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Integrated Stochastic Weather and Production Simulation Modeling

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***Abstract*—High penetration of intermittent renewable generators can substantially increase the variability and uncertainty in power system operations. Energy storage and demand response have been proposed as resources that can be used to mitigate this uncertainty and variability. This paper describes planning system that couples a stochastic weather model, renewable generation models that are driven by the weather, a stochastic production simulation model, and a system stability model. The system is used to simulate operation of the California grid with 33% variable renewable generation in the year 2020. The values of energy storage and demand response are estimated by identifying the avoided costs of the conventional hydro and fossil resources that they displace when providing regulation, load following, and energy arbitrage functions. The impacts on system stability are also assessed.**

***Index Terms*-- power generation planning, power generation dispatch, power system economics, wind energy, solar energy**

I. PLANNING SYSTEM WITH UNCERTAINTY

California has established one of the most aggressive renewable energy goals in the country – requiring 33% of total electricity sold be from renewable energy generation by the year 2020. Increased contributions from wind and solar resources needed to meet this goal will substantially increase the variability and uncertainty in generation resources available to the State's grid operators.

The planning system shown in Fig. 1 has been developed to estimate the value of technologies in the context of this high degree of uncertainty and variability [1]. The system builds upon and extends previous studies conducted by the California Independent System Operator (CAISO) and the California Energy Commission [2, 3, 4].

Some key features of the planning system include:

- use of physics-based atmospheric models and ensemble forecasts to capture uncertainty,
- conversion of weather trajectories into ensembles of renewable generation and net load trajectories,
- day-ahead stochastic unit commitment with hourly time steps,
- economic dispatch at five-minute intervals, and
- system stability checks at sub-second intervals using an electromechanical system simulation model

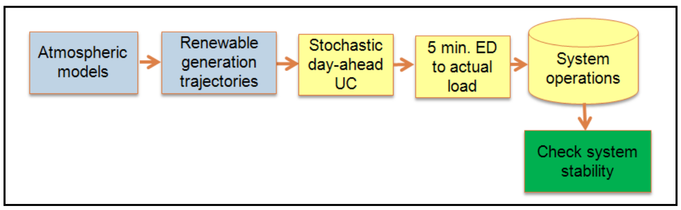

Figure 1. Components of the Planning System

Section II of this paper describes the atmospheric models, including the methods used to capture uncertainty and to generate the ensemble of weather trajectories. Section III describes the production simulation model that is used to optimally schedule production from the dispatchable resources, including storage and demand response. Section IV provides some price and value estimates provided by the production simulation model. Section V provides key results of the regulation and stability analyses. Finally, the paper is summarized in Section VI.

II. ATMOSPHERIC AND RENEWABLE GENERTOR MODELING

A. *Weather Model Description*

The open-source code Weather Research and Forecasting (WRF) was used to develop a multi-scale model of the Western U.S. to simulate weather conditions that drive renewable generators [5]. The three-dimensional governing equations in WRF are the conservation of momentum from

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Newton's laws, the conservation of mass given by the continuity equation, and the conservation of energy described by the first law of thermodynamics. The model also incorporates the ideal gas law, which describes the relationship among density, volume, and temperature.

Numerous physics schemes are available in WRF to parameterize sub-grid scale meteorological phenomena such as turbulent mixing in the planetary boundary layer and surface moisture and heat exchange with the atmosphere. The large suite of available physics options and robust numerical core algorithms makes WRF suitable for atmospheric simulations on scales from meters to thousands of kilometers.

A grid size of 3 km was used in areas of California where there are high concentrations of wind and solar resources. A grid size of 9 km was used in other parts of California, and a grid size of 27 km was used to model the weather in the rest of the western U.S. Fifty terrain-following vertical levels were used. Output was generated at 15 minute intervals.

The atmospheric ensemble forecast system quantifies model uncertainty, and quantifies the evolution of the atmospheric probability distribution function [6]. The two major sources of uncertainty in the day-ahead forecasts are uncertainty about the model physics parameterization and uncertainty about the true initial state of the atmosphere. Both approaches were evaluated for this analysis (note that they are not mutually exclusive). For the reasons discussed below, it was determined that for a day ahead forecast, the uncertainty due to physics parameters was greater and of higher relevance to the objectives of the present study than the uncertainty due to initial conditions.

