OPTIMAL DAILY OPERATION OF A WATER SUPPLY SYSTEM COMPOSED OF A DAM RESERVOIR AND GROUNDWATER WELLS

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This paper investigates the development and application of a daily optimization (DO) model to the short-term operation of the water supply system of Matsuyama, Japan. The main objective of the procedure is to seek the best allocations of water that minimizes the squared deviations between releases and target demands. The daily precipitation for one week ahead is assumed to be deterministic since meteorological short-range forecasts are generally available. The groundwater balance is modeled by Multiple Linear Regression (MLR) and short-term predictions of reservoir inflows are obtained based on the daily precipitations by means of Artificial Neural Networks (ANNs). System operations using fictitious simulation and the DO model under perfect short-term forecast of inflows are used for comparison. The results of the DO procedure using ANN-based inflow predictions are shown to be equivalent to those obtained by DO under perfect short-term forecast of inflows and superior to the ones found by simulation.

Key Words: *Water system operation, optimization, short-term prediction, surface water, groundwater.*

1. INTRODUCTION

Many studies have been carried out in order to produce measures capable of ensuring the sustainable use of the water resources. Optimization models are techniques commonly used for providing a better planning and operation of water supply systems[1), 2), 3), 4), 5)]. However, most of the real-time procedures consider only either the operation of surface water reservoirs or groundwater systems. The conjunctive use of surface water and groundwater is very important for cities which depend on these two types of resources and therefore, it is very important to find better strategies for their optimal exploitation [2), 3)]. Matsuyama, located in southwestern part of Japan, is one of these cities and many researches have been carried out in a tentative of improving and finding adequate policies for its water resource system [6), 7)].

This paper deals with the utilization of a daily quadratic optimization (DO) model for the conjugate real-time operation of Ishitegawa Dam reservoir and Matsuyama groundwater system. For that, it was assumed that daily precipitations for one week ahead are accurately forecasted.

2. STUDY SYSTEM

Matsuyama city water system is composed of a multipurpose reservoir and a set of unconfined wells located around Shigenobu River, which is the main river of its hydrographic basin. The groundwater of the Shigenobu River together with Ishitegawa Dam reservoir is used for supplying all the water needs of this city. Ishitegawa Dam reservoir is also used for flood control in the region. The water use of Matsuyama is detailed in **Table 1**.

Shigenobu River Basin has an area of approximately 445km², an annual precipitation of around 1,250mm and about half a million residents. The layout and location of the water supply system of Matsuyama city is shown in **Fig.1**.

Table 1 Water use in Matsuyama.

Water use	Average daily demand (m³/day)	Water supply source
Domestic	150,000	Dam and wells
Irrigation	100,000	Dam

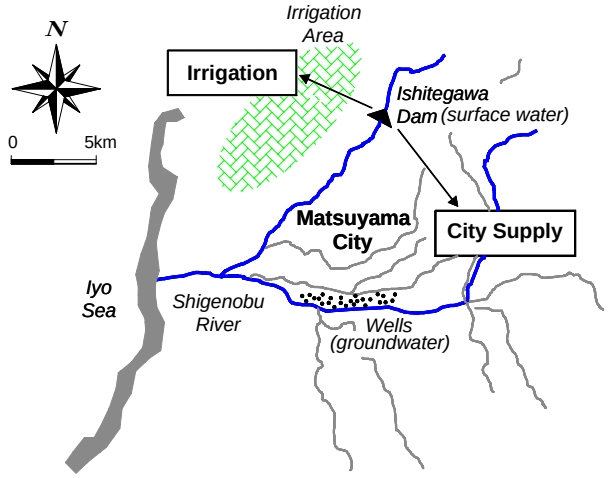

Fig.1 Location and layout of the system.

3. DAILY OPTIMIZATION (DO) MODEL

It is assumed that the main objective of the operation is to find the allocations of water that best satisfy the respective demands without compromising the system. Another aim is to keep the storage high whenever possible, i.e., every time there exists alternative optimal solutions for the releases. The objective function of the optimization problem is thus written as follows:

$$\min \sum_{t=1}^{N}\left\{\left[\frac{Def(t)}{D(t)}\right]^2+\left[\frac{S(t)-S_T(t)}{S_T(t)}\right]^2\right\} \qquad (1)$$

where t is the time index; N is the operating horizon; $Def(t)$ is the deficit during period t; $D(t)$ is the demand during period t; $S(t)$ is the reservoir storage at the end of time interval t; and $S_T(t)$ is the target reservoir storage at the end of period t.

