Decision Support System for Adaptive Water Supply Management

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Abstract: Recent advances in computer technology and water resource modeling, availability of real-time hydroclimatic data, and improvements in our ability to develop user-friendly graphical model interfaces have led to significant growth in the development and application of decision support systems (DSSs) for water resource systems. This study provides an example of the development of a real-time DSS for adaptive management of the reservoir system that provides drinking water to the Boston metropolitan region. The DSS uses a systems framework to link watershed models, reservoir hydraulic models, and a reservoir water quality model with linear and nonlinear optimization algorithms. The DSS offers the ability to optimize daily and weekly reservoir operations toward four objectives based on short-term climate forecasts: (1) maximum water quality, (2) ideal flood control levels, (3) optimum reservoir balancing, and (4) maximum hydropower revenues. Case studies document the value of the DSS as an enhancement of current rule curve operations. The study shows that simple tools, in this case, familiar spreadsheet software, can be used to improve system efficiencies.

DOI: 10.1061/(ASCE)0733-9496(2003)129:3(165)

CE Database subject headings: Decision support systems; Water supply; Boston; Massachusetts; Water management.

Introduction

For many water supply systems, reservoir operations are based on heuristic approaches including rule curves, operator judgment, and other qualitative information. While often reliable and cost effective, such techniques often pertain only to individual objectives, and usually do not offer guidance for adaptively fine tuning a system as real-time conditions change over short time periods. This study is an effort to quantify, organize, and process all sources of information necessary to adaptively manage the water supply system that services the Boston Metropolitan region so that long-term plans can be adapted on a weekly basis to changing conditions and time-varying objectives.

The Massachusetts Water Resources Authority (MWRA) operates a two-reservoir system in central Massachusetts that supplies drinking and industrial water to the Boston Metropolitan region. Historically, operational decisions were made on a monthly basis, with the assistance of rule curves, and the system has been a reliable source of water for many decades. Despite satisfactory yield, however, MWRA managers recognized that the monthly timescale for operational decisions was not compatible with climate variability within each month in New England. Promoting the highest possible water quality and preparing for potential floods require adaptive management of the system as climatic and hydrologic events occur. With real-time climate forecasts and hydrologic data readily available, MWRA managers decided that a real-time DSS could help improve operations with respect to numerous objectives based on expected hydroclimatological conditions.

A real-time DSS is developed for a seven-day planning period, and its output is based on input of current climate forecasts. It allows planners to maximize or minimize, as applicable, any of four objectives individually or in hierarchical multiobjective formulations, depending on circumstances. The four objectives are the minimization of total organic carbon (TOC) in the downstream reservoir, the minimization of deviations from target elevations, balancing the two reservoirs, and the maximization of revenues from three hydropower facilities. It is normally assumed that the water supply system satisfies demand so that water quality and flood control are normally the primary objectives. The MWRA has historically operated the hydropower facilities without economic intent; hence power revenues are always a secondary objective. Nevertheless, we document that hydropower benefits may be increased while still achieving the primary water quality and/or flood control objectives.

The DSS combines hydrologic, hydraulic, and water quality models into a system optimization model that uses both linear programs (LPs) and nonlinear programs (NLPs). Since prospective users of the DSS include engineers, managers, and field operators, practicality and transportability were of paramount importance. Hence, commonly used *Windows*-based software was selected. Model components were developed on spreadsheets using Microsoft *Excel* and *Visual Basic for Applications* (VBA). Visual Basic for Applications provided a mechanism for the de-

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Note. Discussion open until October 1, 2003. Separate discussions must be submitted for individual papers. To extend the closing date by one month, a written request must be filed with the ASCE Managing Editor. The manuscript for this paper was submitted for review and possible publication on November 7, 2001; approved on June 17, 2002. This paper is part of the ***Journal of Water Resources Planning and Management***, Vol. 129, No. 3, May 1, 2003. ©ASCE, ISSN 0733-9496/2003/3-165–177/$18.00.

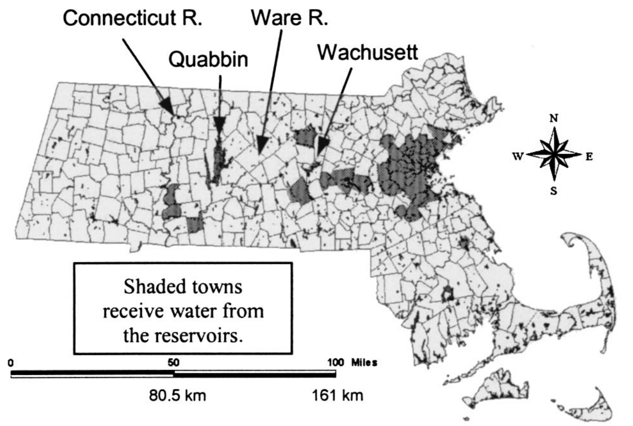

Fig. 1. Massachusetts Water Resources Authority water supply system

velopment of a functional graphical user interface as well as a mechanism for model integration, data transfer, and numerical solutions. Optimization algorithms include those available within an enhanced version of the standard *Excel SOLVER*. The resulting DSS is a single *Excel* workbook that can be easily understood, applied, and modified by engineers and system operators.

System Description and Management Options

The water supply system supplies 46 communities (roughly 2.5 million people) in eastern Massachusetts with an average of 0.96 million m^3 (MCM) of water per day. It consists of two reservoirs in series as depicted in Figs. 1 and 2. The Quabbin Reservoir, located 130 km west of Boston, has a 490 km^2 watershed, and can store up to 1,560 MCM of water (966 MCM active storage). The Wachusett Reservoir, 40 km closer to Boston, has a 277 km^2 watershed, and can store up to 246 MCM of water (36.7 MCM active storage). The Wachusett Reservoir also receives water from the Quabbin Reservoir via the Quabbin Aqueduct, and serves as the final retention basin for the water before it is chemically treated. In between the two basins flows the Ware River. From October 15 through June 14, water in excess of 0.32 MCM/day can be diverted to the Quabbin Reservoir via the Quabbin Aqueduct. However, river diversions significantly restrict other operational activity, and can cause operational conflicts.

The westernmost system component is the Connecticut River. The river does not supply the MWRA system with water, but flow in the river, as measured at the USGS gauging station in Montague, Mass., governs minimum daily downstream releases from the Quabbin Reservoir to the Swift River (which eventually flows into the Connecticut River and is lost from the system). The minimum daily release rate is 0.076 MCM, but this increases to 0.174 MCM when Connecticut River flow drops below 139 m^3/s, and to 0.269 MCM when flow drops below 132 m^3/s. Considering that the estimated value of safe yield from the entire system is roughly 1.14 MCM/day (Vogel and Hellstrom 1988), these minimum downstream release rates represent a significant percentage of available water. The DSS predicts streamflow in the Connecticut River in order to include this important constraint on weekly reservoir operations.

The system includes three hydropower stations, as shown in Fig. 2, with a total capacity of 8 MW. Water released to the Swift River flows through the turbines at Winsor Station. Water transferred from Quabbin to Wachusett can pass either through the turbines at Oakdale or through bypass pipes when flow requirements exceed turbine ratings. Water released from Wachusett into the Cosgrove Tunnel passes through the Cosgrove turbines.

The Quabbin Aqueduct connects the two reservoirs, and relies on gravity to accommodate the three separate operational needs depicted in Fig. 3. First, it can be used to divert water from the Ware River into the Quabbin Reservoir. It can also be used to transfer water from the Quabbin Reservoir to the Wachusett Reservoir, through either a hydropower station or a bypass pipe. The bypass valves are nonregulating valves, and when they are opened, the flow is governed only by the head in the Quabbin Reservoir and the physical characteristics of the aqueduct. Because the turbines are flow limited, the bypass mechanism permits transfer rates nearly twice as high as are possible through the turbines. Operationally, the single aqueduct fulfills three purposes, but only one operational mode is possible at a given time.

