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Key Points:
- Hydropower optimization informed by high-fidelity hydrodynamic and water quality models
- Artificial neural networks emulate high-fidelity hydrodynamic and water quality model predictions
- Computational savings of surrogate modeling enables release scheduling on an operations timescale

Supporting Information:
- Supporting Information S1

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Hydropower Optimization Using Artificial Neural Network Surrogate Models of a High-Fidelity Hydrodynamics and Water Quality Model

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Abstract Hydropower operations optimization subject to environmental constraints is limited by challenges associated with dimensionality and spatial and temporal resolution. The need for high-fidelity hydrodynamic and water quality models within optimization schemes is driven by improved computational capabilities, increased requirements to meet specific points of compliance with greater resolution, and the need to optimize operations of not just single reservoirs but systems of reservoirs. This study describes an important advancement for computing hourly power generation schemes for a hydropower reservoir using high-fidelity models, surrogate modeling techniques, and optimization methods. The predictive power of the high-fidelity hydrodynamic and water quality model CE-QUAL-W2 is successfully emulated by an artificial neural network, then integrated into a genetic algorithm optimization approach to maximize hydropower generation subject to constraints on dam operations and water quality. This methodology is applied to a multipurpose reservoir near Nashville, Tennessee, USA. The model successfully reproduced high-fidelity reservoir information while enabling 6.8% and 6.6% increases in hydropower production value relative to actual operations for dissolved oxygen (DO) limits of 5 and 6 mg/L, respectively, while witnessing an expected decrease in power generation at more restrictive DO constraints. Exploration of simultaneous temperature and DO constraints revealed capability to address multiple water quality constraints at specified locations. The reduced computational requirements of the new modeling approach demonstrated an ability to provide decision support for reservoir operations scheduling while maintaining high-fidelity hydrodynamic and water quality information as part of the optimization decision support routines.

Optimization

Maximize value of hydropower produced over a planning period

Subject to:

- Reservoir surface elevation constraints
- Minimum downstream river flows
- Acceptable downstream WQ (temperature, DO)
- Turbine availability/operations

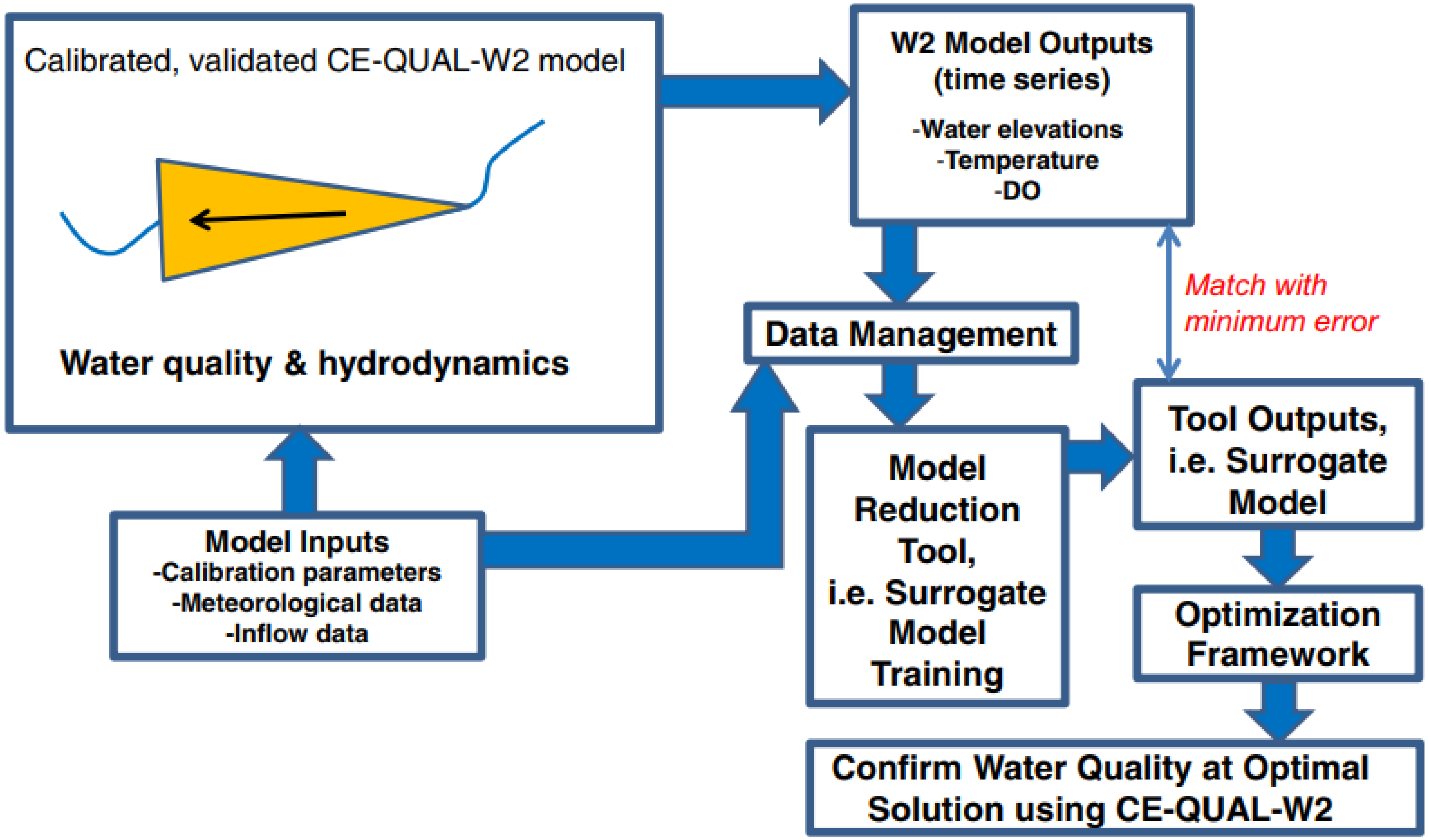

Figure 1. Methodology overall approach.