The deficit at each period is defined by the following equation:

$$Def(t) = D(t) - Rw(t) - Rd(t); \quad \forall t \qquad (2)$$

where $Rd(t)$ and $Rw(t)$ are the optimal releases from the dam and wells during period t, respectively.

Reservoir release and storage at each period are related to inflow and spill through the continuity equation:

$$S(t) = S(t-1) + I(t) - Rd(t) - Sp(t); \quad t = 1,\ldots,N \qquad (3)$$

in which $S(0)$ is the initial reservoir storage; $I(t)$ is the inflow during time t; and $Sp(t)$ is the spill that eventually might occur during time t.

The operation of the set of 26 supply wells is monitored through the Minamitakai Observation Well, whose level represents the groundwater level of Shigenobu River's aquifer. The representative well level is defined by Multiple Linear Regression (MLR) as follows:

$$H(t) = \alpha \times H(t-1) + \beta \times P(t) + \gamma \times Rw(t) + \delta \times PP(t) + \theta;\ t = 1,\ldots,N \qquad (4)$$

where H is the water elevation in the wells (m); P is the daily precipitation (m); Rw is the daily release from wells (m³/s); PP is the number of previous days without precipitation (days) and α, β, γ, δ and θ are the model parameters to be estimated by MLR.

The definition of the target storage $S_T(t)$ is made by determining a possible quantity of available water $AW(t)$ in the reservoir for 30 days ahead of time step t. The calculation of AW is done by the following equations:

$$AW(t) = S(t) - S_{dead} + TI(t); \quad \forall t \qquad (5)$$

$$TI(t) = \sum_{i=1}^{30} ADI(t+i); \quad \forall t \qquad (6)$$

where S_{dead} is the reservoir dead storage; i is the time index for days ahead of period t; $ADI(t+i)$ is the average of historical daily inflows for time step $t+i$; and $TI(t)$ is the summation of the averages of historical daily inflows to the reservoir for 30 days ahead of period t. It is important to observe that the average for each day of the year from the historical data of inflows is used and therefore, there is no need for 30-days-ahead predictions of inflows.

Since in Matsuyama city the water released from the reservoir has lower cost compared to ground water, one objective is to allow the reservoir to release its maximum daily capacity when there is plenty of water and start reservoir water supply hedging when the possible available water for 30-days-ahead is not enough for allowing its maximum daily capacity use. The first hedging rule tries to bring the reservoir storage as close as possible to a level capable of sustaining the maximum daily release from the reservoir. The second reservoir hedging rule starts when the available water is not enough to attend the total demand for 30-days-ahead, i.e., when the total demand minus the maximum release from the wells for 30-days-ahead cannot be supplied by the reservoir. In this case, the hedging

policy tries to keep the reservoir level as close as possible to a level capable of keeping at least a minimum release from the reservoir to attend the total demand. In a tentative of implementing these rules, the target storage $S_T(t)$ is defined as follows:

$$S_T(t) = S(t); \quad if\ AW(t) > TRd_{\max}(t); \forall t \tag{7}$$

$$S_T(t) = S(t) + \left[TRd_{\max}(t) - AW(t)\right]; \quad if\ TRd_{\min}(t) < AW(t) \le TRd_{\max}(t); \forall t \tag{8}$$

$$S_T(t) = S(t) + \left[TRd_{\min}(t) - AW(t)\right]; \quad if\ AW(t) \le TRd_{\min}(t); \forall t \tag{9}$$

$$TRd_{\max}(t) = \sum_{i=1}^{30} Rd_{\max}(t+i); \forall t \tag{10}$$

$$TRd_{\min}(t) = \sum_{i=1}^{30} \left[D(t+i) - Rw_{\max}(t+i)\right]; \forall t \tag{11}$$

where $Rd_{\max}(t)$ is the maximum release from the reservoir at time t; $Rw_{\max}(t)$ is the maximum release from the set of wells at time t; $TRd_{\max}(t)$ is the summation of maximum daily reservoir releases for 30 days ahead of period t; $TRd_{\min}(t)$ is the summation of minimum necessary daily reservoir releases to attend the total demand for 30 days ahead of period t;

