Optimal Control of Water Supply Pumping Systems

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Abstract: The requirements and basic components of a typical optimal control environment for water-supply pumping systems are presented and discussed. Examined model components include hydraulic network models, demand forecast models, and optimal control models. A review of existing optimal control methodologies for water-supply pumping systems is also provided. Examined methodologies are classified on the basis of the type of system to which the methodology can be applied (single source–single tank or multiple source–multiple tank), the type of hydraulic model used (mass balance, regression, or hydraulic simulation), the type of demand model used (distributed or proportional), the type of optimization method used (linear programming, dynamic programming, or nonlinear programming), and the nature of the resulting control policy (implicit or explicit). Advantages and disadvantages of each approach are presented, along with recommendations for future work. The applicability of current technology to an existing water-supply pumping system is examined in light of existing technical limitations and operator acceptance issues.

INTRODUCTION

Due to increased levels of urbanization and consumer demand, most water-distribution-system operations have become increasingly complex. The operational requirements of such systems are typically influenced by pressures from regulatory commissions and the general public to keep operational costs to a minimum. One way to accomplish this objective is through the use of an optimal control system.

This paper reviews the state of the art of optimal control algorithms for water-supply pumping systems. This is preceded by an overview of the components of a typical control system. Potential control algorithms are then examined and categorized on the basis of their applicability to systems of differing characteristics.

OPTIMAL CONTROL SYSTEM

With the increased awareness of the need for better control, many water utilities are installing supervisory-control and data-acquisition (SCADA) systems to improve the operation of their water-supply pumping systems. This trend is likely to continue as the price of the required hardware and software continues to decrease. Such systems enable operators to monitor pressures and flow rates throughout the distribution network and to operate various control elements (i.e., pumps and valves) from a central location. Where such systems are already in place, an optimal control system may be added for a minimal additional cost and potentially significant economic

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savings (Orr and Coulbeck 1989). Once installed, the optimal control system can be used to satisfy the various operational objectives of the system at a minimum cost.

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

Regarding pumping-cost minimization, the purpose of an optimal control system is to provide the operator with the least-cost operation policy for all pump stations in the water-supply system. The operation policy for a pump station is simply a set of rules or a schedule that indicates when a particular pump or group of pumps should be turned on or off over a specified period of time. The optimal policy should result in the lowest total operating cost for a given set of boundary conditions and system constraints.

An optimal control system for a water-supply pumping system will contain three major components: a hydraulic network model, a demand forecast model, and an optimal control model. Each of these components is discussed in the following sections. In general, the optimal control system is directly integrated with an associated SCADA system; alternatively, the control system may be developed as an independent component of the overall operating environment. However, in the latter case, an auxiliary data-acquisition and management system must be provided.

HYDRAULIC NETWORK MODELS

To evaluate the cost of a particular pump-operating policy or 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, and full hydraulic simulation.

Mass-Balance Models

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 in determining the cost to pump a given flow since the operating cost is related to both the discharge and energy added to the flow.

Multidimensional mass-balance models have also been developed. Such models consist of weighted functional relationships between tank flow and pump-station discharge. The weights associated with the functional relationships may be determined using linear regression (Sterling and Coulbeck 1975a) or from a linearization of the nonlinear network (Fallside and Perry 1975).

The main advantage of mass-balance models is that system response can be determined much faster than from simulation models. Thus, they 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 where 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 may be more accurately represented 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 using 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 only contain information for a given network over a given range of demands. If the network changes appreciably or forecasted demands are outside the range of the database, such an approach provides erroneous results. Moreover, regression curves are approximations of the response of the system. Unless the curves are close approximations to 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 Hydraulics

As an intermediate step between a nonlinear regression model and a complete nonlinear network model, simplified hydraulic models may be used. In such cases, the network hydraulics may be approximated using a macroscopic network model or analyzed using a system of linearized hydraulic equations. Macroscopic models represent the system by use of a highly skeletonized network model. Typically only a pump, lumped resistance term (a pipe) and a lumped demand are included. Both 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 significantly impact pump operations. In a similar application, Little and McCrodden (1989) developed a simple linear model for a supply system in which the head 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

Network simulation models provide the capability to model the nonlinear dynamics of a water distribution system by the solution of the governing

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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 may 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 spatial demand variations. 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 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, they are generally more useful with optimal control formulations that require a minimum number of individual system evaluations.

