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Real-time Automation of Water Supply and Distribution for the City of Jacksonville, Florida, USA

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Abstract

JEA's Operation Optimization System (OOS) project is an important advance in real-time water supply and distribution system automation. The challenge in implementation was to draw a balance between the theory and practice of forecasting, modelling, simulation and optimization. The result is a highly practical realization of the AWWA EWQMS model that can be refined in an evolutionary manner to achieve greater energy efficiency. The architectures, development methodology and integration capabilities are best-of-breed for this type of application. The system meets the goal of representing the expertise of JEA's best operators, and provides a solid foundation for extensions to enhance messaging, diagnostics and integration with other JEA software systems. The OOS is expected to result in an enhanced work environment for plant operations personnel. The largest immediate payback achieved by the OOS, as demonstrated, is capital cost reduction. Additional benefits include chemicals and energy savings, improved water quality and many intangible benefits. This project has demonstrated that optimized control results in better use of capital assets. The early success of the OOS has enabled JEA to defer the drilling and equipping of one well, which averages $1.4 million. A return on investment analysis conducted for this project shows that payback is less than one year.

Key Words : real-time management, water resource management, quality control, monitroing, cost reduction, OOS (operation optimization system), SCADA (supervisory control and data acquisition system)

1. Introduction

JEA is the water, wastewater and electric utility provider in Jacksonville, Florida, USA. JEA provides water service to over 250,000 customers with 100% of the supply coming from groundwater sources. Water supply comes from 32 well fields and associated treatment facilities and the distribution network is divided into 2 major grids encompassing a 4-county service area with 2,800 miles of water lines. JEA has been challenged to reduce withdrawal of water from wells in order to meet tighter consumptive use permits (CUP) limits while raising the water quality and lowering total operating costs.

JEA has developed an automated software system for water supply and distribution that substantially improves water operations. The system improves operations through the implementation of a model-based adaptive architecture that both proactively plans for, and reactively responds to, dynamically changing consumption and water system

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changes. This system, called Operations Optimization System (OOS), utilizes a SCADA system and data collected from a number of other sources and minimizes cost while improving the operating performance of the entire water system. This system manages JEA's consumptive use of a regional aquifer, controls and monitors water quality in real-time, maximizes the value of energy for JEA's electric utility and maximizes the existing capacity of water system assets to defer or eliminate the capital cost for new infrastructure.

The OOS was developed in part through a co-funded, tailored collaboration project with the American Water Works Association Research Foundation (AwwaRF) and the St. John's River Water Management District (Florida, USA) titled "Operations Optimization—Development, Calibration, and Operations Integration Experience for the Water Utility Industry." The automation system extends work at JEA and previous Energy and Water Quality Management System (EWQMS) projects sponsored by AwwaRF [1, 2, 3]. Prior to commencing this project, JEA developed a business case for OOS that identified the following opportunities:

- Chemical cost reduction of $US25,000–$50,000 per year
- Energy resale opportunity of $US95,000 per year
- Cost avoidance for exceeding CUP of $US200,000–$US365,000 per year
- Capital infrastructure cost avoidance of at least $US1,000,000

2. Conceptual Design

Each water source, comprising well-pumps, treatment and reservoir(s), feeds the pressurized distribution network. JEA's water distribution system contains storage only at the well fields. In the OOS, water supply and distribution are viewed as separate sub-systems that can be controlled independently. The sources of supply are linked to the distribution network through demand profiles; the total demand for water within the distribution network is met by water supply delivered by each source of supply as shown in **Fig. 1**. Viewed this way, a straightforward approach to automated control is to first develop a planning capability that allocates total demand amongst the available sources of supply and then, based on the allocations, develops detailed schedules for high service pumps and for well-field pumps. Both allocation and detailed well-pump scheduling require adequate models to represent the distribution and supply systems, respectively. Also required is an optimization

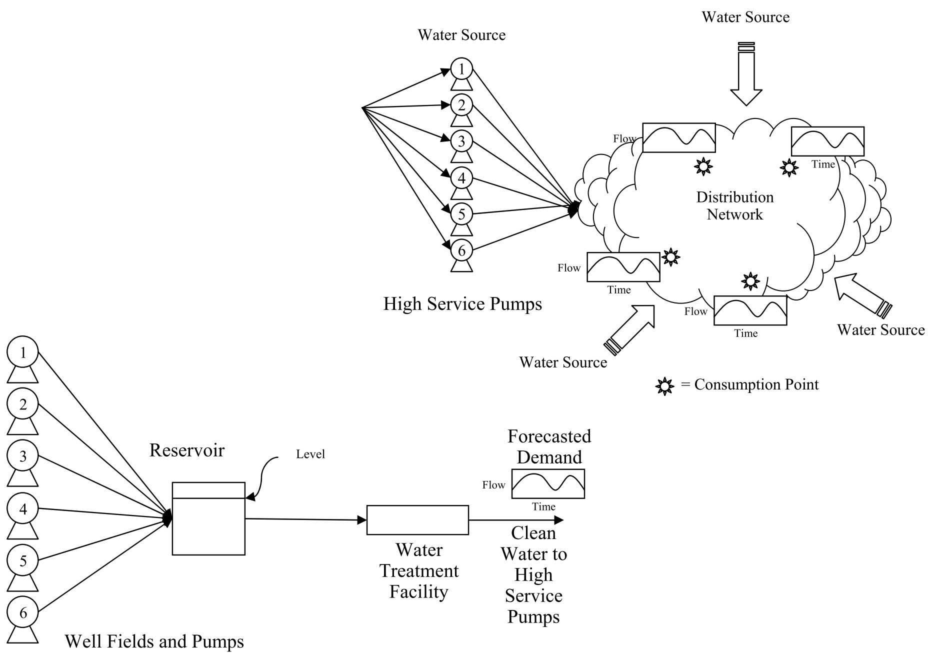

Fig. 1 Conceptual diagrams of water supply and distribution systems.

method that permits specification of a variable number of hard and soft constraints as well as other criteria for determining an optimum. The OOS applies this conceptual design in a real-time system capable of continuous control of the water supply and distribution system.

3. Automation System Architecture

JEA is using a real-time modeling and reasoning technology platform to deploy this application. The general architecture for model-based decision support is shown in **Fig. 2**. Techniques applied include neural network models, non-linear constraint-based optimization, and mechanistic hydraulic and mass-balance water supply and distribution models. The real-time reasoning platform integrates and coordinates these components and provides event detection and condition diagnosis capabilities that significantly improve the stability and reliability of the OOS. The architecture depicted in **Fig. 2** includes models for both water consumption (demand) and supply of water (well-field supply and distribution network). Ensemble neural network technology is applied to develop a non-linear, adaptive consumption forecaster that is capable of retraining when real process conditions change. A hydraulic model of the distribution system was developed and then reduced in complexity to enable application in real-time automation. A mass balance model was developed for use in open-loop decision support as a means of validating the plans and schedules determined automatically by the optimizer. Constrained, linear optimization is used to develop pump and valve schedules. Finally, event detection and condition diagnosis techniques were applied to ensure data quality and to proactively alert operations when important states or conditions occurred that may require intervention. Each of these components is described in greater detail in the sections below.

