OPTIMAL PUMP OPERATION OF WATER DISTRIBUTION SYSTEMS USING GENETIC ALGORITHMS

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ABSTRACT

The water utility industry has started investigating the integration of on-line telemetry and optimal computer control systems in an effort to reduce operating costs and provide more reliable operations. Energy costs constitute the largest expenditure for nearly all water utilities worldwide and can consume up to 65 percent of a water utility's annual operating budget. One of the greatest potential areas for energy cost-savings is the scheduling of daily pump operations. This paper presents a new management model, H_2ONET Scheduler, for optimal control and operation of water distribution systems. The proposed model makes use of the latest advances in genetic algorithm optimization to automatically determine the least-cost pump scheduling/operation policy for each pump station in the water distribution system while satisfying target hydraulic performance requirements. The operation policy for a pump station represents a set of temporal rules or guidelines (individual pump operating times) that indicate when a particular pump or group of pumps should be turned on and off over the control period. System performance requirements prescribe lower and upper limits on nodal pressures; maximum pipe velocities; maximum pumped volumes; maximum and minimum storage tank levels; and final tank volumes at the end of a specified time period to ensure hydraulic periodicity. The resulting model can be effectively used to evaluate various rate schedules, optimize storage/pumping trade-offs, improve operational efficiency, and assure more reliable operations. The method should prove useful to any water utility attempting to optimize pumping operations and reservoir control.

INTRODUCTION

Supplying drinking water and industrial water can consume large amounts of electricity, which generally constitute the largest expenditure for nearly all water utilities worldwide. Energy costs are a function of the energy usage and the energy rate. Energy rates are normally structured to promote off-peak energy usage with lower rates and penalize peak period energy usage with higher rates.

Energy-saving measures in water supply and distribution systems can be realized in many ways, from field testing and proper maintenance of equipment to the use of optimal computer control. Energy usage can be reduced by decreasing the volume of water pumps (e.g., adjusting pressure zone boundaries), lowering the head against which it is pumped (e.g., optimizing tank water level range), or reducing the price of energy (e.g., avoiding peak hour pumping and making effective use of storage tanks such as filling them during off-peak periods and draining them during peak periods), and increasing the efficiency of pumps (e.g., ensuring that pumps are operating near their best efficiency point). Utilities can further reduce energy costs by implementing on-line telemetry and control systems (SCADA), and by managing their energy consumption more effectively and improving overall operations using optimized pumping operations and reservoir control.

There have been several attempts in recent years to develop optimal control algorithms to assist in the operation of complex water distribution systems. The various algorithms were oriented towards determining least-cost pump scheduling policies (proper on-off pump operation) and were based on the use of linear programming, nonlinear programming, dynamic programming, enumeration techniques, and general heuristics. However, the success of these procedures has been very limited and very few have actually been applied to real water distribution systems. Limited acceptance of optimal control models in engineering practice is partly because (1) such techniques are generally quite complex involving a considerable amount of mathematical sophistication (e.g., requiring extensive expertise in systems analysis and careful setting up and fine tuning of parameters); (2) they are generally highly dependent upon the number of pumps and storage tanks being considered along with the duration of the operating period; (3) they are generally subject to oversimplification of the network model and its components along with several simplifying assumptions to accommodate the nonlinear network hydraulics; (4) they tend to be extremely time-consuming resulting in added costs and inefficient use of the computer; and (5) they may be easily trapped at local optima and may not lead to the global optimal solution. Another very important reason for their lack of acceptance and use was the unavailability of suitable and user-friendly pump optimization packages. As a result, most optimal control models developed to date have been mainly used as a research support tool.

This paper focuses on the development of an optimal operations model, H_2ONET Scheduler[1], for real-time control of multi-source, multi-tank water distribution systems. The objective is to minimize the cost of the energy consumed for pumping. The program makes use of the latest advances in genetic algorithms optimization to automatically determine the optimal pump operation policy for each pump station in a water distribution system that will best meet target hydraulic performance requirements. The operation policy for a pump station represents a set of temporal rules or guidelines (individual pump operating times) that indicate when a particular pump or group of pumps should be turned on and off over a specified time horizon (typically 24 hours). The optimal pump policy is the set of control rules (schedule of pump operations) that will result in the lowest total operating cost for the boundary conditions and system constraints specified. These constraints prescribe lower and upper limits on nodal pressures, maximum pipe velocities, maximum and minimum storage tank levels, and final tank volumes at the end of a specified time period (normally 24 hours) to ensure hydraulic periodicity. The optimization model employed is based on a variation of the genetic algorithms delivering reliable solutions in sub-quadratic time.