DEMAND FORECAST MODELS

Network system demands must be known to develop an optimal pump-operating policy. 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 may be incorporated into the optimal control model using either a lumped, proportional, or distributed approach. In a lumped approach, system demands are typically represented by a single lumped value. Such an approach is normally 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 employ three steps: predict the daily demand, distribute the daily demand spatially among the junction nodes, and distribute the junction demands temporarily over a 24-h operating time horizon. Prediction of the daily demand may be accomplished by consideration of such factors as daily weather conditions, weather forecasts, seasons of the year, and past water use trends (Moss 1979; Maidment et al. 1985; Smith 1988; Steiner 1989; Sastri and Valdes 1989). Distribution of the daily system demand among the junction nodes may be accomplished using past meter records or real-time database information. Disaggregation of daily junction demands into smaller time intervals may be accomplished by consideration of the day of the week and seasonal diurnal demand patterns (Bree et al. 1976; Perry 1981; Coulbeck et al. 1985; Chen 1988a).

Techniques for demand estimation are generally available but data availability (both spatial and temporal data) has limited the development and application of many of the available tools. As a result, additional work is still needed in this area including better methods for short-interval prediction

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and spatial disaggregation using historical short-term data. With an increase in the availability of comprehensive SCADA databases, it is expected that improved model formulations and performance will be attainable.

OPTIMIZATION MODELS

The final component of the optimal control system is the optimization model. The optimization model is used to select the values of the decision variables that minimize the total operating cost of the system while satisfying any required system constraints.

Operating Cost

The operating cost for a pumping system is typically comprised 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 is usually based on the peak energy consumption that occurs during a specific time interval. The majority of existing control algorithms for water distribution systems only consider energy-consumption charges. This is primarily due to the wide variability of demand-charge-rate schedules and that the billing period for such charges can vary between one week and a year. When such charges are not explicitly included in the optimal control objective function, they are either ignored or addressed via the system constraints.

When the demand charges are excluded from the objective function, the objective function may be expressed solely in terms of the energy-consumption charge. In general, energy-consumption charges may be reduced by decreasing the water quantity pumped, decreasing the total system head, increasing the overall efficiency of the pump station by proper pump selection, 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 cost savings may 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.

System 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 energy conservation around a loop or between two points of known total grade. Also included in this set are relationships between head loss and discharge through a pipe, pump, or valve. Typically, the external requirements are only to meet the defined demands and maintain acceptable system pressure heads. Pressure-head requirements may have both upper and lower bounds to avoid leakage and ensure satisfying user requirements. Additional constraints may be added to restrict the tank levels to stay within a preset range of values.

When solving the optimization problem, the system state at the time of

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analysis is known and an assumed final condition is set as a target. The initial system state includes the pump operations and tank levels while the final state defines the end of cycle tank levels. The analysis period is usually a one-day cycle although longer periods may 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 that 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 are normally set through the use of the system constraints (Lansey and Awumah 1994) or an approximate cost term (Coulbeck and Sterling 1978).

Decision Variables

The optimal control problem for a water-supply pumping system may be formulated using either a direct or 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 a 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 may then be solved using either linear or nonlinear programming (Jowitt et al. 1988; Chase and Ormsbee 1989). The pump-control policy that results may be classified as explicit (or discrete) since 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 may be expressed indirectly in terms of a surrogate control variable such as tank level or pump-station discharge. Use of such a formulation requires prior development of cost functions expressed in terms of the surrogate control variable. Such cost relationships may 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 may be classified as implicit (or continuous) since the individual pump operating times associated with the optimal state variables are not explicitly determined (Sterling and Coulbeck 1975a; Fallside and Perry 1975; Zessler and Shamir 1989). However, the set of state variables associated with such an implicit solution can normally be converted into an explicit (discrete) policy of pump operating times by subsequent application of a secondary optimization program (DeMoyer and Horowitz 1975; Coulbeck et al. 1988b; Lansey and Awumah 1994).

CLASSIFICATION OF OPTIMAL CONTROL FORMULATIONS

Many researchers have developed optimal control formulations for use in minimizing the operational cost associated with water-supply pumping systems. This section, with Table 1 as the central reference, cites and classifies the various algorithms that have been developed for solving the associated control problem. Model formulations are classified based on the physical composition of the system (i.e., the number of tanks and pump stations). Following the classification, an overall evaluation of the various algorithms is presented.

The key to classifying the various control algorithms is the type of system addressed by the model. Columns 2 and 3 of Table 1 define the number of tanks and sources each model can consider. Sources are defined as the number of alternative pumping locations (either individual pumps or pump stations). Following the description of the type of system to which the model is applicable, the type of hydraulic model and demand model used by the algorithm, the type of control algorithm used, and the resulting control policy (explicit or implicit) are identified. The identified control algorithms include dynamic programming (DP), linear quadratic programming, nonlinear programming, integer programming, and mixed integer linear programming.