The detailed functional architecture for the OOS at JEA is shown in **Fig. 3**. The managed physical assets include the well pumps in each well field, water treatment plant processes, reservoirs and high-pressure distribution pumps. In the OOS these assets are optimally controlled through the existing SCADA system. The software components include the following:

SCADA system—direct interface to sensors, programmable logic controllers (PLC) and human-machine interface.

Operations Planner & Scheduler (OPS)—applies hydraulic models and constrained optimization to allocate demand amongst multiple plants supplying the grid, and then develop schedules for high service pump operations from each plant. The OPS module includes the **Water System Simulator**, a mass balance model used by operators to validate that plans and schedules will meet required operating constraints.

Water Consumption Forecaster—develops water demand profiles for virtual consumption points in the distribution network applying ensemble neural network technol-

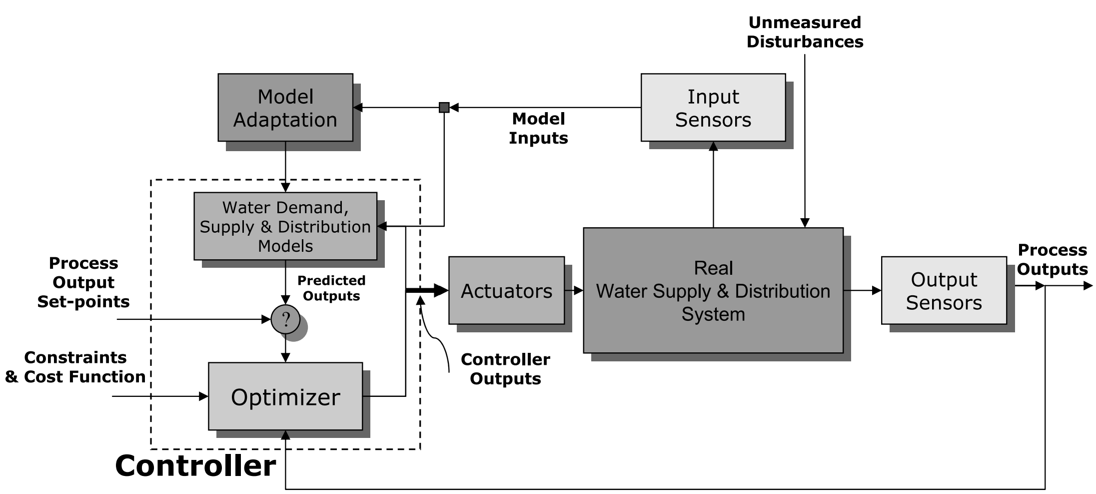

Fig. 2 General architecture for model-based decision support.

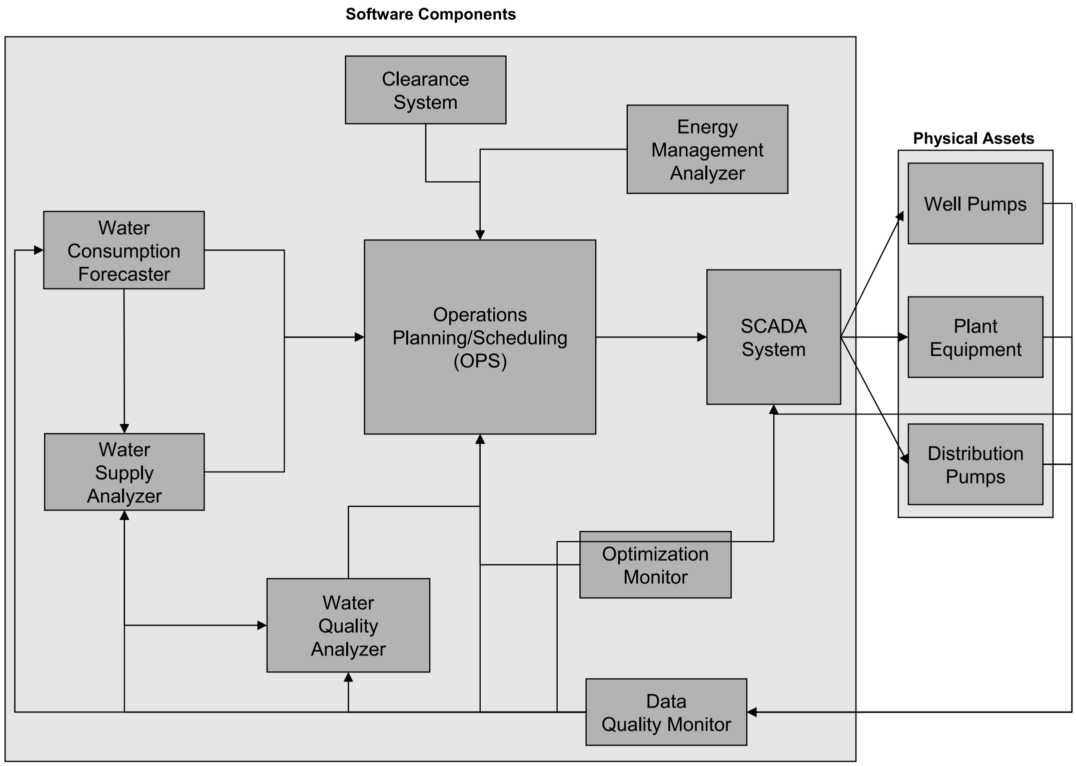

Fig. 3 Operations Optimization System functional modules.

ogy. The Water Consumption Forecaster includes an adaptive feature that enables it to automatically re-train when conditions change in the water distribution system.

Water Supply Analyzer—for each water plant (source of supply) applies models and constrained optimization to develop well-pump schedules for the groundwater sources.

Clearance System—implements a documented and approved process for identifying when equipment (*e.g.*, pumps, valves, chemical feed equipment) is removed from operation.

Water Quality Analyzer—accepts real-time input from a number of sources, including field operators, SCADA, and laboratory information management systems (LIMS), and uses this input to develop water quality operating parameters for the OPS. The Water Quality Analyzer proactively alerts system operators if there is an anticipated or actual water quality excursion in the system.

Energy Management Analyzer—provides input to the OPS, including constraints such as a daily energy cost profile, to enable scheduling of energy consumption that minimizes cost and maximizes the value of JEA generation during on-peak periods. This analyzer is the interface to JEA's electric utility, and in the future can provide data from water facilities for distribution system fault analysis and load studies.

Data Quality Monitor—ensures the integrity of data needed by the OOS to evaluate plans, schedules and controls. Includes smoothing, projection, and filtering combined with data substitution in cases where data points are missing or judged to be incorrect.

Optimization Monitor—compares actual system conditions to the forecast. When actual consumption varies significantly from forecasted consumption or key equipment failures occur during the day, Optimization Monitor will alert operations and can force both a re-forecast of consumption and a re-plan of well-pump and high-service pump schedules.