MODEL FORMULATION

The H_2ONET Scheduler casts the optimal control problem as an implicit nonlinear optimization problem subject to both implicit and explicit constraints. It computes the optimal pump schedule for each pump or pump group based on the specified control time span, such that the overall energy cost is minimized. Pumps are normally grouped together based on their known characteristics such as location, pumping capacity and common control components (storage tanks). The mathematical problem is governed by the energy cost objective function and an associated set of system operational constraints.

Objective Function

The objective of the optimal control problem is to minimize the energy cost while satisfying the hydraulic requirements of the system. The objective cost function can be mathematically expressed as:

Objective Cost Function:

$$\textit{Minimize} \qquad \sum_{n=1}^{N}\left[\sum_{t=0}^{T} E_n(t)C_n(t) + \sum_{bp=1}^{NBPn} Emax_n^{bp} C_n(bp)\right]$$

where N represents the number of pumps; T is the control time span; $C_n(t)$ is the unit energy cost of pump n at schedule time of t; $E_n(t)$ is the energy consumption during the schedule time interval from t to $t+1$ with a pump control setting; $Emax_n^{bp}$ is the maximum energy consumption of pump n during billing period bp; $C_n(bp)$ is the maximum demand charge \$/max.kW for pump n during billing period bp; and $NBPn$ designates the number of billing periods for pump n. The decision variables are the pump control settings for the selected groups of pumps. They are automatically computed to minimize the objective function while satisfying three different kinds of constraints: (1) a set of implicit system constraints; (2) a set of implicit bound constraints; and (3) a set of explicit variable constraints.

Implicit System Constraints

The implicit constraints on the network system are equality constraints defining the hydraulic equilibrium state of the system. They correspond to the conservation of mass at each junction node and conservation of energy around each loop in the network. These represent a set of quasi-linear hydraulic equations that are implicitly solved using the H_2ONET Analyzer. Each function call to the H_2ONET Analyzer with a set of decision variables returns the simulated steady-state hydraulic equilibrium solution for pipe flow velocities, pipe hydraulic gradients, node pressures, and tank water levels.

Implicit Bound Constraints

The implicit bound constraints on the optimization problem represent system performance criteria and may include constraints on junction node pressure (*P*), pipe velocity (*V*), tank water level (*TL*) and pump operation switches for a given network loading condition.

1. Node Constraints:

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

$$Pmin_j \le P_j\ (t) \le Pmax_j \qquad \forall j, \forall t$$

where $P_j\ (t)$ represents the pressure at node *j* at time *t;* $Pmin_j$ is the minimum pressure required at node *j*; and $Pmax_j$ is the maximum pressure allowed at node *j*.

2. Pipe Constraints:

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

$$V_k\ (t) \le Vmax_k \qquad \forall k, \forall t$$

where $V_k\ (t)$ is the flow velocity of pipe *k* at time *t* and $Vmax_k$ represents the maximum allowable flow velocity for pipe *k.*

3. Tank Constraints:

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

$$TVmin_k \le TV_k\,(t) \le TVmax_k \qquad \forall k, \forall t$$

where $TVmin_k$ represents the minimum water storage volume required at tank *k;* $TV_k(t)$ is the water storage volume of tank *k* at time *t*; and $TVmax_k$ denotes the maximum water storage volume allowed at tank *k.* To ensure hydraulic periodicity for the next operating period, the tanks must be refilled to a prescribed storage volume at the end of a scheduling period (resulting in tank trajectories that begin and end at specified target elevations), given as:

$$\left| TV_k^{final} - TV_k^0 \right| \le \Delta TV_k \qquad \forall k$$

where TV_k^{final} designates a specified water storage volume of tank *k* at the end of an operation period; TV_k^0 is the final water storage volume of tank *k* computed for the current trial pump operation set; and ΔTV_k denotes the tolerance of the final water storage volume for tank *k*. In most cases, the beginning and ending tank water levels should be the same.

<u>4. Pump Switching Constraints:</u>

Energy cost may be reduced by turning a pump on and off many times during a control period. However, the more frequent a pump switches on and off the greater the resulting pump maintenance cost due to increasing wear on the pump. The number of pump switching can be used as a surrogate variable for measuring the pump maintenance cost. To restrict the pump-wear-off cost to an acceptable level, the number of pump switching must be less than a maximum allowable value, given as:

$$SW_k \le SWmax_k \qquad \forall k$$

where SW_k represents the number of pump switching for pump group k while $SWmax_k$ designates the maximum number of pump switching for pump group *k*.

When a solution does not satisfy an implicit bound constraint, a penalty method is used to handle the constraint violation. A penalty cost is added to the objective cost function to penalize an infeasible solution (degrade its fitness) and force the search procedure towards the region of feasible solutions. The penalty function is defined as the divergence (distance) of the computed solution from the feasible region.

Explicit Variable Constraints

The explicit variable constraints are used to specify the pump control setting values for a new pump schedule. Pumps should normally be grouped together based on their known physical characteristics such as location, control tank and pump capacity. As such all pumps within a group will possess an identical operating policy.

