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Evaluating Solar PV Effects on California's Hydropower Generation with a Hybrid LP-NLP Optimization Model

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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

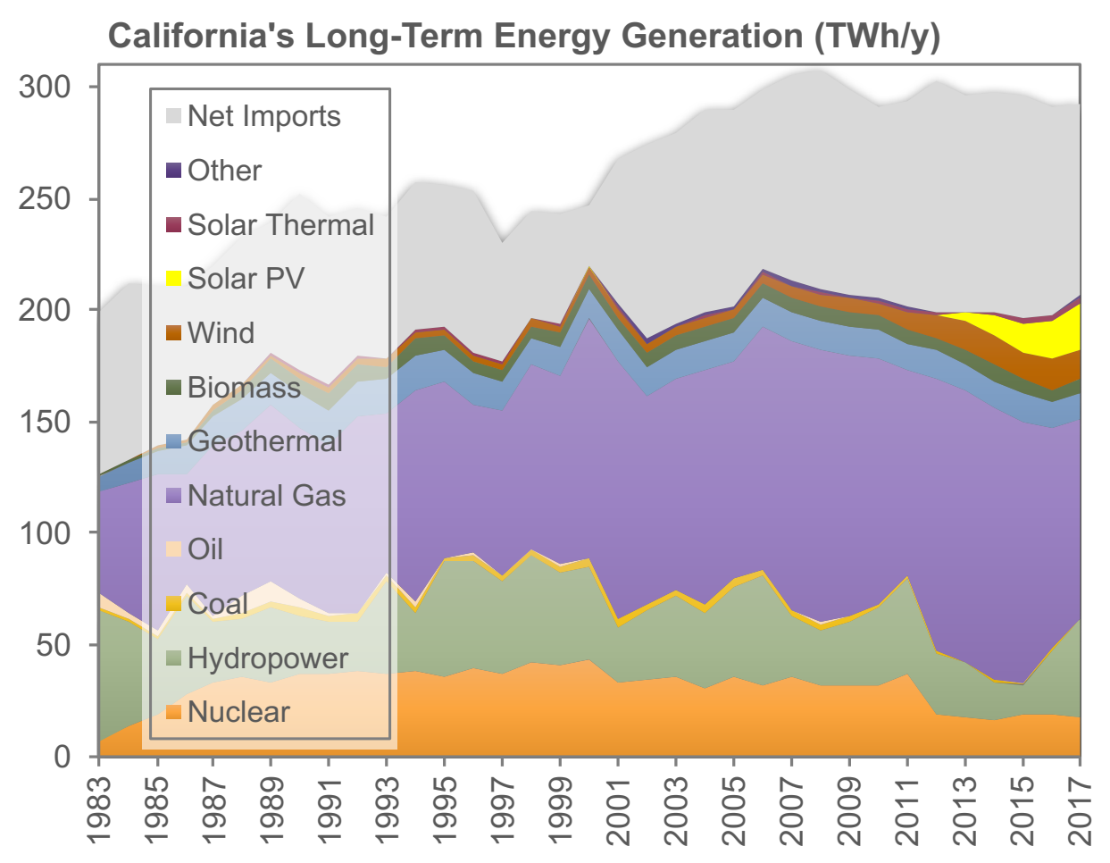


Figure 1. California's long-term electricity generation (TWh/year) from different sources (Data: California Energy Commission Energy Almanac)

