Coping with predictive uncertainties in optimization of sustainable water resources

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Abstract This paper presents a reliability-based water resources management framework that utilizes stochastic optimization techniques to account for uncertainties associated with the prediction of water demand, surface water availability, baseline groundwater levels, a non-anthropogenic reservoir water budget, and hydrological/hydrogeological properties. Except for the hydrogeological properties, these uncertainties are partially caused by uncertainties in prediction of future climate conditions. The framework was developed to manage a water supply system that serves about two million people in the Northern Tampa Bay region in Florida, USA, while protecting wetland ecology and preventing seawater intrusion. The supply sources include about 180 groundwater production wells, three streamflow withdrawals, a regional reservoir, and a desalination plant. The developed method maximizes the reliability of achieving the goals that all protected wetlands in the area are healthy by maintaining high groundwater levels. The framework involves: (1) a distribution system simulation model to represent the water supply operation under an Optimal Regional Operation Plan (OROP), (2) a Monte Carlo simulation model to generate realizations of climatic events, water demand, available surface water quantity, and (3) a unit response matrix (URM) that relates groundwater level response to groundwater extraction. An operator response model simulates how water supply operators adjust the optimized rates of groundwater extraction, surface water withdrawal, and reservoir inflow/outflow according to meeting the water demand in all circumstances. The reliability optimization problem is solved using a differential evolutionary algorithm.

Key words water resources management; climate; uncertainty; water demand; groundwater; optimization; stochastic; socio-economic; reliability; wetland

BACKGROUND

Tampa Bay Water (TBW) is the largest wholesale water supply utility in Florida, USA, and serves approximately two million people in the Northern Tampa Bay Tri-county area. Due to the significant population growth in the past 50 years, the water demand in the region has increased from approximately 1.1 cubic metres per second (m^3/s) in 1950 to approximately 11.4 m^3/s in 2000. Prior to 1998, groundwater was the only water supply sources utilized. The reliance on groundwater led to groundwater level drop in the region.

In April 1998, TBW entered into the Partnership Agreement with the Southwest Florida Water Management District (SWFWMD) to reduce groundwater pumpage in phases to an annual average of 3.9 m^3/s for 1 January 2008. As a part of the Agreement, the SWFWMD is providing funds to assist with development of new and alternative water supply sources including a 3 800 000 m3 off-stream regional reservoir, a 1.1 m^3/s seawater desalination plan, and a 2.9 m^3/s regional water treatment plan. The water use permit also required the TBW to implement the Optimized Regional Operations Plan (OROP) that utilized optimization-simulation models to manage approximately 180 water supply wells in 12 inter-connected wellfields and other surface water sources. The goal is to prevent negative impacts on protected wetlands and the potential for seawater intrusion.

The current OROP model is deterministic and has two components: a four-week short-term model and a one-year long-term model. The model was used to generate the target weekly pumping rate for each water supply well. The objective was formulated to maximize the weighted water levels at key monitoring wells while satisfying various constraints, including demands, physical limits, and operating policy. Example constraints include 36-month average for the wellfields, the peak month average for each well and wellfield, regulatory water levels, well capacities and water transmission capacities. The monitoring wells, also known as control points (CP), were intended to serve as surrogates to the environmental features to be protected, such as wetlands and lakes. Currently, there are 40 wells in the OROP monitoring well networks that provide control for well and wellfield rotations.

The long-term optimization model is based on a water demand level estimated from the historical data. The resulting pumping rate at each well was used as an upper-bound constraint (referred to as the rule-curves) imposed on the short-term optimization model. The short-term optimization model is based on the best-estimates of the water demand and surface water availability.

The results of the optimization include a priority/weighting/ranking system to reduce environmental stress preferentially at selected locations. In addition, the method was used to select and rotate groundwater resources among interconnected supply sources. An integrated surface- and groundwater hydrological model (ISGW) was used to generate a Unit Response Matrix (URM) that simulates the relationships between pumping rates and drawdowns at the control points.