The uncertainty over model physics parameterization is converted into an ensemble of weather trajectories using a *multi-physics* analysis. The multi-physics ensemble approach is a commonly used method to account for model uncertainty and to provide a probabilistic forecast of the dynamically evolving atmosphere [7, 8, 9, 10, 11]. Multi-physics modeling is based on the realization that no single configuration of model physics is a perfect representation of the atmosphere and that multiple methods to resolve atmospheric processes are needed to adequately describe a forecast probability distribution function. The availability of a large suite of physics options within the WRF model makes it ideal for estimating forecasting uncertainty by running multiple forecasts for the same period but with different physics configurations.

The forecast uncertainty due to uncertainty about initial conditions can be analyzed using a *multi-initial condition* ensemble that executes multiple independent forecast simulations from a suite of plausible atmospheric initial conditions that are based on uncertainty over the background state and meteorological observation error.

The primary reason for using a multi-physics ensemble is based on the observation that the variance in a multi-physics ensemble frequently grows at a rate two to six times faster during the first 12 hours of a forecast than the variance simulated by an initial-condition ensemble [12]. Because the focus of this analysis is day ahead forecasting, it is likely that the model output from a multi-initial condition ensemble would under-represent the uncertainty in the ensemble during our forecast horizon because initial condition perturbations take time to grow and impact the numerical solution. Incorporating the multi-initial conditions analysis would substantially increase computation time and analysis effort while making little contribution to the analysis of the uncertainties in the day-ahead time frame.

B. Wind and Solar Generator Models and Net Load

For each of 30 weather trajectories in a multi-physics ensemble, the wind speed and shortwave downward radiative flux estimated with WRF are used to compute power outputs for each of the 5,494 wind and solar sites in the model. For wind sites, the wind speed is converted to MW using a Vestas V90 power curve [13]. For solar sites, the shortwave downward radiative flux is multiplied by a geometric factor that takes into account the relative angle between the sun and the solar panels at fifteen minute intervals. It is also multiplied by a temperature-dependent efficiency factor, using the local temperature.

The base load used for the year 2020 analysis is the realized load in the year 2005 scaled up according to a load forecast. However, the hypothetical weather trajectories in the ensemble would also affect the load. To account for this effect, the year 2020 base load is adjusted for each scenario in the ensemble using a set of coefficients that represent the change in load given a change in temperature for given times of the day, day of the week, and month.

Renewable generation is subtracted from the gross system load for each member of the weather ensemble. This load is then adjusted based upon the temperature deviation of that ensemble member relative to the 2005 weather conditions. In this manner, the members of the weather ensemble are converted to 30 net load scenarios.

Initial experiments with the production simulation model indicated that optimization with respect to 30 net load trajectories is computationally intractable. Hence, statistical clustering methods were used to reduce the number of net load scenarios to be included in the optimization model. Results of this aggregation process are shown in Fig. 2.

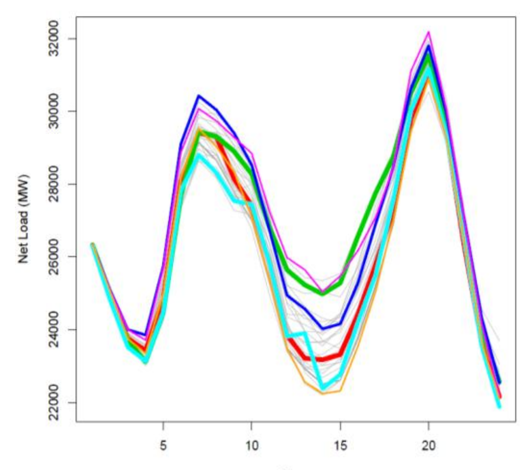

Figure 2. Net Load Trajectories in April 2020

The 30 members of the ensemble are shown as grey lines in the figure. Six representative scenarios are shown as the colored lines in the figure. The width of the line corresponds to the probability assigned to that trajectory. Note that on this spring day in 2020, the net load at 2:00 p.m. may be the lowest load of the day. This is due to the large solar photovoltaic capacity that is assumed to be on line under the 33% renewable scenario.

