Determination of Optimal Operating Schemes for a Multi-Reservoir System Under Environmental Constraints

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Abstract

In stratified reservoirs, both dam tailwater discharge and thermal plant intake water quality and temperature can be highly dependent on structure depth. A two-dimensional laterally-averaged model allows for better prediction of water quality over time at specific depths. Because high-fidelity models are typically too computationally expensive for direct inclusion within optimization algorithms, water quality is incorporated using one dimensional models are simple flow requirements. Water quality predictions can be incorporated within the optimization process through using surrogate modeling methods, in this application artificial neural network (ANN) models. ANNs are flexible machine learning tools for function approximation composed of a structure of neurons assembled within a multi-layer architecture. They are capable of handling large amounts of training data and modeling nonlinear dynamic systems, making ANNs a well-suited method for this application. This report illustrates the development of ANN models to emulate the hydrodynamic and water quality modeling capabilities of the high-fidelity, two-dimensional CE-QUAL-W2 (W2) model, as well as a linked riverine reservoir system optimization process which accounts for energy generation, water balance and hydraulics, and compliance point water quality. A process for hourly hydropower generation planning is demonstrated on a pair of reservoirs linked in series. The two reservoirs are U.S. Army Corps of Engineers projects with hydropower capabilities on the Cumberland River near Nashville, Tennessee, USA. The content presented here is largely a combination of technical papers previously presented at the HydroVision International conference (*Shaw et al.*, 2015, 2016).

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1 Motivation

As computing capabilities improve, high-order multi-dimensional models have been developed to simulate the hydrodynamic and water quality behavior of waterbodies. These models can be particularly useful for controlled reservoirs with hydropower capabilities. In stratified reservoirs, water quality at points of importance in the reservoir, including dam tailwater and thermal plant intake locations, can be dependent on structure depth and dam operations. Using well-calibrated models, operators have the ability to test various operating schemes and observe impacts on water quality, providing more informed guidance during the decision-making process. Unfortunately, models that tend to produce minimal errors tend to be computationally expensive (*Bates et al.*, 2005). This limits the ability to apply mathematical techniques such as optimization and other decision-making processes. Linking a series of such models can also be prohibitively computationally expensive. The computational limitations of using high-order reservoir models can be reduced by developing surrogate models, which can extend the range of results of a computationally expensive model, allowing users to predict model outputs at a lower cost. The goal is to produce a surrogate model that is computationally more efficient than the original model, but still provides accurate predictions at select distances from known data points (*Forrester et al.*, 2008).

This paper describes water quality surrogate model development for a controlled riverine system in series with hydropower capabilities on the Cumberland River, operated by the U.S. Army Corps of Engineerings (USACE) Nashville District. Cordell Hull and Old Hickory reservoirs are presently modeled using CE-QUAL-W2 (W2), a two-dimensional high-fidelity hydrodynamic water quality model that has been extensively studied and verified (*Portland State University*, 2007). W2 can be used as a decision support tool for operators and is particularly useful for modeling vertically-stratified waterbodies, but is not well-structured to support everyday decision-making. Additionally, it does not provide the means for determining optimal dam release patterns subject to constraints. Development of an efficient surrogate model capable of accurately predicting hydrodynamic and water quality results of interest to the system‘s stakeholders enables model execution for applications such as optimization for which W2 is not properly structured. Time-dependent artificial neural network (ANN) models are able to accurately emulate W2 water quality after being trained using a family of W2 simulations.

This paper details the development of an optimization routine which determines hourly control decisions for the linked-reservoir system. This routine combines stakeholder objectives and constraints with genetic algorithms (GAs), a family of heuristic global optimizers, and nonlinear autoregressive with exogenous inputs (NARX) ANN surrogate models in order to determine optimal spill and turbine discharge patterns during times of water quality stress. This work represents a segment of a larger research effort, the objective of which is to perform rule-based simulation and optimization for determination of flow releases from hydropower turbines and control structures along riverine systems subject to constraints on power production, navigability, temperature, water quality, and flooding (*Smith Sawyer et al.*, 2013).

2 Literature Review

2.1 Optimization of Hydropower-Equipped Reservoir Systems

Various techniques have been employed for hydropower optimization. Early studies employed linear programming (LP) (*Crawley and Dandy*, 1993; *Ponnambalam et al.*, 1989; *Seifi and Hipel*, 2001), which entails short computational times but requires functions to be linear or linearizable. This is often not the case for hydropower generation problems. A step up from LP, nonlinear programming (NLP) algorithms do not have the linear function requirement. This is a broad family of techniques which includes sequential linear programming (SLP) (*Barros et al.*, 2003; *Grygier and Stedinger*, 1985), sequential quadratic programming (SQP) (*Tejada-Guibert et al.*, 1990), the augmented Lagrangian method (also known as the method of multipliers, MOM) (*Arnold et al.*, 1994; *Finardi and Scuzziato*, 2013; *Naresh and Sharma*, 2002), and the generalized reduced gradient method (GRG) (*Unver and Mays*, 1990). NLP requires all functions to be differentiable, which may not be the case for hydropower systems. Dynamic programming (DP) methods have been popular in hydropower optimization tool development due to their ability to handle nonconvex and discontinuous functions and structure which emulates the multistage decision-making process involved in reservoir system operations(*Labadie*, 2004). The "curse of dimensionality" arises in these types of problems, which has led to various DP modifications to lessen the computational time of high-dimensional problems. Optimization of many linked reservoirs becomes computationally infeasible using the original DP formulation, which is the reason much of the hydropower optimization by DP literature involves modified DP approaches(*Castelletti et al.*, 2007; *El-Awar et al.*, 1998; *Yi et al.*, 2003; *Yurtal et al.*, 2005; *Zhao et al.*, 2014).

More recently, heuristic programming methods have become popular for investigating hydropower optimal operating patterns. In contrast to earlier algorithmic methods, heuristic techniques are less-structured and can rely on both quantitative and qualitative information. Convergence to an optimal solution cannot be guaranteed, but for complicated problems these techniques may be capable of finding global optimums where algorithmic methods converge to local optimums (*Rani and Moreira*, 2010). Evolutionary methods include genetic algorithms (*Ahmed and Sarma*, 2005; *Oliveira and Loucks*, 1997), simulated annealing (*Teegavarapu and Simonovic*, 2002; *Chiu et al.*, 2007)], and particle swarm optimization (*Kumar and Reddy*, 2007). Fuzzy set theory, which is designed to account for imprecision and uncertainty, has been used for stochastic reservoir optimization applications (*Fontane et al.*, 1997). Artificial neural networks, which serve as black-box emulators of larger models, have been combined with DP and NLP techniques to efficiently determine optimal operating schemes (*Raman and Chandramouli*, 1996). These techniques have all been used in hydropower-related studies, but the literature is limited as many of these procedures were only recently developed.

Multiobjective reservoir optimization applications seek to analyze the trade-off between a variety of outcomes including power generation, flood control, and water supply/quality. These problems have been solved using both classic and heuristic optimization methods. *Fontane et al.* (1997) employed stochastic dynamic programming to quantify optimal operations in terms of hydropower generation, flood control, water supply, and recreational demands. Using genetic algorithms, *Teegavarapu et al.* (2013) analyzed the trade-offs between power generation and downstream water quality and *Liu et al.* (2011) incorporated minimization of flood risk.