Figs. 2 and 3 illustrate the management alternatives for the system. For every 7-day planning period, the following daily decisions are needed: how much water, if any, (1) to divert from the

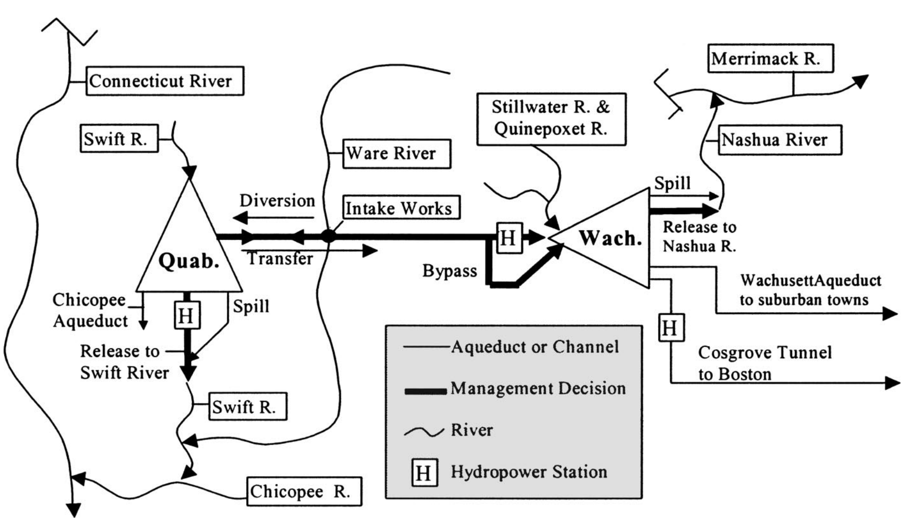

Fig. 2. Schematic of Massachusetts Water Resources Authority water supply system

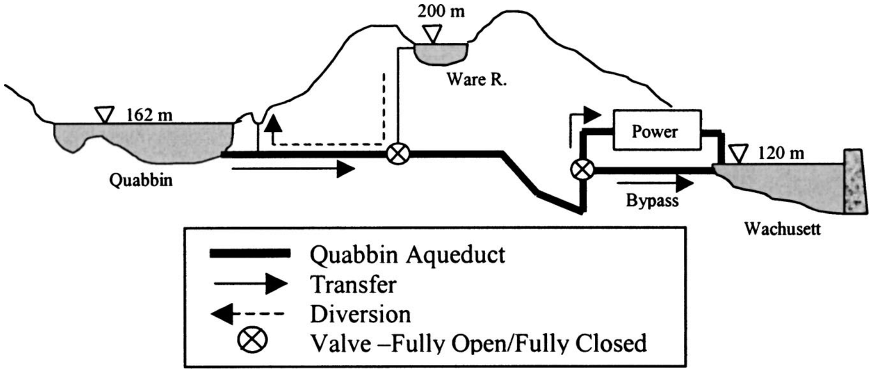

Fig. 3. Schematic of aqueduct transfers and diversions

Ware River, (2) to transfer from Quabbin to Wachusett via Oakdale Station, (3) to transfer via the bypass pipes, (4) to release from Quabbin downstream, and (5) to release from Wachusett downstream. It is the purpose of this DSS to enable such decisions to be made in an objective, adaptive, and optimal fashion.

Program Structure and Interface

Although the entire DSS is contained within a single PC file, its components were designed in a modular framework. The modules are interconnected as illustrated in Fig. 4. The hydrologic models are run as soon as the user inputs climate forecasts, initial conditions, and the constraints that may vary from week to week. The output of the watershed models is then transferred to the hydraulic and optimization modules. The hydraulic models adjust automatically during optimization, and continually update the LP or NLP with values of system variables and constraints.

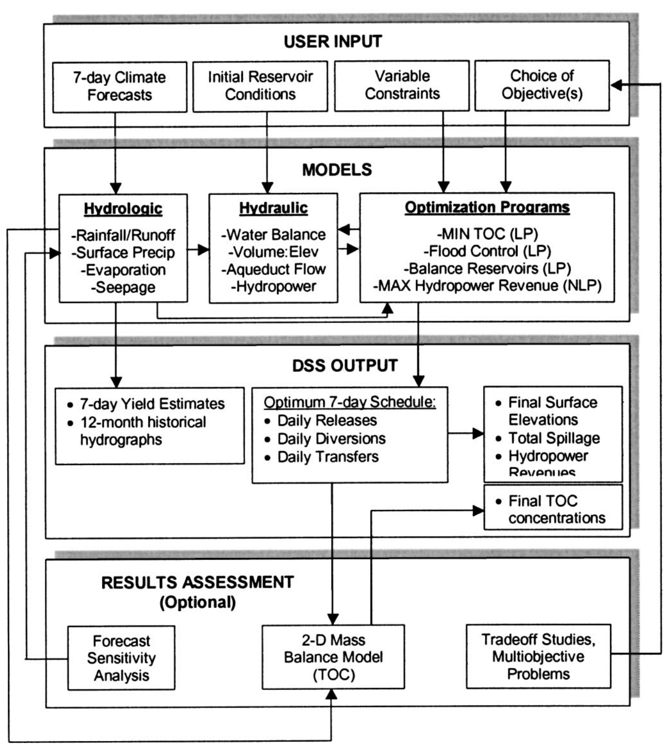

Fig. 4. Block diagram of decision support system

Output is transferred to the user interface three times during the running of the DSS. First, as soon as the hydrology of the four basins is simulated, the predicted flows for the planning period are presented along with 12-month historic hydrographs of each basin. This output allows the users to evaluate runoff predictions in the context of recent trends, and to evaluate the performance of the rainfall-runoff models. The second set of output data is displayed once the optimization module has determined an optimum operating schedule for the chosen objective(s). The 7-day schedule of daily releases, transfers, and diversions is displayed along with predictions of surface levels, 7-day basin yield, total spillage, and hydropower revenues. Finally, water quality graphs based on the optimized schedule are provided after the optimization is complete.

Users interact with the DSS through a control screen that is structured as a flowchart for easy navigation through the program. Each ‘‘button’’ on the control screen, when clicked, calls a VBA subroutine that either displays a dialogue box for data entry or triggers the various modules within the DSS, including LPs and NLPs. From this control screen, optimization can be repeated with different objectives or combinations of objectives. Also, the control screen offers options to evaluate water quality and forecast sensitivity. In this way, all decision-support information is accessible from a single control screen. See Westphal (2001) for the graphics of all interface screens.

Modeling Techniques

Hydrologic Modeling

The hydrologic models predict watershed runoff into both reservoirs and streamflow in the Ware and Connecticut Rivers (system constraints). Streamflow predictions are based on real-time 7-day forecasts of precipitation and temperature ranges. Weekly averaging is used since the operating objectives focus only on end-of-week conditions (not on the day-to-day variability of system conditions), and since this technique avoids unnecessary uncertainty in daily hydrologic responses of the large watersheds. (Operational flows are accounted for on a *daily* basis to allow aqueduct flow in two directions during any given week, yet only the total weekly flows are important in computing the objective functions.) The flow predictions are used in the reservoir optimization model to constrain the natural inflows to the system and to establish mandated constraints on diversions and releases.