2 Solar Photovoltaic (PV) Effects on Energy Prices

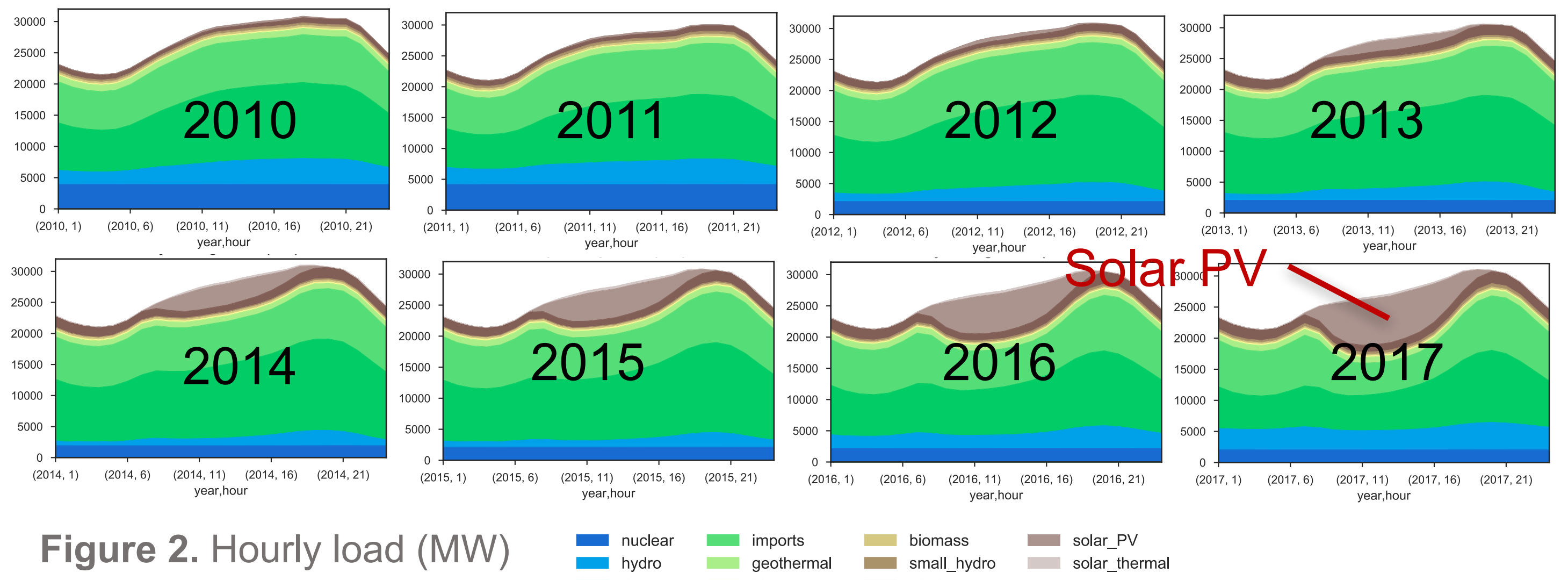


Figure 2. Hourly load (MW) across years (Data: CAISO)

- 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

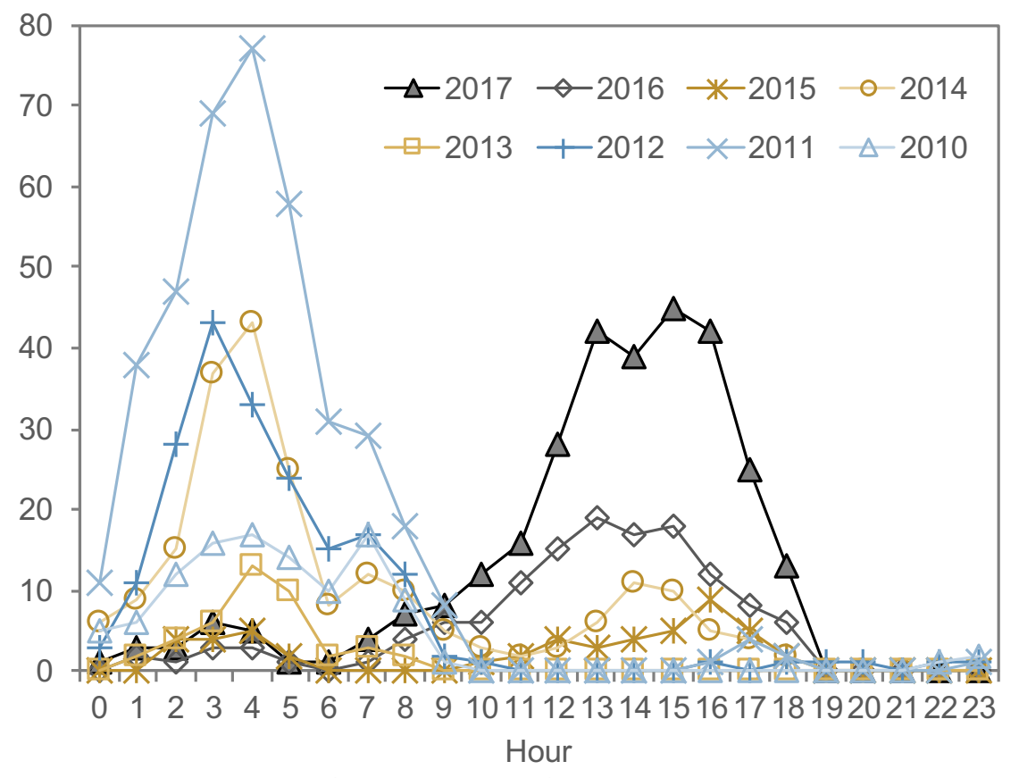


Figure 3. Count of negative hourly energy prices across years and the shifted pattern (Data: CAISO)

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

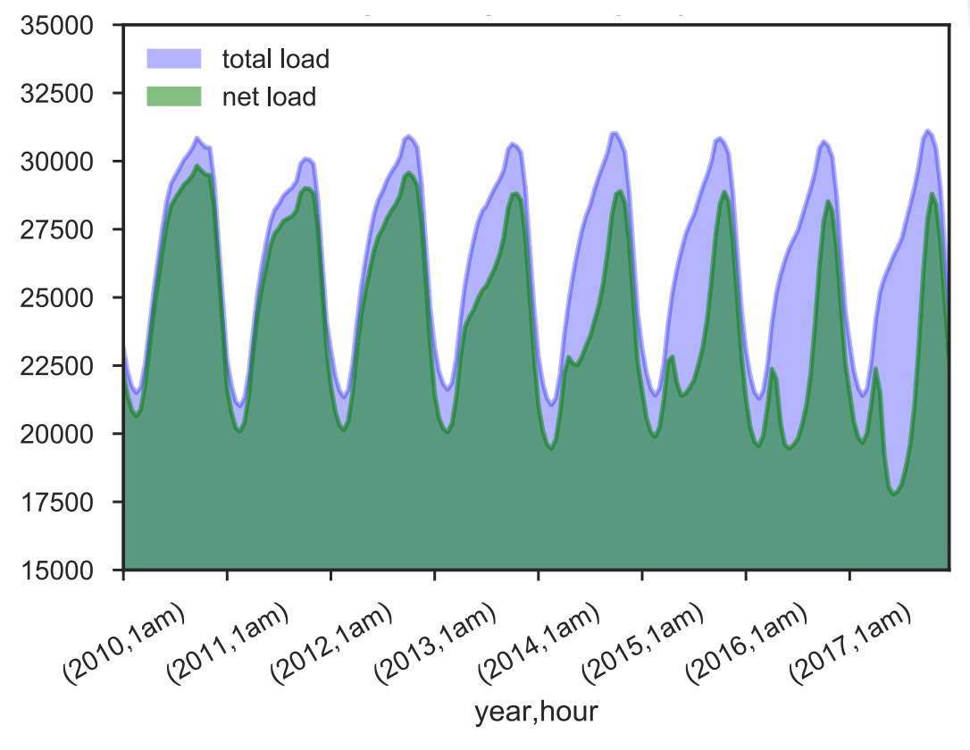


Figure 4. Hourly statewide average total and net load (MW) (Data: CAISO)