Reservoirs with hydropower capabilities are generally operated with the primary goal of maximizing energy production while meeting other legal water regulations (*Jager and Smith*, 2008). More recent hydropower optimization studies have integrated constraints related to wildlife and water quality. The inclusion of water quality has been limited though; such studies have not employed state-of-the-art two-dimensional high-fidelity water quality models, but instead generally incorporate one-dimensional coarse-grid models or minimum flow requirements deemed to support sufficient water quality (*Jager and Smith*, 2008). For example, *Hayes et al.* (1998) integrated the quasi-2D coarse-grid water quality DORM-II model of the upper Cumberland River basin in the southeastern United States into an optimal control model to analyze water quality improvement opportunities through operational changes. While computationally feasible, this work included simplifications such as 24 hour periods of generation, stratification defined by two well-mixed vertical layers with no mixing between layers, and simplified heat transfer and reaeration equations. Optimizing operations for a single reservoir under simulated environmental constraints has proven computationally challenging (*Dhar and Datta*, 2008). To date, high-fidelity water quality models have not been incorporated within hydropower optimization on an operating timescale. Optimization routines, both classic and heuristic, often require many objective and constraint evaluations; this requirement hinders the use of computationally expensive models within these routines. Some methods also require differentiable functions and linear relationships, which numerical models cannot fulfill.

2.2 Artificial Neural Network Models

Feedforward artificial neural networks (ANNs) are flexible tools for function approximation composed of neurons assembled into a multi-layer architecture. The neurons are multiple linear regression models with a nonlinear transformation on the output. They have been used for a variety of complex problems including speech and handwriting recognition, face recognition, currency exchange rate prediction, chemical processes optimization, cancerous cell identification, and spacecraft trajectory prediction (*Cheng and Titterington*, 1994). They are often referred to as "black box models," as they have no explicit function form and are often used to simulate processes that the user does not know or cannot express as a mathematical expression.

There are two main steps in constructing a neural network. First, the architecture must be specified, and secondly, the network must be trained. Modelers specify the model architecture through several parameters, including the number of hidden layers, number of neurons in each hidden layer, and the form of transfer functions. Extensively testing a variety of network structures can be computationally expensive; considering this, the appropriate architecture of ANN applications in the literature are generally decided by trial-and-error. In a review of response surface modeling literature *Razavi et al.* (2012) conclude that single hidden layer ANNs are most popular for water resources applications.

ANNs can be used as inexact emulators for noisy data sources or exact emulators for deterministic computer code. With a sufficiently large structure, ANNs can perform exact emulation of deterministic code, but this may lead to poor performance in unsampled areas of the design space and a risk of overfitting (*Razavi et al.*, 2012). ANNs are capable of handling large amounts of training data and it is generally believed that additional input data results in a better-generalized model; however, large amounts of data can require additional computational time (*Zou et al.*, 2007).

ANNs have been used as surrogate models in surface water resources operations and design optimization problems previously. *Saad et al.* (1996) employed RBF neural networks to decompose the optimal operating policies obtained through dynamic programming for a reservoir system. *Neelakantan and Pundarikanthan* (1999) also used a neural network for simulation of a reservoir system's operation as substitution for a conventional simulation model, with the goal of maximizing drinking water supply. The neural network model was reported to run 300 times faster than the conventional model, and solving the optimization problem took as long as 15 days of continuous computations using the conventional model, but only a few hours with the neural network model. *Castelletti et al.* (2010) used response surface methods, including neural networks, to emulate a 3-D hydrodynamic-ecological model and optimize the number and location of water quality rehabilitation devices (i.e., mixers) in order to improve overall water quality in a reservoir in Australia. The authors estimated it would require 5.5 years to solve this problem on a modern computer using what-if analysis.

2.3 Genetic Algorithms

Genetic algorithms (GAs), first introduced by *Holland* (1975), are a family of algorithms based on the mechanics of genetics and natural selection. They use a variety of methods to transition from one generation population to the next, including inheritance, mutation, selection, and crossover. Populations of candidate solutions are evolved toward better solutions in an iterative process which rewards feasible, near-optimal solutions. Candidate solutions are copied into the next generation, mutated, and combined stochastically based on their assigned fitness levels. This attempts to balance exploration of solutions from new areas of the design space and exploitation of solutions already found in regions of high fitness. This process terminates when stopping criteria has been reached; examples of these criteria include a maximum number of generations or solutions, a satisfactory fitness level, or a population homogeneity level being reached. GAs are global optimizers able to solve problems where functions are non-linear and discontinuous, as no derivatives are required.

One of the earliest introductions of GAs for hydropower operations comes from *Esat and Hall* (1994), where GAs were used to solve the four-reservoir problem. This benchmark problem concerns a system of four reservoirs, with both parallel and series connections, operated over twelve 2 hour periods (a total of 24 hours), searching for optimal releases with constraints related to flood control and turbine capacities. The authors concluded that as system size increases, computational expense for discrete differential dynamic programming (DDDP) increases exponentially while the expense of GAs increase linearly. *Wardlaw and Sharif* (1999) solved the same four-reservoir problem as well as a more complex ten-reservoir problem, testing sensitivities to various GA settings. *Oliveira and Loucks* (1997) combined a genetic search algorithm with simulation models to determine optimal operating policy rules for several multireservoir systems, focusing on satisfying joint water demands and joint energy requirements. Similarly, *Suiadee and Tingsanchali* (2007) used a combined simulation-GA optimization model to determine optimal monthly reservoir rule curves for a single reservoir in Thailand, with the objective function equal to the maximum net system benefit subject to irrigation constraints and the monthly releases computed by the simulation model.

More recently, hydropower optimization problems have been solved by GA in combination with surface water quality models. *Kerachian and Karamouz* (2007) determined optimal operating rules for the Ghomrud Reservoir-River system in Iran for water quality management using a stochastic GA-based conflict resolution technique. A one-dimensional water quality model simulating thermal stratification and water quality at releases from different outlets was used, as well as simulation of pollutants in the downstream river. This one-dimensional model was based on the existing Ghomrud HEC-5Q model, which could not be easily linked to the optimization model. *Dhar and Datta* (2008) linked a CE-QUAL-W2 model with an elitist genetic algorithm to determine optimal reservoir operation policy with the aim of maintaining water quality downstream of the reservoir while minimizing the storage deviation from target storage. The authors employed this method on a hypothetical reservoir on the upstream end of the Middle Willamette River in Oregon, USA for daily operating decisions over a 10 day management period. They concluded that the development of parallel code or integration of metamodels, such as ANNs, could be useful at reducing computational time and increasing the feasibility of solving larger, more complex reservoir system operations problems.

3 Case Study Area

3.1 Cordell Hull and Old Hickory Reservoirs

Cordell Hull and Old Hickory reservoirs are run-of-the-river impounded projects located on the Cumberland River, upstream of Nashville, Tennessee. A schematic of the Cumberland River system is shown in Figure 1. Cordell Hull's primary purposes are navigation, hydropower, and recreation. Cordell Hull dam has 3 Kaplan adjustable blade propeller turbines and 5 tainter gates to allow for spill. Old Hickory's primary purposes are navigation and hydropower generation, but the impounded lake also serves as a form of recreation. The dam's outflow structures consist of 6 tainter gates and 4 Kaplan adjustable blade propeller turbines. Both reservoirs are retained by a combination earthfill and concrete-gravity dam (*U.S. Army Corps of Engineers*, 1998).