For each pump group, the pump control setting is either *on* or *off* at a specific time t, given as:

$$\forall k, \forall t, \forall S_k(t) \in S^0 = \{1, \;\; 0\}$$

where $S_k(t)$ designates the control setting of pump k at time t and takes a value of either 1 (pump on) or 0 (pump off).

SOLUTION METHODOLOGY

To solve the pump scheduling optimization problem as formulated above, a dual-level solution methodology was employed by means of which an efficient quasi-dynamic (Extended Period Simulation) hydraulic network simulator (H_2ONET Analyzer[2]) was directly embedded into the optimization model. Starting with an initial feasible set of design parameters and rehabilitation actions, it is passed to the network solver for use in explicitly satisfying the implicit system constraints and in evaluating the implicit bound constraints. The network hydraulic solution (i.e., junction pressure, flow velocity and tank level) is then passed back to the optimization model for use in quantifying the objective function and any violations in the implicit bound constraints. This information is then utilized to produce an improved pump schedule that automatically satisfies the explicit variable constraints and that seeks to minimize the objective function. This iterative process is repeated until the best solution is found. The optimization model utilized is an efficient variation of genetic algorithms delivering reliable solutions in sub-quadratic time[3-5].

Information required by the program includes the duration of the time interval, the cost of electricity, pump switching characteristics, and system constraints. For most water utilities, the total pumping (electricity) cost is composed of an energy consumption charge ($/kWh) and a demand charge ($/max kW). The energy consumption charge is the cost of electric energy consumed during a billing period. The demand charge represents the cost associated with the maximum amount of power consumed (peak energy consumption) within the charging period. System constraints include the maximum and minimum allowable junction node pressures, maximum pipe velocities, and maximum, minimum and ending tank volumes. Finally, the user must supply pump efficiency data in the form of efficiency curves and pump groupings.

OPTIMIZATION MODEL

The optimization model employs an efficient genetic algorithm (GA) technique as a means of obtaining optimal solutions to the pump scheduling problem. Genetic algorithms are an adaptation procedure based on the mechanics of natural genetics and natural selection[6]. They are designed to perform search procedures of an artificial system by emulating the evolution process (Darwin's evolutionary principle) observed in nature and biological organisms. The evolution process is based on the preferential survival and reproduction of the fittest member of a population with direct inheritance of genetic information from parents to offspring and the occasional mutation of genes. The principal advantage of GAs is their inherent ability to intelligently explore the solution space from many different points simultaneously enabling higher probability for locating global optimum without having to analyze all possible solutions available and without requiring derivatives (or numerical approximations) or other auxiliary knowledge.

Overview of Genetic Algorithms

Genetic algorithms are stochastic numerical search procedures inspired by biological evolution, cross-breeding trial solutions and allowing only the fittest solutions to survive and propagate to successive generations. They deal with a population of individual (candidate) solutions, which undergo constant changes by means of genetic operations of reproduction, crossover, and mutation. These solutions are ranked according to their fitness with respect to the objective function where the fit individuals are more likely to reproduce and propagate to the next generation. Based on their fitness values, individuals (parents) are selected for reproduction of the next generation by exchanging genetic information to form children (crossover). The parents are then removed and replaced in the population by the children to keep a stable population size. The result is a new generation with (normally) better fitness. Occasionally, mutation is introduced into the population to prevent the convergence to a local optimum and help generate unexpected directions in the solution space. The more GAs iterate, the better their chance to generate an optimal solution. After a number of generations, the population is expected to evolve artificially, and the (near) optimal solution will be reached. The measure of success is the convergence to a population with identical members. The global optimum solution however cannot be guaranteed since the convexity of the objective function cannot be proven.

Components of Genetic Algorithms

Standard genetic algorithms involve three basic functions: selection, crossover, and mutation. Each function is briefly described below.

Selection – Individuals in a population are selected for reproduction according to their fitness values. In biology, fitness is the number of offspring that survive to reproduce. Given a population consisting of individuals identified by their chromosomes, selecting two chromosomes as parents to reproduce offspring is guided by a probability rule that the higher the fitness an individual has, the more likely the individual is selected. There are many selection methods available including weighted roulette wheel, sorting schemes, proportionate reproduction, and tournament selection.

Crossover - Selected parents reproduce the offspring by performing a crossover operation on the chromosomes (cut and splice pieces of one parent to those of another). In nature, crossover implies two parents exchange parts of their corresponding chromosomes. In genetic algorithms, crossover operation makes two strings swap their partial strings. Since more fit individuals have a higher probability of producing offspring than less fit ones, the new population will possess on average an improved fitness. The basic crossover is a one-point crossover. Two selected strings create two offspring strings by swapping the partial strings, which are cut by one randomly sampled breakpoint along the chromosome. The one-point crossover can be easily extended to k-point crossover. It randomly samples k breakpoints on chromosomes and then exchanges every second corresponding segments of two parent strings.