III. PRODUCTION SIMULATION MODELING

The WRF model is used in two modes. The first mode computes an ensemble of equally likely trajectories at the start of each day that extend over the full day. The ensemble approximately reproduces the uncertainty that the system operator would have had over the conditions for the following day. A weighted subset of these trajectories is used in the stochastic unit commitment analysis. In the second mode, the model is used to reconstruct the atmospheric conditions that existed during 2005, the weather year used for the analysis. These synthetic observations reproduce the actual atmospheric conditions (primarily wind velocity and solar insolation) that were realized during 2005. These synthetic observations, and the renewable generation patterns they produce, are used for the economic dispatch step in production simulation.

The PLEXOS production simulation software was used to formulate the unit commitment and economic dispatch optimization problem [14]. The optimization problem was then passed by the PLEXOS software to the CPLEX mixed-integer programming solver [15]. The stochastic unit commitment feature of the PLEXOS software was used with hourly time steps. The newly-released interleaved mode allowed us to utilize two different time scales – unit commitment at hourly time steps and economic dispatch at five-minute time steps.

A. *Model Used for Analysis*

A highly-aggregated model of the Western Interconnect developed by the CAISO was adapted for the analysis [2, 3]. The model includes 2,400 generators, 120 transmission corridors, and 42 load centers. Loads for the year 2005 were scaled up to reflect loads expected for the year 2020. CAISO's High Load scenario was selected for analysis.

The CAISO model includes constraints that ensure sufficient flexible capacity is available to follow load given the high uncertainty and variability associated with a 33% renewable system. These constraints were established by computing the 95% confidence limits on the hour-ahead forecasting error associated with an autoregressive-moving average (ARMA) statistical model. One ARMA model was developed for each of the four seasons. For this study, these confidence limits were replaced by corresponding limits associated with our 30 member weather ensemble. Unique limits are used for each hour of the year. The value of the Lagrange multiplier for this constraint was interpreted as the marginal price for procuring flexible capacity to follow load in the markets. Similarly, the Lagrange multiplier for system constraints on required regulation capacity were interpreted as the marginal price of this service.

B. *Modeling Demand Response and Storage*

Forecast capacity of demand response for each hour of the year 2020 was provided by the Demand Response Research Center [16]. Three types of demand response capacity were provided: (1) firm capacity that is bid into the day-ahead market, (2) flexible capacity that can be dispatched at five-minute intervals, and (3) regulation capacity that can be modified at four-second intervals. In general, more firm capacity is available than flexible or regulation capacity. For example, in Southern California Edison's service territory at 4:00 p.m. on August 2, 2020, the forecasts for firm, flexible, and regulation demand response capacities are 2,000 MW, 500 MW, and 400 MW, respectively. Also, more demand response capacity is available in the summer. Capacities of flexible demand response for all hours of the year are depicted in Fig. 3. The maximum capacities available for firm and regulation demand response are 2,600 MW and 300 MW, respectively. The capacity would be available for one hour each day.

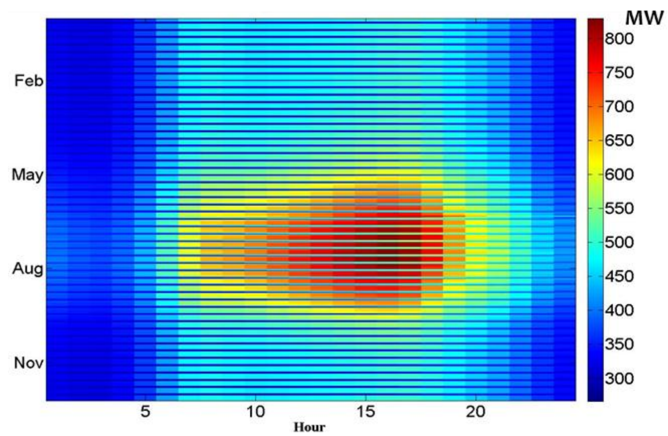

Figure 3. Flexible Demand Response Capacities

Four types of energy storage devices were modeled: (1) lithium-ion battery, (2) zinc-bromide flow battery, (3) flywheels, and (4) compressed air energy storage above and below ground. The Electric Power Research Institute and the California Energy Storage Alliance provided the energy storage capital cost and performance characteristics shown in Table 1 [17]. The capital costs are estimated for a facility built in the year 2020.

