Evaluating solar PV effects on California's hydropower generation with a hybrid LP-NLP optimization model

Mustafa Dogan[1] and Jay Lund[2]

[1]University of California Davis
[2]Univ California Davis

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Abstract

A hybrid Linear Programming (LP) and Nonlinear Programming (NLP) optimization model is developed for California's hydropower operations. Built on top of Pyomo library, a high optimization modeling language in Python, the model can connect to several freely available, state-of-the-art solvers. In this model, fast evaluation of LP and detailed model representation of NLP are fully utilized. The hybrid model solves the same problem with linear approximation (a simplified objective function representation) and with NLP solver, where no simplification is made to objective function. Outputs from LP model are used as initial values (warmstart) for NLP model's decision variables, which reduce number of iterations for convergence and so runtime. The model is capable of representing large network of hydropower plants that are in serial or parallel, or fixed and variable head plants. The model is used to evaluate effects of increased solar photovoltaic (PV) generation in California. California has a goal of generating electricity from renewable resources at least 33% by 2020, and 50% by 2030, and solar PV generation supplies most of renewable generation portfolio during daytime. This expanded use of solar PV changes generation pattern from one daily peak system to two daily peak system. Due to excess generation of solar PV, negative prices can occur during daytime. Therefore, evaluating effects of solar PV on hydropower operations and adapting to new conditions are essential.

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Mustafa S. Dogan* and Jay Lund
*Civil and Env. Engineering, University of California, Davis; *Presenter: msdogan@ucdavis.edu*

1 California's Hydropower System

- California's hydropower averages 19% of its in-state electricity generation
- Hydropower capacity of 14 GW is 18% of total installed capacity
- Most hydropower generation (74%) from high-elevation plants
- CAISO runs the decentralized energy price market and regulate
- Solar photovoltaic (PV) generation is increasing and affecting operations, including hydropower

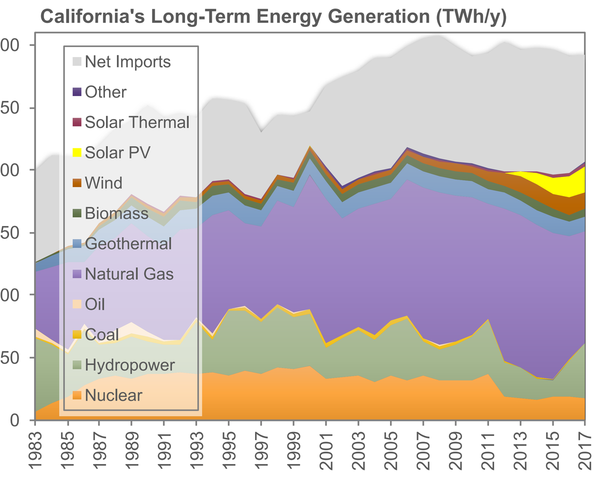


Figure 1. California's long-term electricity generation (TWh/year) from different sources (Data: California Energy Commission Energy Almanac)