Mutation - Mutation is an insurance policy against lost bits. It works on the level of string bits by randomly altering a bit value. With small probability, it randomly selects one bit on a chromosome then inverts the bit from 0 to 1 or vice versa. The operation is designed to prevent GA from premature termination, namely converging to a solution too early.

Figure 1 presents the flowchart for the pump scheduling optimization process.

EXAMPLE APLICATION

The developed optimal operational control model has been applied to a number of water distribution networks of different sizes and degrees of complexity. The performance of the proposed model is illustrated herein using a sample network. The network schematic is shown in Figure 2. It contains 52 pipes, 45 junction nodes, one pressure reducing valve, one treatment plant, one variable storage tank, three pumps located at the treatment plant (one standby), and consists of two pressure zones. Figures 3 to 6 display the pump group, junction pressure constraint, pipe velocity constraint, and tank volume constraint dialog boxes. Figure 7 depicts the optimized pump and tank operations while Figure 8 gives the resulting energy costs for the 24-hour simulation period.

CONCLUSIONS

This paper has presented a rigorous mathematical model for determining least-cost pump operation policies that will best meet target hydraulic performance requirements of the water distribution system for a given time horizon (normally 24 hours). The minimum cost-constraint model links a variation of the genetic algorithm optimization technique with a quasi-dynamic hydraulic network solver to produce the resulting policies. Its interactive, user-friendly interface is designed to assist water distribution system operators and training new operators in selecting and scheduling efficient and cost-effective pump combinations to plan and operate better systems.

The proposed operational model was tested and verified on a number of actual large-scale water distribution systems. The results obtained indicate that the developed model can effectively reduce the cost of energy consumed for pumping in a complex water distribution system while maintaining satisfactory levels of service. Water utility managers now have the tool to help them produce the best possible pumping schedules with a minimum effort and at significant cost-savings.

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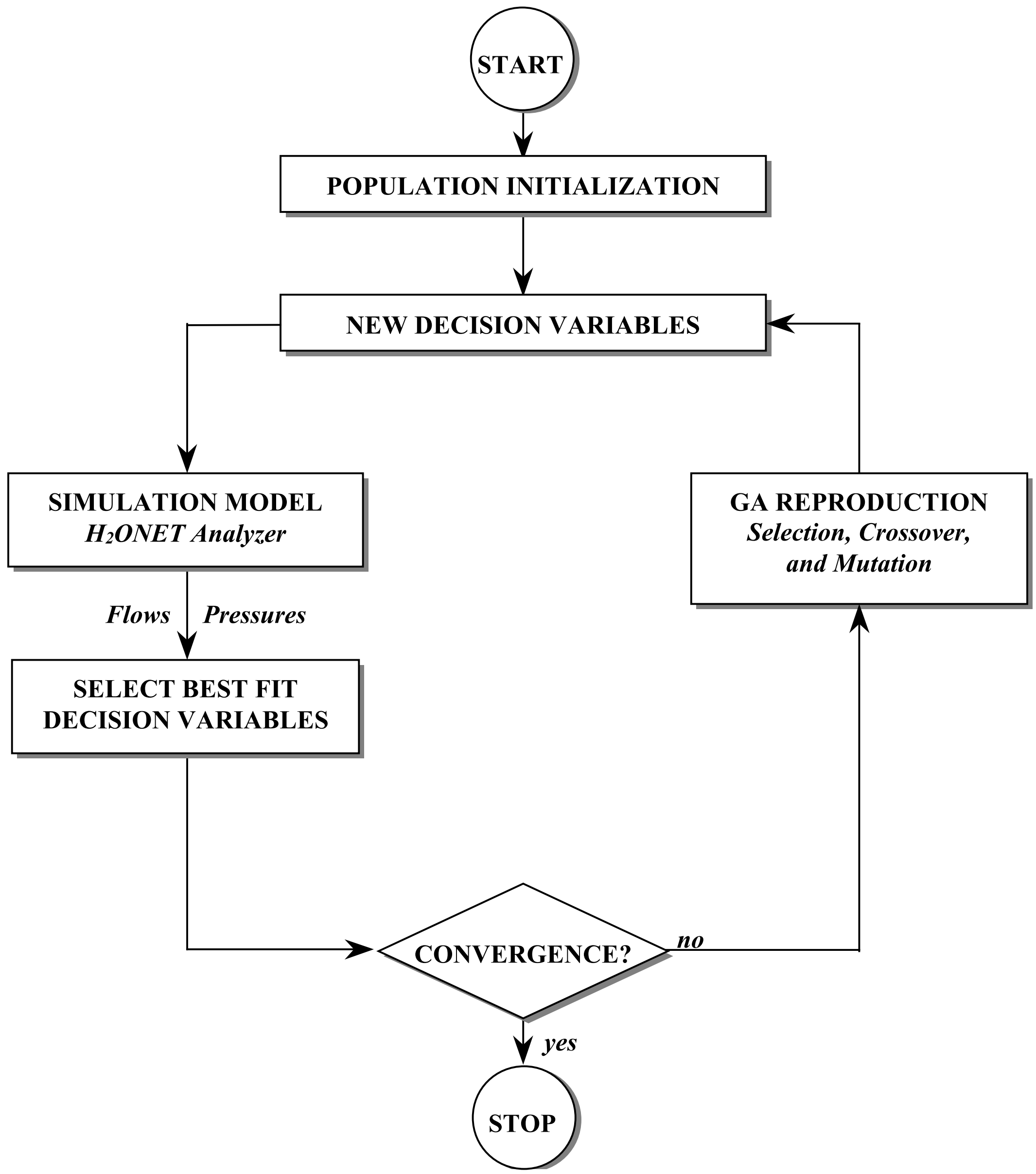