Single- and Multiple-Pump Stations with No Tanks

The majority of research related to the optimal control of water-supply systems has focused on systems with one or more storage tanks. Two investigators have developed control strategies for systems without effective storage. Chen (1988b) considered a network without tanks and determined the optimal allocation of supply between the pump sources. A continuous nonlinear problem was solved assuming the average pump-station efficiency would be reached for each pump station and a lumped-system relationship could be developed. Dynamic programming was then applied to select the actual pumps given the optimal continuous outflows.

In considering a supply system with a constant head discharge, Little and McCrodden (1989) developed an algorithm to select the optimal pump combinations of a single pump source including the energy usage and peak demand charge in the objective function. Their algorithm used the pump operating times as the decision variables.

Single Tank with Single- and Multiple-Pump Stations

One of the earliest published optimization efforts applied to pump operations for a single tank system was completed for a portion of Philadelphia by DeMoyer and Horowitz (1975). Their problem formulation used tank level as the state variable in a dynamic programming model. In a similar application, Sterling and Coulbeck (1975a) also applied DP for a single-reservoir multiple-source problem in which tank level served as the state variable and tank hydraulics were modeled using a mass-balance relationship. A similar formulation was also proposed by Sabet and Helweg (1985). Later, Coulbeck (1984) extended his original formulation to include both fixed and variable speed pumps.

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TABLE 1. Summary of Optimization Models

Reference (1)	Number of tanks (2)	Number of sources (3)	Hydraulic model (4)	Demand model (5)	Control algorithm (6)	Control policy (7)	Comments (8)
DeMoyer and Horowitz (1975)	Single	Single	Simplified hydraulics	Lumped	Dynamic programming (DP)	Explicit	Pump combinations determined in a conventional DP model with a simplified hydraulic representation (macroscopic model).
Sterling and Coulbeck (1975b)	Multiple	Multiple	Mass balance	Lumped	Linear quadratic programming (LQP)	Implicit	Pump-station discharges are determined with a mass-balance–type linear hydraulic model. Extended in Coulbeck and Sterling (1978) and Cembrano et al. (1988)
Sterling and Coulbeck (1975a)	Single	Multiple	Mass balance	Lumped	DP	Implicit	Conventional DP model determines continuous pump-station discharge.
Fallside and Perry (1975)	Multiple	Multiple	Mass balance (linearized hydraulic equation)	Lumped	LQP	Implicit	Spatial decomposition with fixed transfers between subsystems. Lagrangian relaxation, like Sterling and Coulbeck (1975a), is applied. Optimization later dropped for heuristic-based pump priority logic.
Joalland and Cohen (1980); Carpentier and Cohen (1984)	Multiple	Multiple	Mass balance	Lumped	DP	Implicit	Extension of Fallside and Perry (1975). Spatial transfers are optimized with discrete pump operations. Each subsystem has a single-tank and pump source.
Coulbeck (1984)	Single	Single	Simplified hydraulics	Lumped	DP	Explicit	Approach for an in-line source-resistance-tank-demand supply system. Simplified hydraulics are similar to DeMoyer and Horowitz (1975). Extended to special cases of multisource and -tank systems.
Sabet and Helweg (1985)	Single	Multiple	Nonlinear regression	Proportional	DP	Implicit	Uses single pump sources but neglects the interaction between pumps in developing hydraulic relationships.
Whaley and Hume (1986)	Multiple	Multiple	Nonlinear system equation	Proportional	Nonlinear programming (NLP)	Explicit	Gradient-based NLP algorithm with penalty weights.
Solanos and Montoliu (1988)	Multiple	Multiple	Mass balance	Lumped	DP/LQP	Implicit	Optimal lumped controls are determined in an iterative DP-optimal control approach.