4. Automation System Operation

The OOS process flow in relation to decision time scales is shown in **Fig. 4**. In response to an operator request or at a minimum once each day at midnight, the system initiates

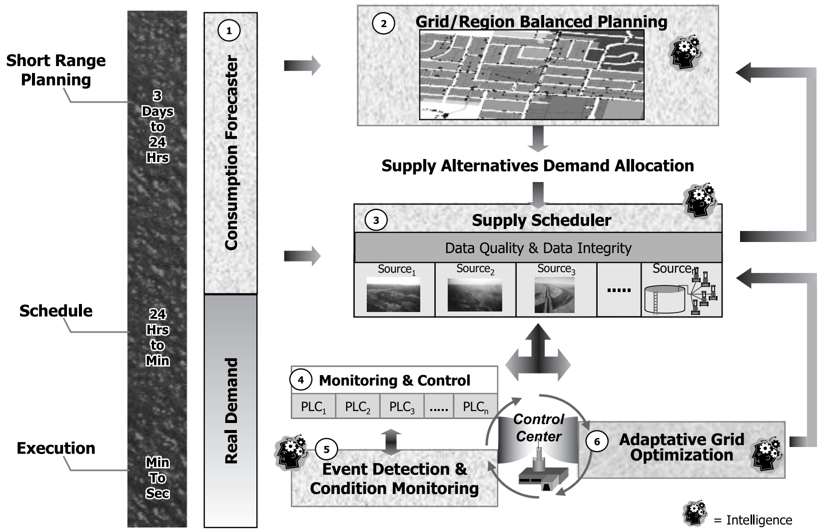

Fig. 4　Operations Optimization System process flow against decision time scale.

by calling the Water Consumption Forecaster (①), which provides hourly forecasted consumption across a user-specified horizon (24 hours by default) for operating areas within the water system called sub-grids. Given this forecast the system applies hard and soft constraints in an optimization (②) that allocates consumption amongst the available well fields while minimizing the cost of pumping water within the distribution system. This requires the use of a hydraulic model of the distribution network. The allocated demand is a flow profile (flow versus time across the specified horizon) that must be met by each water source. Scheduling of the high service pumps is done by the existing control strategy given the flow profile to meet and a flow-pressure controller developed for this project. Given separate water source allocations, the system then applies a different set of constraints to prepare detailed well-field pump schedules (③). Typical constraints applied in steps ② and ③ are shown in **Table 1**. These can be varied and changed dynamically as needed to adapt the automation system to real-time changes in the supply and distribution network. Detailed pump operating schedules are transmitted directly to PLCs that control the well-field and high-service pumps (④).

Data from the SCADA system that is required by the automation system is examined by the Data Quality Module, which applies smoothing and filtering algorithms to ensure continuous signals. The Data Quality Module substitutes for missing or poorly conditioned data. Both the Data Quality Module and Water Quality Analyzer generate alerts or alarms to inform operators or managers of important events or water system conditions (⑤).

Table 1　Typical constraints used in distribution network and supply planning and scheduling

Distribution Network	Supply
Pump availability	Pump availability
Pressure range	Reservoir level
Pump curve characteristics	Individual well conductivity
Flow capacity limits	CUP
Transfer costs	Pump starts/stops
	Well draw-down
	Pump total run-time
	Energy cost profile

Events are indicators of problems or transitions that can trigger modifications or adaptations needed to make corrections during operation. Adaptation routines (⑥) in the system trim plans, schedules and control actions. Especially for dynamic, real-time systems applying model predictive techniques, the positive impact of adding these routines is dramatic. Dynamic systems are subject to disturbances that cause slow and fast changes. When changes occur it is important to have modules that can respond by correcting forecasts, schedules and controls.

5. Hydraulic Models

In parallel with the development of the Operations Optimization system, JEA is developing a dynamic hydraulic and water quality model of their distribution system. JEA has selected the WaterGEMS hydraulic and water quality model developed by Haestad Methods, Inc. (Waterbury, Connecticut). **Fig. 5** shows a screen shot of the WaterGEMS model of the JEA distribution system. The hydraulic model has been calibrated using historical sampled and real-time data from the JEA distribution network.

5.1 Application of Hydraulic Models in Real-Time Automation and Decision Support

Model developers and practitioners use hydraulic models extensively in off-line analysis and tactical decision support. In real time distribution system control where fast response times are a priority, the challenge in applying large-scale hydraulic models is finding a balance between model complexity and optimization performance. These are conflicting objectives as more complex models take longer to simulate. Optimization routines require thousands of iterations to search for a solution, so in real-time automation developers faced with this balance look for a "satisficing" solution rather than a theoretical optimum. They recognize that in a dynamic environment the best often conflicts with the good.

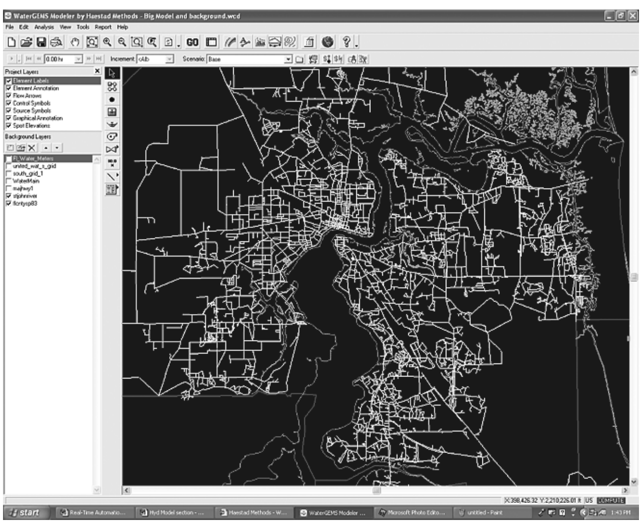

Fig. 5 JEA WaterGEMS™ hydraulic model.

In operational decision support the response time requirement is relaxed and large-scale hydraulic models can validate operating plans (pump/value schedules) evaluated with simpler mechanistic or heuristic models in an "optimize the optimum" approach applying both optimization and simulation. In this usage scenario, the process model in the box labelled **Controller** in **Fig. 2** is a simplified model and the **Controller Outputs** indicated by a bold arrow are routed to a large-scale hydraulic model, which confirms that the operating plans will work as expected. The validation step is necessary because we have to allow for the possibility that use of a simplified model may not result in feasible plans. Validation with a complex hydraulic model is efficient since only a small subset of solutions is examined.

6. Consumption Forecasting Using Ensemble Neural Networks

Given historical and real-time data shown below, the Water Consumption Forecaster learns a set, or "ensemble", of models. The models may be both linear and non-linear and cross-correlation among input variables, a common source of inaccuracy, is handled through variable reduction techniques. In making projections, the Forecaster applies a voting scheme to determine the best prediction based on a confidence measure. Mathematically, the voting process is done to ensure the most robust prediction, one that is not severely impacted by outliers. These techniques result in a more robust forecast that maximizes the information content of the training data.