Critical to the success of any real-time DSS is its ability to accurately predict watershed runoff using a minimum of input

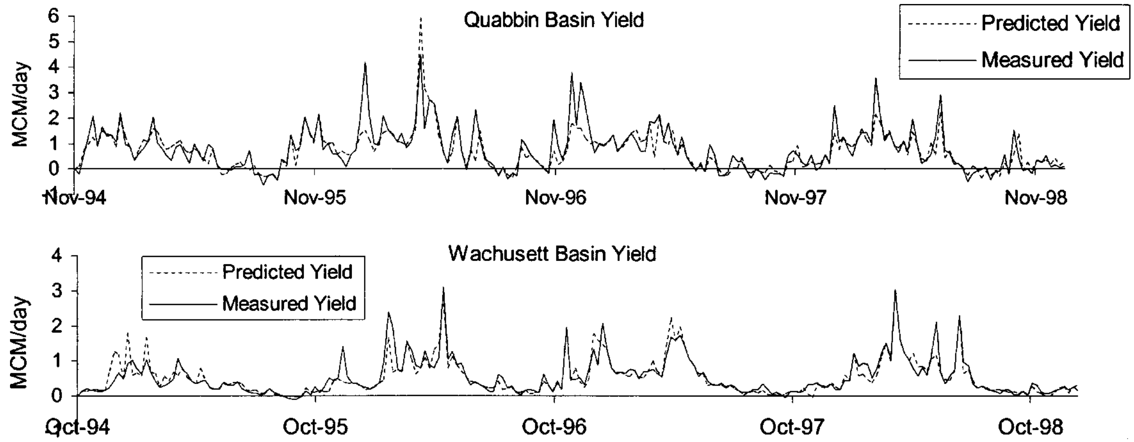

Fig. 5. Weekly yield model performance

data (Loucks 1995). Four independent watershed models are developed to predict the watershed yield for the Quabbin and Wachusett Reservoirs and flow in the Ware and Connecticut Rivers. Reservoir yield Y is defined as

$$Y_{ti}=Q_{ti}+P_{ti}-E_{ti}+G_{ti} \tag{1}$$

where Q = streamflow; P = precipitation onto the reservoir surface; E = free-surface evaporation; and G = groundwater seepage for planning period t at site i. Streamflow, evaporation, and groundwater seepage are determined using independently calibrated models based on expected precipitation and temperature.

Streamflow is predicted using a modified version of the *abcd* water balance model introduced by Thomas (1981). This model uses four physically based parameters (a, b, c, and d) to compute inflows and outflows from two storage variables; near-surface soil moisture and groundwater (aquifer) storage, according to the following equations:

$$\text{Available water:}\quad W_t=P_t+S_{t-1} \tag{2}$$

Evapotranspiration opportunity:

$$Y_t=\left[\frac{W_t+b}{2a}-\sqrt{[(W_t+b)/2a]^2-bW_t/a}\right] \tag{3}$$

$$\text{Soil moisture storage:}\quad S_t=Y_t\exp\left(\frac{-PE_t}{b}\right) \tag{4}$$

$$\text{Groundwater storage:}\quad G_t=\frac{c(W_t-Y_t)+G_{t-1}}{1+d} \tag{5}$$

$$\text{Actual evapotranspiration:}\quad E_t=Y_t-S_t \tag{6}$$

$$\text{Streamflow:}\quad Q_t=[(1-c)(W_t-Y_t)+dG_t] \tag{7}$$

For each timestep, the model computes *available water* (W_t) as the sum of previous soil moisture (S_{t-1}) and current precipitation (P_t). *Evapotranspiration opportunity* (Y_t) is defined as the water that will eventually leave the basin through evapotranspiration, and is used to help define how much of the available water remains in the basin during each timestep. Potential evapotranspiration (PE_t) is estimated using the Hargreaves method (Hargreaves and Samani 1982); among all temperature-based methods of potential evapotranspiration, the Hargreaves method is the only one recommended by Shuttleworth and Maidment (1993). The equations distribute available water between runoff, percolation to groundwater, change in soil moisture storage, and evapotranspiration (E_t). Groundwater storage (G_t) and soil moisture (S_t) are simulated as separate storage reservoirs. Streamflow (Q_t) is simply the sum of baseflow and runoff, where baseflow is estimated as a linear function of groundwater storage. Modifications were added to account for snow accumulation and melting, and the reduction in evapotranspiration caused by subfreezing air temperatures. The *abcd* model is an attractive watershed model for this DSS because (1) its parameters are physically based (see Fernandez et al. 2000), (2) it is a parsimonious model having only five parameters with the addition of the snowmelt modifications, thereby conforming to recommendations by Hornberger et al. (1985), Hooper et al. (1988), Beven (1989), and Jakeman and Hornberger (1993), (3) it requires only precipitation and temperature as input, (4) it provides estimates of internal watershed state variables including groundwater storage, soil moisture storage, and actual evapotranspiration, and (5) it compares favorably with other commonly used water balance models (see Alley 1984; Vanderwiele et al. 1992).

Ideally, free-surface evaporation would be estimated from either pan evaporation data or the Penman-Montieth approach for estimating potential evaporation. Since data are unavailable for either approach, the following temperature-based approach to estimating reservoir evaporation was employed:

$$SE_{ti}=a_{ti}PE_{ti}A_{ti} \tag{8}$$

where SE_{ti} = free-surface evaporation for week t and reservoir i; a_{ti} = calibrated coefficient; PE_{ti} = potential evapotranspiration computed using the Hargreaves method; and A_{ti} = reservoir surface area. The calibration parameters in Eq. (8) were obtained by comparing regional regression equations developed by Fennessey and Vogel (1996) for estimating monthly mean potential evaporation (PE) from very limited data. Fennessey and Vogel show that their regression equations reproduce long-term monthly average values of PE based on the widely used but data-intensive Penman-Monteith approach. Finally, a seepage model was developed for each reservoir based on modeled groundwater storage levels and time of year (Westphal 2001). The models of each hydrologic contributor are combined for each reservoir to estimate reservoir yield using Eq. (1). The results shown in Fig. 5 indicate that the reservoir yield models reproduce average daily yield for 7-day periods with reasonable accuracy, explaining roughly 75–80% of the weekly variations in overall yield. Addi-

Table 1. Controlled Reservoir Releases

Release from	Release to	Medium	Method of determining flow
Quabbin	Swift River (min)	Winsor Power Station	Connecticut River model
	Swift River (extra)	Winsor Power Station	Optimization program
	Springfield suburbs	Chicopee Valley Aqueduct	User input
Wachusett	Nashua River (min)	Fountain at Dam	User input
	Nashua River (extra)	"Waste Gates"	Optimization program
	Lancaster Mills	Fountain at Dam	User input
	Town of Clinton	Pipeline	User input
	Town of Leominster	Pipeline	User input
	Metro West Towns	Wachusett Aqueduct	User input
	Boston Metro	Cosgrove Power Station, Cosgrove Tunnel	User input

tionally, the Connecticut River model predicts the correct flow regime 92% of the time, and the Ware River model exhibits similar accuracy.

Hydraulic Reservoir Models

Reservoir operations for each reservoir are modeled using the continuity equation

$$S_t = S_{t-1} + \sum_j Inflow_j - \sum_k Outflow_k \qquad (9)$$

where S_t = storage volume at the end of week t. The inflows and outflows to each reservoir can be disaggregated for any weekly period using

$$\sum Inflows_j = Drainage + Precip_{\text{surf}} + \sum_{i=1}^{7} Transfer_{i\ \text{in}} + \sum_{i=1}^{7} Div_i \qquad (10a)$$

$$\sum Outflows_k = Evaporation + Seepage + 7\sum_n REL_n + \sum_{i=1}^{7} Transfer_{i\ \text{out}} + Spill \qquad (10b)$$

where each value of REL_n represents one of n possible controlled daily releases from the reservoir, and i is a daily index.