Figure 1 – Flowchart of H_2ONET Scheduler

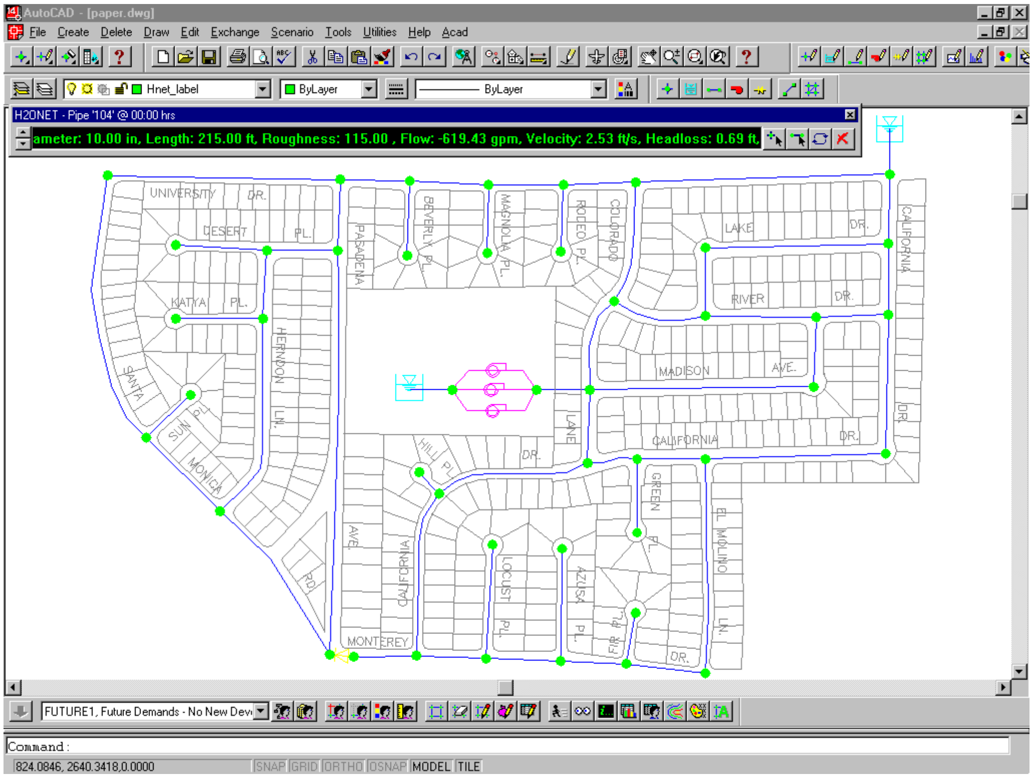

Figure 2 – Example network schematic

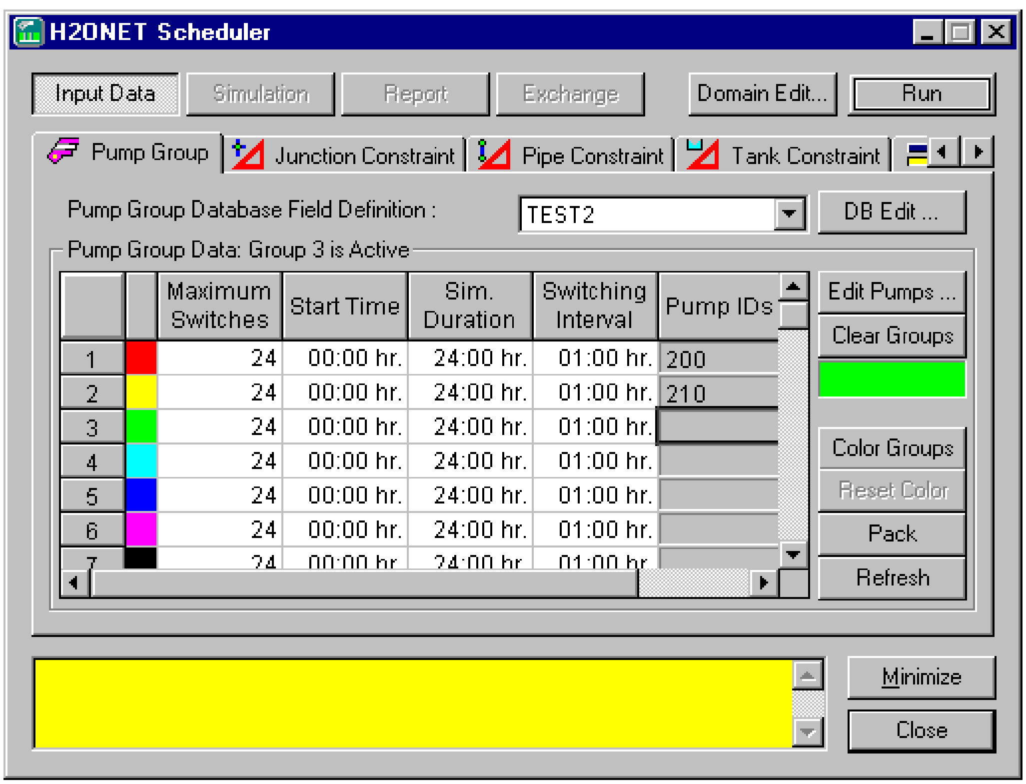

