APPLICATION OF REAL TIME MODELS FOR REAL TIME CONTROL

Water distribution systems may be controlled to satisfy various objectives, including hydraulic performance, water quality performance and economic efficiency. Measures of hydraulic performance include pressure levels, fire protection, water quality, and various measures of system reliability. Measures of water quality performance include water age and disinfection residual levels. Economic efficiency is influenced by such factors as general operation and maintenance costs and pumping costs. In conventional water supply systems, pumping of treated water represents the major fraction of the total energy budget. In ground-water systems, the pumping costs normally represent the major fraction of the total operating cost. Therefore, most optimal control strategies for water distribution systems have focused on minimizing such operational costs.

With respect to the minimization of operational costs, the purpose of an optimal control system is to provide the operator with the least-cost operation policy for control units (e.g. pump stations, booster chlorinators, etc.) in the water-supply system. The operation policy for a system is simply a set of rules or a schedule that indicates when a particular control unit or group of control units should be turned on or off over a specified time period. The optimal policy should result in the lowest total operating cost for a given set of boundary conditions and system constraints.

Any real-time control system will contain three major components in addition to the associated SCADA system: a hydraulic network model, a demand forecast model, and an optimal control model. Each of these components is discussed in the following sections.

Hydraulic Network Models

In order to evaluate the cost of a particular pump-operating policy or to assess the associated operational constraints, some type of mathematical model of the distribution system is required. Potential model structures include mass balance, regression, simplified hydraulic, full hydraulic simulation, and the use of artificial neural networks.

Mass Balance Models

Mass balance models are normally restricted to systems which contain a single storage tank. In a simple mass-balance model of a single-tank system, the flow into the system equals the demand plus the rate of change in storage in the tank. The pressure-head requirements to achieve the flow into the tank are neglected, and it is assumed that a pump combination is available that achieves the desired change in storage. Nodal pressure requirements are commonly assumed to be satisfied if the tank remains within a desired range. When using a mass-balance model, care must be taken when determining the cost to pump a given flow because the operating cost is related to both the discharge and energy added to the flow.

In addition to use of a mass balance approach for single tank systems, multidimensional mass-balance models also have been developed. These models consist of weighted functional relationships between tank flow and pump-station discharge. The weights associated with the

functional relationships can be determined using linear regression (Sterling and Coulbeck, 1975a) or linearization of the nonlinear network (Faliside and Perry, 1975).

The main advantage of mass-balance models is that the system's response can be determined much faster than it can from simulation models. Thus, these models are well suited for use with optimization strategies that require large numbers of simulation analyses (Joalland and Cohen, 1980). In general, mass-balance models are more appropriate for regional supply systems in which flow is carried primarily by major pipelines rather than by distribution networks in which the hydraulics are commonly dominated by looped piping systems.

Regression Models

Instead of using a simple mass-balance model, the nonlinear nature of the system hydraulics can be represented more accurately by using a set of nonlinear regression equations. Information required to construct such models can be obtained in a variety of ways. Regression curves can be generated by repeated execution of a calibrated simulation model for different tank levels and loading conditions (Ormsbee et al., 1987) or by the use of information from actual operating conditions to form a database relating pump head, pump discharge, tank levels, and system demands (Tarquin and Dowdy, 1989).

Regression models have the advantage of being able to incorporate some degree of system nonlinearity while providing a time-efficient mechanism for evaluating system response. However, regression curves and databases contain information only for a given network over a given range of demands. If the network changes appreciably or if forecasted demands are outside the range of the database, such an approach provides erroneous results. Moreover, regression curves are approximations of the system's response. Unless the curves are close approximations of the actual response, errors may accumulate over the course of operation that can adversely affect the optimization algorithm and the accuracy and acceptability of its results.