The hydrologic terms are discussed in the previous section. Transfers occur in the Quabbin Aqueduct, and since the system is entirely gravity fed water can only be transferred from Quabbin to Wachusett (Figs. 2 and 3). Regulated transfer flow can be passed through turbines at the Oakdale hydropower station. Alternatively, flow in excess of the maximum turbine rating can be transferred into Wachusett by bypassing the turbines via nonregulating (full-flow) valves. In such cases, flow is determined not by valve settings but by the physical features of the aqueduct and relative head levels in the reservoirs. Diversions represent flow that is diverted from the Ware River into the Quabbin Reservoir, and are expressed by the daily decision variables Div_i. Controlled releases represent reservoir withdrawals for downstream flow or MWRA water users. Release values are determined via user input, results of hydrologic modeling, or system optimization, as outlined in Table 1. Spills from Quabbin are estimated from initial elevation, and spills from Wachusett are estimated from mass balance estimates (assuming that all excess water in Wachusett can spill within one week).

Because only one aqueduct fulfills three purposes, only one operational mode is possible at a given time, and the simulated aqueduct is limited to only one function per day. Eqs. (11*a*) and (11*b*) combine continuous and binary variables to define daily flow in the aqueduct with linear equations, based on physical and operational limitations

$$Transfer_i = Q_{\min}(CheckTran_i) + Tran_i + Limit_{\text{bypass}}(CheckByp_i) \qquad (11a)$$

$$Div_i = f(CheckDiv_i, Constraints) \qquad (11b)$$

where $Q_{\min}$ = minimum rated turbine flow; $Tran_i$ = transfer through turbines in excess of $Q_{\min}$ on day i (continuously variable from zero to an upper bound); and $Limit_{\text{bypass}}$ = hydraulic limit computed for the bypass circuit as a function of differential head. $CheckTran_i$, $CheckByp_i$, and $CheckDiv_i$ are all binary variables that are set equal to 1 if their corresponding function is determined to be optimum, or 0 if not, and the sum of the three for any daily value of i is constrained to 1. $Tran_i$ is also constrained to 0 if $CheckTran_i$ is 0. The upper bound of $Tran_i$ is estimated each week as a constant from historical records based on relative initial head levels, and the value of $Limit_{\text{bypass}}$ is determined each week as a constant using the energy equation and the Darcy-Weisbach equation with calibrated friction factors. The values of Div_i are optimized, and vary from 0 to an upper limit computed from hydrologic simulation and numerous hydraulic, operational, and legislated constraints (presented later). They are constrained to 0 if $CheckDiv_i$ is equal to 0. This technique converts nonlinear functions and discontinuities into a simple, mixed-integer linear format, by segmenting the equations into continuous and discrete blocks: $Transfer_i$ is either the sum of a discrete minimum value and the continuous variable $Tran_i$, or it is equal to the discrete value of the maximum bypass flow.

Other important hydraulic relationships are those between reservoir volume, surface elevation, and surface area. Surface elevation is a measurable quantity, and is used by MWRA as a primary guide in operational decision making. Unfortunately, surface elevation is a nonlinear function of reservoir volume, and the DSS, as designed, uses LPs for greatest efficiency. Storage, however, is a linear function of inflows and outflows [Eqs. (9)–(10*b*)], and this linearity permits fully linear simulation of the reservoir hydraulics. User input and DSS output are expressed in terms of surface elevation, since this is the familiar standard. The program simply converts elevation to volume prior to, and following, the optimization algorithm. The MWRA has developed the following regression relationships between volume and elevation ($R^2 > 0.99$):

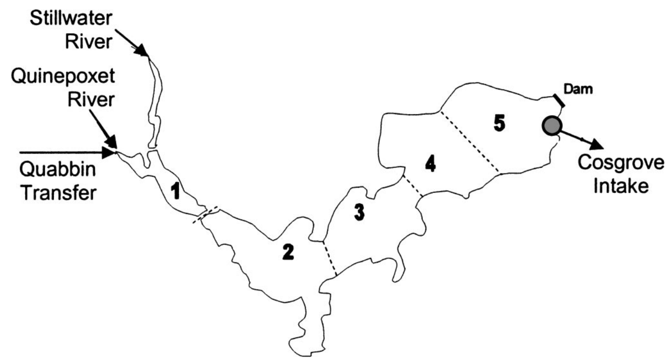

Fig. 6. Segmentation of Wachusett Reservoir in water quality model

$$S_{\text{Quab}}=7{,}958{,}351-36{,}561.5(E_{\text{Quab}})+42.1227(E_{\text{Quab}})^2 \tag{12a}$$

$$S_{\text{Wach}}=829{,}121.402-5{,}237.9906(E_{\text{Wach}})+8.36311946(E_{\text{Wach}})^2 \tag{12b}$$

where S and E represent reservoir volume in millions of gallons and elevation in feet above Boston City Base (MWRA's units). The surface area is assumed to be relatively constant for each week, and is computed using similar relationships.

The hydropower stations were simulated with nonlinear equations (head and head loss are nonlinearly related to flow). An alternate linear approach would be to optimize a set of decision variables representing time periods of operation at discrete operating points with predetermined head loss, head, and flow. However, the lack of reliable turbine efficiency curves rendered such incremental analysis unreliable. Turbine efficiency was simply estimated at 80%, although actual efficiency will vary with flow and head. This value is consistent with MWRA long-term planning models, and has proven to be a reasonable estimator. The total revenue generated in a 1-week period is modeled as

$$REVENUE=\sum_{i=1}^{3}\sum_{t=1}^{7} Q_{it}(\overline{H_i}-h_{Li})\rho g\eta P_i \tag{13}$$

where Q_{it} = flow at station i on day t; H_i = average head over a weekly period; h_{Li} = head loss in penstock i; ρ = density of water; g = gravitational acceleration; η = overall efficiency; and P_i = price per kilowatthour at station i, with appropriate conversion factors. The head loss terms are estimated with the Darcy-Weisbach equation using calibrated friction factors.

Water Quality Modeling

A two-dimensional mass balance model for total organic carbon was developed as a way to assess the impacts of any optimized operations schedule on water quality in the Wachusett Reservoir. This downstream reservoir was analyzed because it is the final point of storage before the water is chemically treated and discharged to the distribution system. Hydrologic inflow and outflow predictions and optimized transfer and discharge flow are automatically input to the model to simulate the water balance. The reservoir is divided into five longitudinal elements as shown in Fig. 6. Differential equations for TOC concentration are then solved for each segment of the discretized reservoir.

Measuring organic content in water can be difficult. However, organic material absorbs light, while inorganic material tends to scatter light. Measurements of light absorbance tend to offer reasonable estimates of organic content in the water, while being much easier to obtain. The MWRA uses the absorbance of ultraviolet light at a wavelength of 254 nm (UV-254 absorbance) to indicate required chlorination levels and expected levels of disinfection byproducts (DBPs). From a modeling perspective, predicting rates of light absorbance is difficult, but TOC can be modeled by considering the advection, diffusion, settling, and production of organic material throughout the reservoir. Our model simulates TOC and the results are correlated to levels of UV-254 absorbance using

$$\text{UV-254}=0.4456(\text{TOC})-0.5918 \tag{14}$$

where UV-254 is in units of absorbance in a 10 cm cell, and TOC is expressed in mg/L. This correlation is based on 29 available data points, and the model exhibits an R^2 value of 0.73. It is heavily influenced by four outliers (without which the R^2 value increases to 0.85). MacCraith et al. (1993) and Matsche and Stumwöhrer (1996) confirm that UV-254 and TOC are well correlated, although the relationships are known to be site specific. As more data become available, the correlation model can easily be refined. As it is, the numerical water quality model provides MWRA with an estimate of the effects of any optimized schedule on the TOC in the reservoir, and the correlation relationship offers a reasonable estimate of the resulting level of UV-254 near the treatment plant intake. The authors are developing a separate manuscript that will describe the water quality model and the correlation between UV-254 and TOC in greater detail.