The inputs provided to the Forecaster include:

Temperature from t-1 hour to t-24 hour: Temp(t-1), Temp(t-2), ..., Temp(t-24)

Dew point from t-1 hour to t-24 hour: Dew point: DEWP(t-1), DEWP(t-2), ..., DEWP(t-24)

Relative humidity at t hour: RH(t-1)

Wind speed at t hour: SPD(t-1)

Day of Week at t hour: DW(t) = 1 if weekday, DW(t) = 0 if weekend

Flow from t-1 hour to t-25 hour: Flow(t-1), Flow(t-3), ..., Flow(t-25)

The output of the neural network is the flow at hour t, is expressed as:

Flow(t) = N(Temp(t-1), Temp(t-2), ..., Temp(t-24), Dewp(t-1), Dewp (t-2), ..., Dewp(t-24), RH(t), SPD(t), DW(t), Flow(t-1), Flow(t-3), ..., Flow(t-25))

where,

N is the ensemble neural network function

t is an integer

The consumption forecaster predicts water consumption by taking into account factors such as historical consumption and on-line data including weather forecasts. The forecaster monitors events and can both re-train and re-forecast if one of the inputs (*i.e.* weather forecast) changes significantly between regularly-scheduled runs. An alerting system is included to inform appropriate personnel if there is a significant deviation between the actual consumption and the consumption predicted by the forecaster.

We define the forecast error and our performance criteria as:

$$ForecastError = \left| \frac{ForecastConsumption(j)}{ActualConsumption(j)} - 1 \right| \le 15\% \quad (1)$$

where,

ForecastedConsumption(j) is the hourly consumption forecast at hour j

ActualConsumption(j) is the actual consumption at hour j

We define the forecast accuracy as (1-ForecastError).

7. Total System Optimization at JEA

The control objectives of the OOS are:

1. to control the high service pumps at each plant to meet allocated flow profiles, and
2. to generate well-field (on-off) pump schedules

Both the distribution and supply optimization apply constraints gathered in real-time, including system hydraulics, water quality and consumptive use permit (CUP) value, to minimize distribution and well field costs. As shown in **Fig. 1**, the total system is logically subdivided into supply and distribution sub-systems linked by a water consumption profile. The essential problem is to match total system water consumption to water supply while maintaining system pressure and minimizing total system cost. The solution requires reduction of the larger network into interacting sub-grids and water sources.

7.1 Distribution Network Optimization

For a typical grid, in which water is supplied from many sources over a wide distribution area, maintaining high service levels with minimum cost is an important business objective. To achieve this, we consider JEA's Consumptive Use Permit (CUP) limits for each well-field, the energy costs for water distribution, pressures at both pumping stations and in a grid, the water quality of each plant and many other factors. We must also take into account the dynamic nature of each of these factors.

The distribution network optimization problem is shown below as **Model 1**. Model 1 implements a source-demand proximity strategy by which the closest plants serve the local consumption area, augmented by plants further away if needed to meet demand. This model includes a non-linear objective function that allocates a sub-grid's water demand to water sources (treatment plants and associated well fields) based on their capacities and the hydraulic properties of the virtual pipes. The objective function is based on the Hazen-Williams equation, which relates energy consumption to flow through a pipe and forces the optimizer to create hydraulically feasible solutions. Coefficients for this function are empirically estimated using a hydraulic model calibrated from the actual grid pressure and flow history. It may be necessary to re-calibrate this model while the OOS is in operation. So that linear optimization techniques can be applied, a piece-wise linear function is substituted for equation (2) with 4 intervals in the range [0, hourly plant capacity]. This is an approximation and can be refined by increasing the number of intervals.

Model 1: Distribution Network Optimization

Objective Function:

$$\mathrm{Min} \sum (P_i X1_{ijk} + C_{ijk} X1_{ijk}^{2.852}) \quad (2)$$

Subject to:

$$\sum_j X1_{ijk} \le \mathbf{L1_{ik}} \quad (3)$$

$$\sum_j X1_{ijk} + X2_{jk} - X3_{jk} = \mathbf{L2_{jk}} \quad (4)$$

$$\sum_j X1_{ijk} \le \mathbf{L3_i} \quad (5)$$

Where:

Indices: i plant, j sub-grid, k time (hour)

$X1_{ijk}$ = scheduled flow from plant i to sub-grid j at hour k, adjustable

$X2_{jk}$ = deviation variable representing the flow deficit at sub-grid j at hour k; the scheduler tries to minimize this variable

$X3_{jk}$ = deviation variable representing the flow surplus at sub-grid j at hour k; the scheduler tries to minimize this variable

C_{ijk} = cost coefficient for virtual pipe from plant i to sub-grid j at hour k

P_i = the cost coefficient for plant i, this cost is also a function of water quality and CUP usage of the plant

$\mathbf{L1_{ik}}$ = hourly plant i capacity at hour k (constraint equation (3))

$\mathbf{L2_{jk}}$ = forecasted demand for sub-grid j at hour k (constraint equation (4))

$\mathbf{L3_{i}}$ = daily plant i capacity (constraint equation (5))

The output from distribution network optimization is a set of flow profiles ($X1_{ijk}$) that meet the constraints listed above.

7.1.1 Real-Time Control of High Service Pumps

The optimal flow profile for each plant is the flow set-point for total flow from the high service pumps at that plant. If the optimization is correct, maintaining these flow profiles will maintain distribution system pressure within a desired range. In the JEA application, the distribution system has no storage; therefore, pressures must be constantly monitored and controlled. For this reason, a cascaded flow/pressure controller (**Fig. 6**) was developed that adjusts pressure set-point to drive flow to meet the optimal flow profile. If the distribution system pressure falls outside the desired range, the pressure controller dominates and system pressure is maintained.

7.2 Supply Optimization

At JEA 100% of the water supply comes from the Floridian aquifer. Many well-fields have been constructed to supply water, each location comprising a number of well pumps, one or more storage reservoirs and treatment facilities (**Fig. 1**). Once a demand is assigned to the plant by the distribution network optimizer, constraints and operating conditions are read from both the SCADA system and the real time database. This information is input to the supply optimization module.

7.2.1 Water Supply Constraints

Supply optimization must consider the dynamic nature of the system, including current pump operating conditions, well conditions, water quality, blending, and the variation of energy costs from day to day as well as seasonally. Pumping water from the aquifer is an energy-intensive operation. The cost of energy (electricity) varies during the day, creating an opportunity that the optimizer can exploit. In solving for the optimal well pump schedule, the energy cost-profile function, which defines the energy cost as a function of time, is fed to the model.