Simplified Network Models

As an intermediate step between a nonlinear regression model and a complete nonlinear network model, simplified hydraulic models can be used. In such cases, the network hydraulics can be approximated using a macroscopic network model or be analyzed using a system of linearized hydraulic equations. Macroscopic models represent the system by using a highly skeletonized network model. Typically, only a pump, a lumped resistance term (a pipe), and a lumped demand are included. DeMoyer and Horowitz (1975) and Coulbeck (1984) used macroscopic models that had multiple terms relating the effect of various system components but in a single equation.

In certain cases (i.e., where the system boundary conditions are essentially independent of pump-station discharge), it may be possible to represent the system hydraulics using a simple linear model. Jowitt and Germanopoulos (1992) appropriately used an approximate linear model for a system dominated by large pump heads. In this case, small variations in tank levels did not have a significant impact on pump operations. In a similar application, Little and McCrodden (1989) developed a simple linear model for a supply system in which the bead in the controlling tank was held constant. The coefficients for both model types may be determined after extensive

system analysis. As a result, such models must be evaluated on a system-dependent basis to judge their acceptability.

Full Hydraulic Simulation Models

Network simulation models provide the capability to model the nonlinear dynamics of a water distribution system by solving the governing set of quasi-steady-state hydraulic equations. For a water distribution system, the governing equations include conservation of mass and conservation of energy. These equations can be solved in terms of adjustment factors for junction grades (Shamir and Howard, 1968), loop flow rates (Epp and Fowler, 1970), and pipe flow rates (Wood and Charles, 1972).

In contrast to both mass-balance and regression models, simulation models are adaptive to both system changes and variations in spatial demands. For example, if a tank or large main were suddenly taken out of service, a well-calibrated simulation model could still provide the hydraulic response of the modified system. A mass- balance or regression model, on the other hand, would require modification of the database or regression curves to account for the changes in the system's response. Although simulation models are more robust than either mass-balance or regression models, they generally require more data to formulate. They also require a significant amount of work to calibrate properly. Because such models require a greater computational effort than either mass-balance or regression models do, they generally are more useful with optimal control formulations that require a minimum number of individual system evaluations.

Neural Network Models

To reduce the computational requirements of a full hydraulic simulation model, the model can be replaced with a neural network representation of the system's response (Ormsbee and Lingireddy, 1995b). In this case, the neural network can be completely trained off-line, and then used instead of the network model. The data required to train the neural network can come from multiple applications of a previously calibrated hydraulic simulation model. Alternatively, the neural network can be trained on-line using real time or archived data obtained from a SCADA system.

Neural networks comprise a set of highly interconnected but simple processing units, each responsible for carrying out only a few rudimentary computations. When provided with a sequential set of inputs and outputs for a given system, the network can organize itself internally in a way that allows it to reproduce an expected output for another given input. The internal process of self-organization or developing generalized representation of the system is referred to as the training process and is crucial for the efficient reproduction phase of the neural network. A neural network is said to be well-trained if the deviation between the output from the neural network and the specified output is within a tolerable limit. On the basis of the network topology, node characteristics, and learning process, several types of neural networks can be developed.

Demand Forecast Models

To develop an optimal pump-operating policy, network system demands must be known.

Because the actual daily demand schedule for a municipality is not known in advance, the optimal operating policy is estimated using forecasted demands from a demand-forecast model. Forecasted demands can be incorporated into the optimal control model using a lumped, proportional, or distributed approach. In a lumped approach, system demands typically are represented by a single lumped value. Such an approach normally is used in conjunction with mass-balance hydraulic models. Proportional demand models are normally used in conjunction with regression-based hydraulic models. In such instances, regression relationships are derived from a single demand pattern that may vary proportionally to the total system demand. A distributed demand approach is applicable when using a full network simulation model. In such an approach, the total system demand may be distributed both temporally and spatially among the various network demand points. Such an approach enables the development of optimal control policies that are adaptable to significant variations in system demand that may occur over the course of the designated operating period.