RELIABILITY-BASED STOCHASTIC OPTIMIZATION FRAMEWORK

The current OROP optimizes the water supply operation weekly by looking ahead four weeks of water demand and availability of non-groundwater resources. In the current formulation, a set of rule-curves is used as constraints in the weekly optimization model to prevent over-pumping. The rule-curves were developed for a one-year time window. Although the rule-curve constraints have been imposed, these constraints might not be a “binding” condition. In such a case, the weekly optimal solution does not account for the seasonal variations of hydrological conditions. To include seasonal variations, a new OROP formulation (referred to as OROP II) was developed to extend the time window from four weeks to one year. The extension to a one-year period allows scheduled events (such as wellfield maintenance and shutdown) to be incorporated into the optimization.

The uncertainties associated with the forecasting of water demand and availability of non-groundwater resources increase with the timescale of forecasting. As the time window of OROP II is extended to cover a one-year period, it is important that the OROP II formulation accounts for the forecasting and predictive uncertainties associated with the current OROP model. The OROP II framework utilizes a stochastic optimization formulation to account for the uncertainties associated with:

(1) the water demand forecasts at the Points of Connection (POC) where water is distributed to the customers,
(2) non-groundwater source availability at supply locations,
(3) the unit response matrix (URM) that relates the changes of groundwater level at the control points (CP) to the change in pumping rates at the production wells,
(4) the estimates of precipitation onto and evaporation from the regional reservoir, and
(5) the predicted groundwater levels at the CP under baseline/referenced (historical average) pumping condition.

It is recognized that wellfield operators have been making adjustments to the optimized operating schedules in response to the actual water demand and availability of non-groundwater sources in all circumstances. Operator's adjustments were not addressed in the current OROP, but they are accounted for in the OROP II formulation.

Overview of the reliability-based optimization framework

The OROP II retains a majority of the current OROP utilities. The conceptual framework of OROP II is depicted on Fig. 1. The OROP II procedures compute the optimized operation schedule of: (1) groundwater extraction, q, (2) surface water withdrawal, s, and (3) water flow into or from the regional reservoir, f. The operation schedule consists of 16 time steps covering a period of one year: 1-week time steps for the first four weeks followed by twelve 4-week time steps. The procedures will be applied every week using the latest collected data to adaptively update the weekly operation schedule. All stochastic models are conditioned on the collected data.

The operator response simulator in OROP II mimics the adjustment of the optimized operation schedule by operators, in response to the actual water demand and non-groundwater availability. The uncertainties considered in OROP II are addressed using a Monte Carlo simulation approach. The stochastic realization generator produces a pre-selected number of equally likely scenarios (1000 realizations, for example) that capture the variability of the five uncertain quantities listed above, conditioned on past observations. Let i be the index of a realization, D_i be a realization of the generated time histories of the demand, A_i be a realization of surface water availability, and R_i be a realization of the net aerial replenishment (precipitation minus evaporation) over the reservoir surface area. With known D_i and A_i, the operator response simulator adjusts the deterministic OROP schedule resulting in a modified schedule of (1) groundwater extraction, Q_i, (2) surface water withdrawal, S_i, and (3) flow to the regional reservoir, F_i (negative if water is withdrawn from the reservoir). Subsequently, for each realization, the global optimizer uses the generated baseline groundwater level, Ho_i, the URM, U_i, and the groundwater extraction rate, Q_i to calculate the resulting groundwater levels at the control points, H_i. The global