The physical limitations of the system define intervals which deficit, reservoir and wells releases, reservoir storage, well level and spill must belong to:

$$0 \le Def(t) \le D(t); \quad \forall t \tag{12}$$

$$0 \le Rd(t) \le Rd_{\max}(t); \quad \forall t \tag{13}$$

$$0 \le Rw(t) \le Rw_{\max}(t); \quad \forall t \tag{14}$$

$$S_{\text{dead}} \le S(t) \le S_{\max}(t); \quad \forall t \tag{15}$$

$$H(t) \ge H_{\min}; \quad \forall t \tag{16}$$

$$Sp(t) \ge 0; \quad \forall t \tag{17}$$

where $S_{\max}(t)$ is the maximum storage at time step t; and $H_{\min}$ is the minimum allowed level for withdrawing water from the set of wells.

The model is solved by Quadratic Programming (QP) through the use of the MATLAB Optimization Toolbox[8].

4. ANN-BASED PREDICTION MODEL

An Artificial Neural Network (ANN) model trained by the back-propagation algorithm is employed for estimating up to seven-day-ahead reservoir inflows. The methodology is applied to Ishitegawa Dam, which belongs to the water supply system of Matsuyama city, Japan.

(1) Architecture and topology

The architecture of the network is formed by the input layer, one hidden layer and the output layer. The input layer is composed of eight neurons, which are the current reservoir inflow $I(t)$, and the forecasted precipitation for seven days ahead: $P(t+1)$, $P(t+2)$, $P(t+3)$, $P(t+4)$, $P(t+5)$, $P(t+6)$, $P(t+7)$. The number of neurons in the hidden layer is determined based on a trial-error procedure. The best training results were achieved with three neurons in the hidden layer. The inflows for the next seven days ahead, $I(t+1)$, $I(t+2)$, $I(t+3)$, $I(t+4)$, $I(t+5)$, $I(t+6)$, $I(t+7)$, are the neurons of the output layer. In this study the network topology is constrained to be feed-forward, i.e., the connections are allowed from the input layer to the hidden layer and from the hidden layer to the output layer. The network topology of this study is illustrated in **Fig.2**.

(2) Activation functions

The tan-sigmoid function is chosen as the activation function for the hidden neurons. For the output layer neuron, a linear activation function is used.

(3) Training process

The original data (input and desired outputs) are conveniently scaled before the training in order to improve the efficiency of the ANN. The scaling approach consists of normalizing the inputs and targets so that they will have a mean and standard deviation equal to zero and one, respectively[9]. The training is performed by the back-propagation algorithm which has been successfully applied to water resources systems[10]. In this approach, the Levenberg-Marquardt (LM) algorithm is used for the back-propagation training. A detailed explanation of the LM algorithm is provided by Hagan & Menhaj[11]. The network training is supervised, i.e., the series of

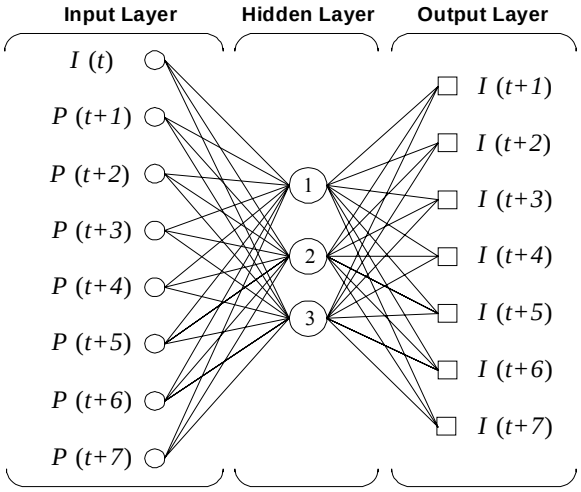

Fig.2 Topology of the ANN-based prediction model.

weights between the neurons and the bias are adjusted through the iterations (epochs) in order to fit the series of inputs to another series of known outputs. The training also occurs in the batch mode. In this mode, the weights and biases are updated only after the entire training set has been applied to the network. In order to improve generalization, the training is stopped by the Early Stopping Method[9]. This technique avoids a problem called overfitting that occurs during the neural network training. The network seems to be very well trained by showing very small errors from the training data set, but when new inputs are used the error is large.