Distributed demand forecast models typically employ three steps: (1) they predict the daily demand, (2) they distribute the daily demand spatially among the junction nodes, and (3) they distribute the junction demands temporarily over a 24-h operating time horizon. Prediction of the daily demand can be accomplished by considering such factors as daily weather conditions, weather forecasts, seasons of the year, and past trends in water use (Maidment et al., 1985; Moss, 1979; Ormsbee and Jain, 1994; Sastri and Valdes, 1989; Smith, 1988; Steiner, 1989). Distribution of the daily system demand among the junction nodes can be accomplished using past meter records or real-time database information. Disaggregation of daily junction demands into smarter time intervals can be accomplished by considering the day of the week and seasonal patterns of diurnal demand (Bree et al., 1976; Chen, 1988a; Coulbeck et al., 1985; Perry, 1981).

Techniques for estimating demand are generally available but the availability of data (both spatial and temporal data) has limited the development and application of many available tools. As a result, additional work is still needed in this area, including better methods for short-interval prediction and spatial desegregation using historical short-term data. With an increase in the availability of comprehensive SCADA databases, improved model formulations and performance is expected to be attainable.

Control Models

Proper selection of the optimization algorithm for use in solving the associated control model can often mean the difference between a sluggish or even nonperforming control model and one that functions extremely well. The choice of an appropriate optimization algorithm should be governed by the characteristics of the problem to be solved. Several mathematical programming techniques, such as linear programming (LP), dynamic programming (DP), and nonlinear programming (NLP), are available to solve the optimal control problem. By far, DP has been the optimization algorithm of choice by past researchers. Typically, DP has been used in an implicit control formulation with tank water level generally serving as the control variable. When DP is used, the control problem is broken down into a series of discrete time steps (stages) that have a prescribed set of potential control variable values (states). The optimal solution to the control problem is found by evaluating all state transitions between adjacent stages as opposed to evaluating all state transitions between all stages (i.e. total enumeration). By evaluating the state

transitions between individual stages, a complex problem involving multiple sub problems can be reduced to a series of problems involving a single variable. The main problem associated with the use of DP is the "curse of dimensionality:' in which the computational efficiency of the method significantly decreases as the number of control variables increases. Attempts to circumvent this problem have relied on the use of spatial decomposition schemes or the recasting of the problem in terms of alternate decision variables and solving using other mathematical programming techniques.

LP is the branch of mathematical programming that is used to solve problems where the objective function and all constraints are linear functions of nonnegative decision variables. Nonlinear problems are frequently solved via LP by assuming that portions of the object function and constrained solution space are approximately linear within a prescribed interval. LP problems are solved using an approach called the simplex method, which originally was developed by Dantzig in the late 1940s. The simplex method offers an efficient means of finding the optimum solution of a linear optimization problem by repeatedly selecting the decision variable that causes the greatest improvement in the objective function. As a result of the nature of the linear solution space, the optimal solution of a LP problem will always lie at the intersection of two or more constraints. The simplex method uses this feature of convex problems to its advantage by traveling along constraints to the intersection of other constraints. Once an initial feasible solution is determined, the algorithm identifies an adjacent point that will improve the objective function, then moves along a constraint to the new point. By examining the gradients of each constraint passing through the current point, a new point is selected and the process is repeated until the optimal solution is found.

The third type of control model uses NLP. As the name implies, NLP is useful for problems where the objective function or the constraints of an optimization problem, or both are nonlinear. Unlike LP and DP, NLP involves a large number of different techniques that can be used to solve an optimization problem. Such techniques range from elaborate gradient-based techniques to conceptually simple direct search methods. Recently, several researchers have begun to investigate the use of more heuristically based methods, such as simulated annealing and genetic algorithms.