2 Solar Photovoltaic (PV) Effects on Energy Prices

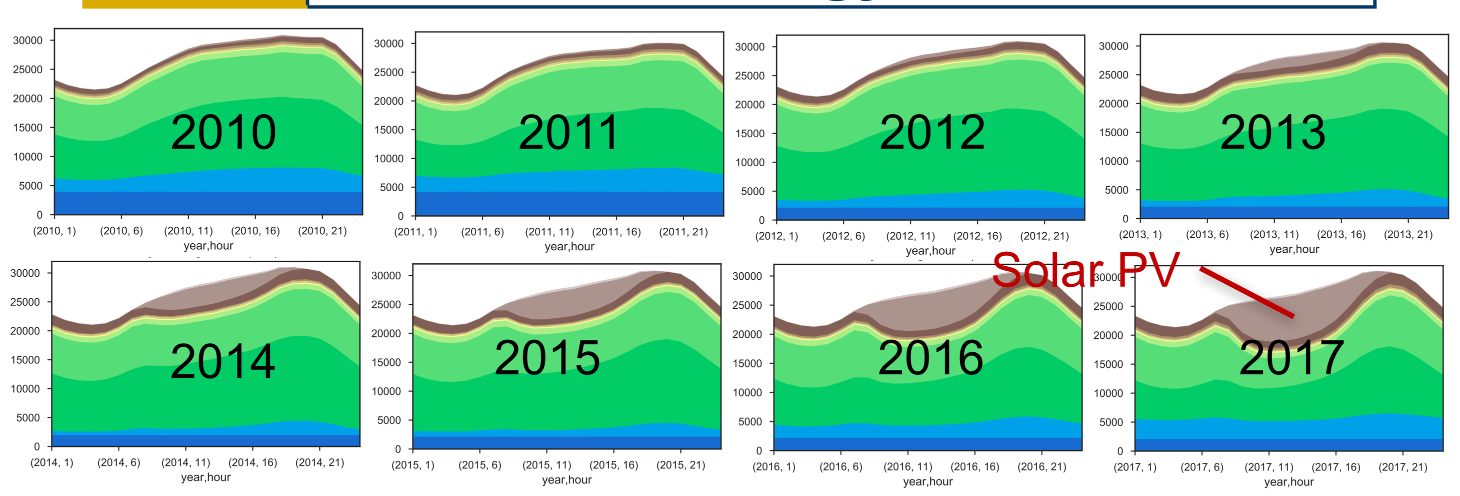


Figure 2. Hourly load (MW) across years (Data: CAISO)

- Net load = total load – variable (solar + wind) load
- Solar PV is about 11% of total in-state electricity generation in 2017
- Solar PV reduces daytime net load and affect energy prices
- Negative price pattern shift from night to daytime

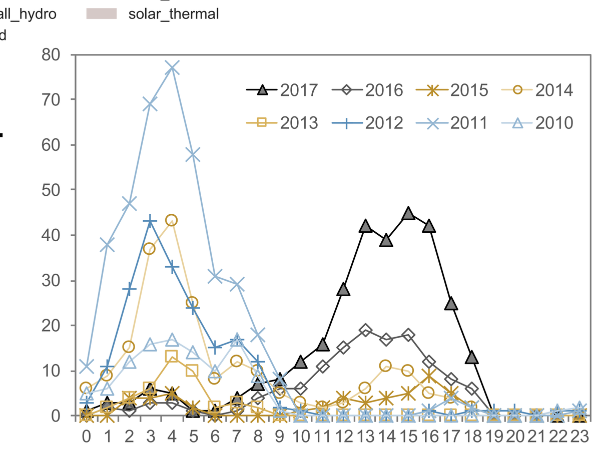


Figure 3. Count of negative hourly energy prices across years and the shifted pattern (Data: CAISO)

3 Increased Energy Price Volatility

- Energy prices are highly correlated with net load
- Shifting from one-peak to two-peak system
- Solar PV decreases net load and increases energy price volatility
- The changed price pattern affect hydropower operations, especially plants with sizable storage capacity

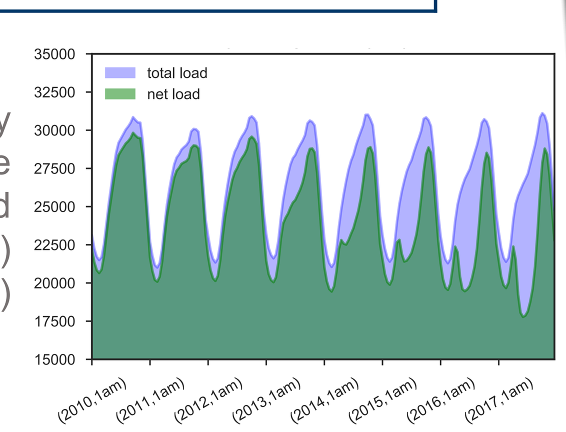


Figure 4. Hourly statewide average total and net load (MW) (Data: CAISO)