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Chen (1988)	None	Multiple	Mass balance	Lumped	NLP	Implicit	Determines allocation of demand between sources using Lagrangian function.
Jowitt et al. (1988)	Multiple	Multiple	Mass balance	Lumped	Linear programming (LP)	Explicit	Pump run times are determined.
Tatejewski (1988)	Multiple	Multiple	Mass balance	Lumped	LQP	Implicit	Two-level approach with pump station flows determined in an upper level using continuous cost approximations.
Coulbeck et al. (1988a, b)	Multiple	Multiple	Mass balance	Lumped	NLP/integer programming (IP)	Explicit	Three-level model that fixed tank trajectories by NLP in the upper level. These are passed to two lower levels to select pump combinations in an IP.
Ormsbee et al. (1989)	Single	Multiple	Nonlinear regression	Proportional	DP	Explicit	Optimal tank trajectories are determined in a DP model using regression curves for cost and hydraulics. Enumeration is then used to determine exact pump combinations.
Lannuzel and Ortalano (1989)	Single	Multiple	Nonlinear system equation	Distributed	Heuristic	Explicit	Operation heuristics are captured in an expert system linked with a simulator.
Little and McCrodden (1989)	None	Single	Simplified hydraulics	None	Mixed-integer linear programming (MILP)	Explicit	Pump operation times for a supply system to a constant elevation tank via a pipeline are determined in an integer-LP model.
Zessler and Shamir (1989)	Multiple	Multiple	Mass balance	Lumped	DP	Implicit	Regional supply system is spatially decomposed with a single tank and equivalent demand node in each subsystem. Optimal flows are determined by DP and converted by logic to discrete operations.
Chase and Ormsbee (1989, 1991)	Multiple	Multiple	Nonlinear system equation	Distributed	NLP	Explicit	Linked optimization-simulation model using pump run times as decisions for fixed time intervals (Chase and Ormsbee 1989) and variable time intervals (Chase and Ormsbee 1991).
Lansey and Zhong (1990)	Multiple	Multiple	Nonlinear system equation	Distributed	NLP	Explicit	Linked optimization-simulation determines optimal pump-station added energy. Converted to discrete operations in a DP model.

TABLE 1. (*Continued*)

1	2	3	4	5	6	7	8
Ulanicki and Orr (1991)	Multiple	Multiple	Mass balance	Distributed	NLP/MILP	Explicit	Two-level model selects pump run times to meet a desired upper-level tank flows. Approximate mass-balance model used in the upper level and full system equations in the lower level.
Brion and Mays (1991)	Multiple	Multiple	Nonlinear system equation	Distributed	NLP	Explicit	Extension of Chase and Ormsbee (1989) to consider analytical gradients.
Jowitt and Germanopoulos (1992)	Multiple	Multiple	Simplified hydraulics	Distributed	DP	Explicit	Pump run times are decisions with constant pump output due to elevation difference between sources and users.
Awumah and Lansey (1992a)	Single	Multiple	Nonlinear regression	Proportional	IP	Explicit	Solution is actual operating pump combinations.
Awumah and Lansey (1992b)	Single	Multiple	Nonlinear regression	Proportional	DP	Explicit	Discrete pump operations with pump switching limits.

To provide greater flexibility in the consideration of potential pump combinations, Ormsbee et al. (1989) developed a dual-level methodology that provides both the optimal tank trajectory for a single-tank system as well as the associated pump combination operations required to produce the trajectory. The optimal-tank-trajectory problem is solved using dynamic programming, and the lower-level pump-operation problem is solved by enumeration. Cost functions for use in the upper-level problem are constructed from multiple applications of the lower-level algorithm. Cost and hydraulic functions for use in solving the lower level problem are derived using nonlinear regression of results of multiple applications of a nonlinear simulation model of the associated system (Ormsbee et al. 1987).

More recently, Lansey and Awumah (1994) incorporated pump-switching constraints in integer and dynamic programming control models. The formulations are similar in principle to Ormsbee et al. (1989), but transition and cost-regression functions were developed for each pump combination since pump-switching constraints are considered.

Multiple-Tank and Multiple-Source Systems

In general, dynamic programming has been a very efficient algorithm for use in obtaining optimal control policies for single-tank systems. Extension of the approach to multiple-tank systems is greatly limited due to the increased computational burden that results from multiple decision variables and state variables. One way to avoid this problem is through the use of spatial decomposition techniques (Joalland and Cohen 1980; Coulbeck 1988; Zessler and Shamir 1989). In this approach, the system is broken into subnetworks that contain only one or two tanks. Optimal control policies are then developed for each subsystem that are coordinated at an upper control level through the use of relationships that then link the resulting policies together.

Rather than attempting to overcome the limitations to DP through decomposition schemes, other researchers have formulated the control problem using different decision variables other than tank level (Fallside and Perry 1975; Sterling and Coulbeck 1975a; Coulbeck and Sterling 1978; Cembrano et al. 1988; Solanos and Montoliu 1988; Tatejewski 1988; Lansey and Zhong 1990). By using a continuous variable such as pump-station discharge or pump head, a dual-level optimization scheme can be developed that allows a direct consideration of multiple-tank systems. Such methods first determine the optimal discharge or added head associated with each pump station. The pump-operation schedules associated with the resulting optimal discharges or pump heads are then determined by solving a secondary series of discrete optimization problems.