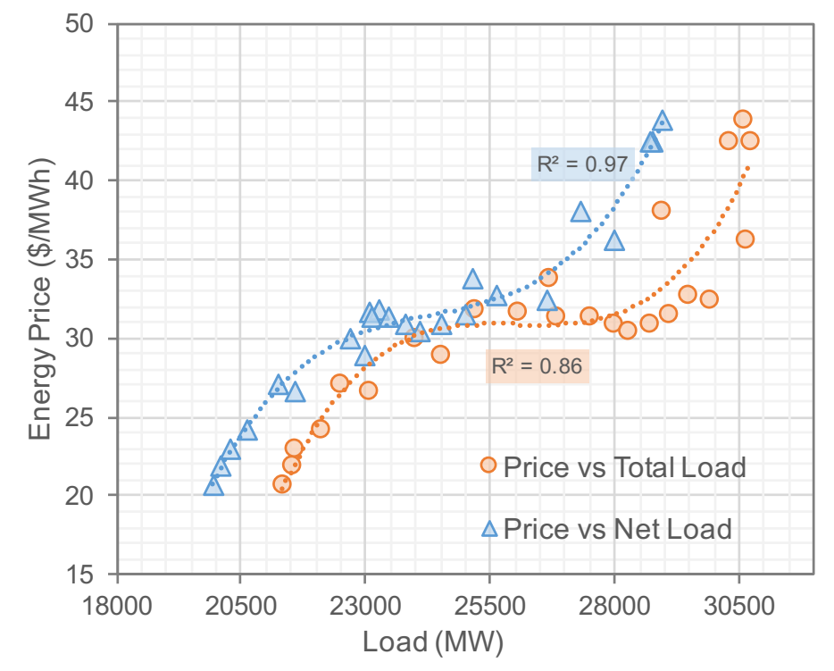


Figure 5. Hourly energy price ($/MWh) vs total and net load (MW) Between 2010 - 2017 (Data: CAISO)

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

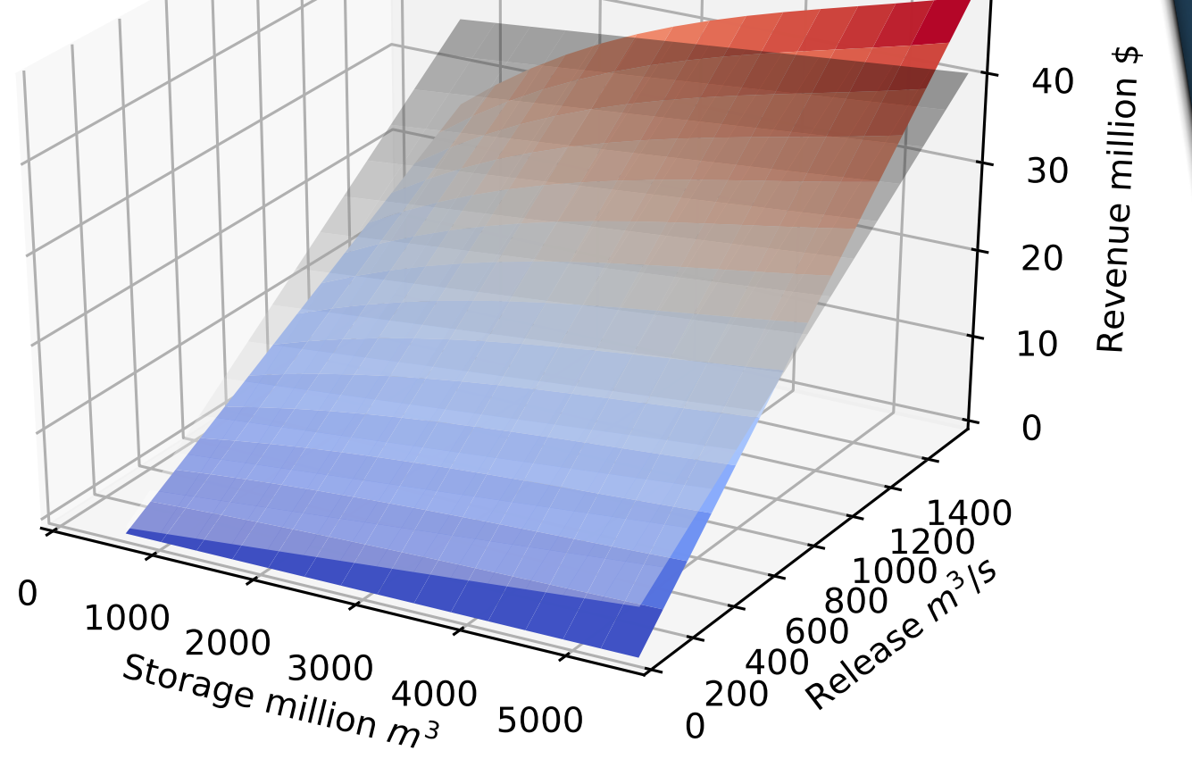


Figure 6. Hydropower revenue curve for a single plant and time-step as a function of storage and release with a linear approximation