Table 1. Energy Storage Cost and Performance Parameters

Technology	Capital costs and efficiency		
	$M/MW	***$M/MWh***	***Efficiency (%)***
Li-ion (15 min)	1.25	5	83
Li-ion (4 hr)	3.6	0.9	85
Zinc-bromide flow (5 hr)	1.86	0.372	65
Flywheel (15 min)	1.9	7.6	87
Copressed air above gr. (5 hr)	2	0.4	70
Compressed air below gr. (5 hr)	1.5	0.15	70

Storage capacities ranging from 10 MW to 1200 MW for each storage technology were added to the PG&E and SCE systems.

C. Computational Challenges and Solutions

The production simulation model, including demand response and storage resources, was solved for each day of the year. Multiple configurations of the system were analyzed so that a total of 3,000 days were simulated. Each day of simulation would require approximately eight hours on a workstation, which implies a wall clock time of 2.7 years to conduct the entire analysis campaign on a single work station. However, the analysis campaign was conducted in approximately one month using high performance computing resources at Lawrence Livermore National Laboratory with thousands of cores. Use of high performance computing allowed compression of the time required by a factor of 30.

IV. PRODUCTION SIMULATION RESULTS

Computed generation patterns for the original CAISO model (without addition of demand response or energy storage resources) are shown in Fig. 4. Solar generation provides approximately 1,000 MW at noon, but is unavailable by 7:00 p.m. This drop in availability causes a sharp peak in imports and hydroelectric pumped storage usage at that time. Some wind energy is available on this day in the evening and early morning, which is typical of California.

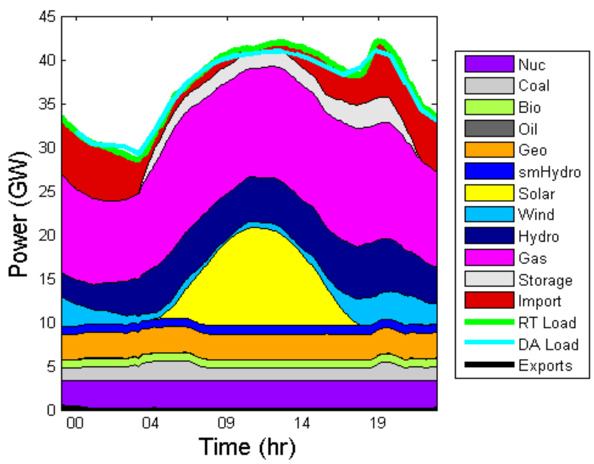

Figure 4. Generation patters in April 2020

Marginal energy prices are shown in Fig. 5. As indicated in the figure, during the winter, spring, and fall, there are two periods of higher prices, while during the summer there is a single period of high prices. This suggests one charging cycle for batteries during the summer and two during other seasons.

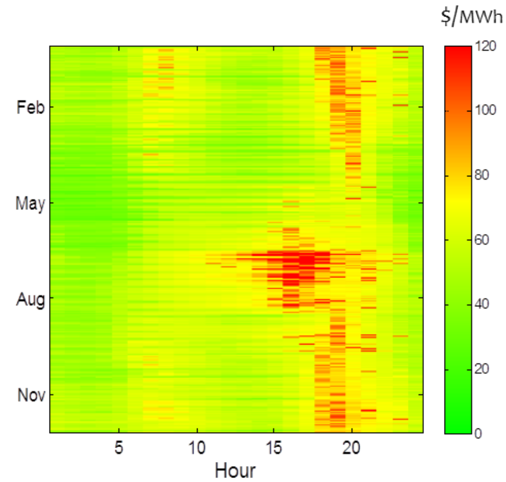

Figure 5. Marginal energy prices in April 2020

Prices for load following up are depicted in Fig. 6. As indicated by the data in the figure, prices for load following have the same general temporal patterns as energy prices, albeit at lower overall levels.