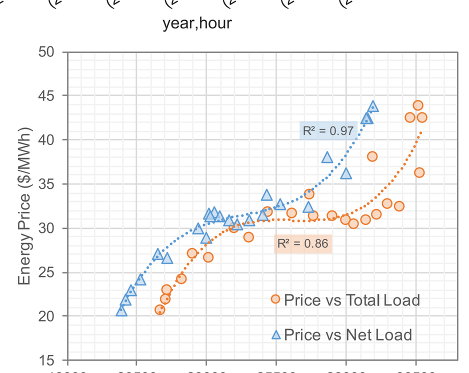


Figure 5. Hourly energy price ($/MWh) vs total and net load (MW) Between 2010 - 2017 (Data: CAISO)

4 Hybrid LP-NLP Hydropower Optimization Model

- Evaluate effects of changed price patterns with a hybrid LP-NLP optimization model
- Built using Pyomo, a high-level Python-based optimization modeling language
- The objective is to maximize total hydropower revenue within water availability and capacity constraints
- The problem is solved first with a linear approximation (LP), then nonlinear (NLP) model is initialized and solved
- LP is fast but less accurate, NLP is slow but more accurate
- Linear approximation reduces NLP iterations and runtime
- Network-flow optimization model with nodes and links

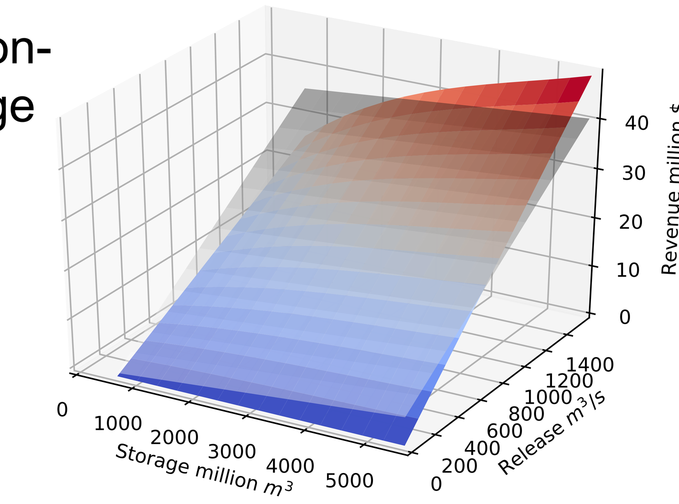


Figure 6. Hydropower revenue curve for a single plant and time-step as a function of storage and release with a linear approximation

