"Water for the Elephant" : Water Management in Elephant Butte Dam to Allow for Photovoltaic Hydropower Sustainability

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Abstract

This project is part of a research initiative for establishing a robust simulation-optimization framework for Hybrid Floating Photovoltaic-Hydropower (HFPVHP) systems and ensure that growing energy needs as well as international water agreements can be met. Focusing on Elephant Butte Dam in the Rio Grande basin, it integrates water runoff forecasting, reservoir operations, and power modeling using machine learning, hydrological models, and optimization tools. By simulating the dynamics of water inflows, outflows, and energy output during summer months, this research aims to build predictive models that inform sustainable reservoir and energy management strategies.

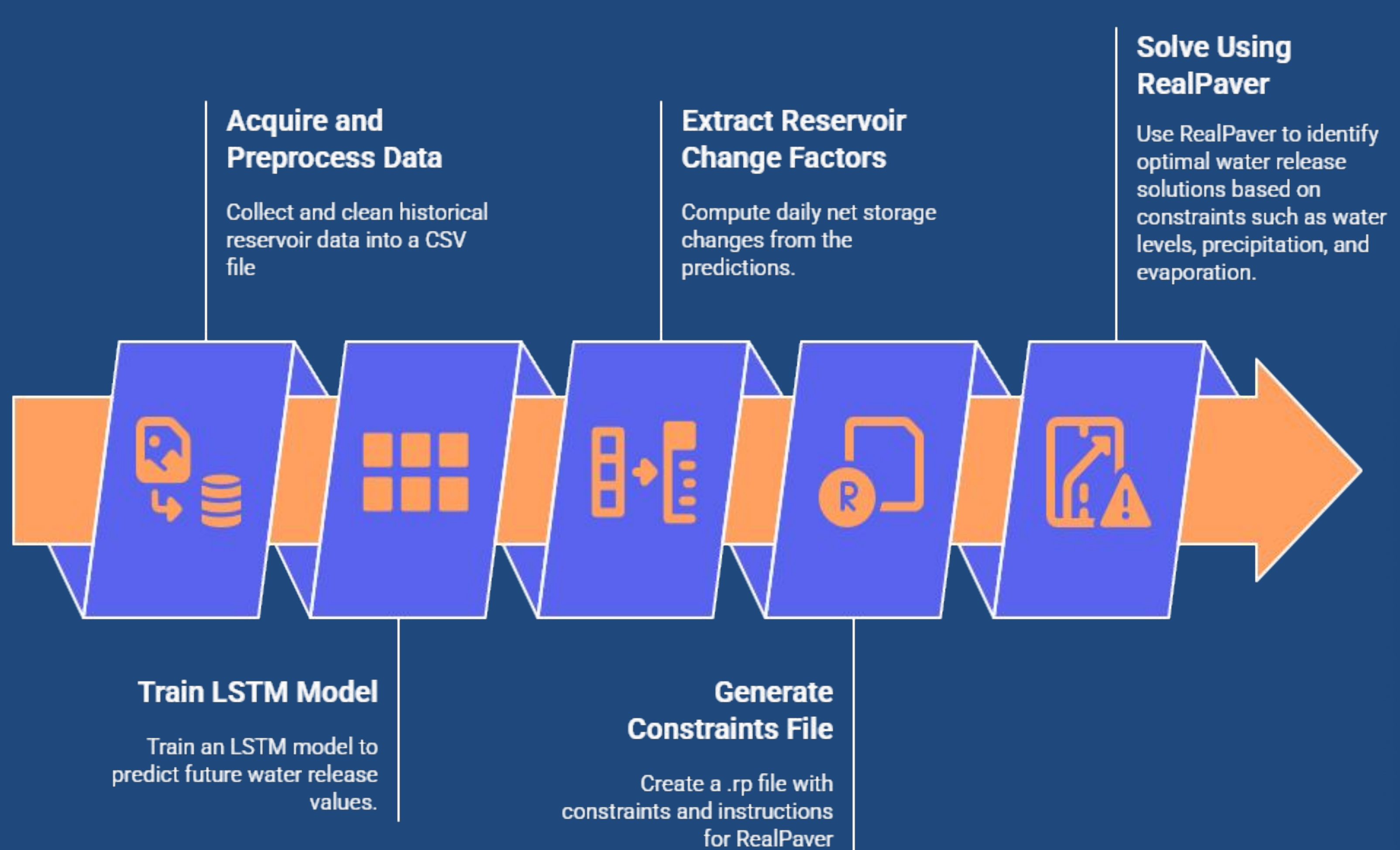
Introduction

Reservoirs are essential water and energy systems that support irrigation, urban supply, hydropower, and emerging technologies like Hybrid Floating Photovoltaic-Hydropower Plants (HFPVHP). Managing them effectively requires anticipating how storage levels respond to environmental and operational factors. Predicting reservoir levels is a complex challenge shaped by inflows, outflows, evaporation, and operational rules. As summer temperatures increase and water demands shift, there is a pressing need for predictive models that are both accurate and adaptable.

In this study, we propose a predictive modeling framework that uses historical reservoir data—storage, inflow, outflow, and evaporation—and use these predictions to create and validate water release schedules. The model is designed to learn from past trends and incorporate variables like rainfall, temperature, and evaporation to improve performance across diverse systems.