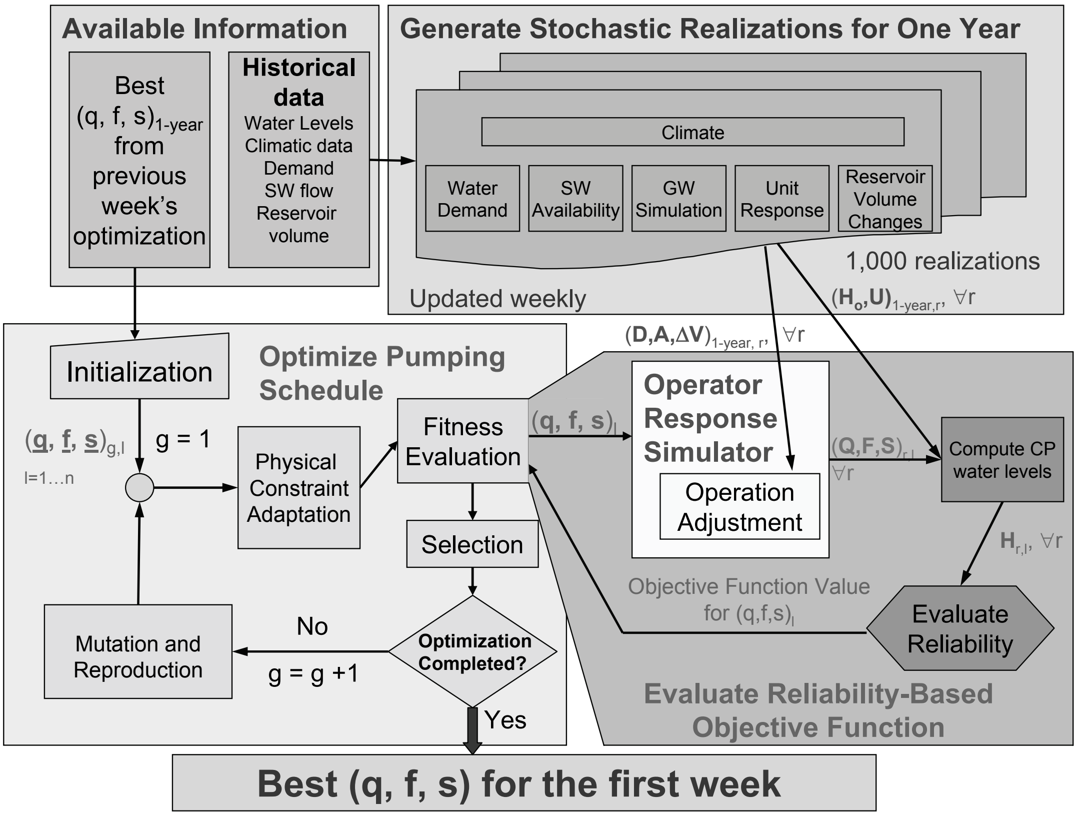

Fig. 1 Conceptual framework of stochastic optimization.

objective function is defined as the probability of meeting the target head criteria and can be evaluated by counting the number of realizations that satisfy these criteria. The global optimizer continues the iterative procedure to search for a target operation schedule that maximizes the objective function.

Stochastic Realization Generator

The stochastic realization generator consists of five models that produce statistically independent and equally-likely realizations of the five uncertain quantities as described above, all conditioned on past observations. The last number generated by the random number generator used in a stochastic model is used as the seed number for the random number generator used in another stochastic model. Because the temporal variation of groundwater level is small compared to the thickness of the aquifer system, the URM is practically insensitive to the hydrological and hydrogeological conditions. This behaviour has been verified by numerical experiments. The sample of URM realizations needs to be generated once and will be re-used every week when the stochastic optimization is performed. The other four models are conditioned on the latest historical data collected and their realizations will be generated every week. These models are strongly dependent on rainfall and temperature factors, so the outputs from these models are correlated to some degree. A stochastic climatic model will be used to generate realizations of rainfall and temperature variables, which are inputs to the stochastic models. It is important that the same climatic model realization is used to generate a single sample of realizations of water demand, surface water availability, and baseline groundwater levels. The five stochastic simulation models are described below.

Unit Response Matrix Model A stochastic URM model is derived from the newly developed Integrated Hydrologic Model (IHM) using a first-order second-moment (FOSM) approach (Cacuci, 2003). The IHM model is based on a commonly used groundwater code, MODFLOW, and a surface water code, HSPF, and has been calibrated using historical groundwater level, streamflow, and springflow data. The major IHM model parameters include aquifer transmissivity, leakance, storage, and surface water hydrologic parameters. The parallel version of the model inversion computer code, PEST, is used to compute the covariance matrix that characterizes the uncertainty associated with the IHM model parameters. Based on the covariance matrix, Monte Carlo realizations of the IHM model parameters are generated.

The URM is treated as a linear function of the IHM parameters. The linearization of the URM terms was evaluated by perturbing the IHM model parameters around the calibrated values. For each stochastically generated realization of the set of IHM model parameters, the corresponding URM terms are computed using the linearized results.