Real-time well conditions are obtained through the mea-

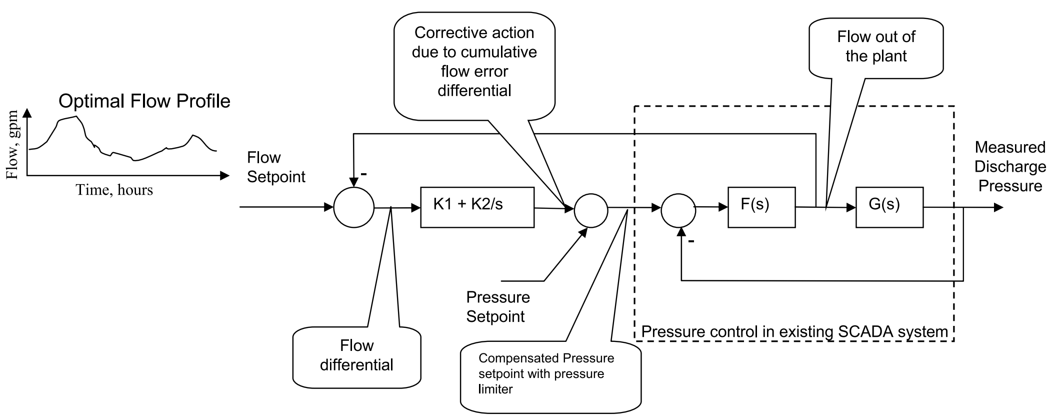

Fig. 6 Cascade control of plant output flow via pressure differential.

surement of physical well properties like run levels, pump run time and water conductivity. This determines how each well can best be utilized on a particular day, that is, how many hours the pump can be scheduled and the maximum amount of water that can be withdrawn from the well.

7.2.2 Solving for Well Pump Schedules

The optimization strategy for supply minimizes energy consumption during high energy cost hours according to the cost-profile function while maintaining the reservoir levels within the user-defined minimum and maximum values. To create a well pump schedule for a particular plant, a production schedule is needed for the plant. This production schedule comes from **Model 1** distribution optimization. The supply optimization problem is shown below as **Model 2**. The optimizer generates suitable and stable operation schedules while reducing pumping during peak hours, thus minimizing energy costs. **Model 2** takes advantage of reservoir capacity in creating well-pump schedules.

Model 2: Well Pump Scheduling

Objective function:

$$\mathrm{Min} \sum \mathbf{C_{ijk}} X1_{ijk} + \sum \mathbf{P}_1 X4_{ij} - \sum \mathbf{P}_2 X6_{ij} \tag{6}$$

Subject to:

$$\sum_k X1_{ijk} \leq \mathbf{L1_{ij}} \tag{7}$$

$$\sum_j \boldsymbol{\alpha_{ij}} X1_{ijk} = X2_{ij} \tag{8}$$

$$\boldsymbol{\beta_i} X2_{ik} + X3_{i(k-1)} - X3_{ik} = D_{ik} \tag{9}$$

$$X3_{ik} + X4_{ik} - X5_{ik} = \mathbf{L4}_{ik} \tag{10}$$

$$\sum_j \delta_{ij} X1_{ijk} + X6_{ik} - X7_{ik} = 0 \tag{11}$$

$$\sum_{jk} X2_{ijk} \leq \mathbf{L6}_i \tag{12}$$

Where:

Indices: i plant, j well, k time (hour)

$X1_{ijk}$ = extraction time at plant i, well j during hour k, calculated

$X2_{ik}$ = input flow to reservoir tank at plant i at hour k, calculated

$X3_{ik}$ = reservoir level at plant i, hour k, calculated

$X4_{ik}$, $X5_{ik}$ = deviation variables representing the water level below and above $\mathbf{L4}_{ik}$, respectively, at hour k; the scheduler tries to minimize $X4_{ik}$, any non-zero value of $X4_{ik}$ will cause a penalty in constraint equation (10)

$X6_{ik}$, $X7_{ik}$ = deviation variables representing the relative conductivity below and above 0, respectively, for plant i at hour k; the scheduler tries to maximize $X6_{ik}$

$\mathbf{C_{ijk}}$ = hourly operation cost for plant i well j at hour k, based on cost profile

$\mathbf{P_1}$ = penalty associated with target reservoir level violation

$\mathbf{P_2}$ = penalty associated with maximum conductivity violation

$\mathbf{L1}_{ij}$ = maximum extraction for plant i, well j (depends on maximum run level)

$\boldsymbol{\alpha_{ij}}$ = gal/hr (conversion factor)

$\boldsymbol{\beta_i}$ = ft^3/gal * area (conversion factor)

$\mathbf{D_{ik}}$ = demand for plant i at hour k

$\mathbf{L4}_{ik}$ = reservoir minimum level at plant i at hour k (target level at the end of the day)

$\boldsymbol{\delta_{ij}}$ = normalized well conductivity factor of well j at plant i, this conductivity is relative to the conductivity of the water in the reservoir

$\mathbf{L6}_i$ = Maximum day extraction for plant i

The constraints in equations (7) to (12) are:

(7) Well extraction capacity—limits the amount of water that can be withdraw from a particular well

(8) Reservoir input flow—an estimate of the input flow to a reservoir as the sum of flows from all the wells

(9) Reservoir level—an estimate of reservoir level through the day evaluated from a mass balance

(10) Reservoir minimum level

(11) Minimum desirable conductivity

(12) CUP limit—maximum quantity of water that can be withdrawn from all the wells in a day

7.2.3 Control and Monitoring

Given an optimal well-pump schedule, control of the well pumps is straightforward; on off commands for each pump are sent to the SCADA system. The OOS contains a user interface for reporting system status, making adjustments to constraints and reporting. For example, the projected reservoir level is provided so that operators can compare projections against actual reservoir level. This same information is used by the OOS to automatically adapt to changing conditions. When the difference between projected and actual reservoir level exceeds magnitude and rate of change criteria, a new set of constraints from the SCADA and real time database are collected and a new schedule is generated. This combination of feed-forward and feed-back capabilities enable a highly adaptive control that makes the best use of both forecasts and real-time events.

8. Operating Results

JEA implemented the OOS in a short period of time. Well field optimization was placed into service less than 8 weeks from project conception. The first sub-grid of the distribution system was ready for on-line testing and calibration 6 months after project conception. This success was achieved by JEA operations and engineering staff who carefully evaluated appropriate technologies, put together a dedicated team of managers, practitioners and technical experts, and drove success with strong management support. System operators have been important to the success of the project by working closely with developers to incorporate their expert knowledge into the system and actively participating in on-line testing. The result has been substantial improvement of system operations and an enhanced working environment for plant operations personnel.

8.1 Data Quality, Event Detection and Condition Diagnosis

JEA's data collection and management infrastructure (SCADA) shown in **Fig. 7** maintains the raw data required by the OOS. The Data Quality Manager and Water Quality Analyzer modules apply predefined templates for filtering, bounds checking, default value assignment, and substitution for critical analog data. These modules create events such as alerts or notifications as shown in **Fig. 8** to indicate issues with data quality, water quality, or for the water system assets.

8.2 Consumption Forecasting

Fig. 9 illustrates a forecasted consumption profile for one of the sub-grids (Ridenour) at JEA along with the forecast accuracy for one week in January of 2004. In operations the daily forecast error (equation 1) is always 10% or less (≥ 90% accurate), however the hourly forecast errors are 50% or less (≥ 50% accurate). More recently, the hourly forecast errors have decreased through adjustment of input data, data frequency and modifications to training procedures. Preliminary data analysis indicates that near-term forecasts across a 4 to 6 hour horizon have a smaller error, which suggests that re-forecasting in response to a discrepancy trigger may further reduce forecast errors.