The Optimal Control Problem

The optimal control problem for a water distribution system can be expressed in terms of a set of decision variables (the things to be varied or controlled), an objective function (an equation written in terms of the decision variables that quantifies the objective - e.g. cost), and constraints that represent restrictions on the values that the decision variables may assume. Mathematically the problem can be expressed as:

Minimize $F(X_1, X_2, \ldots X_n)$ (1)

Subject to: $G(X_1, X_2, \ldots X_n) = 0$ (2)

$H(X_1, X_2, \ldots X_n) > 0$ (3)

$X_H > X_1, X_2, \ldots X_n > X_L$ (4)

Where $F(X_1, X_2, \ldots X_n)$ is the objective function written in terms of a set of n decision variables, $G(X_1, X_2, \ldots X_n) = 0$ represent several implicit system constraints, $H(X_1, X_2, \ldots X_n) > 0$ represents several implicit bound constraints, and $X_H > X_1, X_2, \ldots X_n > X_L$ represents several explicit bound constraints. In the following discussion the optimal control problem will be illustrated by considering the problem of optimal pump control

Decision variables

The optimal control problem for a water-supply pumping system can be formulated using either a direct or an indirect approach, depending on the choice of the decision variable. Direct formulation of the optimal control problem divides the operating period into a series of time intervals. For each time interval, a decision variable is assigned for each pump, indicating the fraction of time the pump is operating during the time interval. The objective function for the control algorithm is then composed of the sum of the energy costs associated with the operation of each pump for each time interval. The problem can then be solved using either LP or NLP (Chase and Ormsbee, 1989; Jowitt et al., 1988; Ormsbee and Lingireddy, 1995a, 1995b). The pump-control policy that results can be classified as explicit (or discrete) because the policy is composed of the required pump combinations and their associated operating times.

Instead of formulating the control problem directly in terms of pump operating times, the problem can be expressed indirectly as a surrogate control variable. Such cost relationships can be developed from multiple regression analyses of actual cost data or from the results of multiple mathematical simulations of the particular system. When tank level is used as the surrogate control variable, the objective becomes one of determining the least-cost tank-level trajectory over the specified operating period. When pump-station discharge (or pump head) is used as the control variable, the objective is to determine the least-cost time distribution of flows (or heads) from all the pump stations. The pump-control policies that result from such formulations can be classified as implicit (or continuous) since the individual pump operating times associated with the optimal state variables are not determined explicitly (Fallside and Perry, 1975; Sterling and Coulbeck, 1975a; Zessler and Shamir, 1989). However, the set of state variables associated with such an implicit solution normally can be converted into an explicit (discrete) policy of pump operating times by subsequent application of a secondary optimization program (Coulbeck et al., 1988b; DeMoyer and Horowitz, 1975; Lansey and Awumah, 1994).

The Objective Function

The operating cost for a pumping system typically is composed of an energy consumption charge and a demand charge. The energy consumption charge is the portion of the electric utility bill based on the kilowatt-hours of electric energy consumed during the billing period. The demand charge represents the cost of providing surplus energy and usually is based on the peak consumption of energy that occurs during a specific time interval. The majority of existing control algorithms for water distribution systems only considers energy-consumption charges. This is primarily the result of the wide variability of demand-charge-rate schedules and that the billing period for such charges can vary between 1 week and 1 year. When such charges are not

explicitly included in the optimal control objective function, they are either ignored or are addressed via the system constraints.

When the demand charges are excluded from the objective function, the objective function can be expressed solely in terms of the energy-consumption charge. In general, energy-consumption charges can be reduced by decreasing the quantity of water pumped, decreasing the total system head, increasing the overall efficiency of the pump station by proper selection of pumps, or using tanks to maintain uniform, highly efficient pump operations. In most instances, efficiency can be improved by using an optimal control algorithm to select the most efficient combination of pumps to meet a given demand. Additional savings can be achieved by shifting pump operations to off-peak water-demand periods through proper filling and draining of tanks. Off-peak pumping is particularly beneficial for systems operating under a variable electric-rate schedule.