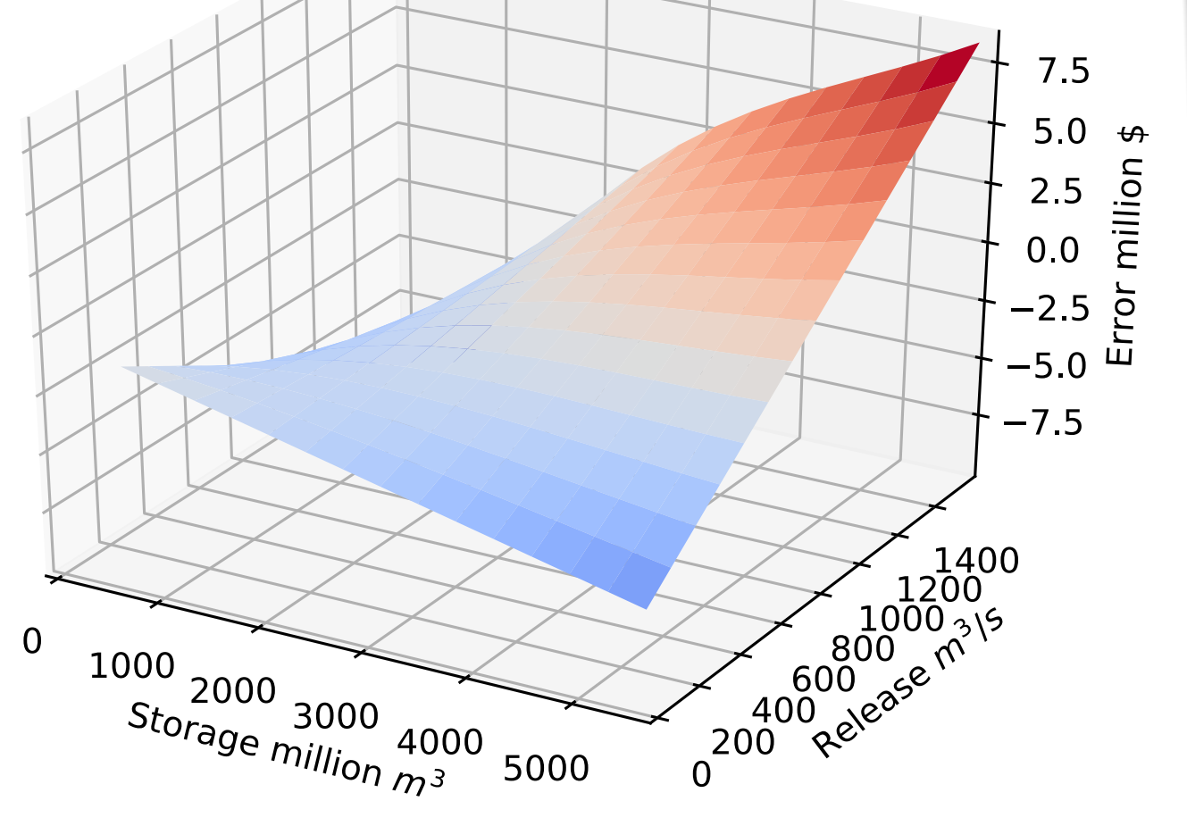


Figure 7. Residuals (error) between the nonlinear curve and linear approximation

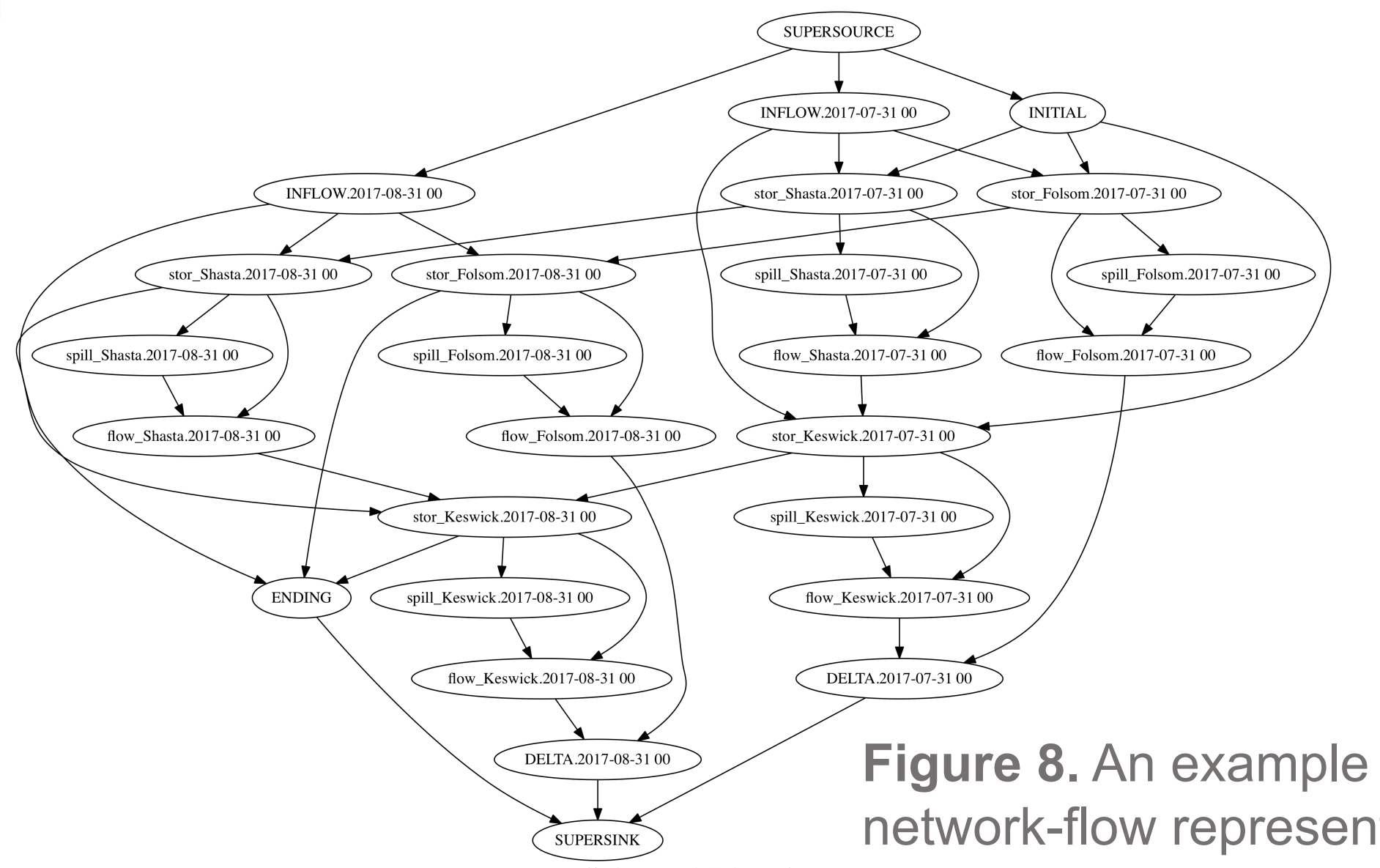


Figure 8. An example network-flow representation of the hybrid model

5 The Mathematical Formulation & Data Flow

__LP model formulation:__

Objective function

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

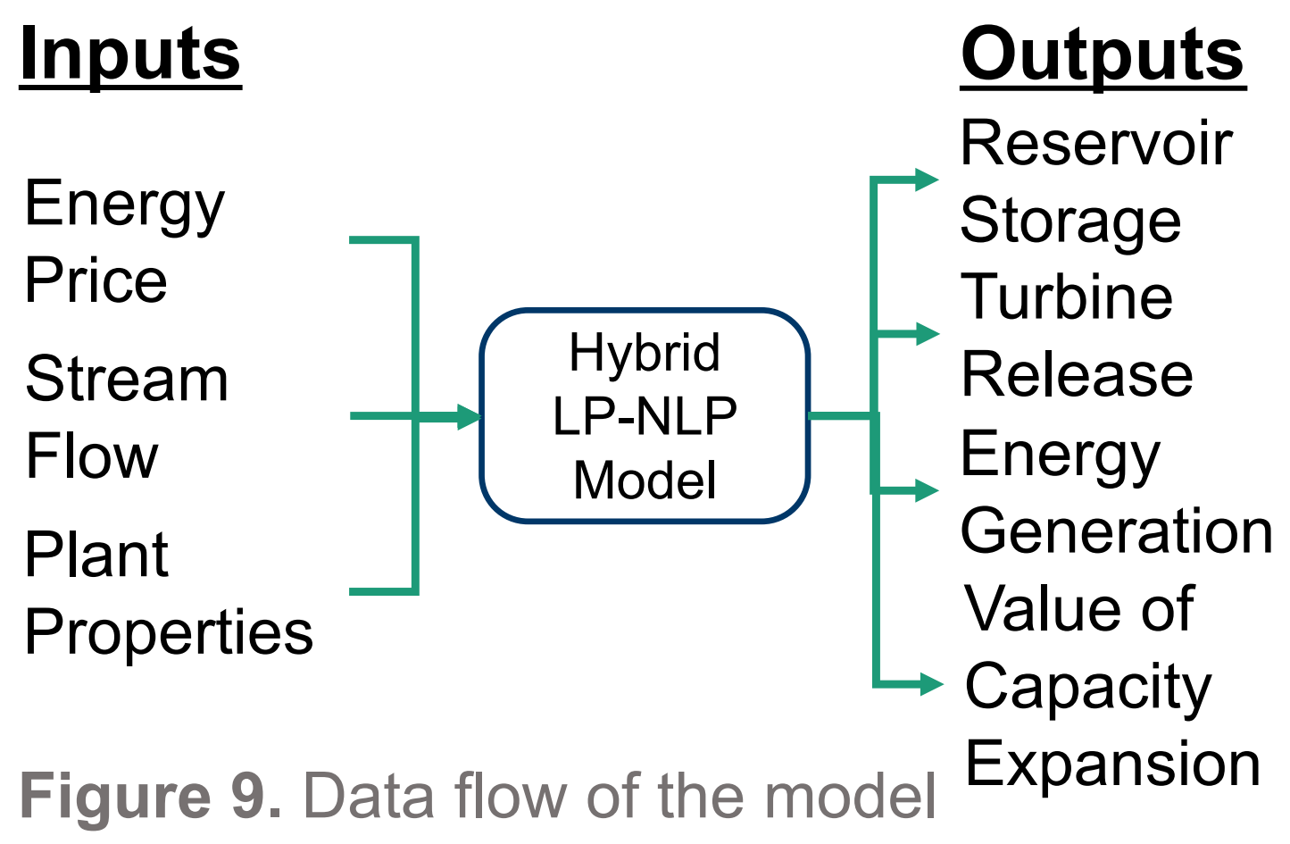
__Decision variables:__
X: flow