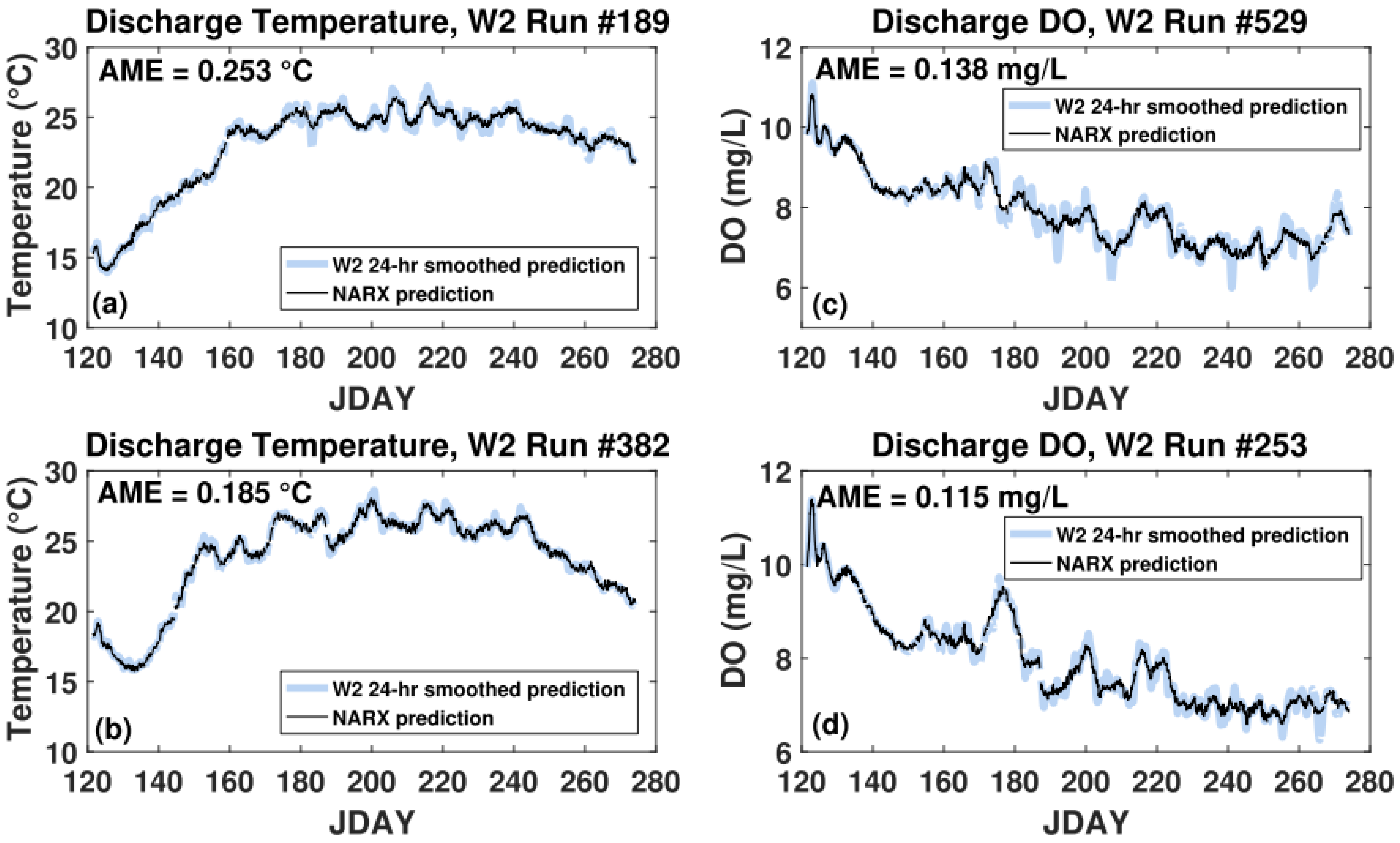

Figure 4. Examples of validation simulation results for (a and b) Old Hickory discharge temperature and (c and d) Old Hickory discharge DO. Discontinuities in the curves represent times with neither spill nor turbine discharge present. CE-QUAL-W2 outcomes shown here and used in initial NARX training are smoothed on a 24 h moving average.

Model	Single Model Runtime	Optimized Schedule Computation Time	Feasible
CE-QUAL-W2	6 min	7 months	NO
NARX	2 sec	40 hours	YES

Table 3
Summary of Experiment 1 and Experiment 2 Results

	DO constraint	Temperature constraint	Iterations required	Time (min)[a]	Mean hourly DO violation (mg/L)	Mean hourly temperature violation (°C)	Energy produced (MW h)	Generation value ($)[b]
Exp. 1:								
	$\geq$ 5 mg/L		3	190.8	0		10,050	$868,250
	$\geq$ 6 mg/L		4	254.3	0		10,100	$866,500
	$\geq$ 7 mg/L		16	997.3	0.035		8,825	$730,000
	$\geq$ 8 mg/L		14	1436.1	0.344		2,600	$171,500
Exp. 2:								
	$\geq$ 7 mg/L	$\geq$ 25°C	13	1915.9	0.005	0.071	4,300	$316,000

[a]Time to complete optimization of series of subproblems, not including CE-QUAL-W2 simulation or NARX retraining time.
[b]Generation value determined using assumed cost curve shown in Figure S2.

~7% increase in $$$ relative to actual operations