While data pertaining to TOC concentrations, reservoir levels, and inflows were readily available, other data that would have been useful in the development and calibration of a fully mechanistic model were not. Algal biomass, phosphorus, nitrogen, and temperature data were either sparse or unavailable, and hence stratification and the occurrence of spring algae blooms were based on historical trends. In a real-time model, however, this poses no problem, since users can use available real-time monitoring data to answer yes/no questions about the state of the reservoir each week (such as, "Is the reservoir fully stratified?"). Their answers are converted to binary variables that simulate the state of the reservoir mathematically.

Stratification is particularly important in this model, since the thermal structure of the stored water affects the flow paths of two major source rivers and the water transferred from Quabbin, all of which enter at the western end of the reservoir (see Fig. 6). The reservoir is typically stratified from mid-May through mid-October. Quabbin water is usually much colder than Wachusett water, and we might expect that it would plunge downward toward the hypolimnion. However, when Thomas Basin (section 1 in Fig. 6) receives water from both the aqueduct and rivers, the mixing effect tends to equalize the temperature of all the incoming water. The result is that the well-mixed inflow temperature falls somewhere between the warm epilimnion temperature and the colder hypolimnion temperature. The incoming water therefore flows along the very narrow metalimnion of the stratified reservoir downstream of Thomas Basin. This "interflow" provides a direct conduit for the water from one end of the reservoir to the other, and its effect is a reduction of the residence time for most of the incoming water from 6–7 months to roughly 2–4 weeks (Camp Dresser & McKee 1996). The depth of the intake gates at the Cosgrove Intake coincides with the depth of the metalimnion during periods of stratification, so the water flows straight through and out of the reservoir very quickly. Based on measured historic temperature profiles, the model simulates the reservoir in either the stratified (three-layer) or nonstratified (one-layer) configuration (see Fig. 7). During periods of complete

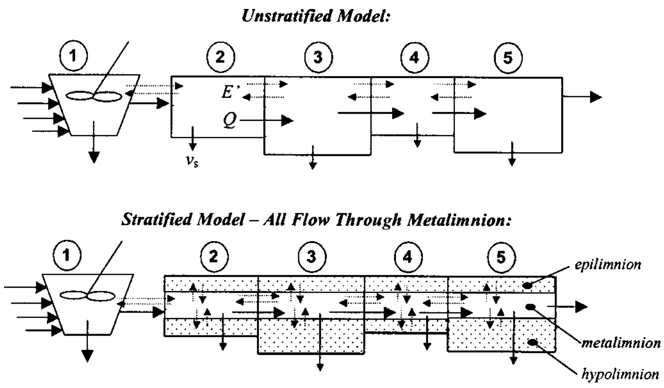

Fig. 7. Structure of total organic carbon model

stratification, all flow is routed through the thin metalimnion, and the resultant decrease in segment volume greatly increases the advective transport rate.

The five longitudinal segments were chosen using natural divisions in reservoir bathymetry, and so that each segment could be associated with historical temperature profile measurements. Segment volumes for the five segments shown in Figs. 6 and 7 were computed from bathymetric maps and historic records of temperature variation with depth. The TOC model reproduces the 6–7 month transport time when each segment is well mixed, and the 2–4 week stratified transport time, both with very reasonable accuracy.

The transport times make it difficult to use the TOC model directly with the optimization program, since operational activity during any week will not impact water quality near the treatment plant for at least 2 weeks, and usually much longer. Hence, the TOC model is used to predict TOC concentrations in each of the five segments shown in Fig. 7, although the effects of operations are usually observed immediately only in the receiving basin (segment 1). Operators can make decisions based on this response with the understanding that the remaining segments will follow this signal, with a response analogous to that of a low-pass filter.

Fig. 7 illustrates the structure and mechanisms of the TOC model. The model simulates advection, diffusion (horizontal and vertical), settling, and production during certain springtime periods. The four input flows represent the two source rivers, the transfer aqueduct, and local hydrology at the receiving basin. Flow in each segment is computed using a nested loop algorithm, in which the spatial segments (either 5 or 13, depending on stratification) are simulated for each step within a temporal loop, discretized with a timestep of 0.1 day. The general equations for the TOC concentrations are solved numerically using the Euler method (first order, explicit), where the superscript t is the temporal index, and the subscript i is the spatial index.

For the unstratified reservoir

$$\frac{dM_i^t}{dt}=Qin_i^t c_{i-1}^t - Qin_{i+1}^t c_i^t + \frac{E_{i-1}A_{i-1}}{\Delta x_{i-1}}(c_{i-1}^t - c_i^t) + \frac{E_i A_i}{\Delta x_i}(c_{i+1}^t - c_i^t) - vs_i As_i c_i^t + kg_i As_i \tag{15}$$

$$M_i^{t+1}=M_i^t+\frac{dM_i^t}{dt}(\text{timestep}) \tag{16}$$

$$c_i^{t+1}=\frac{M_i^{t+1}}{V_i^{t+1}} \tag{17}$$

where V = volume; A = cross-sectional area between segments; As = settling area; Q = flow; M = mass; c = concentration; E = diffusion coefficient; Δx = horizontal mixing length; vs = settling rate; and kg = areal growth rate.

For the stratified reservoir

$$\frac{dMm_i^t}{dt}=Qin_i^t c_{i-1}^t - Qin_{i+1}^t c_i^t + \frac{E_{i-1}Am_{i-1}}{\Delta x_{i-1}}(c_{i-1}^t - c_i^t) + \frac{E_i Am_i}{\Delta x_i}(c_{i+1}^t - c_i^t) + \frac{Ev_i Ame_i}{Lme_i}(ce_i^t - c_i^t) + \frac{Ev_i Amh_i}{Lmh_i}(ch_i^t - c_i^t) - vs_i As_i c_i^t + kg_i As_i \tag{18}$$

$$Mm_i^{t+1}=Mm_i^t+\frac{dMm_i^t}{dt}(\text{timestep}) \tag{19}$$

$$c_i^{t+1}=\frac{Mm_i^{t+1}}{Vm_i^{t+1}} \tag{20}$$

where Am, Vm, and Mm are, respectively, the vertical cross-sectional diffusion area, volume, and organic mass associated with the metalimnion. Ev_i are the vertical diffusion coefficients. Ame_i are the areas of the horizontal planes separating the epilimnion and metalimnion in each section, and Amh_i are the areas of the horizontal planes separating the hypolimnion and metalimnion in each section. Likewise, Lme_i and Lmh_i represent the vertical mixing lengths characterizing mixing across each section. Finally, c_i represents concentrations in the metalimnion, while ce_i and ch_i represent the concentrations in the other two layers, both of which are calculated similarly, but without an advective transport component.

Fig. 8 illustrates the results of model calibration. The model output in the weekly DSS illustrates the response of each segment, including the receiving basin (C1), which responds immediately to operational activity and can provide meaningful estimates of the effects of operational plans on eventual water quality downstream. The calibration parameters were settling, diffusion, and production rates, all of which were bounded by physically plausible limits for northeastern U.S. lakes (Westphal 2001).

Optimization Objectives

Operators can select from among four operating objectives for any given week, as conditions warrant: minimize TOC, optimize flood control operations, balance overall system vulnerability to floods, or maximize hydropower revenues (always a secondary objective). These objectives may be optimized individually for tradeoff studies, or sequentially in certain multiobjective combinations. The constraint method is employed for multiobjective formulations, as recommended by Cohon and Marks (1975) for reservoir optimization problems with fewer than four objectives. Reservoir target elevations can be optimized as a primary objective with any other objective optimized as a secondary objective simply by constraining upper and lower reservoir bounds. Water quality can also be optimized with hydropower as a secondary objective. The program is run twice, first to optimize water quality, and then to optimize hydropower production based on constrained flow rates and surface elevations for optimum water quality.