Constraints

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

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

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



__Inputs__
Energy Price
Stream Flow
Plant Properties

Hybrid LP-NLP Model

__Outputs__
Reservoir Storage
Turbine Release
Energy Generation
Value of Capacity Expansion

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

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

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

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

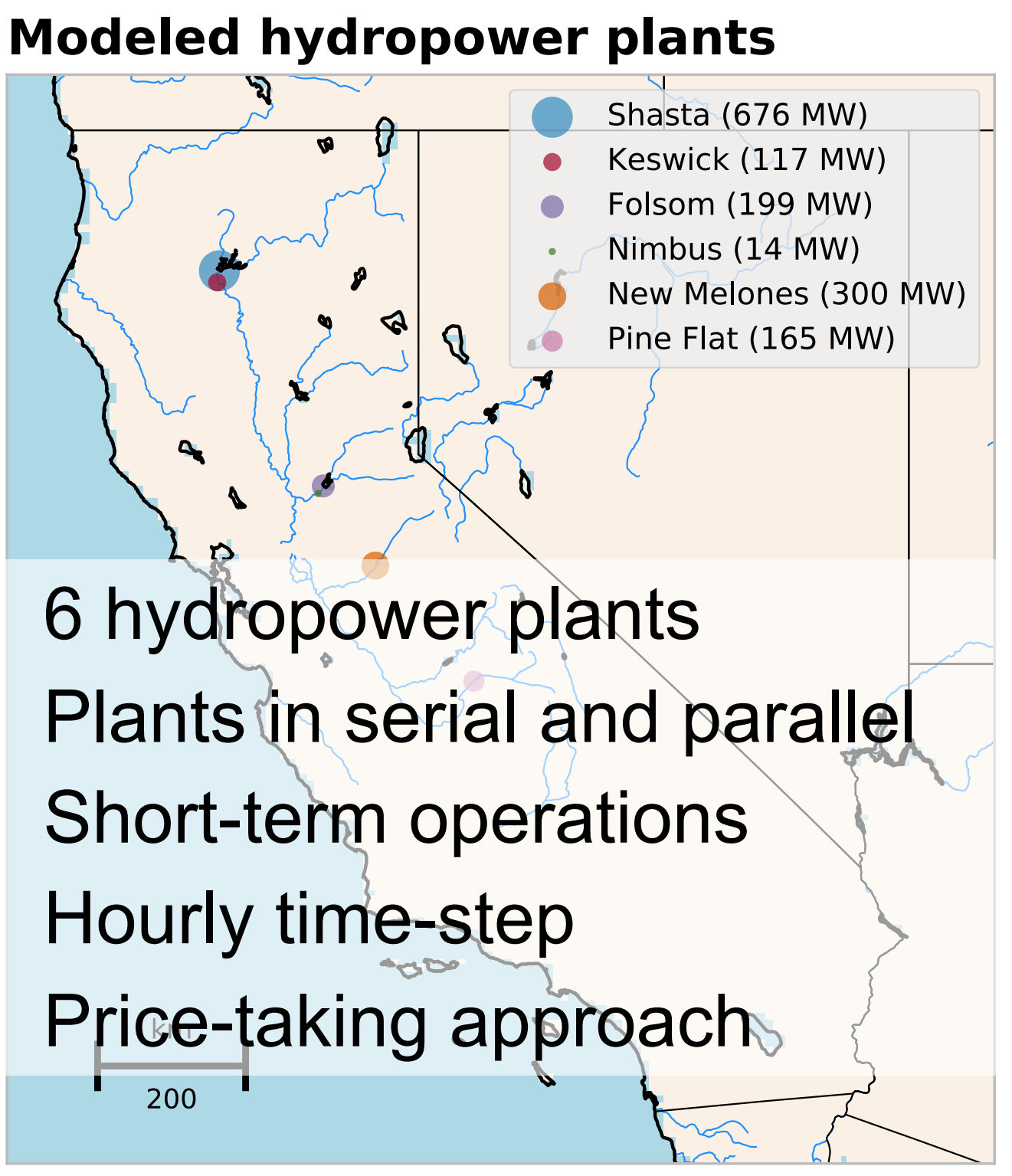
$$Y_n \geq Deadpool_n, \forall n \in A_{stor} \quad \text{(Lower bound)}$$

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

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

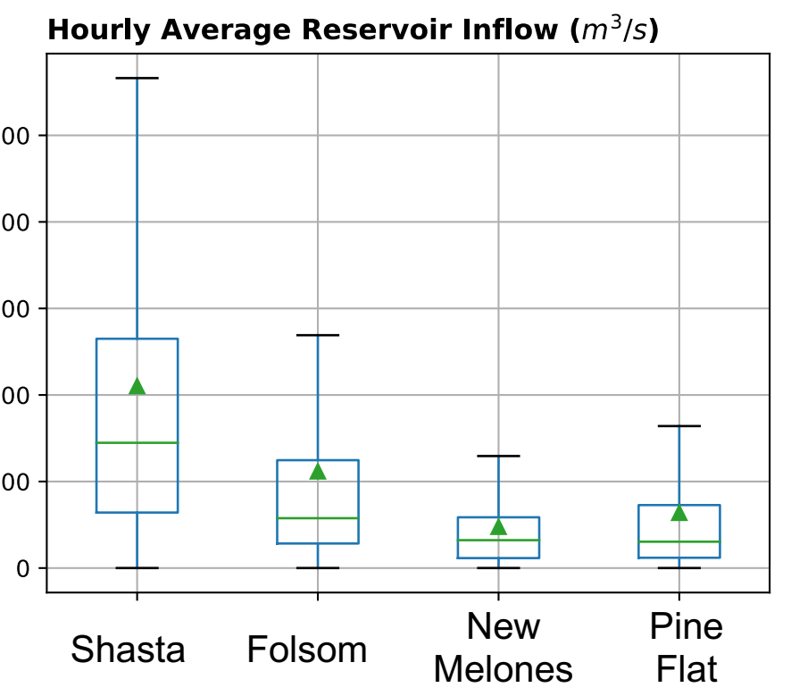


Figure 10. Hourly average reservoir inflow (m^3/s) of modeled hydropower plants (Data: CDEC)