3.2 CE-QUAL-W2 Models

W2 models of Cordell Hull and Old Hickory reservoirs were obtained from the U.S. Army Corps of Engineers Nashville District; upgraded to W2 version 3.5; calibrated over the year 1988 for Old Hickory and 2000 for Cordell Hull; and validated over the year 2005 for both reservoirs. Calibration and validation were performed for water balance as well as in-pool and discharge temperature and dissolved oxygen (DO).The plan view bathymetries for the two models are shown in Figures 2 and 3, with Branch 1 representing the reservoir mainstem in each case. Located on the Old Hickory reservoir, the Gallatin steam plant draws cooling water from the mainstem and discharges heated water back into the mainstem, a process

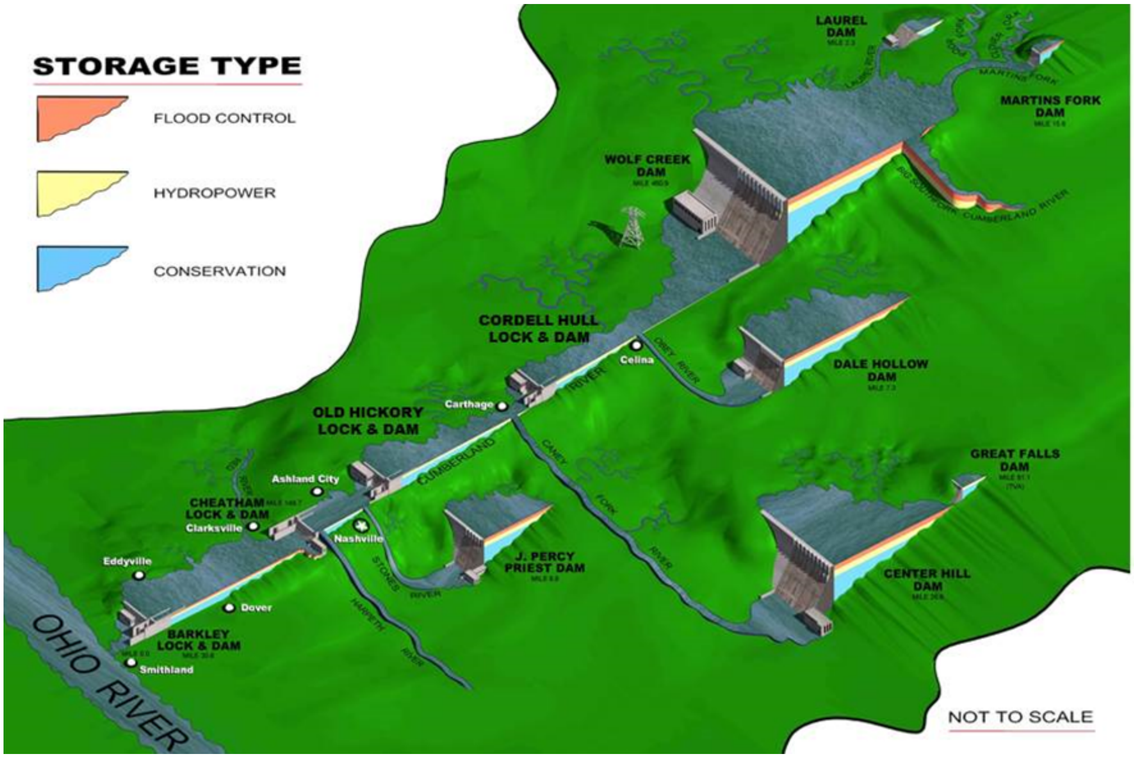

Figure 1: Projects on the Cumberland River System (courtesy of USACE Nashville District).

which is modeled as a reservoir withdrawal and one of the tributary inflows. The W2 models require the following input data: inflow concentrations and flowrates, meteorological data, wind sheltering and shade coefficients, sediment and friction coefficients, and bathymetry data. The model can output hydrodynamic and water quality data as time series text files, which is used to train surrogate models which can be implemented as constraints for reservoir optimization.

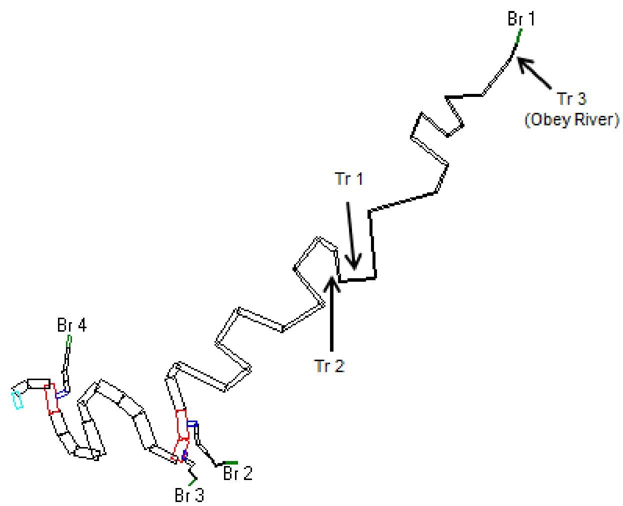

Figure 2: CE-QUAL-W2 Model Bathymetry for Cordell Hull Reservoir.

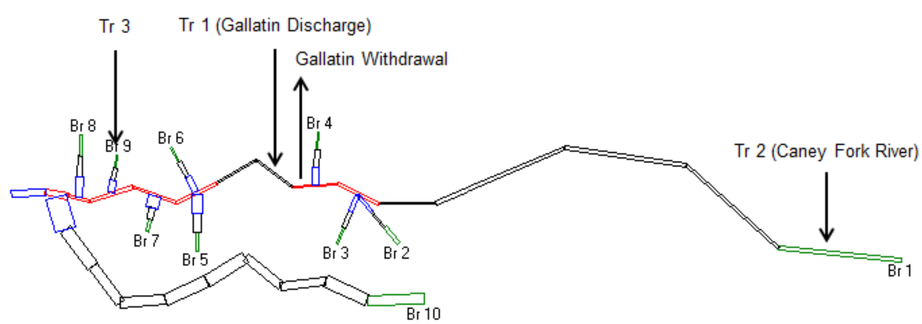

Figure 3: CE-QUAL-W2 Model Bathymetry for Old Hickory Reservoir.

4 Water Quality Surrogate Models

4.1 Design of Experiments

The goal of the design of W2 experiments to support this effort was to provide sufficient training data to demonstrate the functionality of the optimization tool. For each reservoir, a design of experiments was created based on the concept of running W2 simulations under various combinations of 6 dominant input conditions. These dominant inputs were determined through sensitivity testing. For each input file, three variations were considered, with one of the variations identical to the "base case" 2005 values. Meteorological conditions consisted of the 2005, 2006, and 2007 values. Inflow temperatures and dissolved oxygen concentrations were increased and decreased by 5% from the "base case" values. Inflows were not varied, but outflows were varied to create heavy spill and heavy turbine scenarios. The heavy spill scenario was created by allocating 20% of the 2005 turbine outflow to the spill gates, and the heavy turbine scenario was created by allocating 20% of the 2005 spill outflow to the turbine structure outflow. Spill and turbine scenarios were not combined exhaustively, but instead were paired to maintain an equivalent total outflow to maintain water balance stability in the W2 simulations. This process means the surrogate model can be used to explore the trade-off between releases through the turbines and spill gates. An exhaustive combination of all variables, with the exception of the paired spill and turbine inputs as explained, resulted in a total of 729 W2 model simulations for each reservoir. The input file scenarios tested are shown in Table 1.