Operational Constraints

Constraints associated with the optimal control problem consist of physical system limitations, governing physical laws, and externally defined requirements. Physical system constraints include bounds on the volume of water that can be stored in tanks, the amount of water that can be supplied from a source, and valve or pump settings. The physical laws related to a supply and distribution system are the conservation of flow at nodes (conservation of mass) and conservation of energy around a loop or between two points of known total grade. Also included in this set are relationships between headloss and discharge through a pipe, pump, or valve. Typically, the only external requirements are to meet the defined demands and to maintain acceptable system pressure heads. Pressure-head requirements can have both upper and lower bounds to avoid leakage and ensure satisfying user requirements. Additional constraints can be added to restrict the tank levels to stay within a preset range of values.

When solving the optimization problem, the system's state at the time of analysis is known and an assumed final condition is set as a target. The initial state of the system includes the pump operations and tank levels, whereas the final state defines the end of cycle tank levels. The period of analysis usually is a 1-day cycle, although longer periods can be considered. The cycle for most control schemes typically begins with all tanks either completely full or at a preset lower level and ends 24 h later with the same condition (Shamir, 1985).

Although not normally considered explicitly in most control algorithms, it should be recognized that pump maintenance costs may constitute a significant secondary component of any pump operation budget. Pump wear is directly related to the number of times a pump is turned on and off over a given life cycle. As a result, operators will attempt to minimize the number of pump switches while simultaneously determining least- cost operations. This problem is not as significant for newer pumps, which are better designed and made of more durable materials, but it is a major concern in many older systems. Unfortunately, sufficient data are not currently available to permit the incorporation of such costs directly into the objective function. Instead, limits on pump switches normally are set through the use of the system constraints (Lansey and Awumah, 1994) or an approximate cost term (Coulbeck and Sterling, 1978).

Summary

Many researchers have developed optimal control formulations to minimize the operating costs associated with water-supply pumping systems. For a more in depth review the reader is referred to Chapter 16 of or an earlier review by Ormsbee and Lansey. The choice of the appropriate algorithm for a particular application will depend largely on the physical characteristics of the system. The most straightforward approach for single-tank systems is a formulation with tank level as the state variable in a DP model. Such an approach is generally efficient when the system demands are lumped at a single node or are assumed to vary proportionally. Attempts to incorporate the impact of the spatial variability of demand or changes in the operational status of various system components normally require the use of an alternative formulation. For systems that contain a reasonable number of pumps, it may be plausible to use a pump-run-time model (Chase and Ormsbee, 1991; Ormsbee and Lingireddy 1995a, 1995b). When the total number of pumps is large, the use of an implicit pump-station decision variable may be more appropriate (Lansey and Zhong, 1990).

For multisource-multitank systems that are highly serial or permit a convenient subdivision into distinct hydraulic units, a dynamic programming spatial decomposition approach may be feasible. However, for systems that do not readily permit spatial decomposition, control algorithms normally require lumped-pump-station models and the pump-run-time models to accommodate directly the nonlinear dynamics of most multisource/multitank systems that makes the use of nonlinear optimization an acceptable trade-off. As more tanks and distributed demands are considered, a more detailed simulation model is necessary. The trade-off is then between optimization time requirements, accuracy, and the precision of the associated hydraulic model. Typically, these trade-offs must be evaluated on a network-by-network basis because rules of thumb are difficult to derive.

When using pump-station discharge as a surrogate control variable, the selection of a discharge-cost relationship must be made with extreme car. In most cases, pump-station discharge will vary with both demand and tank level. As a result, the associated cost and hydraulic relationships must have two independent variables (demand and tank level) (Ormsbee et al, 1989), or they must account for the required pressure head in other approximate ways (Coulbeck, 1984). In addition, using pump discharge as the decision variable in a lumped hydraulic model implicitly assumes there is a combination of pumps that will supply the optimal flow under the correct amount of pressure to cause the desired change in tank level. This assumption can be increasingly difficult to satisfy as the network hydraulics become more complex in multiple-source and multiple-tank systems.