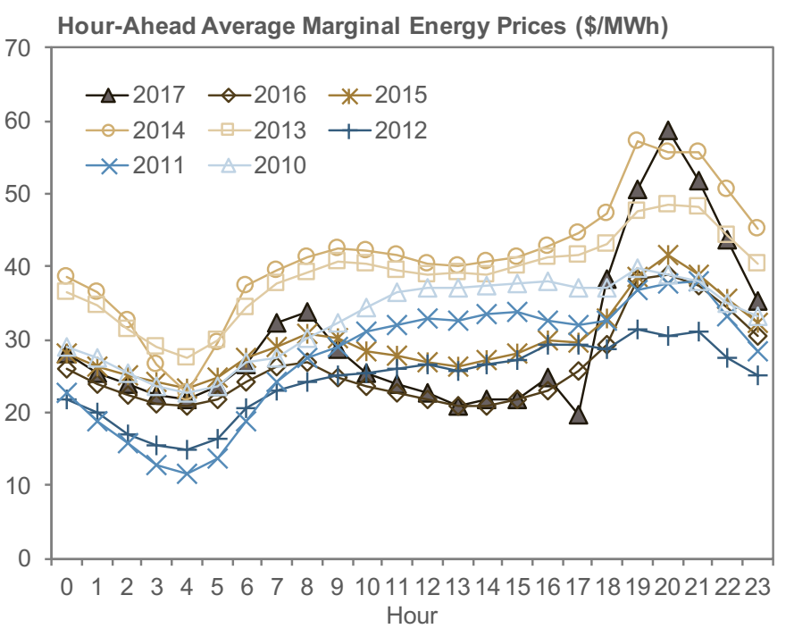


Figure 11. Hourly average energy price ($/MWh) between 2010-17 (Data: CAISO)

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

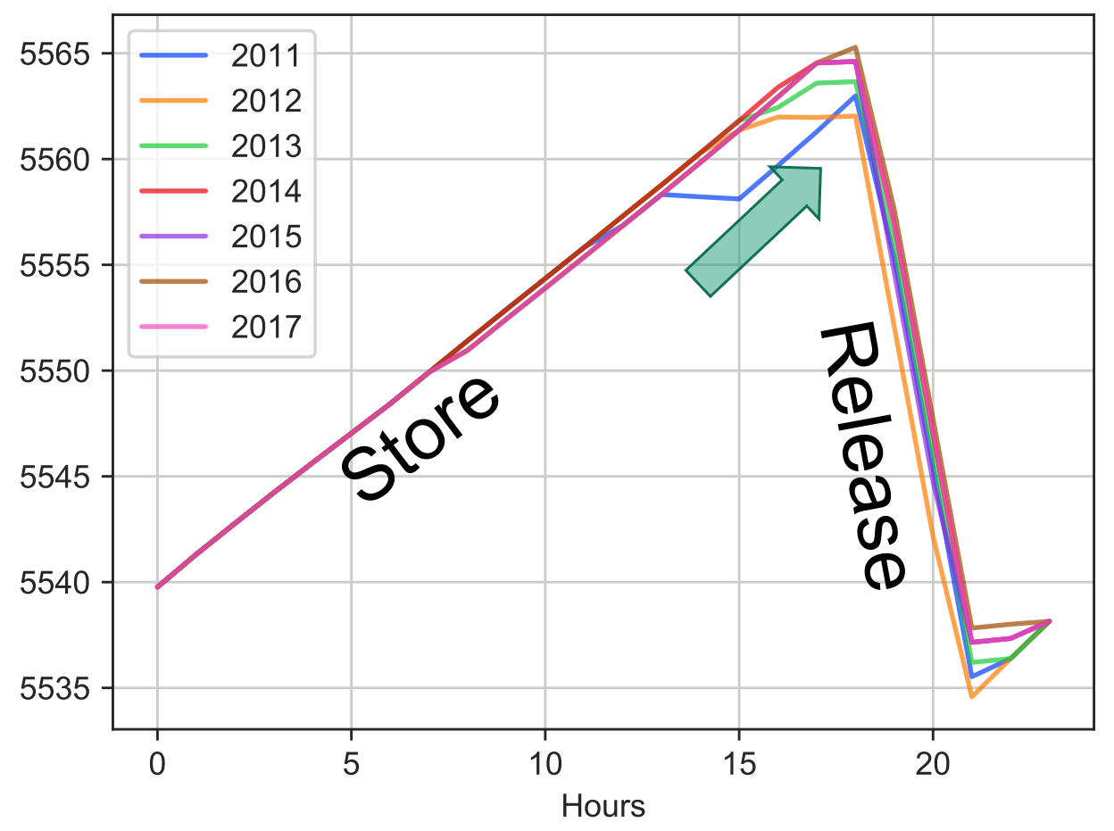


Figure 12. Modeled hourly average storage (million m^3)