By focusing on simulation and prediction, this research aims to support more informed water and energy planning under changing conditions.

Methodology

Reservoir Management Process



Reservoir Outflow Forecasting with LSTM + RealPaver Validation

1. Acquire and Preprocess Historical Data Daily reservoir data (storage, inflow, outflow) is collected and cleaned into a single CSV file. This dataset includes decades of real measurements from Elephant Butte Reservoir.
2. Train an LSTM Model to Predict Outflow Using TensorFlow/Keras, an LSTM model is trained to predict 10 days of future outflow_af values. It learns patterns from a 30-day sliding window of historical data ending on the target forecast date (2025-06-01).
3. Extract Reservoir Change Factors From the same dataset, the 'unaccounted_af' column is used to compute daily net storage changes. These constants represent how reservoir levels shift due to factors beyond measured inflow/outflow.
4. Generate RealPaver-Compatible Constraint File A Python class generates a .rp file formatted for RealPaver, containing:- Initial storage (w0)- Daily change constants (c1..c10)- Predicted releases (R1..R10)- Storage constraints (reservoir Min/Max)- Optional total release band (due ± delta)- RealPaver solving instructions.
5. - Use RealPaver to verify that the proposed release schedule meets all physical constraints. RealPaver then returns concise solution intervals for each release variable (R1–R10).

- **Mass Balance Equation:** $Storage_{t+1} = Storage_t + Inflow_t - Outflow_t - Evaporation_t$