The first three objectives are formulated as mixed-integer LPs, and solutions can be obtained with the simplex algorithm and branch and bound programming in 10–15 s with a 600 MHz

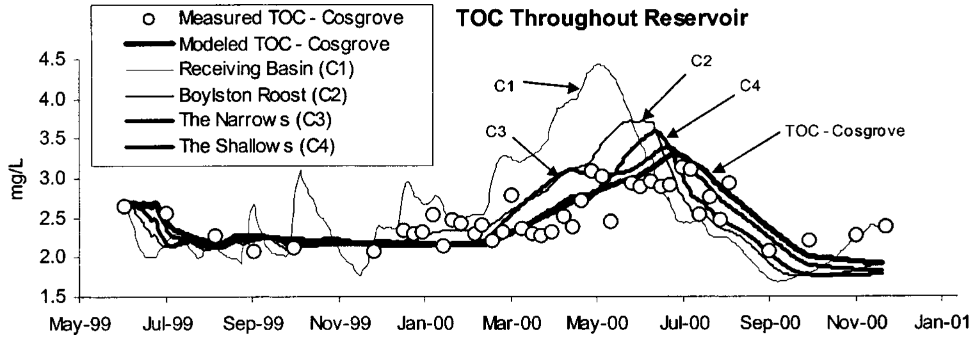

Fig. 8. Total organic carbon model calibration results

Pentium III processor. The fourth objective, hydropower optimization, is nonlinear, and optimum operating schedules are obtained with the generalized reduced gradient algorithm in roughly 1–5 min with the same processing hardware. To avoid the problem of local maxima, users are encouraged to iterate several times with different initial conditions to check for apparent convergence toward a true optimum. Typically, though, the decision space is tightly constrained, especially since hydropower production will be maximized only as a secondary hierarchical objective, and local maxima have not proven to be particularly troublesome during initial tests.

Water Quality Objective

Linking the water quality objective directly to the water quality model was problematic because the TOC concentration of primary interest (at the downstream end of Wachusett Reservoir) does not depend on reservoir operations within the 7-day simulation period. Alternatively, the TOC model for the upstream receiving basin could have been linked to the LP, since receiving basin concentration responds very quickly to operational inputs. However, no data existed with which to calibrate the TOC concentration anywhere but at the downstream intake to the treatment plant. In this initial study we employ the TOC model as an assessment tool and an alternative objective function is developed for quantifying reservoir water quality.

The water quality objective is based on the total weekly transfer of water to Wachusett and the water surface elevation in Wachusett. Each of these variables is linked to improvements in water quality. Quabbin water is generally much cleaner than Wachusett water, due to much lower levels of watershed development and a much higher residence time that allows for settling and natural purification. Transferring water from Quabbin to Wachusett promotes dilution of impurities in Wachusett water year round. High water surface elevations in Wachusett impede light penetration and subsequent plant growth, and also discourage gull roosting in the shallow areas. Thus, to optimize water quality, the transfers and surface elevation of Wachusett are maximized. To maintain linearity, the LP maximizes reservoir volume in lieu of elevation. Thus, the objective function for optimizing water quality can be expressed as follows:

$$MAX\left[S_{\mathrm{Wach}}+\sum_{i=1}^{7} Transfer_i\right] \tag{21}$$

where S_{Wach} = ending storage in the Wachusett reservoir defined by Eqs. (9)–(10*b*); and $Transfer_i$ = total daily transfer from the Quabbin to the Wachusett Reservoir, defined by Eq. (11*a*).

Flood Control Objective

For flood control, the objective is simply to minimize the difference between the ending volume and a target volume based on desired flood storage capacity input by the user. Only the Wachusett Reservoir is considered in the objective function formulation, since its smaller size makes its volume more sensitive to operational flow levels. Desired storage levels in the Quabbin are governed by upper and lower constraints input by the user. The flood control objective is expressed as

$$MIN|S_{\mathrm{computed}}-S_{\mathrm{target}}|_{\mathrm{Wach}} \tag{22}$$

To enable a linear formulation of the absolute value in this objective function, dummy variables are introduced as suggested by Revelle et al. (1997).

Reservoir Balancing Objective

Reservoir balancing can be selected as the objective if both reservoirs are above their normal elevations. Normal elevations were determined by the MWRA and Vogel and Hellstrom (1988) based on historical reservoir operations. The reservoir balancing objective attempts to ensure that both reservoirs end the planning period with the same percentage of excess storage available (above normal). For example, if Quabbin begins a week with 20% of its excess storage utilized and Wachusett begins the week with 90% of its excess storage utilized, the LP will "balance" the system so that they might both end the week with 30% of excess storage utilized. This objective balances the vulnerability of the overall system to downstream flood damage by ensuring that both reservoirs have approximately equal absorption capacity with respect to their basin areas. The objective is expressed using

$$MIN|\%Excess_{\mathrm{Quab}}-\%Excess_{\mathrm{Wach}}| \tag{23a}$$

where

$$\%Excess_i=\left[\frac{S_{\mathrm{computed}}-S_{\mathrm{normal}}}{S_{\max}-S_{\mathrm{normal}}}\right]_i\times 100 \tag{23b}$$

Hydropower Objective

The objective for hydropower revenue maximization is simply the maximization of hydropower revenues given in Eq. (13). Because the MWRA does not operate the system with economic intent, hydropower revenues are considered a residual benefit, and are maximized only as a secondary objective to water quality or flood control. Flow for Winsor Station is the sum of minimum downstream releases and the extra release, which is a fraction of the decision variable (REL^+) proportional to the Quabbin drainage

Table 2. Decision Variables

DIV_i	Continuous	Daily diversion from Ware River to Quabbin Reservoir	$i=1–7$
$TRAN_i$	Continuous	Daily transfer from Quabbin to Wachusett via hydroplant in excess of minimum turbine rating	$i=1–7$
REL^+	Continuous	Combined daily extra downstream release above req. min.	
$CheckDiv_i$	Binary	$=1$ if Ware River is diverted on day i, else$=0$	$i=1–7$
$CheckTran_i$	Binary	$=1$ if Quabbin-Wachusett transfer through hydroplant occurs on day i, else$=0$	$i=1–7$
$CheckByp_i$	Binary	$=1$ if transfer through bypass pipe occurs on day i, else$=0$	$i=1–7$
Z^+	Continuous	Dummy variable used when objective function contains absolute value	
Z^-	Continuous	Dummy variable used when objective function contains absolute value	

(MWRA strives to keep extra releases in check by distributing excess water evenly throughout the system, based on basin area). Flow for Oakdale Station is expressed using Eq. (11*a*), and flow for Cosgrove Station is governed by the demand constraint for the Cosgrove Tunnel (servicing Boston). Average head is computed as the difference between the elevation of the turbines and the midpoint between the starting and ending reservoir elevations.

Constraints and Decision Variables

The overall weekly optimization problem consists of 36 to 38 decision variables (see Table 2). The nature of the water supply system necessitates numerous *ON/OFF* control values within the model formulation, and hence the optimization is formulated as a mixed-integer linear program.

Roughly 250 constraints bound the variables for any 7-day planning period. Some constraints vary with circumstance, and are either updated automatically by logical programming prior to optimization, or are input by users based on preference or circumstance. For example, users may choose to allow diversions from the Ware River in order to assist with flood relief even if legislated constraints would normally prohibit such action in the interest of water conservation. The interface gives users access to some of the constraints that may, from time to time, be relaxed. Users can also constrain upper and lower reservoir elevations. Users also enter expected demand for each planning period. Otherwise, the constraints are generally fixed, and represent physical limitations, legislated mandates, known best practices, and operational limitations. Unlike many long-term planning models, in which a small set of general constraints is replicated for each time step, this real-time model requires extremely detailed constraints to ensure that the behavior of the entire water supply system is reproduced as accurately as possible. The constraints are tabulated in Table 3, using the notation at the end of this paper.