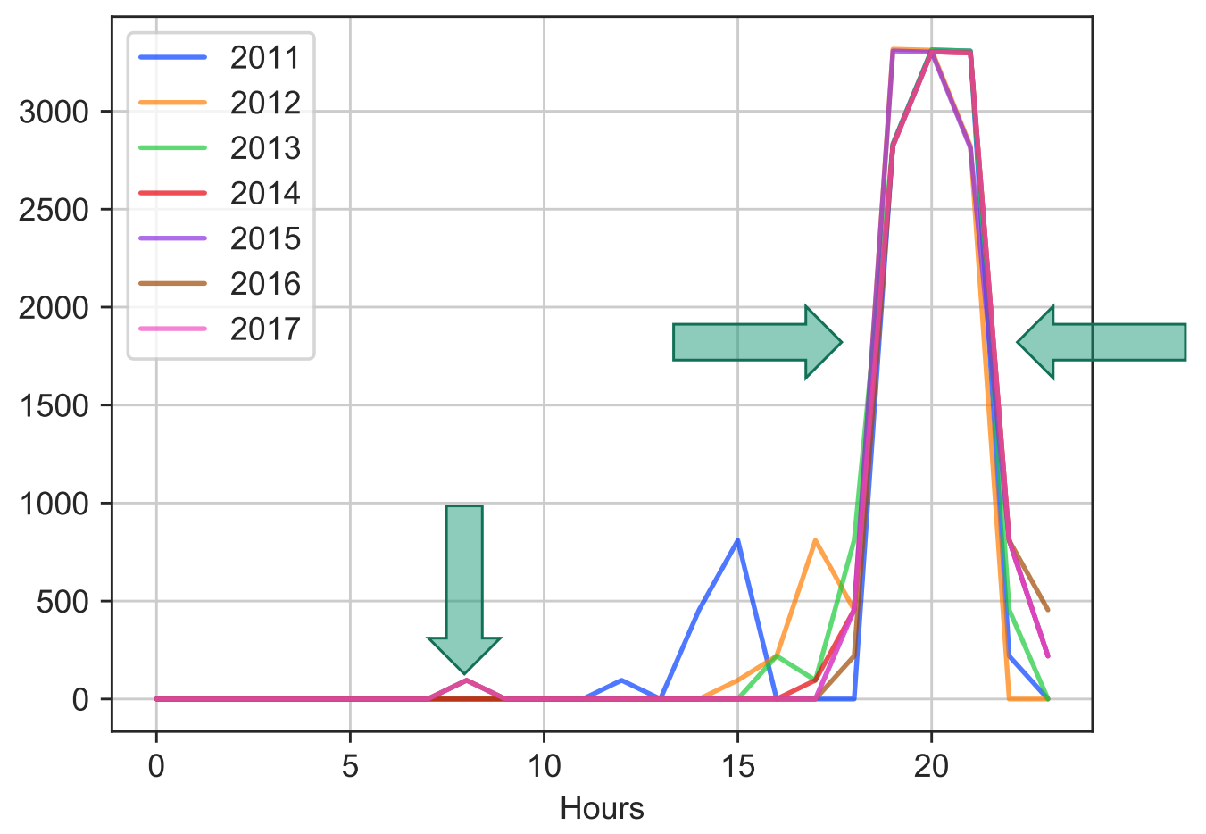


Figure 13. Modeled hourly average generation (MWh)

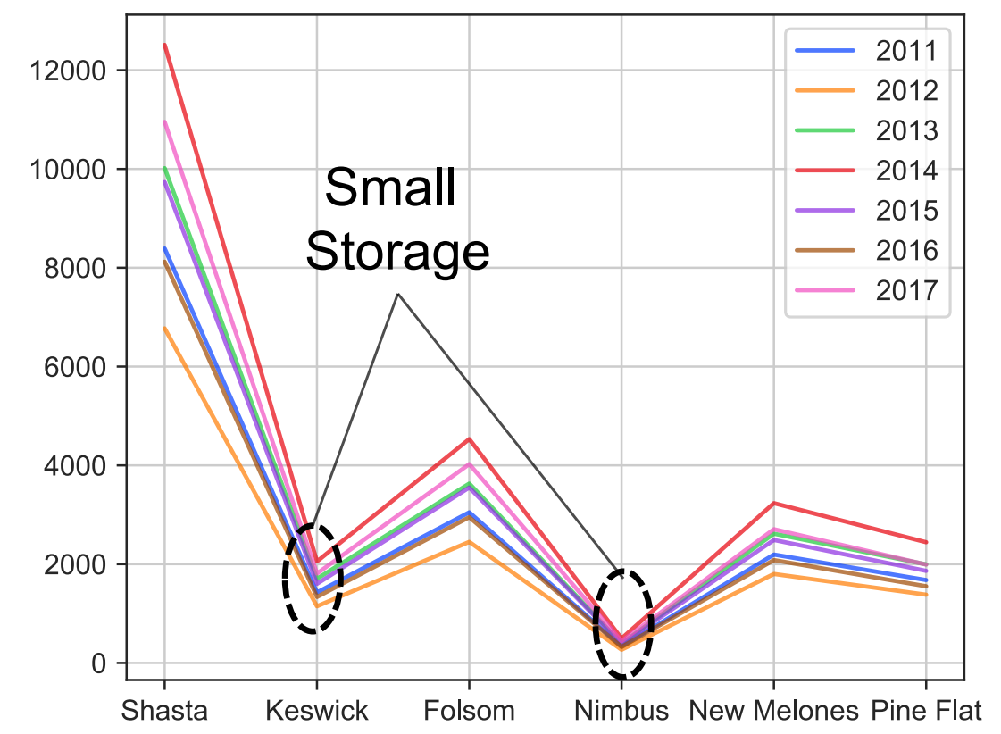


Figure 14. Hourly average hydropower revenue ($)

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