4.2 Simulation Automation and Data Management

To ensure variety and robustness in the training data, numerous W2 simulations were performed as detailed earlier. It is especially critical to evaluate a variety of turbine and spill flow scenarios, since this factor comprises the decision variable in the optimization algorithm that will apply this surrogate model for water quality predictions. A large amount of W2 input and output data is required for neural network training. The Vanderbilt Institute for Software Integrated Systems has assisted in this aspect of the project, developing W2 input file generation, W2 batch run, and W2 data collection automation tools. With the W2 input generation tools, the project team now has the capabilities to edit most input files and create simulation trials as defined by combinations of various input file scenarios. The run automation tool specifies the executable to be used, specifies the location of the working directory for the simulations, and allows for parallel processing of a multiple simulation set. The W2 data collection tool collects the data of interest from the various W2 input and output text files into a set of comma-delimited csv files, which are easily imported into MATLAB® (R2014b, The MathWorks Inc., Natick, Massachusetts, United States).

4.3 NARX Models for Discharge Temperature and DO

A nonlinear autoregressive network with exogenous inputs (NARX) neural network model can simulate time series predictions using training data obtained from W2 model runs. ANN was selected for its ability to approximate time-dependent functions that are dependent upon

Table 1: CE-QUAL-W2 Simulation Design of Experiments Input Scenarios.

Cordell Hull		**Old Hickory**	
Variable	**Scenarios**	**Variable**	**Scenarios**
Meteorological data	2005, 2006, and 2007 data	Meteorological data	2005, 2006, and 2007 data
Mainstem (BR1) inflow temperature	2005 data, 2005 data +5%, and 2005 data -5%	Mainstem (BR1) inflow temperature	2005 data, 2005 data +5%, and 2005 data -5%
Obey River (TR3) inflow temperature	2005 data, 2005 data +5%, and 2005 data -5%	Caney Fork River (TR2) inflow temperature	2005 data, 2005 data +5%, and 2005 data -5%
Mainstem (BR1) inflow dissolved oxygen concentrations	2005 data, 2005 data +5%, and 2005 data -5%	Mainstem (BR1) inflow dissolved oxygen concentrations	2005 data, 2005 data +5%, and 2005 data -5%
Obey River (TR3) inflow dissolved oxygen concentrations	2005 data, 2005 data +5%, and 2005 data -5%	Caney Fork River (TR2) inflow dissolved oxygen concentrations	2005 data, 2005 data +5%, and 2005 data -5%
Turbine flow	2005 turbine data*, 2005 turbine + 20% 2005 spill data**, and 80% 2005 turbine data***	Turbine flow	2005 turbine data*, 2005 turbine + 20% 2005 spill data**, and 80% 2005 turbine data***
Spill flow	2005 spill data*, 80% 2005 spill data**, and 2005 spill + 20% 2005 turbine data***	Spill flow	2005 spill data*, 80% 2005 spill data**, and 2005 spill + 20% 2005 turbine data***

Note: Turbine and spill flow values are not exhaustively combined, but rather combined in three pair sets as marked by matching flags of *, **, and *** for each reservoir.

a large number of inputs, and for the training, visualization, and prediction tools available in the MATLAB® Neural Network Toolbox. This model relates past values of the same series in the following way:

$$y(t) = f\big(y(t-1), y(t-2), \ldots, y(t-n_y), u(t-1), u(t-2), \ldots, u(t-n_u)\big) \tag{1}$$

where $y(t)$ is/are the variable(s) of interest and $u(t)$ is/are the exogenous variable(s). f is a nonlinear function, in our case an artificial neural network. In the equation as written, the model is a function of feedback delays defined by the set $[n_{y,1} : n_{y,2}]$ and input delays defined by the set $[n_{u,1} : n_{u,2}]$. A NARX model can be used to simulate the tailwater dissolved oxygen and temperature time series at Old Hickory reservoir over a desired period of time.

4.3.1 Training

Training data for the NARX model consist of W2 exogenous inputs and outputs. The exogenous inputs included are those which the outputs have been determined to be sensitive toward. Using the 2005 Cordell Hull and Old Hickory W2 models, correlation tests were performed in order to narrow the set of exogenous inputs to the main driving factors and to estimate the appropriate set of input delays. Figure 4 displays examples of cross correlations between several exogenous inputs and Old Hickory discharge temperature at various lag times. Inputs shown in (a), (b), and (c) are considered correlated with discharge temperature and are included in the NARX model exogenous variables, while input (d) is not. An input delay set of 1 and 12 hours was determined during correlation testing, as these delays generally incorporates the maximum correlation between exogenous inputs and the discharge temperature and dissolved oxygen outputs. The last network architecture features, the number of hidden layers and neurons, are set to the MATLAB® Neural Network Toolbox default values of 1 and 10, respectively. A larger network may be able to provide more accurate predictions for complex problems, but larger networks require more resources to train and risk overfitting the data.

Network training is performed in two phases: open loop and closed loop. First, the network is trained in open loop. The open loop architecture uses the already-available time series of output values (in this case the discharge water quality predictions from W2) at the appropriate feedback delays as inputs into the NARX model. This is not a realistic architecture for prediction, as the full time series of output values are not known in advance, but this training is performed first because it is computationally inexpensive and gives a rough estimate of network weights and biases. Then the network is converted to closed loop form and further trained, which requires considerably more computational time than open loop training. Closed loop architecture uses previous NARX output estimates to construct the feedback output values to be used as inputs for predictions at the next time step. This is the process used during prediction, and training as a closed loop problem helps minimize error propagation. Figure 5 provides visualizations of the network architecture as both configurations. Note that the major difference between the two architectures is the source of the lagged y(t) values. During both phases, the training data is randomly divided to training (70%), validation (15%), and test (15%) sets. These percentages are the toolbox default values for data division. Network biases and weights evolve during training based on the data in the training set. Error on the validation set is computed during training, and