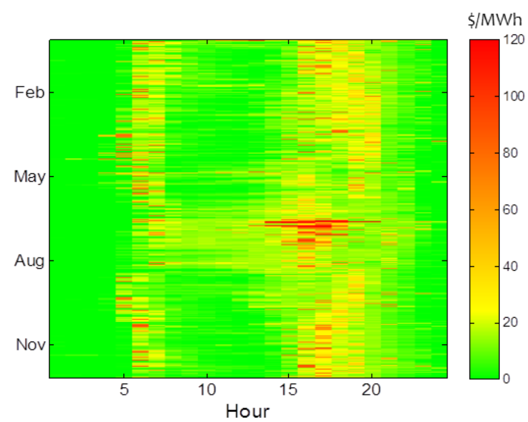

Figure 6. Prices for load following up

Compressed air energy storage provided the highest net revenues (revenues from discharging less cost of energy used for charging) from energy arbitrage. The first MW of capacity provided $70,000 per year. The first MW of Li-ion and flow batteries provided $45,000 and $20,000 MW of net revenues, respectively. The marginal value of additional capacity decreases by 30% to 50% when 1,200 MW are added to the system. Parametric studies indicated that battery discharge times of more than four hours provided little additional benefit.

The potential revenues from providing ancillary services were also estimated. Load following up, regulation up, and spinning reserve could each provide approximately $100,000 per year in revenues for the first MW of capacity offered.

Demand response could reduce annual operating costs. The capacity estimates described previously would reduce costs of load following by $84 million per year. Regulation costs would be reduced by $31 million per year.

V. REGULATION AND STABILITY ASSESSMENT

High penetration of renewable generation can exacerbate the frequency deviations caused by contingencies in the system due to the reduction in system inertia. An electromechanical simulation model developed by DNV KEMA and other software tools developed for this project were used to evaluate system response with and without storage providing regulation services [4].

A contingency involving the loss of 2,000 MW of generation capacity was introduced to the system without any energy storage capacity providing regulation. The simulation was conducted for a March day when there was large amount of renewable generation online. The simulation was repeated after the addition of 200 MW of storage providing regulation. Results are shown in Fig. 7. As indicated in the figure, the addition of 200 MW of energy storage reduces the negative frequency deviation from -0.1 Hz to -0.07 Hz for this contingency.

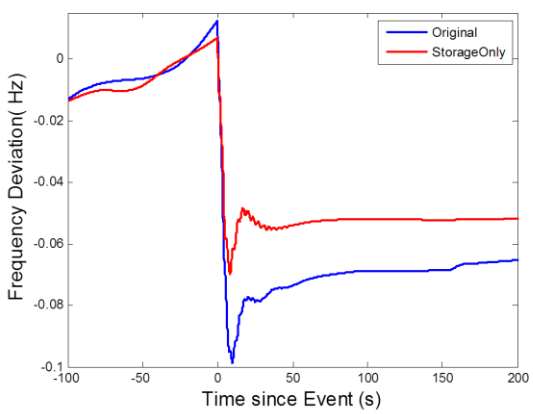

Figure 7. Frequency deviation with and without storage

Energy storage providing regulation can also reduce cycling of thermal units that are on line. Cycling is measured in terms of the sum of the absolute values of the MW of instructed changes in output over a given time period. The addition of 100 MW of energy storage on regulation can reduce cycling of thermal units on line by 20,000 MW per year.

Batteries on regulation could become completely charged or discharged, and hence become incapable of providing load following down, or load following up, respectively. Results indicate that 200 MW of battery capacity would have a 4% chance per day of becoming discharged and unable to provide regulation up. The same capacity would have a 1% change of becoming fully charged and unable to provide regulation down.

VI. SUMMARY AND CONCLUSIONS

This study describes the development of a modeling and analysis platform that integrates a stochastic weather model, renewable generator models, a stochastic production simulation model, and a stability analysis model that was used to estimate the value of introducing demand response and energy storage into a system with high renewable penetration. Estimates of the operating profits that energy storage could earn through energy arbitrage and sale of ancillary services were developed. Estimates of the value that demand response could provide were also developed.

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