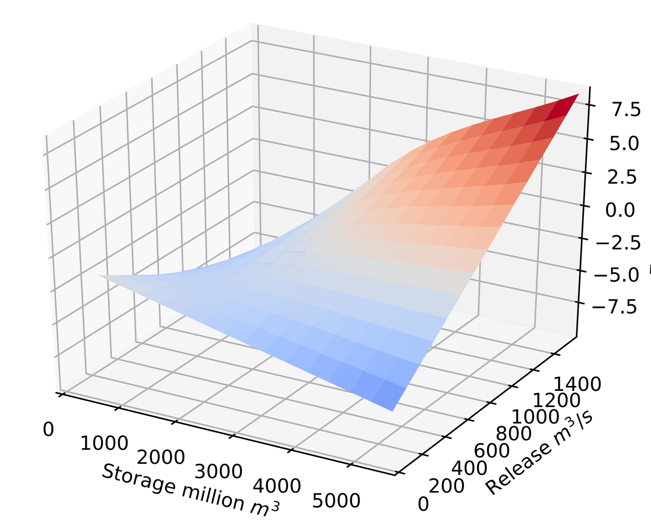


Figure 7. Residuals (error) between the nonlinear curve and linear approximation

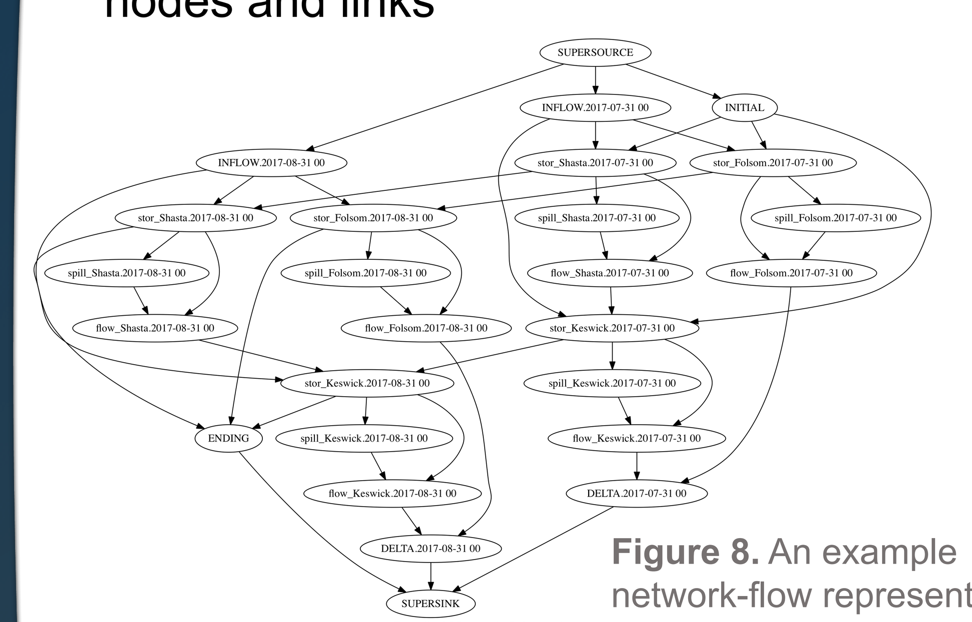


Figure 8. An example network-flow representation of the hybrid model

5 The Mathematical Formulation & Data Flow

LP model formulation:

Objective function

$$max\ Z = \sum_i \sum_j p_{ij} \cdot X_{ij}, \forall (i,j) \in A$$

Decision variables:
X: flow

Constraints

$$X_{ij} \le u_{ij}, \forall (i,j) \in A \quad \textit{(Upper bound)}$$

$$X_{ij} \ge l_{ij}, \forall (i,j) \in A \quad \textit{(Lower bound)}$$

$$\sum_i X_{ji} - \sum_i X_{ij} = 0, \forall j \in N \quad \textit{(Mass balance)}$$

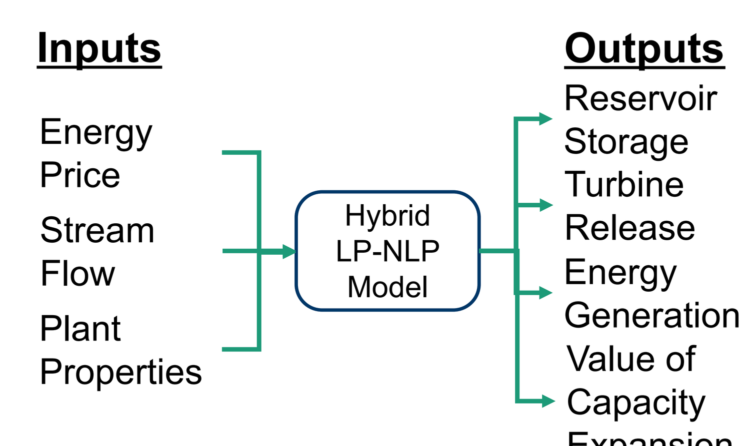


Figure 9. Data flow of the model with typical inputs and outputs

NLP model formulation:

Objective function

$$max\ Z = \sum_{m \in A_{flow}} \sum_{n \in A_{stor}} e_n \cdot \rho \cdot g \cdot X_m \cdot (\alpha Y_n{}^3 + \beta Y_n{}^2 + \gamma Y_n + c) \cdot \Delta t \cdot p_m + \sum_{m \in A_{flow}} p_m X_m$$

Decision variables:
X: flow
Y: storage

Constraints

$$X_m \le Flow\ cap_m, \forall m \in A_{flow}$$

$$Y_n \le Storage\ cap_n, \forall n \in A_{stor} \quad \textit{(Upper bound)}$$

$$X_m \ge l_m, \forall m \in A_{flow}$$

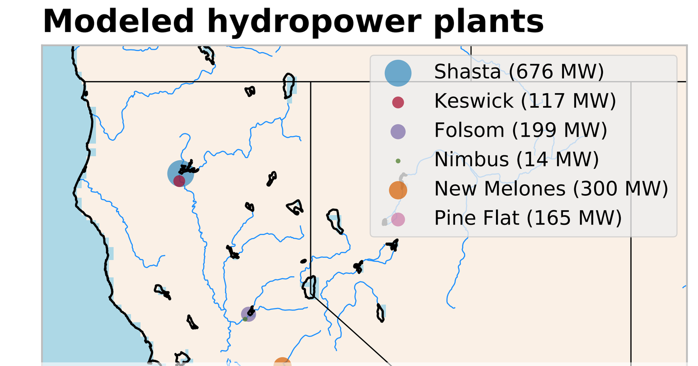
$$Y_n \ge Deadpool_n, \forall n \in A_{stor} \quad \textit{(Lower bound)}$$

$$\left[\sum_i X_{ji} + \sum_i Y_{ji}\right] - \left[\sum_i X_{ij} + \sum_i Y_{ij}\right] = 0, \forall j \in N_{flow}, \forall j \in N_{stor} \quad \textit{(Mass balance)}$$

e: plant efficiency
ρ: water density
g: gravitational constant
α, β, γ, c: polynomial parameters for head
p: energy price (NLP) or unit benefit (LP)
X: flow
Y: storage

6 Model Application to California

Modeled hydropower plants



- 6 hydropower plants
- Plants in serial and parallel
- Short-term operations
- Hourly time-step
- Price-taking approach

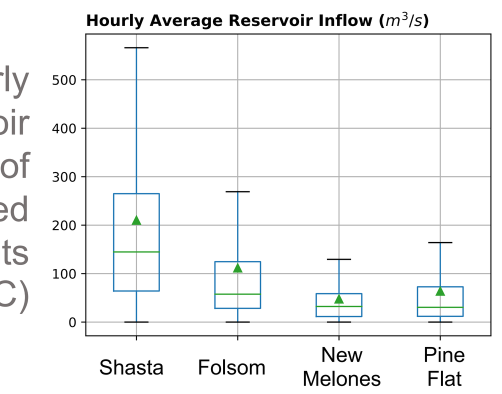


Figure 10. Hourly average reservoir inflow (m^3/s) of modeled hydropower plants (Data: CDEC)

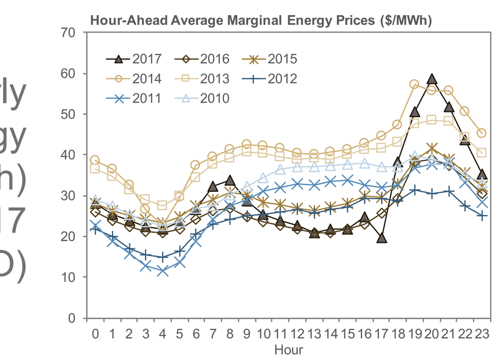


Figure 11. Hourly average energy price ($/MWh) between 2010-17 (Data: CAISO)

7 Preliminary Results: Water Storage, Generation & Revenue

- Hourly runs for each year
- 2011-2017 average hourly streamflow for each plant
- Store water to gain head and release during peak hours
- Most turbine releases occur during peak hours 19-22
- As solar PV increases, storage peak converges to one point, less daytime release and generation
- Some generation occurs during morning peak hours 7-8
- Plants with smaller storage have less adaptation flexibility