5. APPLICATION AND RESULTS

(1) Groundwater balance

The estimation of the groundwater level, which is measured from the surface of Minamitakai Observation Well, was fitted to the historical data by the MLR model as presented in **Eq.(4)**. **Table 2** shows the values of the calibrated parameters. Five years of daily data (1997-2001) were used for the calibration and two years (2002 and 2003) for test. The results from calibration and test are shown in **Figs 3** and **4**, respectively. The high correlation (r) and low root mean square error (RMSE) between observed and estimated groundwater levels indicate that the calibrated MLR model is very reliable and thus can be used for the groundwater balance needed by the DO model. Salas[12] provides the equations to calculate the correlation and the root mean square error. The best fit between observed and calculated values, which is unlikely to happen, would have r = 1 and RMSE = 0.

(2) ANN-based prediction model

The historical data utilized in the procedure contain 13 years of daily data (1991 – 2003). The ANN model was calibrated using the data from the year 1993 to 2003 and the test was carried out over the years 1991 and 1992. The model calibration used the Early Stopping Method, and therefore the calibration data set was divided in two subsets: the first was used for the ANN model training (1993-2001), and the second for validation (2002-2003) to specify when to stop the network training. The comparison between six-day-ahead observed and predicted inflows is displayed in **Fig.5**. The results were shown to be very accurate and, therefore, this model was chosen to predict the short-term inflows needed for the application of the DO procedure to the water supply system of Matsuyama.

Table 2 Calibrated parameters of the MLR model.

α	β	γ	δ	θ
0.9794	3.5933	-0.0315	-0.0043	-0.0280

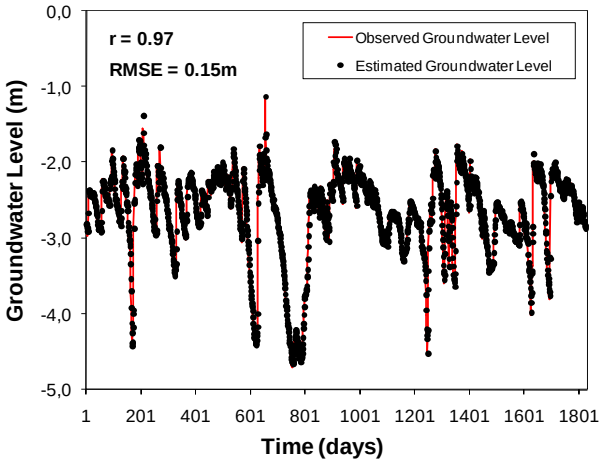

Fig.3 Comparison between observed and estimated groundwater levels for the calibration data set.

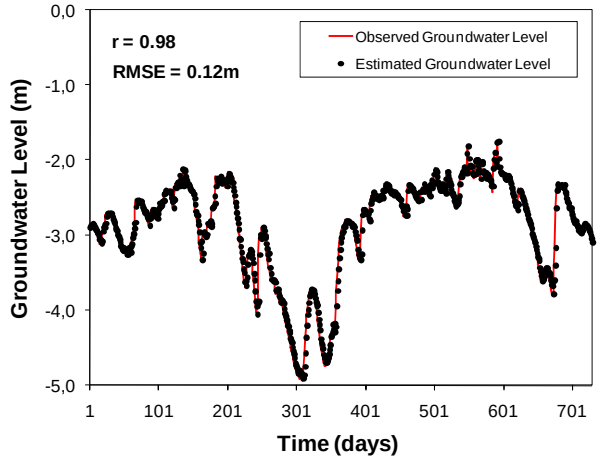

Fig.4 Comparison between observed and estimated groundwater levels for the test data set.