Case Studies

To test the effectiveness of the DSS, two cases were simulated and the resulting optimal operations schedules were compared with records of actual water management. The objective was to see if the DSS could generate operating schedules that would have improved operations toward a specific set of objectives. Since the constraints are based on the principles used to develop the original monthly rule curves, and on all of the legal restrictions imposed on system operations, any such improvements can be considered to be *refinements* of the traditional rule curves (by the addition of optimization algorithms and the inclusion of within-month climate and system variabilities in the analysis), not a replacement based on new rules. Overcoming misperceptions of the tool as a replacement rather than an enhancement, and understanding the risks associated with basing operations on predicted climatology and hydrology, were perceived as the key obstacles to the eventual acceptance and utility of the DSS. These case studies were designed to help planners and operators understand the potential value of DSS recommendations by addressing the uncertainty inherent in the predictive model elements, and by demonstrating whether or not the DSS could actually add value to the traditional operating methods while operating in full accordance with long-standing regulations and operating rules.

Planning periods were chosen which were not coincident with calibration periods for the individual model components of the DSS. In each case, actual climate records were used in lieu of forecasts in order to isolate model error from forecast error. The assumption of perfect forecast information does not necessarily create an unfair comparison here, since traditional methods of planning have relied on initial conditions and time of year, and not on climate forecasts. Still, in an attempt to minimize any unfair benefits obtained from such an assumption, weeks during which no rain occurred were selected for each test, since the occurrence of no rain can usually be forecast with reasonable accuracy. To account for forecast uncertainty during real-time planning, the DSS is equipped with a forecast sensitivity module that compares optimized operating schedules derived from minimum, maximum, and average expected precipitation in each basin. The relative impact of forecast error with respect to model errors will be carefully evaluated over time as the DSS is phased into use.

Case Study 1: Optimizing Water Quality and Hydropower Revenues

A dry week, ending October 24, 1998, was selected for the first study. Since both reservoirs were well below full capacity, MWRA operators would likely have been most concerned with water quality, as opposed to flood control or reservoir balancing. Thus maximizing water quality was selected as the primary objective, and maximization of hydropower revenues as a secondary objective.

The hydrologic models predicted a net hydrologic loss of -0.072 MCM/day for Quabbin, and this compared favorably with a measured value of -0.064 MCM/day. To provide a sense of scale, the long-term mean yield is 0.78 MCM/day. Wachusett yield was predicted as 0.064 MCM/day, and actual measurements revealed a true gain of 0.10 MCM/day. In comparison to the long-term mean of 0.54 MCM/day, the model error was very

Table 3. Model Constraints

Type	Constraint	Notes
Capacity	$S_k > S_{k\text{-min}}$	
Hydraulic	$Q''_{ix} < Q_{x\text{-max}}$	
Flooding	$\left[\frac{S_k - S_{k\text{-max}}}{7}\right] + R_{DS-k} + REL_k^+ \leqslant FC_k$	Term in brackets represents daily spill
Water quality	$CheckTran_i + CheckByp_i = [1, —]$	Force transfer from 5/1 to 10/30
	$CheckTran_i + CheckByp_i = [1, —]$	Force transfer if water in Quabbin Aqueduct is stagnant for 30 days
Legislated	$DIV_i = [0, —]$	Diversions are not allowed from 6/15 to 10/14
	$DIV_i \leqslant Q_{\text{Ware}} - 0.32$ MCM/day	Can only divert Ware flow in excess of 85 mgd (minimum instream flow)
	$R_{\text{DS-Quab}} = [0.076, 0.17, 0.27]'$ MCM/day	Minimum release to Swift River is governed by predicted flow in Connecticut River
Operational	$DIV_i = [0, —]$	Cannot divert Ware River if Quabbin is above *NORM*
	$REL^+ = [0, —]$	Can only release extra water if both res. above *NORM*
	DIV_i, $TRAN_i$, REL^+, Z^+, $Z^- \geqslant 0$	Continuous decision variables cannot be negative
Binary	$CheckDiv_i$, $CheckTran_i$, $CheckByp = [0, 1]$	Definition of binary decision variables
	$CheckDiv_i + CheckTran_i + CheckByp \leqslant 1$	Quabbin Aqueduct can only be used for one purpose at a time
	$DIV_i - CheckDiv_i \geqslant -0.999$	If $DIV_i = 0$, this forces $CheckDiv_i = 0$
	$1000 * CheckDiv_i - DIV \geqslant 0$	If $DIV_i > 0$, this forces $CheckDiv_i = 1$
	$TRAN_i - CheckTran_i \geqslant -0.999$	If $TRAN_i = 0$, this forces $CheckTran_i = 0$
	$1000 * CheckTran_i - TRAN_i \geqslant 0$	If $TRAN_i > 0$, this forces $CheckTran_i = 1$
Hydrology	$Q_i = Q'_i$	Hydrology constrained by model predictions
	$E_k = E'_k$	
	$SP_k = SP'_k$	[see Eqs. (2)–(7)]
Demand	$R_y = \underline{R_y}$	
Water balance	$S_{kt} = S_{kt-1} + \sum_i \sum_{j,x} Inflow_{j,x} - \sum_i \sum_{x,y} Outflow_{x,y}$	Reference Eqs. (9)–(10*b*)
Hydropower	$P_z = Q''_z (H_z - h_z^-) \rho g$	Reference Eq. (7)
Unusual operations	$CheckByp_i = [0, —]$	Can force any transfers through the hydrostation at Oakdale by disallowing bypass flow
	$DIV_i = [MIN(MAX\ constraints^*), —]$	Can force Ware diversions if necessary to reduce Ware River flooding
		*Not all max constraints apply, as this option overrides minimum instream flow and Quabbin volume constraints
	$DIV_i = [MIN(MAX\ constraints), —]$	If Ware River diversions are allowable, divert the maximum allowable amount
Absolute values	$S_{\text{Wach}} - T_{arget} - Z^+ + Z^- = 0$	Defines Z^+ and Z^- when optimizing Wachusett volume toward a target
	$[(S_{\text{Quab}} - S_{NORM\text{-}Q})/S_{NORM\text{-}Q}] - [(S_{\text{Wach}} - S_{NORM\text{-}W})/S_{NORM\text{-}W}] - Z^+ + Z^- = 0$	Defines Z^+ and Z^- when balancing reservoirs

small. These yield prediction errors are orders of magnitude smaller than typical operational flows, and were therefore assumed to have very little influence on the results. The models predicted the correct hydrologic regime for the Connecticut River, and hence minimum downstream releases from Quabbin were accurately constrained.

Fig. 9 illustrates the effectiveness of the DSS in optimizing both objectives with hierarchical prioritization. Actual operations reduced TOC concentration in the receiving basin of Wachusett by roughly 8%, while optimized operations could have reduced TOC concentration by 14%. At the same time, by optimally distributing the total transfers (optimized for water quality) over 7 days, the DSS schedule increased simulated hydropower revenues by roughly 20%, or $10,000 for the week (actual revenues were corrected based on the assumed efficiency of 80% in order to compare identical systems). Hydropower could have been increased further, but the optimized flows for water quality were binding constraints in this secondary optimization.