In general, as the number of pumps or pump combinations increases, so does the computational advantage of the lumped-pump-station parameter approach over the pump-run-time approach. However, it should be remembered that although the pump run-time approach yields the desired pump operational policy directly, the solution obtained using the lumped-pump-station-parameter approach subsequently must be translated into an appropriate pump policy. Although the computational time associated with this sub problem typically is a small fraction of the time required to solve the implicit control problem, it still can be significant.

In general, the majority of optimal control algorithms have been developed for applications with fixed-speed pumps. Variable-speed pumps can simplify or exacerbate the difficulty of the problem, depending on the decision variable. If pump run time is chosen, each variable speed pump can be represented by a series of fixed-speed pumps. However, such a formulation increases the total number of decision variables and, hence, computation times. On the other hand, the wider continuous-range pump output of variable-speed pumps provides a better mechanism for implementing the continuous solutions associated with formulations of lumped-pump-station parameters. Alternatively, pump speed can be chosen as a continuous decision variable in the lumped-system formulation (Lansey and Zhong, 1990).

Despite the multitude of control algorithms that have been developed for optimal control of water supply pumping systems, several areas of potential research still remain. For example, few researchers have investigated the development of optimal control policies for long-term (weekly) planning horizons. Similarly, little research has been conducted on the impact of final pump operations on pump maintenance requirements. Robustness of operations also has been a neglected area. Finally, the design of water distribution systems is a well-examined area, but little emphasis has been placed on the implications of design on operation and vice versa.

Although the use of expert-system technology or neural-network technology in either developing or implementing optimal control strategies seemingly has great potential, little work has been conducted in this area. Two applications of knowledge-based selection were described by Fallside (1988) and Lannuzel and Ortolano (1989). Fallside and Perry (1975) applied a decomposition approach to an existing system: however, after gaining experience and performing extensive systems analysis, they dropped the scheme in favor of a heuristic described as "pump priority logic" (Fallside, 1988). Lannuzel and Ortolano (1989) also examined a water supply pumping system and developed an operational heuristic from experience. These rules of thumb were then combined with a simulation model in an expert system. Although both studies have limited applicability to other systems, they nevertheless provide some insight into the usefulness of such an approach. Although several successful applications of optimal pumping control exist in Europe and Israel (Alla and Jarrige, 1989; Orr and Coulbeck, 1989; Orr et al., 1990; Zessler and Shamir, 1989), widespread application of such technology in the United States has been severely limited. Future widespread applications of optimal control technology to domestic water supply systems are likely to depend on increased use of more sophisticated SCADA systems and the availability of more commercially available off-the-shelf control software. Additional problems to overcome include the necessity of well-calibrated network models and the availability of accurate demand-forecast models. Even when such technical problems can be overcome, however, it appears that one great roadblock to the implementation of such technology is not the lack of the necessary tools but the unwillingness of utility staff to use them. Previous attempts at developing energy cost minimization programs have revealed that many pump-station operators have an intrinsic mistrust of computers in general and automated operations in particular. In part, the reason may be the conservative nature of most water utilities and their justifiable concern for the impact of "optimal policies" on consumers. In other cases, system operators may have significant concerns about the impacts of such technology on their job security.

Such concerns highlight the need for systems analysts to work closely with operations personnel to develop and implement a particular control environment. In most cases, experienced operators already possess valuable insights into the operation of their system that may prove to be crucial to the development of a successful control scheme. Ideally, the system analyst should work in concert with the system operator to develop an environment that the operator is not only comfortable with but feels some degree of "authorship" as well. In particular, the system should reflect the operator's existing wants and needs as much as possible while providing a framework for expanded control capabilities. In the final analysis, the real challenge of system analysis may not lie in the development of more sophisticated computer algorithms but in the development of more efficient strategies and programs for their implementation.

Additional Papers

Additional papers on the topic of optimal control of water distribution systems can be accessed here:

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