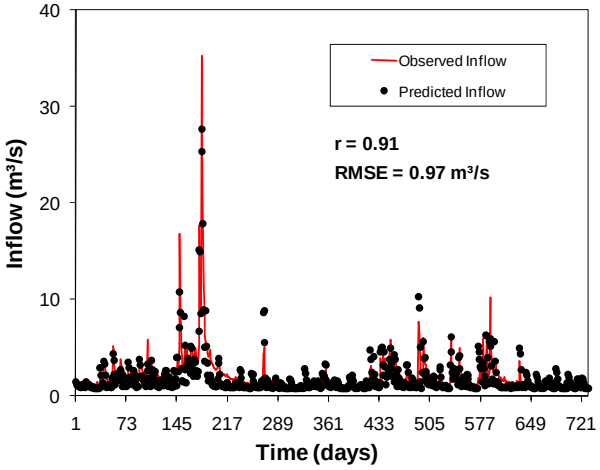

Fig.5 Comparison between 6-day-ahead observed and predicted inflows for the test data set.

(3) Daily optimization model

The DO procedure was applied to the real-time operation of the water resources system that supplies the city of Matsuyama, located in Ehime Prefecture, Japan. The maximum reservoir storage (S_{max}) is 8,500,000m³ during the rainy season and 12,800,000m³ for other periods. The minimum groundwater level for water withdrawal was assumed to be only -3m, different from the actual minimum level of -5m, because it was desired to observe many shortage situations and then compare how they are handled by the models. The DO procedure was applied to the data of the year 1991. The initial reservoir storage and representative well level were set to S_{max} and -2.14m (historical value), respectively.

The DO model was run under an operating horizon N of seven days. The values of inflows for seven days counting from the current day were obtained through the ANN-based prediction model considering the precipitations of seven days ahead. These precipitations were assumed as deterministic values since meteorological short-range forecasts are generally available. The representative well level is updated through the groundwater balance equation defined by **Eq.(4)**. The procedure is run and the optimal releases for the seven days are found. Nevertheless, only the allocations for the current day are used. The procedure is repeated for the next day and so forth until the final day of operation (end of the year) is reached.

Results obtained from the utilization of the DO model assuming the operating horizon of inflows as perfect forecasts were used for comparison. The operation of the system using the short-term perfect-forecast situation gives us the "ideal" releases that should be employed for the operating horizon since it has knowledge of all future inflow values. For comparison purposes, a fictitious simulation where all the demands should be met whenever possible (prioritizing the use of the reservoir storage), was also considered and compared with the DO optimal operations.

The results displayed in **Fig.6** show how the allocations from the water supply system try to meet the target demands for the period between September and December of 1991. Comparing the results from the DO under perfect short-term forecast of inflows with those from the fictitious simulation, it can be