Results and Discussion

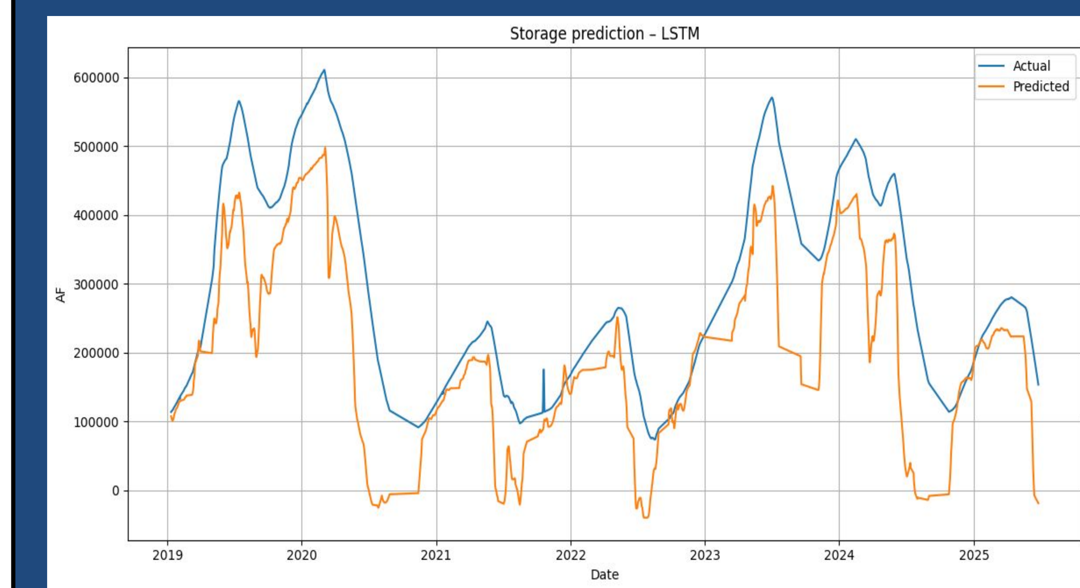


Figure 1 – LSTM Storage Prediction

*Demonstration of **LSTM neural network's** effectiveness in forecasting **Elephant Butte Reservoir's** storage levels, orange line showing predicted values closely tracking the actual blue line, despite some discrepancies during rapid changes. Trained on historical daily data including inflow, outflow, and evaporation, the **LSTM's** ability to manage **temporal dependencies** makes it well-suited for hydrological time-series predictions.*

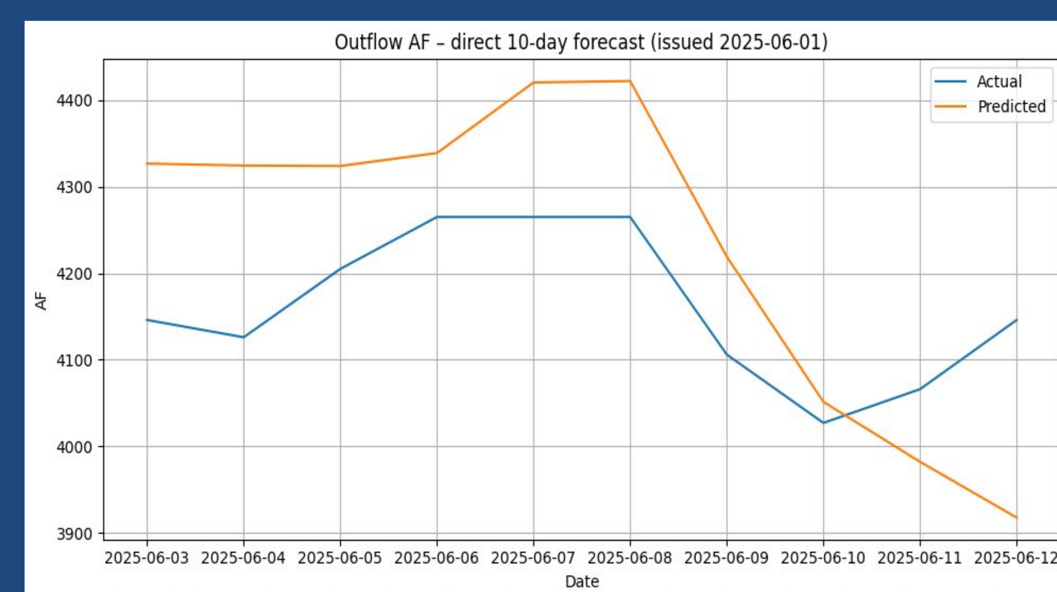


Figure 2 – A direct 10-day forecast; Outflow measured in Acre Feet

*This figure displays a **10-day forecast** of daily outflow from **Elephant Butte Reservoir** for June 1, 2025. An **LSTM machine learning model** and **RealPaver constraint-based simulator** predict outflows (orange curve) that respect operational limits, ensuring realistic and safe forecasts compared to actual observations (blue curve). This **hybrid approach** gives water managers **actionable short-term forecasts**, boosting confidence in dam release decisions. Future enhancements will include **uncertainty quantification**.*