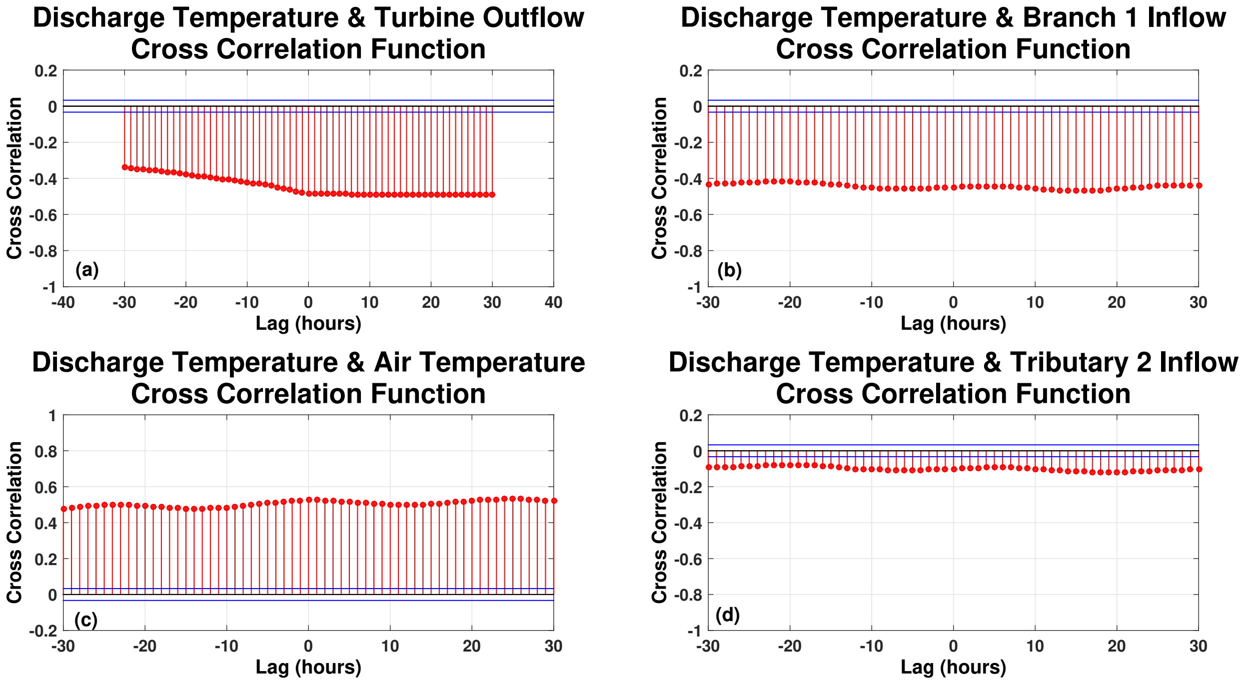

Figure 4: Old Hickory Discharge Temperature Lagged Cross Correlation Test Examples for (a) Turbine Outflow, (b) Branch 1 Inflow, (c) Air Temperature, and (d) Tributary 2 Inflow with 95% Confidence Bounds.

when this converges training process terminates. The test set is not used directly during training, but can be compared to the validation set during training and should have a similar prediction performance.

The networks for each reservoir were trained and validated using hourly data from May-September from the collection of 729 W2 simulations and the "base case" 2005 simulation. 70% of the runs were dedicated for training and 30% were saved for validation. Training was performed on a 12 core server with Windows Server 2008 R2 Enterprise operating system equipped with two 3.1 GHz AMD® Opteron™ CPUs, employing MATLAB® Parallel Toolbox for parallel computations. The models are trained using an optimization algorithm that incorporates a random process, so each network was trained a total of 5 times. After 5 resulting networks have been built and bias correction performed, an interior point constrained nonlinear optimization algorithm is employed to compute weights for the networks (which sum to 1) that minimize the validation set error. Any networks with a weight less than 25% of the maximum weight is removed and the weights are recomputed. This reduces computational expense when the NARX models are deployed during reservoir operations optimization by removing inferior networks from the set, while still maintaining a "family" of networks that may provide better global predictions than a single trained network.

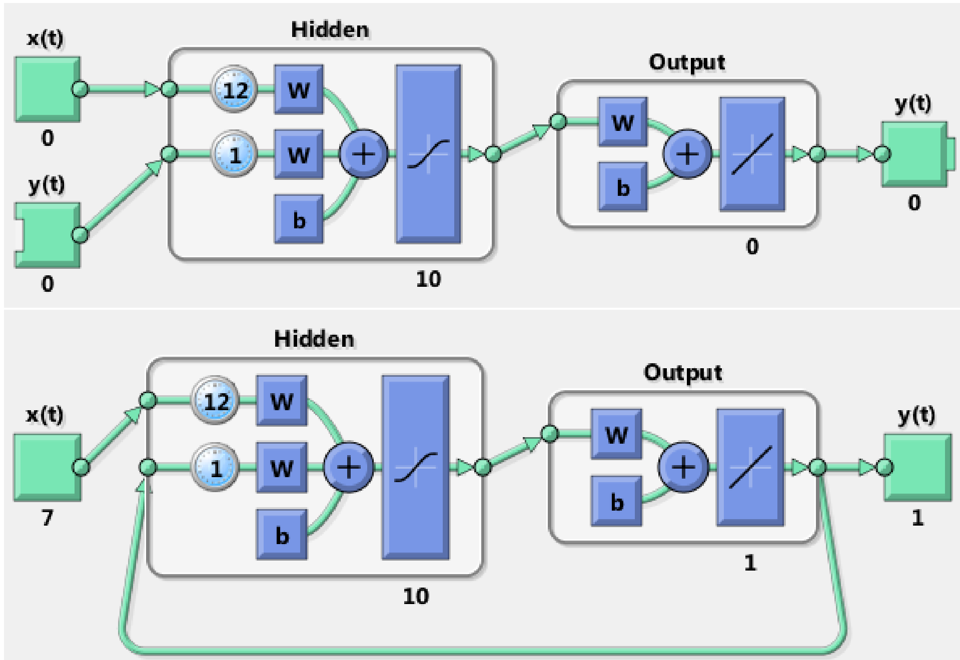

Figure 5: Open Loop (Top) and Closed Loop (Bottom) Network Configurations for Old Hickory Discharge Temperature Model.

4.3.2 Validation

As previously mentioned, 30% of the available W2 simulations were left out of the overall data set used during training in order to use them for validation testing. Validation is an important step to confirm there is no overfitting and allows one to quantify the predictive error of the model on new input scenarios that are independent of those used for training. The predictive error on this model set can be compared to the predictive error on the training data set. For the temperature and dissolved oxygen models, the full 5 summer months of predictions were made using the NARX models and then compared to the W2 simulation output. This was performed for both the training (including all data from the NARX training, validation, and test subsets) and validation simulation sets. The absolute mean error (AME) metrics are provided in Table 2. AME is the error metric most often used to confirm the predictive ability of W2 models. The training and validation sets have comparable error measurements, suggesting the neural network models are performing well. These errors are also considerably less than the thresholds typically thought of as representing a properly calibrated W2 model, which are less than 1 °C error for temperature and less than 1.5 mg/L for dissolved oxygen (*Cole and Wells*, 2007). Figure 6 provides examples of the NARX model predictions for two validation runs as compared to W2 computed outputs for temperature and dissolved oxygen, respectively. The predictions closely track the seasonal trends, but the models are unable to reproduce major peaks. A larger neural network architecture may be able to better simulate these complex scenarios, but further testing is needed to confirm this.

Table 2: Absolute Mean Error (AME) for NARX Models for Training and Validation Sets.

	Cordell Hull		**Old Hickory**	
	Temperature	Dissolved Oxygen	Temperature	Dissolved Oxygen
Training Set	0.208 °C	0.126 mg/L	0.246 °C	0.120 mg/L
Validation Set	0.208 °C	0.129 mg/L	0.247 °C	0.120 mg/L