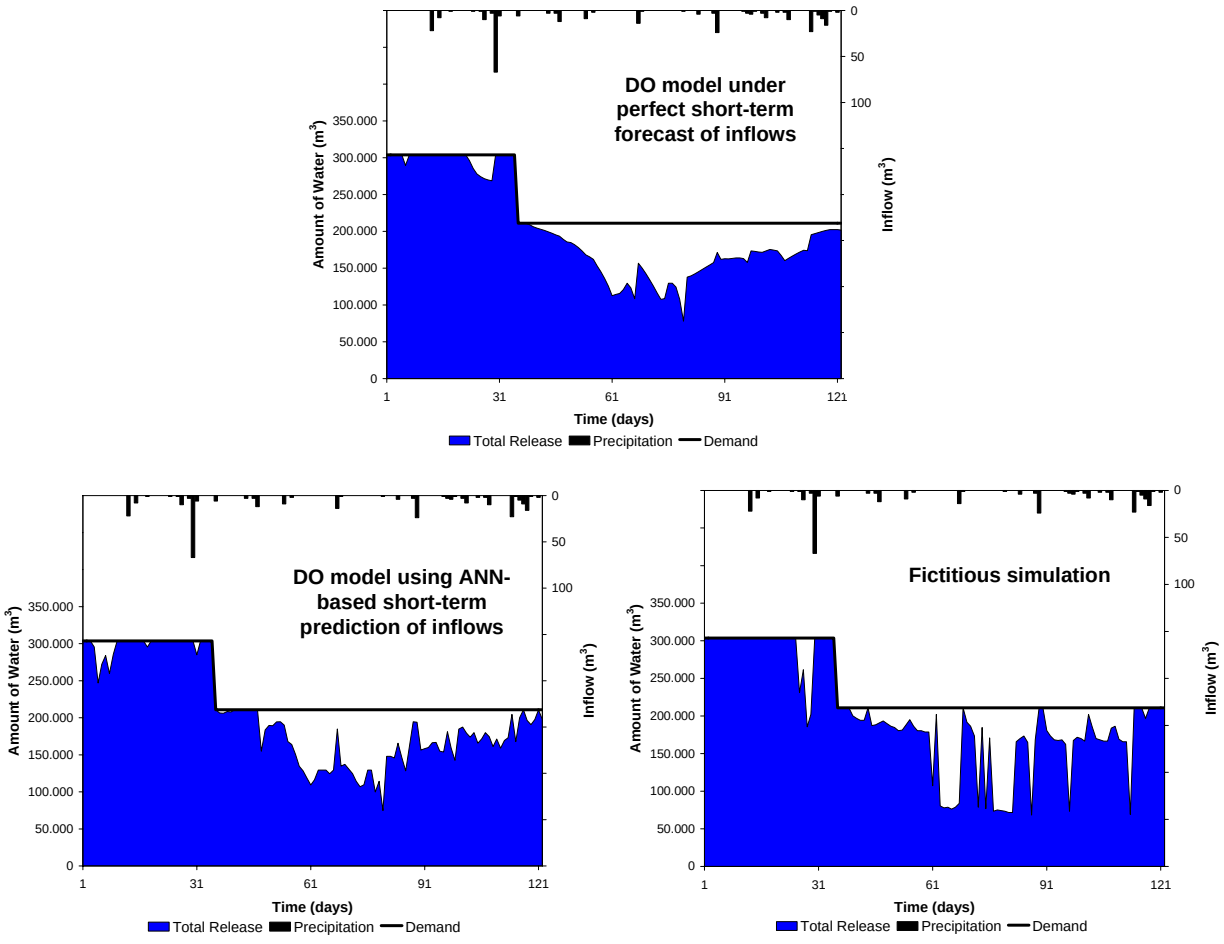

Fig.6 Results for the period between September 1st and December 31st of 1991.

Table 3 Summation of the squared deviations between releases and target demands for all procedures.

Procedures	$\sum_{t=1}^{365}\left[\frac{Def(t)}{D(t)}\right]^2$
DO under perfect forecast of inflows	6.3
DO under ANN-based predicted inflows	6.3
Fictitious simulation	8.9

seen that the optimization model tries to mitigate the great concentrated deficits that happen with the simulation by decreasing the releases prior to shortages periods so that the overall deficit also diminishes. The results of the DO procedure using ANN-based inflow predictions try to allocate water in a way very similar to the DO under the perfect forecast of inflows. This information indicates that the release policies obtained by DO with ANN-based predicted inflows were quite satisfactory given the fact that they have information only on the precipitation forecasts, whereas the DO under the perfect forecast has knowledge of inflows for the operating horizon and thus better means to define superior policies.

The summation of the daily squared deviations between releases and target demands were computed from January to December of 1991. These values are presented in **Table 3**. The squared deviation results showed that, as well as seen in **Fig.6**, DO using ANN-based predicted inflows produced results similar to the DO under perfect short-term forecast of inflows and superior policies if compared to the fictitious simulation.

6. CONCLUSIONS

A quadratic optimization problem was applied to the short-term operation of Ishitegawa Dam reservoir and a set of groundwater wells in Matsuyama, Ehime. The groundwater balance, which was modeled by a MLR model, and the short-term ANN-based predictions of reservoir inflows were obtained based on the short-range forecast of daily precipitations.

Analysis of the MLR and ANN models showed that they were very trustworthy, and consequently could produce consistent data for the application of the DO procedure to the water supply system of Matsuyama.

The results indicate that the DO model using the ANN-based predicted inflows found more reasonable operating policies than fictitious simulation that tried to meet all the demands without taking the future situation into account. As conclusion, this suggests that the DO model using short-term ANN-based predicted inflows may be useful for the sustainable operation of water supply systems with conjunctive use of surface water and groundwater.

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(Received September 30, 2007)