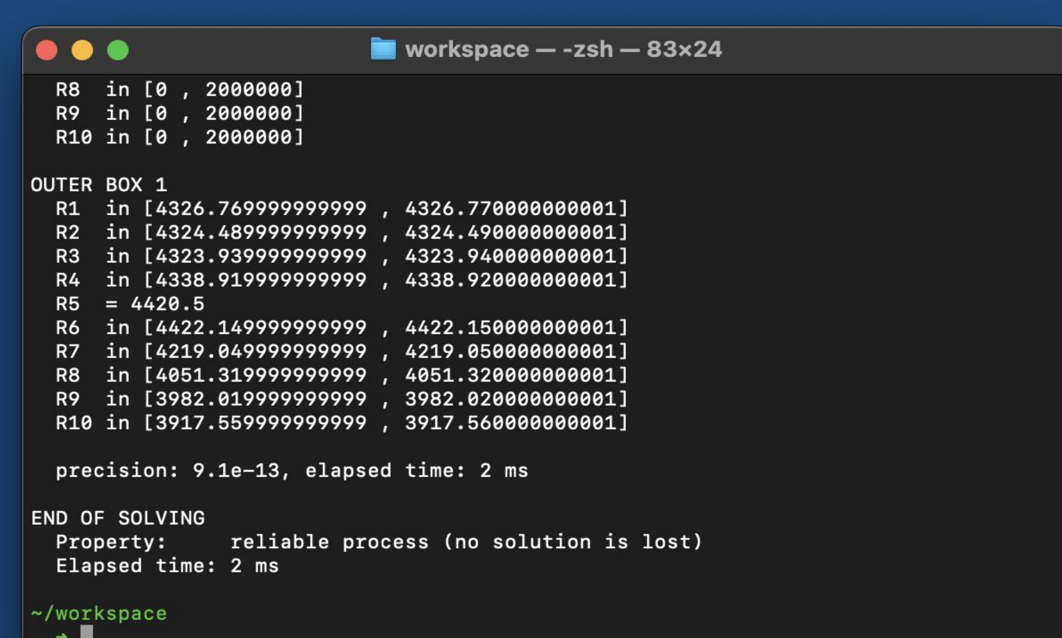


Figure 3- RealPaver Feasibility Output for the 10-Day Release Schedule

*The terminal snapshot documents the final interval solution produced by **RealPaver v0.4** after evaluating the constraint file derived from our LSTM forecast. RealPaver takes the LSTM-predicted 10-day release vector and tries to identify the amounts of releases (Ri) that keeps Elephant Butte within its storage limits. Starting from the wide range 0-2 000 000 AF day^{-1} for each day, the solver contracts every variable to a single, near-exact value (e.g., R1 ≈ 4 327 AF, R5 = 4 420 AF). The global precision of 9 × 10^{-13} and the message "reliable process (no solution is lost)" confirm that this schedule is the unique feasible solution and that all constraints are satisfied in just 2 ms of computation.*

Potential Lesson Plan Elements

Subject	Objective/TEKS	Project Concepts
AP Computer Science Principles	DAT-1.D 2.2 Data Compression 1.D Evaluate solution options. DAT-2.A, DAT-2.B, DAT-2.C 2.3 Extracting Information from Data 5.B Explain how knowledge can be generated from data. 5.D Describe the impact of gathering data.	Data: Water datasets Algorithms: Constraint solvers and LSTM (time-series ML). Global Impact: Energy/water conservation. Real-world simulation, modeling, basic ML, and environmental issues.
Principles of Engineering	C-5- (D): The student describes the factors that affect the progression of technology and the potential intended and unintended consequences of technological advances. The student is expected to predict possible changes caused by the advances of technology.	Utilize the LSTM by having students collect water data for the dam and simulate predictive analysis experiments to calculate possible changes.
Introduction to Unmanned Aerial Vehicle (UAV) Flight	C-2- (F): Students are expected to use UAV technological resources in diverse and changing personal, community, and workplace environments.	Topographical Studies of the Coastal Area and Timelapse Aerial Photography Showing Water Levels. Students can see firsthand water level changes over time.

Conclusion

This study demonstrates that by combining data-driven forecasts with formal constraint satisfaction, we generate reservoir release schedules that are both informed by historical patterns and guaranteed to comply with all operational and physical limits. By training an LSTM model on historical storage and discharge records, and then passing its 10-day outflow predictions through a RealPaver constraint set, we produced release trajectories that respect Elephant Butte's storage limits and daily mass-balance requirements. RealPaver's narrow solution box confirms that the machine-learning output is not only statistically plausible but also physically implementable under existing operating rules.
The resulting workflow provides a transferable template for reservoir managers: a machine-learning layer captures short-term system dynamics, and a symbolic solver guarantees compliance with hydraulic constraints. Future extensions will embed hydro-economic objectives (e.g., maximizing hybrid floating photovoltaic-hydropower revenue) and incorporate additional exogenous variables such as price forecasts or inflow scenarios. Ultimately, this hybrid approach provides a scalable decision-support tool for multi-objective water and energy management.

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