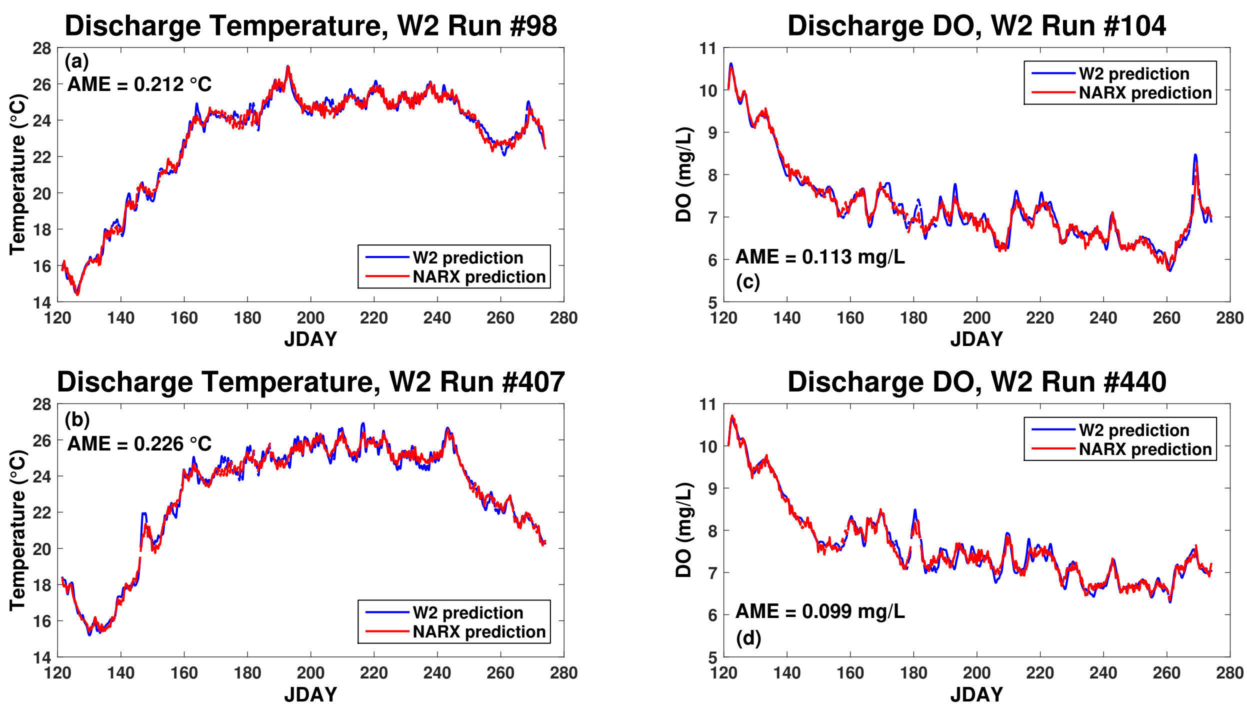

Figure 6: Examples of Validation Simulation Results for (a-b) Old Hickory Discharge Temperature and (c-d) Old Hickory Discharge DO.

5 Optimization Routine

5.1 Optimization Formulation

The optimization problem is formulated to determine turbine operations that generate the maximum power value, subject to multiple constraints. This objective can be written as:

$$\max \sum_{i=1}^{n} C(i) \cdot x_i \cdot r \tag{2}$$

where n is the number of hours in the planning period, $C(i)$ is the power value at time i as defined by a cost curve, x_i is the number of active turbines at time i and is also the decision variable, and r is the turbine power rating in megawatts (MW). The cost curve allows the operator to define times of higher power value, which is important due to changes in electricity demand and the use of hydropower traditionally as peaking power to supplement thermal power production. The cost curve used in this experiment is shown in Figure 7. For the two reservoirs in this problem, turbine power ratings were fixed at 33.3 MW for Cordell Hull and 25 MW for Old Hickory. The problem is nonlinear with integer decision variables, x_i, representing the number of active turbines at each hourly time period i. Optimization is performed for a defined planning period. The planning period is divided into daily sub-problems, which are solved consecutively. This type of problem can be solved globally using a GA with creation and mutation functions modified to produce populations consisting of solely integer values for the decision variables.

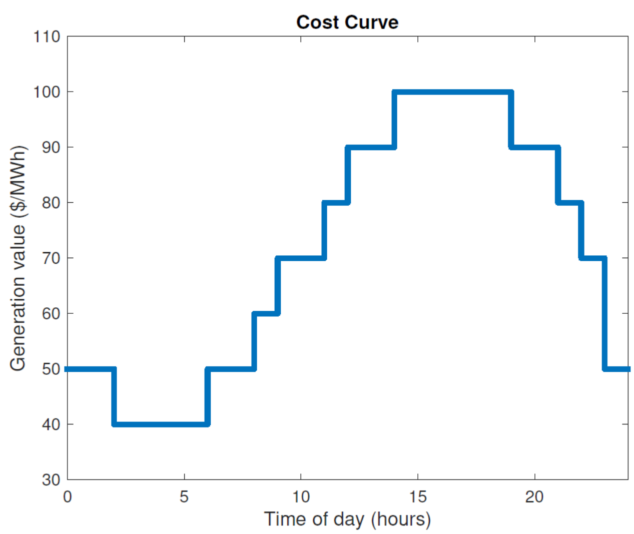

Figure 7: Cost Curve.

The multipurpose reservoir system used to develop and demonstrate this optimization process must be operated to fulfill many requirements. These can be formulated as a set of hard constraints. Prior to determining the optimal operations for maximization of power production for each daily sub-problem, the feasibility of each constraint is examined one by one by solving a series of genetic algorithm optimization problems. In cases where a particular constraint cannot meet the constraint limit, the constraint limit is modified before proceeding to power generation optimization. Additionally, soft constraints can be added which the algorithm seeks to match, but if not able to be fulfilled completely the algorithm will still proceed as normal. Soft constraints are integrated into the objective function by use of a penalty parameter. Several hard constraints and a single soft constraint applied in this problem are described below and summarized in Table 3. A flow chart of the detailed optimization approach is given in Figure 8.

Table 3: Constraint Definitions and Settings.

Constraint Definitions			**Constraint Settings**	
Name	**Definition**	**Hard/Soft**	**Cordell Hull**	**Old Hickory**
Pool elevations	$p_l \leq E(x_i) \leq p_u$	Hard	$p_l = 153.314$ m $p_u = 153.772$ m	$p_l = 134.722$ m $p_u = 135.636$ m
Zero-generation hours	$\sum_{i}^{i+z} x_i \geq 0 \;\; \forall \; i = 1:(n-z)$	Hard	----	$z = 6$ hrs
Rate of change of active turbines	$\lvert x_{i+1} - x_i \rvert \leq c \;\; \forall \; i = 1:(n-1)$	Hard	$c = 2$ units/hr	$c = 1$ units/hr
Turbine bounds	$\{x_i \in \mathbb{Z} \mid 0 \leq x_i \leq a\} \;\; \forall \; i = 1:n$	Hard	$a = 3$ units	$a = 4$ units
Oscillations	$(x_i \leq x_{i+1} \leq x_{i+2} \leq x_{i+3}) \vee (x_i \geq x_{i+1} \geq x_{i+2} \geq x_{i+3}) \;\; \forall \; i = 1:(n-3)$	Hard	no reservoir-specific setting	no reservoir-specific setting
Discharge dissolved oxygen	$O(x_n) \geq o_l$	Hard	----	$o_l = 8$ mg/L
Midnight target elevations	$E(x_n) = p_T$	Soft	User-defined or assumed from W2 initial run elevations	User-defined or assumed from W2 initial run elevations

The two case study reservoirs are operated on seasonal guide curves, where the power pool has defined upper and lower bounds. These are accounted for in the pool elevations constraint. The bathtub elevation model is a function of all inflows and outflows. An average spill rate for each sub-problem is computed during elevation computations based on the user-provided midnight target elevation values. First, water elevation is computed based on the hourly turbine settings with zero water spilled through the gates. If the ending elevation is less than the target elevation, spill remains zero. If the ending elevation is greater than the target elevation, an average daily spill rate is assigned which results in the ending water surface elevation being equal to the target value. This enables spill incorporation without requiring additional decision variables, which is important since spill or gate flow is often engaged to improve downstream water quality. In an effort to maintain minimum flows along the river for water quality purposes, a constraint on the maximum number of consecutive hours without power generation is applied to Old Hickory reservoir. Each reservoir has a