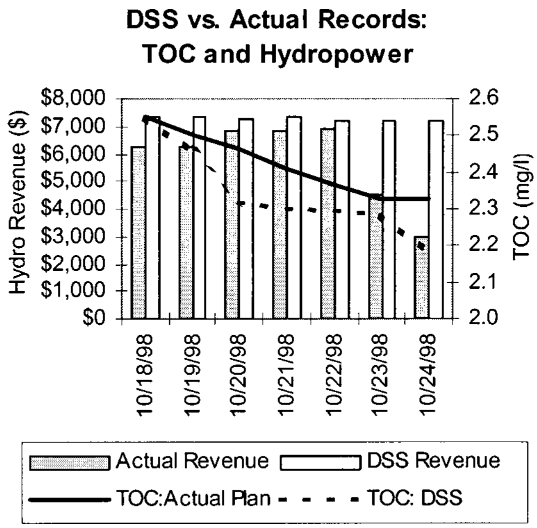

Fig. 9. Results of case study 1: Water quality and hydropower optimization

Case Study 2: Optimizing Flood Control

A second case study was conducted for the week ending March 20, 1996. While no precipitation fell during the week, a large amount of snowmelt was observed, and the hydrologic model was tested for its ability to accurately simulate streamflow due to snowmelt. The objective for this week was to reduce the risk of downstream channel flooding by lowering the elevation of Wachusett. Wachusett began the week at full spillway capacity, and with expected snowmelt the MWRA strives to maintain excess storage capacity to store runoff while keeping uncontrolled spills to a minimum. The Quabbin model overpredicted yield by 15%, while the Wachusett model underpredicted yield by 11.6% (actual yield at both sites exceeded the respective long-term averages). The errors were on the order of 0.095–0.114 MDM/day, which is still smaller than mean yield and typical operational flows by nearly an order of magnitude. Ware River flow was predicted within 10%, and the correct flow regime of the Connecticut River was predicted, thereby establishing accurate constraints.

Records indicate that actual reservoir operations for the week resulted in a lowering of the Wachusett water level by 0.07 m. The optimum DSS schedule predicted a decrease of 0.06 m. However, the model satisfied all best-practice constraints, while actual operations did not. The MWRA strives to distribute excess water releases equally around the system. This self-imposed control of downstream releases was binding in the DSS schedule, and severely limited operational flows. While high downstream releases from Wachusett were desired, the total system release (above mandated minimum levels) was distributed evenly between the two reservoirs, and binding constraints at Quabbin limited the amount that could actually be released from either.

In this case, the optimized operational flows were so low that they approached the values of error in the hydrologic predictions. However, if the DSS recommends very low operational flows, it is indicating that the system is very nearly optimal at the beginning of the planning period, and very little improvement can be made if all constraints are satisfied. Seeing this, operators may wish to evaluate the effects of suspending self-imposed operating rules, especially when faced with impending flood conditions. In this case study, binding MWRA-imposed constraints of balanced releases prevented the DSS from generating a schedule that offered much progress toward the objective of reducing the water elevation and associated flood risk. Based on this information, operators could rerun the optimization without the binding self-imposed constraint to quantitatively assess the value of a temporary suspension of best practices. In this example, the DSS suggested that the Wachusett water level could have been safely reduced by up to 0.3 m had the water simply been released from Wachusett, a significant improvement over the 0.06 m reduction obtainable with fully enforced constraints on balanced releases.

Summary and Conclusions

As graphical software tools have become more prevalent and intuitive, many water resource managers have recognized the value of integrated modeling and decision support systems [see Watkins and McKinney (1995) for a review]. Integrated decision support models aggregate and process all pertinent hydrologic, hydraulic, water quality, legal, economic, and other important system factors to enable decision makers to evaluate the impacts of various decisions and tradeoffs between competing objectives in a systematic and comprehensive fashion.

This study demonstrates that adaptive management of a water supply system by developing optimum flow schedules for short-term planning periods can refine traditional policies, as evidenced by improved water quality, better flood control, and increased revenues. The study emphasizes that use of simple and familiar software within the framework of a DSS offers opportunities for (1) aggregating, managing, and exploiting climatic, hydrologic, and hydraulic information, (2) producing accurate predictions of hydrologic and reservoir system state variables, (3) developing optimum real-time operating schedules, and (4) performing tradeoff studies to examine the values associated with various system objectives. The study also shows that optimization algorithms can be effectively formulated and executed, and tradeoff studies can be conducted, in a matter of minutes using the programmable interface capabilities of desktop spreadsheets. The familiar format of the DSS should encourage its use and enable MWRA engineers to modify or adapt it, either as more data become available or as the water system changes. The case studies demonstrate that this DSS is an effective tool for planning real-time operations of the MWRA water supply system based on single and multiple objectives. The first case study suggested that the DSS could be effectively used to improve water quality by scheduling optimum reservoir operations known to promote low levels of TOC. This case study also revealed that hydropower production could be simultaneously improved by distributing previously optimized total flows for optimum turbine output.

The second case study (flood control) also revealed that the DSS can produce reasonable flood control operating schedules, but also identified an important limitation. When the operating plan specifies very low operational flows relative to long-term mean inflow, the confidence in the results decreases. This can occur under low-flow conditions, when model errors associated with the hydrologic predictions may approach or exceed the order of magnitude of natural and operational flows. This is not expected to have significant consequences, since operators could adjust the optimized plan throughout the week based on observed hydrologic phenomena, and since the need for flood control will not often coincide with low-flow periods. Furthermore, low levels of operational flow will have very little overall effect on the system, adverse or otherwise, and if low operational flows are prescribed, the system can be considered to be nearly optimal at the start of the period.

Still, a DSS solves only part of the decision problem. Results from a DSS are intended to guide and support decisions, not to make them, and in such a role, the true utility of a DSS is measured in part by the comfort level of those who use it. Once accepted by the users, its reliability can then only be fully measured with actual use over time. At the time of this writing, MWRA personnel have been testing the predictive strength of the hydrologic model elements against very recent records, which were unavailable during the development of the tool. These tests have been designed to build confidence in the model's predictive accuracy, so that its ultimate output, in the form of recommended operating schedules, can be considered to be reliable.

The DSS has been used occasionally to support general planning decisions, but its full implementation is not planned until the hydrologic models have demonstrated enough predictive accuracy, based on recent records, to satisfy both operators and planners. Recent world events, unfortunately, set the testing schedule back, as the MWRA refocused its attention on security issues. The current plan is to complete the hydrologic verification, then use the model in a hypothetical mode by comparing its recommendations against actual operations (additional case studies, conducted in real time) for a period of several weeks or months, and ultimately to make the tool available to those who will make the daily and weekly operational decisions. We believe that the MWRA's approach to the implementation of the model is a good example for others considering the development of decision support tools.

1. The MWRA will build confidence in the model by conducting additional verification tests on key model elements;
2. The MWRA will compare results from the fully integrated model against traditional operations as decisions are made and results measured, further evaluating accuracy and consistency;
3. Any required refinements or recalibration can be easily accomplished by MWRA engineers and planners because of the familiarity of the software;
4. The MWRA is identifying reliable sources of real-time climate data and forecasts so that weekly collection and input of data can become nearly automatic;
5. Once the model has demonstrated its robustness and reliability, it will become available to planners and operators as a tool for refining traditional rule-curve decisions. It is intended for guidance only, and not as a mandate. Perhaps more clearly, it is intended by the authors and by MWRA to supplement operator judgment, not to replace it.

Acknowledgments

The writers wish to thank the following people from MWRA for their advice and technical support of this work: Steven Estes-Smargiassi, Daniel Nvule, Marcis Kempe, Windsor Sung, and Guy Foss. We also thank Charles Howard for his inspiration, and two anonymous reviewers for their perceptive and thoughtful comments, the inclusion of which helped improve both the quality and focus of this work.

Constraint Notation

Indices

i = daily index ($i=1-7$);
j = basin index (Quabbin, Wachusett, Ware, Connecticut);
k = reservoir index (Quabbin, Wachusett);
t = weekly index;
x = operational flow index (transfers, diversions, extra releases);
y = demand index (Cosgrove Aqueduct, Wachusett Aqueduct, Chicopee Valley Aqueduct, etc.); and
z = hydropower station index.

Abbreviations

DS = downstream;
E = daily surface evaporation;
FC = flood capacity;
H = head;
h^- = head loss;
$NORM$ = normal volume;
P = power;
Q = natural streamflow (daily);
Q'' = operational flow (daily);
R = daily release;
S = final storage; and
SP = daily seepage.

Other

$[a,b]$ = different values apply at different times or are conditional on logical comparisons;
<u>*Value*</u> = user input;
— = no constraint; and
$'$ = model prediction.

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