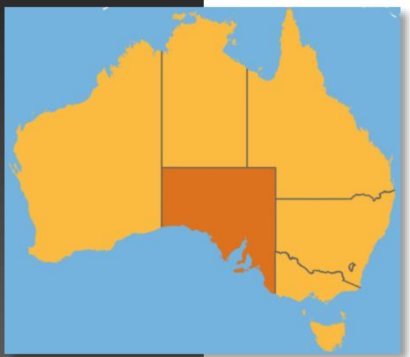
Power and Water Co-optimization in South Australia

How stochastic optimization provides a realistic solution



PLEXOS Integrated Energy Model Software

Co-optimized the operation of the water system in an integrated water-electricity model with both Monte Carlo and two-stage stochastic optimisation methods.

Situation

Water processing and pumping stations run on energy from the electricity grid, but if the demand is large enough to change the system's marginal generator, it will directly affect the price of electricity. This means water can't be optimized alone. Add to that the additional variables of hydro inflows, wind generation, demand and forced outages, and it may seem unlikely to find real-world simulation method.

Solution

Energy Exemplar conducted a study comparing two stochastic methods to run the co-optimized model of South Australia. Using PLEXOS, the model used Mixed Integer Linear Programming to minimize the overall running cost. The stochastic variables of the study were:

- The water inflow into the state's main reservoir
- South Australia's wind speed
- Energy prices in the neighboring state of Victoria

Electricity and water demand were treated as deterministic inputs and included in PLEXOS using historical profiles. The stochastic methods to optimize the model were:

- Monte Carlo simulation with 14 historic samples
- Two-stage Stochastic Optimization (non-recursive) with scenario reduction

Results

Beginning with a cost comparison, the Monte Carlo simulation is less costly that the stochastic operation.

Method	Avg Total Cost	Avg Pumped water (1000m3)	Avg Pumping Cost ($/1000m3)
Monte Carlo	76,651.9	3,263.3	23.5
Stochastic Optimization	93,247.7	3,244.4	28.7

This is what we'd expect since the Monte Carlo method anticipates the future behavior of the stochastic variables when making operational decisions at the present stages; each of its independent samples run with perfect foresight throughout the entire simulation period.

In contrast, stochastic optimization does not anticipate the variables. The variables stay uncertain at each stage, and the decision is based only on the probabilities of each distinct scenario.

The results of the stochastic optimization will reflect more conservative and realistic operations compared with a method that assumes perfect foresight.

The main advantage of stochastic optimization is that it provides the optimal decisions under uncertainty. This non-anticipatory method is the best policy over the simulation period – better than any of the samples of the Monte Carlo simulation or their averages.

There are additional advantages of stochastic optimization as shown in figures 1 and 2. The graphs show a one-day snapshot of the optimal operation of the water reservoir in the model.

Figure 01 – Monte Carlo's optimal water injection (blue) and withdrawal (red) over electricity prices (grey).

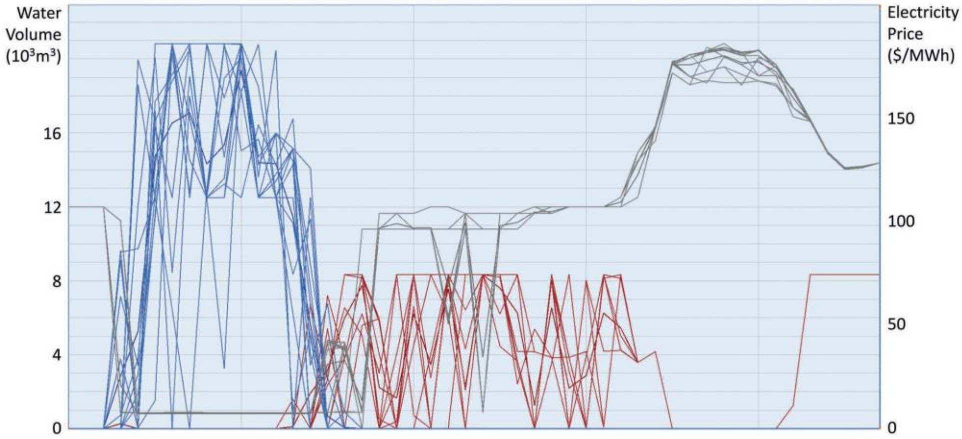
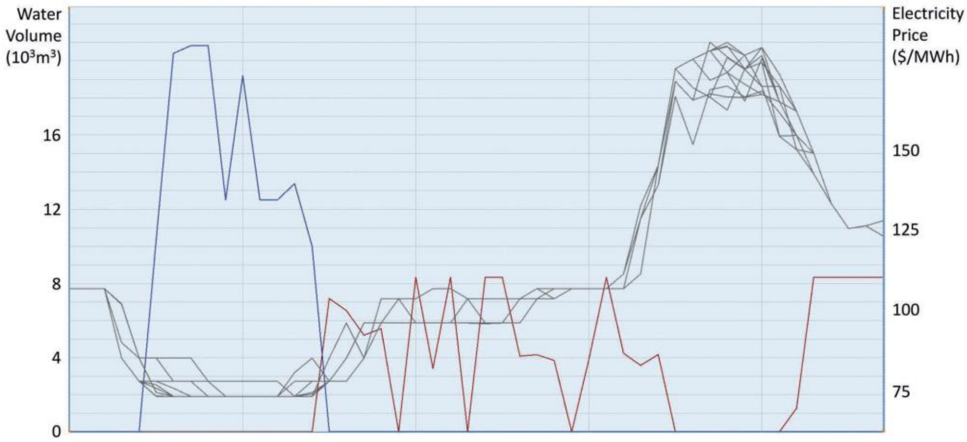


Figure 02 – Stochastic optimization's water injection (blue) and withdrawal (red) over electricity prices (grey).



Both solutions see water operation in periods of low electricity prices. However, stochastic optimization provides one clear solution over different price outcomes while Monte Carlo gives a collection or 14 optimal decisions – one for each price outcome. The Monte Carlo method may be overwhelming for decision-making while stochastic optimization guides planners with the best policy.

Two-Stage Stochastic Optimization
Stochastic optimisation can model uncertainty at each decision stage, providing a more conservative and realistic solution. This method also provides a single optimal strategy, which is more useful for planners and operators.

Monte Carlo Method
Although the Monte Carlo method appeared to provide better solutions, these were only achieved through the perfect foresight of stochastic variables, an unrealistic approach to real-world simulations.