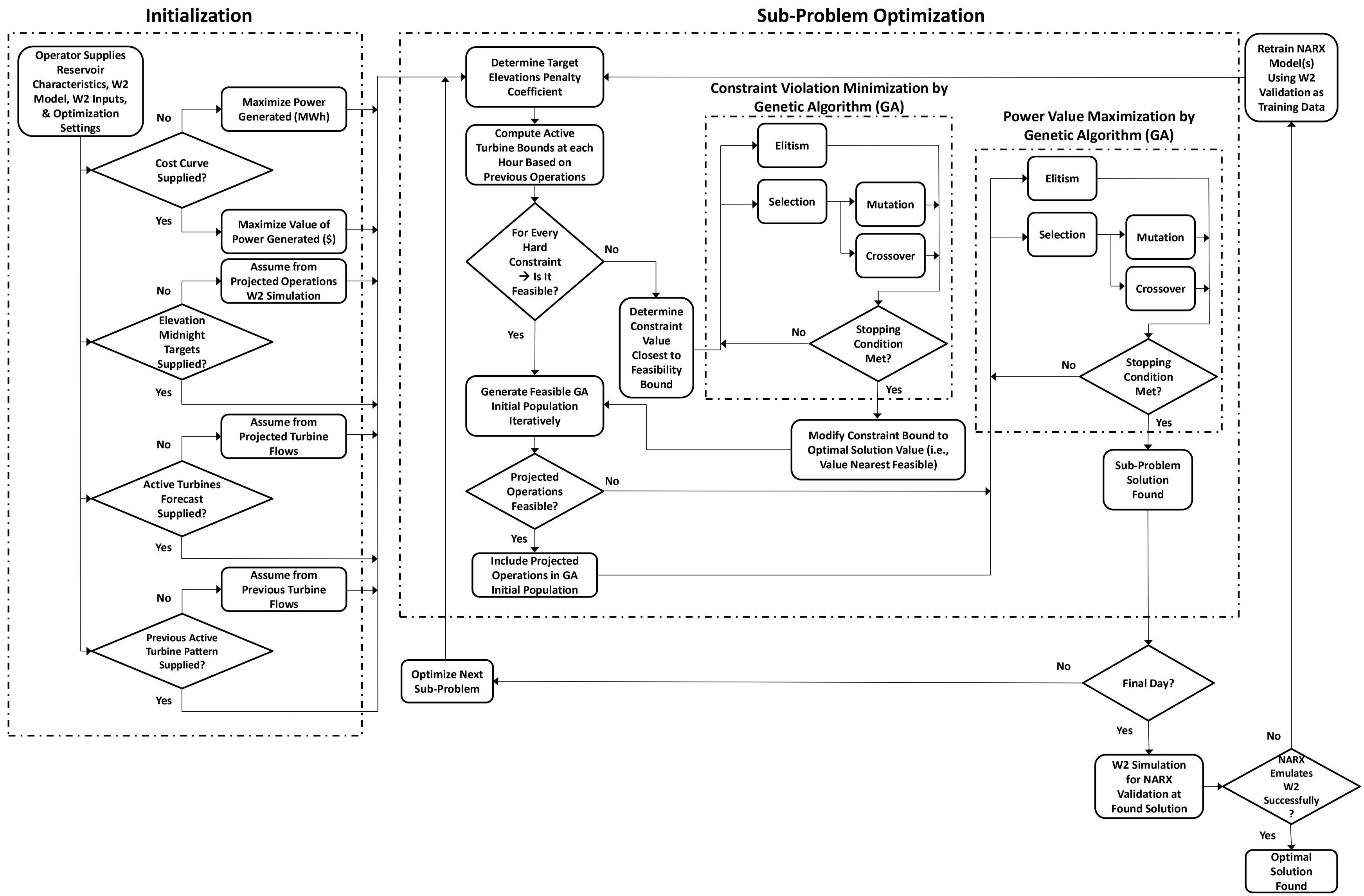

Figure 8: Schematic of Optimization Methodology.

defined limit on the hourly rate of change of active turbines, which minimize fluctuations in the surface elevation and adverse impacts on pool stability. Each reservoir has a defined number of available hydropower turbines, which is accounted for in the turbine bounds constraint. A constraint to minimize oscillations over time is formulated with logic that states that, except in cases of ramping turbines up or down, the number of active turbines must be fixed for at least three hours consecutively before changing. This minimizes oscillations in the solutions found, which is desired to minimize equipment wear. A constraint on water quality exists, with the water quality predictions provided by NARX neural network models. This constraint is currently formulated to check the feasibility of the discharge dissolved oxygen at the end of each daily sub-problem time period for Old Hickory reservoir. The USACE Nashville District monitors the dissolved oxygen levels in the Old Hickory dam discharge and implements this constraint at that location. This is particularly important at the Old Hickory discharge location, as this is directly upstream of the metropolitan Nashville area and historically the water quality at this location has proven to be a strong indicator of water quality system-wide.

A single soft constraint penalizes deviations below target midnight elevations. This keeps the solution from draining to the bottom of the power pool at the end of each daily optimized sub-problem. At the end of each daily sub-problem potential solution the pool elevation is found, the penalty computed, and a deduction to the objective function value is made for pool elevations below target levels. Prior to the start of the genetic algorithm solver, a penalty coefficient is computed. The penalty coefficient value is greater the closer the target pool elevation is to the bottom of the power pool. At the end of each day, the deviation of pool elevation from the target elevation is multiplied by the penalty coefficient, and this value is subtracted from the objective function power value.

5.2 Optimization Results

The optimization methodology described is demonstrated on the Cordell Hull and Old Hickory linked reservoir system. The 10 day operating period from July 15 to July 25, 2005 (Julian days 196-206) was chosen. This time represents a period in the summer when water quality issues appear within zones of the reservoirs and dam discharges. In order to demonstrate the effectiveness of this tool for improving water quality and the impact that high-fidelity water quality model incorporation can have on optimal power generation solutions, the algorithm was used to determine the optimal hourly turbine operations for both reservoirs, as well as a daily average spill flowrate for each, with a constraint on water quality incorporated by use of NARX neural network models.

The optimal turbine operations and spill operations for this period, as well as the resulting water surface elevations, discharge temperatures, and discharge dissolved oxygen concentrations, are shown in Figures 9 and 10. Water quality estimations provided by the NARX models should be confirmed by W2 simulations. The optimal solution is compared to projected operations (or in this case, the actual operations from 2005). In this trial, the optimal solution produces less overall power (15,050 MWh as compared to 18,783 MWh from the projected operations) and the average power value per MWh produced for the optimal and projected scenarios are comparable at \$76.05/MWh and \$78.55/MWh, respectively. However, the optimized solution maintains dissolved oxygen concentrations at or above the

8 mg/L constraint threshold. The loss in power production results from the addition of spill, which enables the improvement in water quality. Additionally, the pool elevation is maintained at the same level for both projected and optimal operations at the end of the operating period. The Old Hickory discharge DO predictions are maintained at or above the constraint threshold of 8 mg/L. It is important to note that these results represent an initial optimization trial; the water quality predictions should be validated using a W2 simulation, and if necessary the NARX water quality predictors retrained using the W2 validation simulation data.