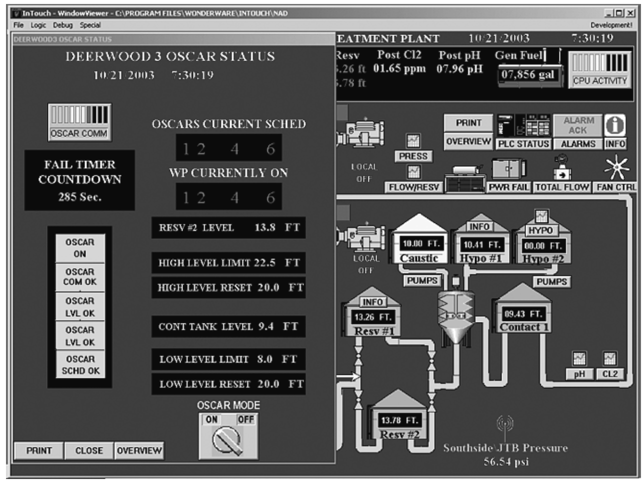

Fig. 7 JEA SCADA system graphical user interface showing OOS ("OSCAR") status.

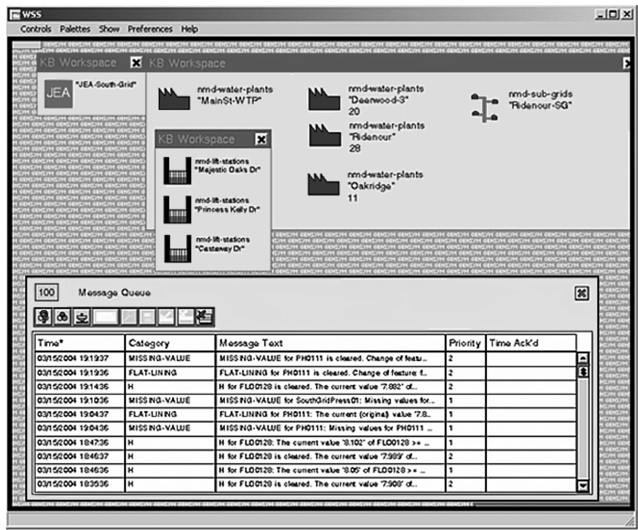

Fig. 8 Event detection and condition diagnosis messages from Data Quality Manager and Water Quality Analyzer.

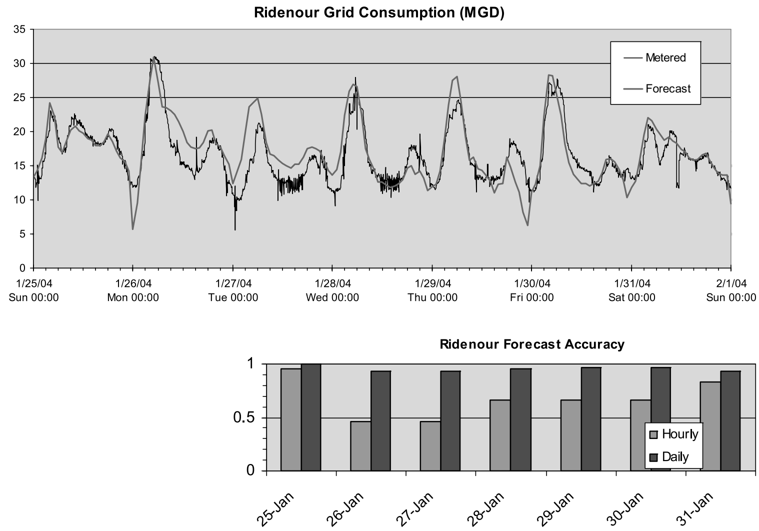

Fig. 9　Ridenour sub-grid consumption forecast (top) and forecast accuracy (bottom).

8.3　Distribution and Supply Optimization

8.3.1　High Service Pump Control

Distribution optimization results in a flow versus time profile that each water plant must meet. The optimal flow profile is input to a cascade flow-pressure control strategy for the high-service pumps that drives water plant output to meet the flow profile by adjusting pressure as shown in **Fig. 6**. In operation, this technique has the advantage of a natural fall-back (a default) to pressure control if needed to maintain distribution system pressure. This will occur if the flow profiles are not evaluated correctly in the planning phase.

An example of the allocation of consumption within a sub-grid amongst water sources is shown in **Fig. 10**. In this example the Ridenour sub-grid, comprising three plants each of which contains several well pumps, has a total forecasted consumption that follows a diurnal pattern (top curve). The allocation of this demand amongst the three available water sources is shown in the three lower curves. The percentage allocation depends upon the factors and their relationships as represented in Model 1 above. Experience with distribution optimization has shown that tuning of cost factors is required to obtain suitable flow allocations and that reactive modification is essential. These two characteristics relate directly to feed-forward and feed-back capabilities, respectively. Both are needed to obtain the most effective real-time control.

8.3.2　Well-Field Pump Scheduling

The flow profiles allocated to the plant define the demand that must be met by raw water pumped from the well-field or treated water available in plant reservoirs. The OPS allows the reservoir levels to fluctuate within a range in order to meet demand while taking advantage of the energy cost profile during a day. All other constraints shown in **Table 1** are also met.

An example of the output of the OPS well pump scheduler is shown in **Fig. 11**. The OPS specifies the combinations of well pumps to run at each hour and the order for running pumps across a 24-hour period for each of the wells at a plant. This schedule is assessed each day and can be reassessed on demand to meet changing conditions or constraints input dynamically during the day by system operators, or OPS, to re-schedule pumps. For example, Operations have the option to either accept the proposed schedule or modify the schedule based on changes in constraints (*e.g.*, a pump taken out of service for maintenance), then re-run the optimization. The schedule is designed to take into consideration the consumed flow over a period longer than one day, thus permitting a smarter management of daily pump schedules. For example, large increases in expected consumption at the end of the forecasted period can be accommodated by pumping at a higher rate earlier in

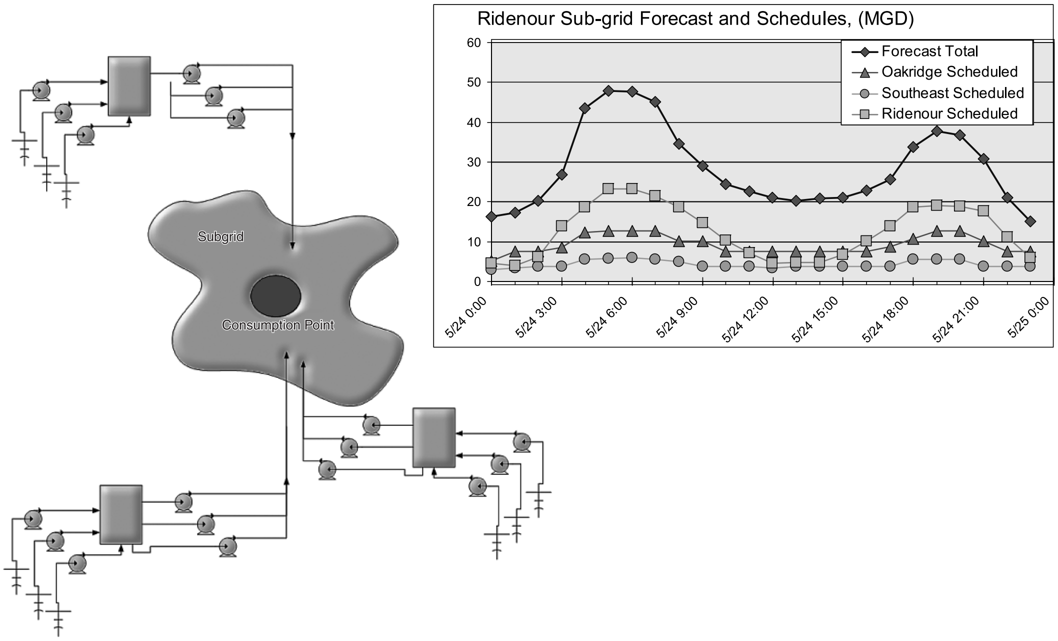

Fig. 10 Allocation of consumption in the Ridenour sub-grid.