Figure 3 – Pump grouping dialog box

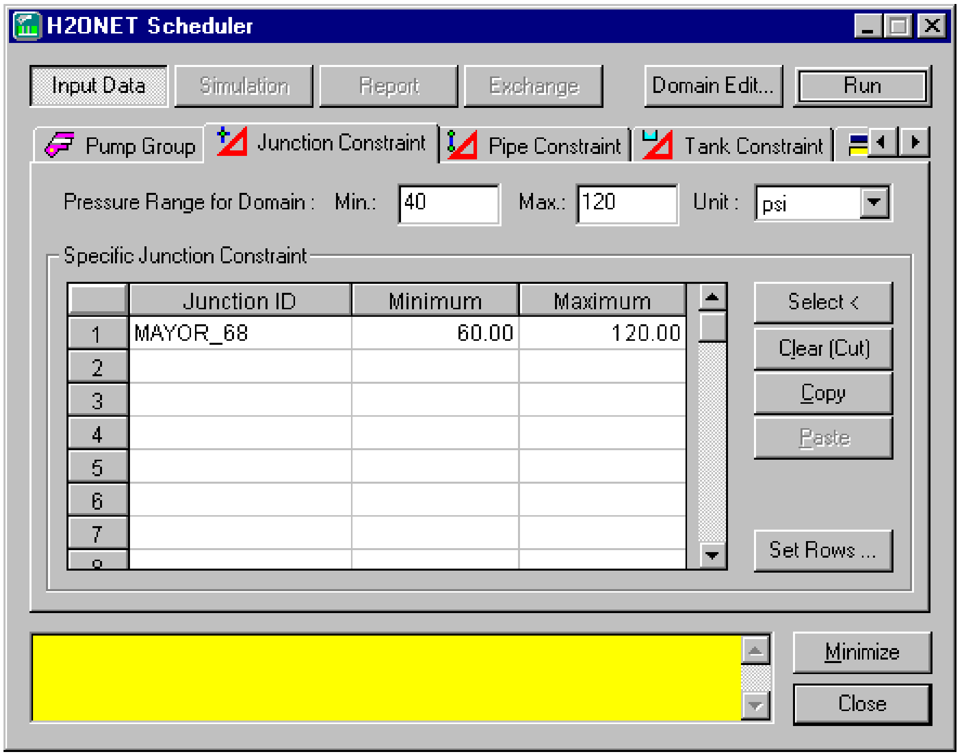

Figure 4 – Junction node pressure constraint dialog box

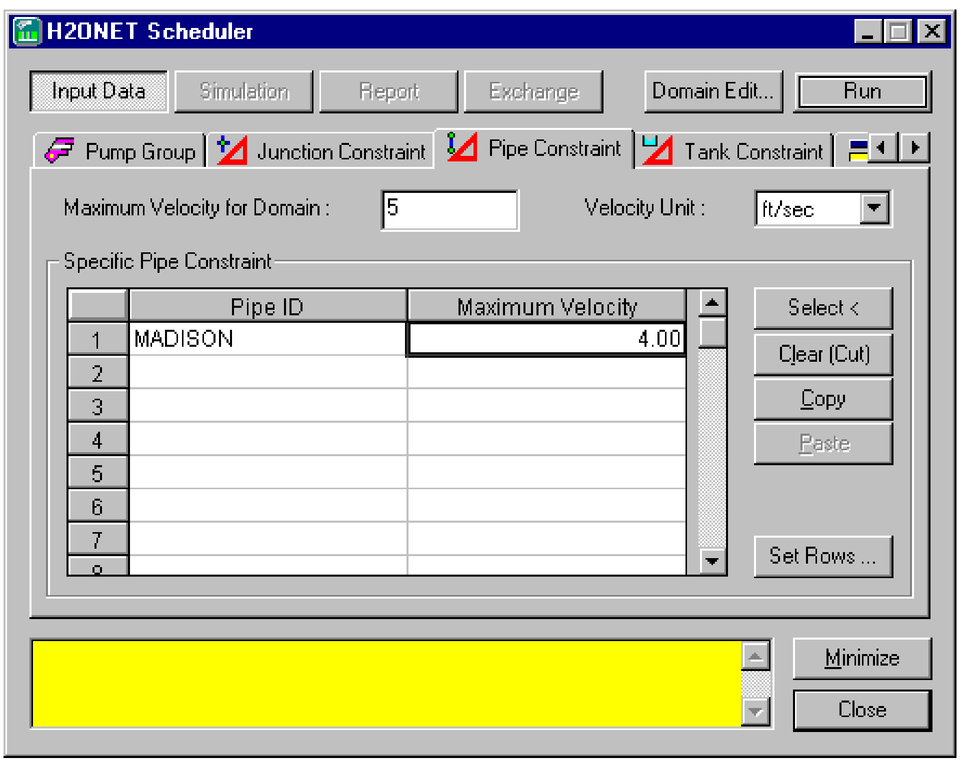