Water Demand Forecasting Model The water demand forecasting model is based on (1) an artificial neural network (ANN) model that predicts the water demand in the first four weekly time steps, and (2) a series of econometric models that relate demand to climatic and socioeconomic variables for the subsequent twelve 4-week time steps. While these models have been developed, upgrades and improvements will be made based on data availability and need. The primary input variables of the ANN model are the characteristics of the predicted precipitation, temperature, and moisture at selected stations. The socioeconomic models were developed based on the results of regression analysis using historical data of water use to estimate the unit water demand per single family home, multi-family dwelling, and employee in commercial sectors. Monte Carlo simulations are used to represent the uncertainties of these models.

Surface Water Availability Forecasting Model The surface water availability forecasting model is based on (1) an ANN model that predicts the streamflow at gauging stations in the first four weekly time steps, and (2) seasonal auto-regressive models with precipitation as exogenous variables (SARX) (Makridakis *et al*., 1997) for the Alafia River and Hillsborough River for the subsequent twelve 4-week time steps. The SARX models have been developed. The primary input variables of the ANN model are the characteristics of the predicted precipitation at selected stations. Monte Carlo simulations are used to represent the uncertainties of these models.

Baseline Groundwater Level Prediction Model The baseline groundwater level prediction model is generated based on (1) an ANN model for the first four weekly time steps and (2) the IHM model for the subsequent twelve 4-week time steps based on historically averaged groundwater pumpage. The primary input variables of the ANN model are the characteristics of the predicted precipitation at selected stations, as well as the pumping rates at the water production wells.

Reservoir Storage Volume Change Model A reservoir storage volume change model is generated based on consideration of water balance. The water budget includes the contribution of precipitation and evaporation events generated by the stochastic climatic model.

Operator Response Simulator

The operator response simulator is an optimization routine that mimics operators' logic to operate wellfields and surface water facilities guided by an OROP weekly production schedule. The schedule generated by this simulator is deterministic. It is obtained from running the current OROP model with best estimate inputs. Inputs to the simulator include a list of priority for each well and its maximum permissible rate. Depending on the realizations of water demands and available surface water, the simulator will adjust the production according to the well priority with the objective to closely follow the schedule provided. If more or less water is needed, the simulator will turn wells on or off according to the priority. Development of the simulator will be modified from the current OROP model by: (1) replacing the objective with the one that minimizes the production differences, (2) replacing deterministic inputs with the realizations of stochastic inputs, and (3) adding constraints representing operators' logic to adhere to the schedule provided.

Evolutionary Global Optimizer

The Evolutionary Algorithm (EA) is a class of global optimization methods. Among many EA methods published in the literature, the Differential Evolution (DE) method has been reported as one of the most efficient algorithms. The solution starts with an initial population (a collection of individuals) in which their associated values (a vector of decision variables) are chosen either randomly or strategically. Through cross-over, mutation, and selection processes (known as genetic operators), the population evolves into the next generation that gradually improves the objective function value towards a global optimum. In the OROP II framework, the constraints considered in the current OROP are addressed through the procedures modified from the current OROP. These modified procedures are nested within the DE iteration. Each DE iteration involves a search scheme that manages genetic operators to provide a subsequent generation or a preliminary solution. The resulting solution is further mutated (adjusted) by the modified OROP-I procedures, which searches for the new production schedule that satisfies all the constraints and minimizes the differences resulting from operator adjustment. The DE-iteration continues until the solution converges.

Objective Function The objective function is defined as the probability that all wetlands are healthy. The formulation involves the following three criteria expressed in terms of the groundwater level time histories at each CP:

- the water level must be higher than a target level more than 50% of the time;
- the water level must be higher than a minimum level at all times;
- the water level must be higher than a critical level continuously over a minimum duration.

The probability is computed by counting the number of realizations that all three criteria are satisfied at all control points, and dividing the count by the total number of realizations. The global optimization (Evolutionary Algorithm) searches for a solution that maximizes this probability value.

CONCLUSION

The stochastic optimization method described in this paper provides a useful tool to estimate the optimal use of groundwater and surface water to meet the water demand in all circumstances. Weekly application of the model to reflect the current hydrological condition adaptively adjusts the groundwater usage to minimize the potential impact of groundwater utilization on wetland health.

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