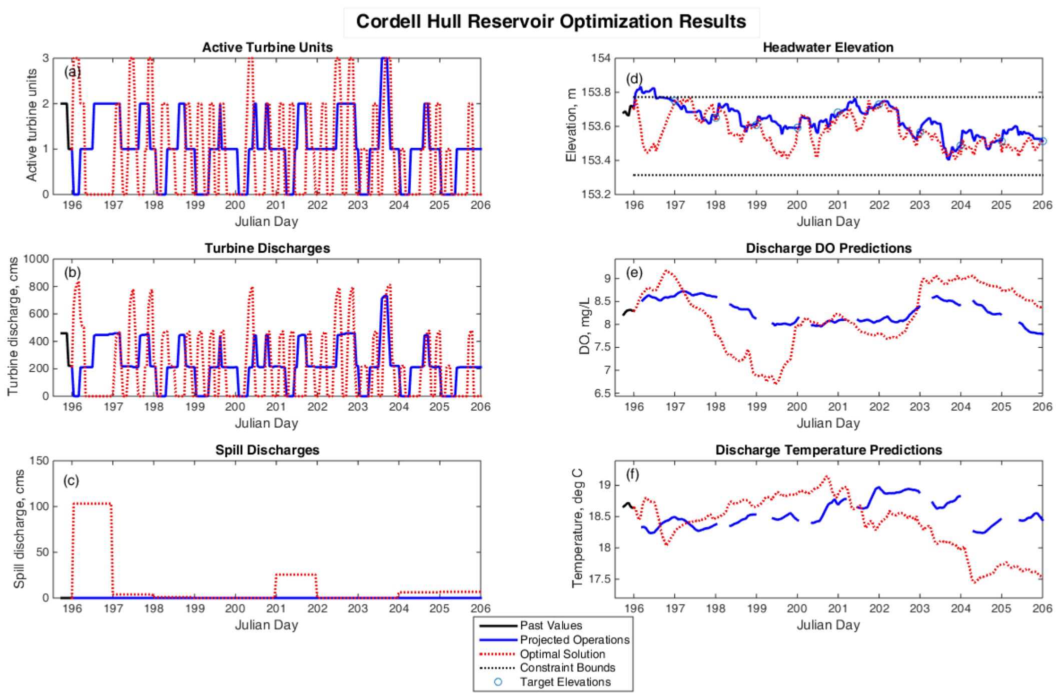

Figure 9: Cordell Hull Reservoir Optimization Results.

Optimizing the reservoir system over the 10 day operating period, formulated as a series of daily sub-problems, required a total of 201,804 evaluations of objective and constraint function pairs. Based on a required computational time of 26 minutes to complete W2 model runs for both reservoirs for a simulation period of a year, the time required to make a W2 simulation from January 1, 2005 through July 25, 2005, or roughly half of a calendar year, would be approximately 13 minutes. To provide 201,804 water quality predictions via W2 would require around 5 years of computational time. The entire optimization methodology demonstrated here, in total, required approximately 6.6 hours on the same desktop computer.

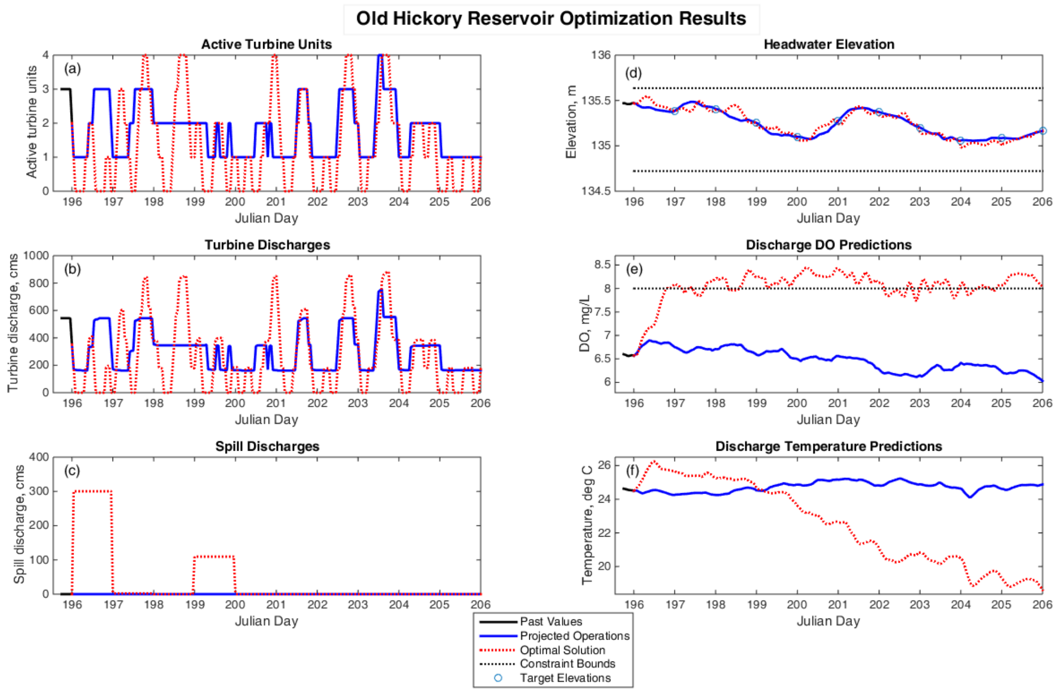

Figure 10: Old Hickory Reservoir Optimization Results.

6 Conclusions and Future Work

This work has demonstrated a process for emulating the water quality predictions of a high-fidelity water quality model, in this case CE-QUAL-W2, using an artificial neural network model. The nonlinear autoregressive with exogenous inputs (NARX) network model form, available in the Matlab® Neural Network Toolbox, was employed. Emulators for discharge temperature and discharge dissolved oxygen were constructed, and validation tests confirm these models provide useful predictive power.

This efficient NARX surrogate model was incorporated into a hydropower generation optimization routine, a process requiring a large number of model evaluations. This is not possible using the original, computationally expensive CE-QUAL-W2 hydrodynamic and water quality simulation model. Optimization was demonstrated on a two-reservoir system in series, a subset of the projects on the Cumberland River system. Use of the NARX models provides considerable computational efficiency over the original high-fidelity models. Even though validation tests performed during training suggest useful predictive power, when implementing these NARX models for prediction the solution should be confirmed with the original simulation model, as the optimization routine could "travel" to areas in the decision space with poor training coverage.

For the case study presented here, dissolved oxygen is the constituent of concern; however, this methodology could be applied to other water quality concerns and incorporate different high-fidelity simulation models. Additionally, the water quality constraint in this demonstration was applied at the tailwater discharge of one of the linked reservoirs, but this process could easily incorporate in-pool water quality constraints. This would be useful for optimizing systems where the temperature or water quality at a fixed location of an intake pipe is important.

This optimization process was first developed for a single case study reservoir and was then expanded to the linked system, as discussed here. There is value in expanding the process to even larger river systems; however, the computational expense will continue to increase substantially and minimizes the usefulness of this method for real-time river planning. Model reduction methods, such as fixed-point iterative techniques, will be explored to assist in optimization of larger multireservoir systems. This will enable optimization of power production along river systems, subject to numerous constraints including high-fidelity simulation-informed constraints on water quality.

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