Figure 5 – Pipe velocity constraint dialog box

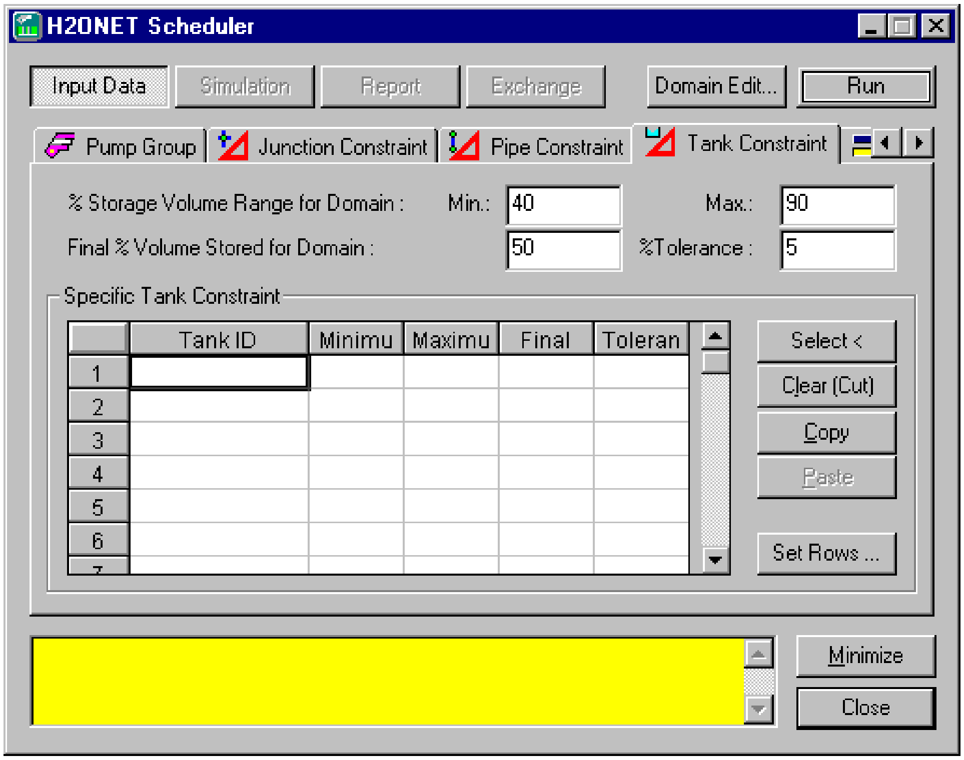

Figure 6 – Storage tank volume constraint dialog box