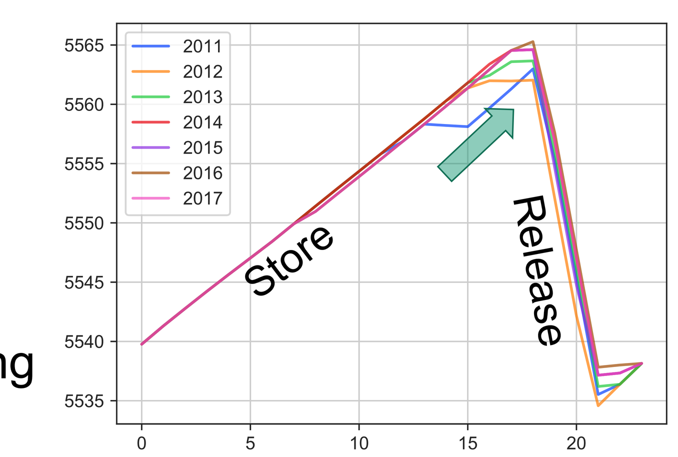


Figure 12. Modeled hourly average storage (million m^3)

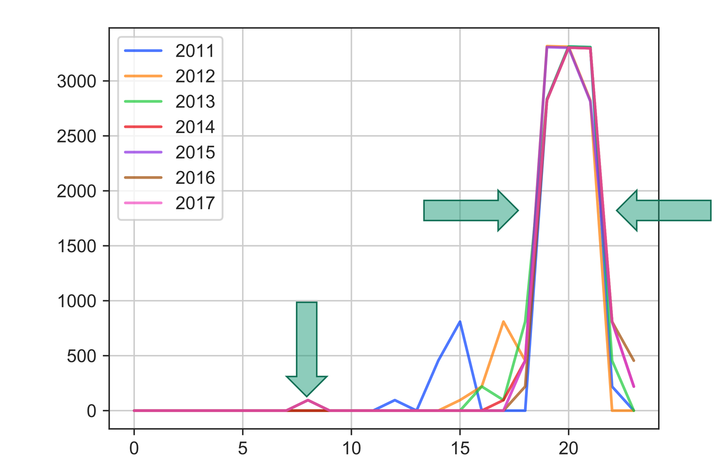


Figure 13. Modeled hourly average generation (MWh)

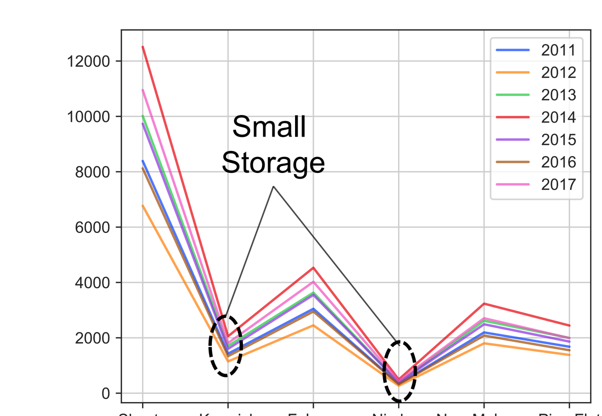


Figure 14. Hourly average hydropower revenue ($)

8 Conclusions

- Solar PV reduces operational flexibility for hydropower decisions
- Hours when solar PV peaks become less valuable in terms of hydropower revenue resulting in less generation
- As storage capacity increases, capability to adapt to price volatilities increases

References:

- CAISO: http://oasis.caiso.com/mrioasis
- CDEC: http://cdec.water.ca.gov
- CEC Energy Almanac: https://www.energy.ca.gov/almanac
- Pyomo: http://www.pyomo.org
- GitHub page (currently private repo): https://msdogan.github.io/pyomo_hydropower