Instead of developing a dual-level optimization algorithm in which the pump-operating times are expressed in terms of some other implicit decision variable, optimal control algorithms can be developed that explicitly consider pump run times as the decision variables. Such formulations can then be solved using linear programming (Jowitt et al. 1988; Jowitt and Germanopoulos 1992) or nonlinear programming (Whaley and Hume 1986; Chase and Ormsbee 1989; Brion and Mays 1991; Ulanicki and Orr 1991; Chase and Ormsbee 1991).

COMMENT

Summary of Previous Work

As can be seen from the previous citations, numerous methodologies have been proposed for use in developing optimal control algorithms for water-supply pumping systems. The choice of the appropriate algorithm for a particular application will be largely dependent on the physical characteristics of the system. The most straightforward approach for use with single-tank systems is a formulation with tank level as the state variable in a DP model. Such an approach is generally very 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 will 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). Where the total number of pumps is considerable, 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 will normally require the use of lumped-pump-station models or a pump-run-time approach. Both the lumped pump-station models and the pump run-time models are normally solved using some form of nonlinear optimization. Where significant approximations to the system hydraulics are feasible, it may be possible to solve the formulation using quadratic programming or even linear programming. However, it is the capability of both the lumped pump-station parameter models and the pump run-time models to directly accommodate the nonlinear dynamics of most multi-source/multi-tank 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 will be necessary. The trade-off is then between optimization time requirements, accuracy, and the precision of the associated hydraulic model. These trade-offs must typically be evaluated on a network-by-network basis since 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 care. 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) as was shown in 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 in a lumped hydraulic model implicitly assumes there is a pump combination that will supply the optimal flow under the correct amount of pressure to cause the desired change in tank level. This assumption may be increasingly difficult to satisfy as the network hydraulics become more complex in multiple-source and -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 while the pump-run-time approach yields the desired pump operational policy directly, the solution obtained using the lumped-pump-station–parameter approach must be subsequently translated into an appropriate pump policy. While the computational time associated with this subproblem is typically a small fraction of the time required for solution of the implicit control problem, it can still 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 increase 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 results in an increase in 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 lumped-pump-station–parameter formulations. Alternatively, pump speed can be chosen as a continuous decision variable in the lumped-system formulation (Lansey and Zhong 1990).

Future Research

Despite the multitude of control algorithms that have been developed for use in the 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 performed to study the impact of final pump operations on pump maintenance requirements. Robustness of operations has also been a neglected area. Finally, water-distribution-system design is a well-examined area, but little emphasis has been placed on the implications of design on operation, and vice versa.

Although seemingly an area of great potential, little work has been conducted on the possible use of expert-system technology or neural-network technology in either developing or implementing optimal control strategies. Two applications of knowledge-based selection are Fallside (1988) and Lannuzel and Ortolano (1989). Fallside and Perry (1975) applied a decomposition approach to an existing system, but after gaining experience and performing extensive systems analysis, the scheme was dropped 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 utility of such an approach.

Practical Applications

Although several successful applications of optimal pumping control exist in Europe and Israel (Alla and Jarrige 1989; Orr and Coulbeck 1989; Zessler and Shamir 1989; Orr et al. 1990), widespread application of such technology in the United States has been severely limited. With the exception of a control system for Albuquerque, N.M. (Jentgen and Hume 1989), the writers are unaware of any other large municipality that has a capability to control its pump operations using computer-generated pump policies. The writers are aware of several municipalities that have implemented some form of computer-assisted pump selection or are considering an investigation of computer control technology for their system (Hutchinson 1991), but actual applications appear to be very limited.

Future widespread applications of optimal control technology to domestic water-supply systems are likely to be dependent on an increase in the use of more sophisticated SCADA systems and the availability of more commercially available off-the-shelf control software. Additional problems to be overcome include the necessity of well-calibrated network models and the availability of accurate demand forecast models. Even where such technical problems can be overcome, however, it is the writers' opinion that one of the greatest roadblocks to the implementation of such technology is not the lack of the necessary tools but the willingness of a utility staff to use them. The writers have seen that many pump-station operators have an intrinsic mistrust of computers in general and automated operations in particular. This may be partially due to 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 in both the development and implementation of a particular control environment. In most cases, experienced operators will already possess valuable insights into the operation of their system that may prove critical in the development of a successful control scheme. Ideally, the system analyst should work in concert with the system operator in developing an environment with which the operator is both comfortable and feels some degree of "authorship." In particular, the system should reflect the existing wants and needs of the operator as much as possible while at the same time 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.

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