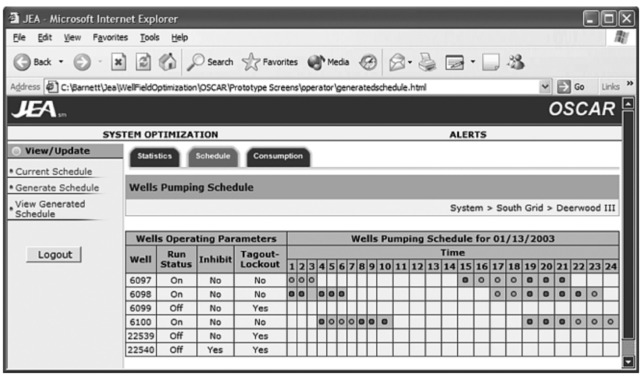

Fig. 11 Example well-pump schedule.

the first day, which allows for lower pumping rates, or even resting wells, during the second day. Conversely, high consumption at the beginning of a forecasted period does not necessitate high pumping rates, if it is known that the additional volume can be achieved on the following day. Strategies such as these can be represented in the constraints and objectives specified in the application and applied to more intelligently manage pump schedules.

The option exists to run the optimizer on demand to generate a partial schedule for the remainder of the day. The time-based flow plan is weighted by time of day; pumping when power is cheaper, yet maintaining capacity and appropriate “safety stocks” in the reservoir to account for forecast variance. Once a final schedule is accepted, the schedule along with the forecast, and constraints used in the optimization are stored in the OOS database.

8.4 Water System Simulator

The Water System Simulator (WSS) is shown in **Fig. 12**. The Operations Planner and Scheduler (OPS) uses the WSS to examine water system operation under different scenar-

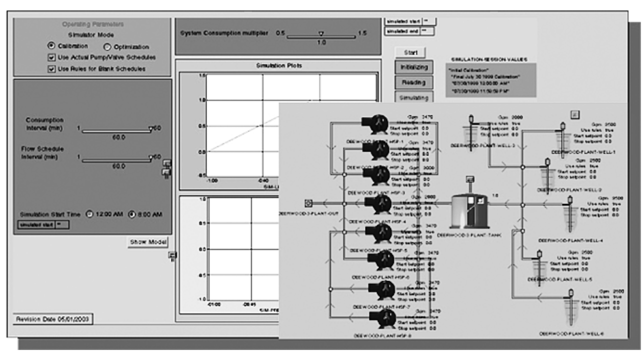

Fig. 12 Water System Simulator control center screen and Deerwood 3 Plant.

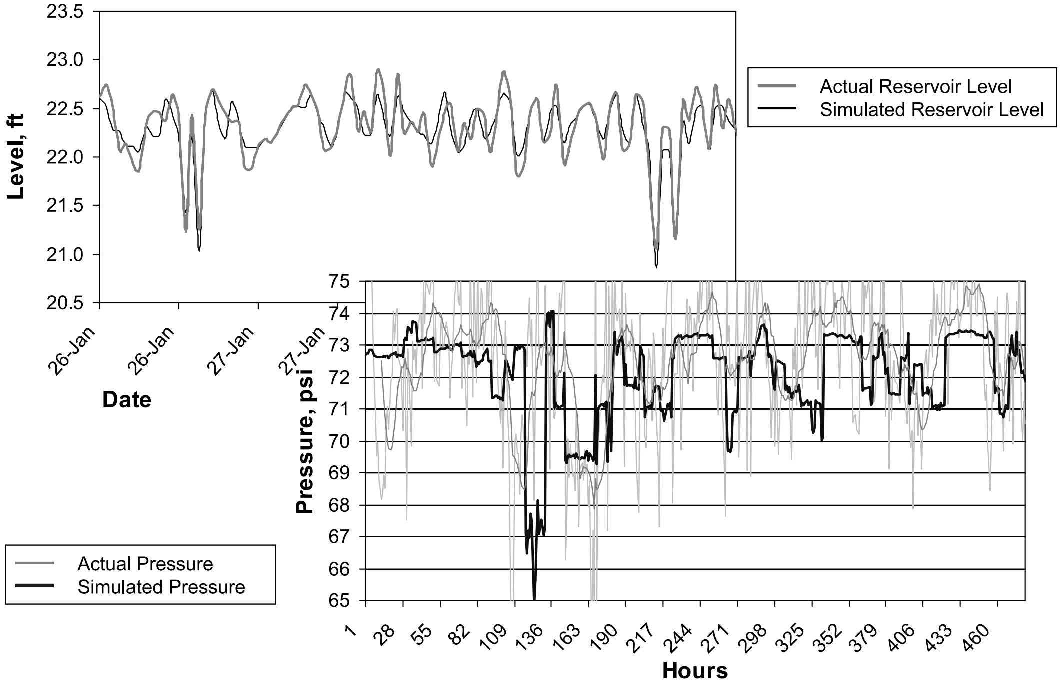

Fig. 13 Water System Simulator reservoir level and pressure simulation results.

ios. It allows the OPS to verify that a proposed optimized control schedule satisfies constraints and to identify constraints that may be violated. The WSS uses a water system model and operating schedule information including flows from plants, pump schedules, consumption, and energy costs. For a specified time period (*e.g.*, one day), it dynamically simulates system operation to determine tank levels, pressure at plants, and overall operating costs. The simulator calculates flow through each plant, flow from active pumps, pressure at each pressure point in the model, and consumption in each water consumption area. At the end of the simulation time period the WSS displays the result of the simulation, including the optimum pump schedule, and stores this information for further analysis. The WSS uses a mass balance model as the reference object model.

The WSS supports an object-oriented graphical user interface (GUI) that displays the system model and allows the user to modify parameters, schedules, and settings of the system. The WSS also displays the performance of key metrics for the operations optimization system and serves as the user control center for the OOS. Schedules and performance results are displayed in graphic form on the system model and in trending charts. Constraint violations such as tank levels and pressures are flagged and displayed for user intervention. Results from simulations can be stored in a repository for further analysis. **Fig. 13** illustrates actual performance of the distribution system versus simulated performance using the WSS.

