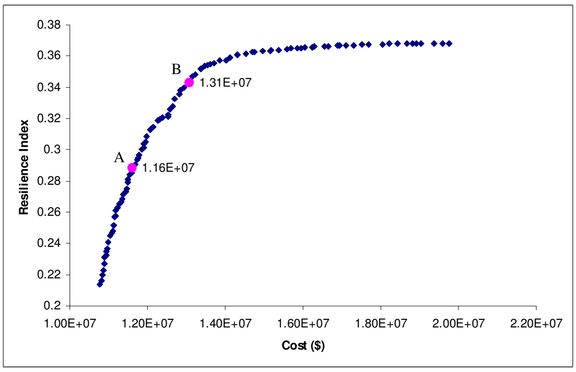

Fig.2: Anytown Network: Cost Vs Resilience Index

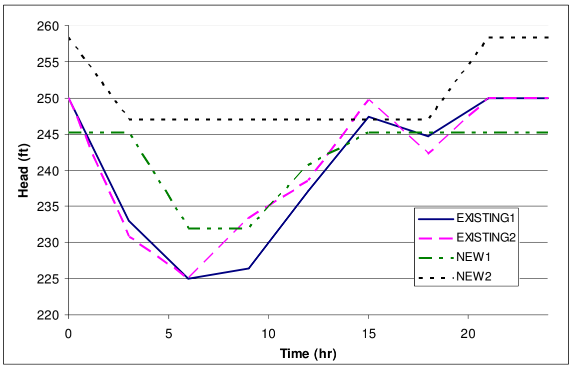

Fig.3: Tanks water level variation of least cost solution

Next the multiobjective model was solved using minimization of cost and maximization of flow entropy as the objective, and Eqs.2 – 4 as constraints. Fig.4 shows the trade-off curve between cost and flow entropy. For the purpose of demonstration of the efficacy of the model two typical solutions marked C and D on the Pareto curve were selected. The cost of these solutions are $\$11.65\times10^6$ and $\$13.23\times10^6$. These solutions were then analysed using EPANET and variation of water levels in the tanks are presented in Fig.5a and 5b, respectively.

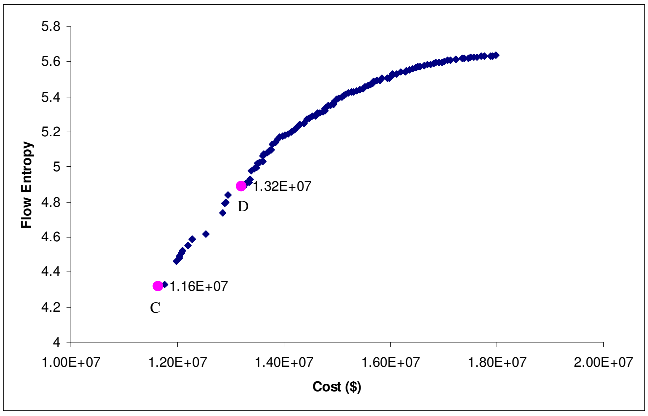

Fig.4 Anytown Network: Cost Vs Flow Entropy

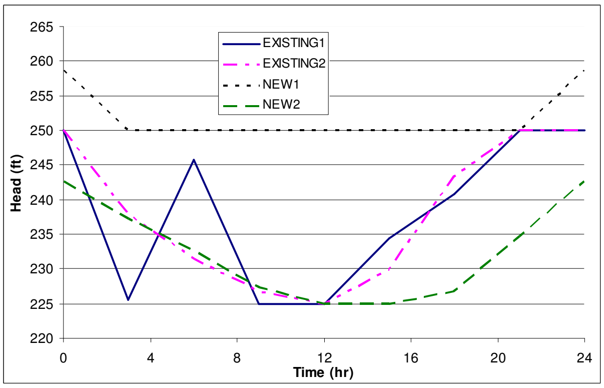

Fig.5a Tanks water level variation of Network C

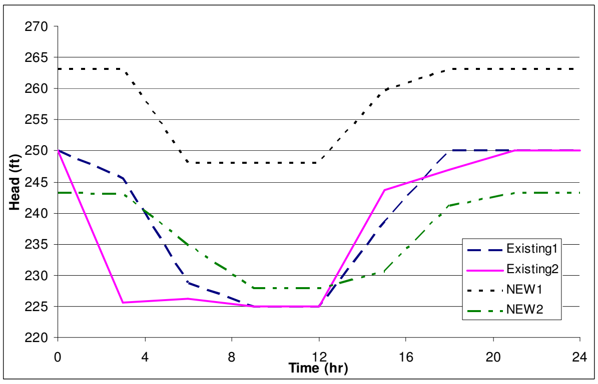

Fig. 5b Tanks water level variation of Network D

Finally, we wanted to compare the effectiveness of the surrogate reliability measures considered in this study. For this purpose two solutions each for each reliability measure studied are considered. They are marked as A and B in Fig.2, and C and D in Fig.4. Solutions A and C have of similar total cost, and costs of solutions B and D are also in the same range. Due to time constraints this task could not be completed before the due date for paper submission. However, it is expected that these results will be presented at the conference.

6. CONCLUSIONS

In this study, a multiobjective model for optimal design of pumped water distribution networks with storage has been presented. A multiobjective genetic algorithm, namely NSGA-II has been used to solve the above model. Minimization of network cost and maximization of a surrogate reliability measures were considered as the objectives. The surrogate reliability measures considered in this study are Resilience Index and Flow entropy. A modified approach for tank sizing is proposed, which treats tank shape parameters as decision variables. The proposed approach for tank sizing allows for seamless integration of EPANET simulator with the optimizer. For the first time, in this study, full extended period simulation for each trial solution has been performed, which allowed accurate estimation of energy costs, vis-à-vis fitness of a solution. The operational constraints in the model have been handled using a ranking approach, in which pressure constraints are treated as hard constraints and all other constraints as soft constraints. This allows for some tolerance in the constraint satisfaction, while supplying demands at required pressures. The proposed model has been applied to a well-known example, the “Anytown” water distribution network. Two cases were investigated, one considering Resilience Index and the other considering Flow Entropy. The hydraulic Performance of the proposed least-cost solutions has been assessed and found that they are satisfying all the constraints.

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