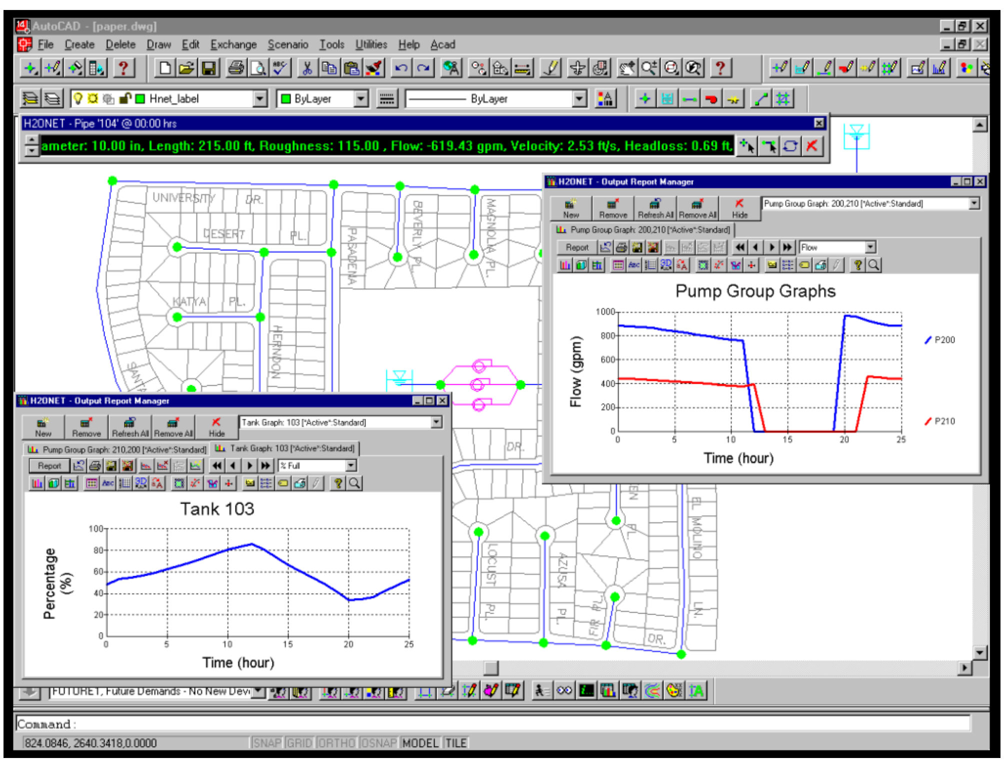

Figure 7 – Pump and tank operational results

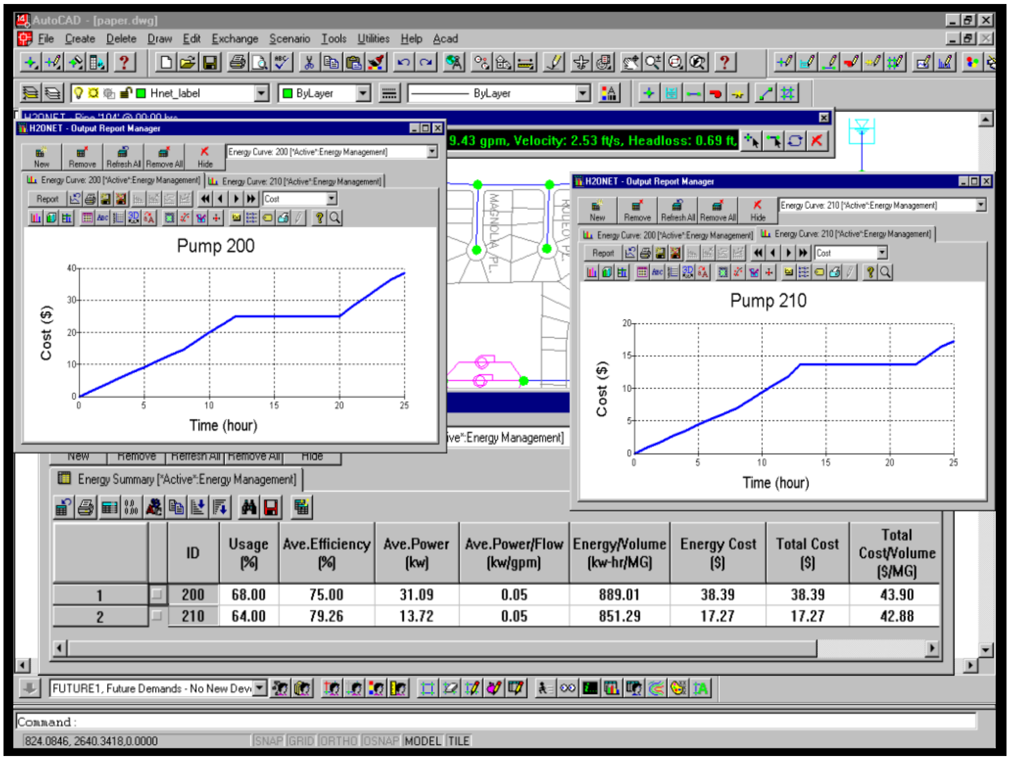

Figure 8 – Optimized energy cost