8.5 Energy, Water Quality and Asset Management

Fig. 14 illustrates historical versus optimized flow for

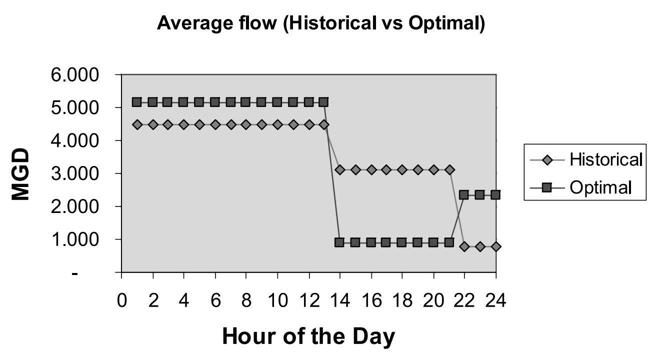

Fig. 14 System Scheduler optimizes well field pumping to reduce energy.

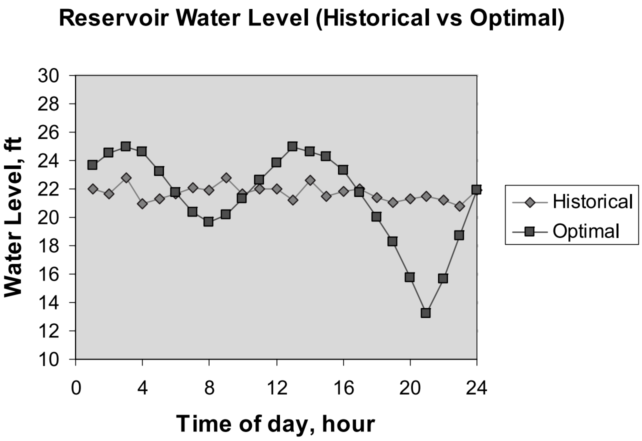

Fig. 15 Deerwood III reservoir is drafted to optimize well field pumping.

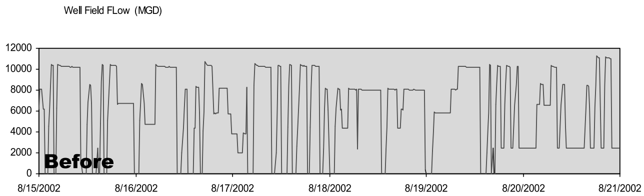

Fig. 17a Well field flow (MGD) August 2002.

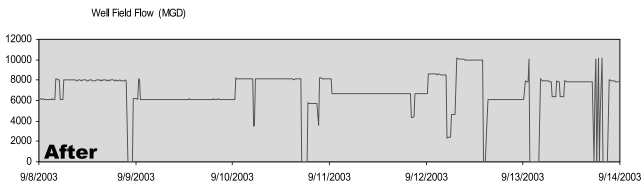

Fig. 17b Well field flow (MGD) September 2003.

JEA's Deerwood III well field. JEA currently pumps substantially less water on-peak when electrical costs are high and pumps more off-peak when electrical costs are lower. **Fig. 15** illustrates historical and optimized Deerwood III reservoir levels for a 24-hour period. Reservoir minimums required to meet "fire levels" are hard constraints that can not be violated, however there remains significant volume to buffer large swings in consumption. Optimization makes better use of reservoir capacity by drafting as needed to minimize cost and maximize quality. Improvement in well field conductivity is illustrated in **Fig. 16**. By considering water quality parameters (*e.g.*, conductivity) as a constraint, the System Scheduler lowers the conductivity level. For some wells, we have observed a downward trend in conductivity suggesting that the health of these wells may be increasing.

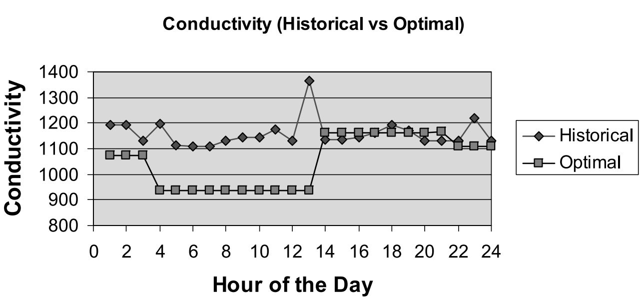

Fig. 16 Improvements in conductivity are measured.

Asset management benefits are also evident after implementation of the OOS at JEA. Reduction in pump cycling is one positive by-product of the optimization system. This is illustrated in **Fig. 17a** and **17b** which show well field flow over a six-day period in 2002 when the wells were manually controlled (**Fig. 17a**) versus a similar period after the OOS was implemented in 2003 (**Fig. 17b**). Constraints in **Model 2** enforce minimum pump run times, which limits pump starts and stops and results in substantially reduced well pump cycling.

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フロリダ州ジャクソンビル市における上水システムのリアルタイム自動化

Michael Barnett 他

要　約

フロリダ州ジャクソンビル市に位置する JEA（Jacksonville Electricity Authority：ジャクソンビル電力公社）は，上下水サービスおよび電力を供給する組織である。現在，JEA は約 25 万のユーザーに，地下水のみを水源として水道を提供している。水道水は，32 箇所の地下水汲上げおよび付帯処理施設を水源とし，大きく 2 つの敷設網に区分された 4 郡にまたがる総延長 2,800 マイル（約 4,500 km）におよぶ水道管設備網を通じて供給されている。近年の地下水取水制限（CUP: Consumptive Use Permits）の強化に伴い，JEA は水質の向上とトータル運転コストの削減を図りつつ，同時に，地下水汲上げ量の低減を迫られることになった。

JEA は上水施設自動化システムを開発し，保有施設の運転管理を大幅に改善した。このシステムは，動的に変化する上水の消費と供給状況に対して，モデルに基づいた適応制御系による先行予測的な計画（proactively plans）と事後的な対応（reactively responds）の両者を適用することによって，上水施設の運転管理を改善するものである。システムは OOS（Operations Optimization System：運転管理最適化システム）と名づけられ，上水施設の SCADA システム（Supervisory Control And Data Acquisition System：監視制御データ表示システム），ならびに，その他の様々なソースから収集した情報を活用することによって，上水設備全体の性能向上とコスト最少化を実現するものである。OOS は，JEA の地下水資源消費管理，水質のリアルタイム制御および監視，JEA が消費するエネルギーの価値の極大化，そして，JEA 保有施設の最大限有効活用による新規インフラストラクチャ導入コストの削減を実現している。

OOS は全米水道協会基金等による共同プロジェクトによって開発されたものであるが，JEA はこのプロジェクトの事前ケーススタディで，以下の可能性が見込まれるとの結果を得ている。

- 薬品コスト　年間 25,000 ～ 50,000 ドル削減
- エネルギー販売収入　年間 95,000 ドル増収
- 取水制限超過による負担金　年間 200,000 ～ 365,000 ドル節約
- インフラストラクチャ新規導入コスト　1,000,000 ドル以上

キーワード：リアルタイム上水施設運転管理，水資源消費管理，水質制御，水質監視，コスト削減，運転管理最適化システム（OOS），SCADA

（訳　後藤雅史）