Rulemaking No.: 13-12-010
Exhibit No.: ______________
Witness: Dr. Shucheng Liu

Order Instituting Rulemaking to Integrate and Refine Procurement Policies and Consider Long-Term Procurement Plans.	Rulemaking 13-12-010

PHASE I.A. STOCHASTIC STUDY TESTIMONY OF DR. SHUCHENG LIU
ON BEHALF OF THE
CALIFORNIA INDEPENDENT SYSTEM OPERATOR CORPORATION

Dated November 20, 2014

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BEFORE THE PUBLIC UTILITIES COMMISSION OF THE STATE OF CALIFORNIA

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PHASE I.A. STOCHASTIC TESTIMONY OF DR. SHUCHENG LIU ON BEHALF OF THE CALIFORNIA INDEPENDENT SYSTEM OPERATOR CORPORATION

I. BACKGROUND AND TESTIMONY SUMMARY

Q. What is your name and by whom are you employed?

A. My name is Shucheng Liu. I am employed by the California Independent System Operator (CAISO), 250 Outcropping Way, Folsom, California as Principal, Market Development.

Q. Have you previously submitted testimony in this proceeding?

A. Yes. I submitted testimony on August 13, 2014 and October 22, 2014 supporting and describing the results of the CAISO's 2014 Long-Term Procurement Plan (LTPP) deterministic study.

Q. What is the purpose of this testimony?

A. My testimony describes the construct of the CAISO's stochastic model, the development of the stochastic variables and the capacity shortfalls and renewable curtailments identified by the model.

Q. Please describe how your testimony is organized.

A. My testimony is divided in to three main sections and a comprehensive Technical Appendix. Section II of this testimony addresses the stochastic model developed by the CAISO and the assumptions contained therein. Section III discusses the development of the load, solar generation, wind generation and forced outage stochastic variables and the processes by which the CAISO validated the stochastic variables. Section IV presents the capacity shortfalls and renewable curtailments observed in the CAISO's 500-iteration stochastic model simulations. The Technical Appendix presents additional details regarding the development of the CAISO's stochastic model, the stochastic variables and the results of the simulations.

II. THE BASE MODEL

Q. Please provide an overview of the CAISO's 2014 LTPP stochastic production simulation model.

A. The CAISO's stochastic production simulation model is based on the Trajectory scenario deterministic zonal model the CAISO developed for the 2014 LTPP study pursuant to this proceeding's Administrative Law Judge's request. The model has four stochastic variables – forced outage, load, solar generation and wind generation. The CAISO conducted 500-iteration full-year hourly chronological Monte Carlo simulations with the model. The CAISO produced frequency distributions for capacity shortfalls and renewable generation curtailments based on results of these simulations. The inclusion of stochastic variables for the main inputs of load, wind generation, solar generation and conventional generation outages captures the variations of system conditions hour-by-hour for the entire year.

Q. What is the difference between a deterministic and stochastic variable in simulations of this study?

A. A deterministic variable has a single given input of a load, solar or wind profile for the year. The deterministic simulation runs only once from the beginning to the end of the year in hourly intervals. It represents a single prediction of the future based on the best knowledge and available information. The results are represented as single data points. The deterministic approach assumes that there is perfect foresight what the conditions for every hour of the year 10 years out.

A stochastic simulation complements the deterministic simulation by exploring not just a single point forecast of future conditions but rather studies a range of conditions that may exist. A stochastic variable has a built-in mathematical mechanism that derives its value from one hour to the next, from the beginning to the end of the year. The process will repeat many times and each time the value of the stochastic variable is different. This enables the variable to capture more possible conditions. The stochastic simulation runs in multiple iterations with the multiple sets of input values for each stochastic variable. The stochastic results are presented in frequency distribution format. In this study, the stochastic model is aligned with the deterministic model for comparison and compliment purposes.

Q. Explain how the CAISO's deterministic model was used a basis for the stochastic model.

A. Inside the CAISO footprint, the stochastic model is essentially the same as the deterministic model: generation resources, load, operational constraints and internal transmission limits were modeled in the same manner. Both models also use the same unit commitment and economic dispatch methodologies. For details, see Appendix A, Section II.A.

Q. Please describe how the CAISO's stochastic model differs from deterministic model.

A. The only significant differences between the two models are the inclusion of the stochastic variables in the stochastic model and the more limited modeling of the Western Electricity Coordinating Council (WECC) generation resources and load outside the CAISO.

Q. Please describe the more limited modeling of the external zones in the stochastic model.

A. The stochastic simulation model is a streamlined version of the deterministic zonal production simulation model using the Trajectory scenario assumptions. Because running the stochastic model requires a significant amount of time and computing power, the CAISO used a model that covered only California in detail. Individual generation resources and load outside of the CAISO are aggregated and represented by a single external zone in the stochastic model rather than in the greater detail included in the deterministic model. The external zone is directly connected to the CAISO through the PG&E_VALLEY, SCE and SDG&E zones and has the resources to provide the CAISO with dedicated and economic imports. The external zone also takes the CAISO's export when economic, subject to the CAISO zero net export limit. This allowed the CAISO to complete the stochastic simulations more quickly, which enabled the CAISO to complete the analysis to present in this testimony. The long run time necessary for Monte Carlo simulations is a significant challenge of stochastic modeling.

Q. Explain the significance of the 500-iteration full-year hourly chronological Monte Carlo simulations produced by the CAISO's model.

A. The deterministic Trajectory scenario represents only one possible set of outcomes based on one set of assumptions whereas the stochastic model simulates 500 cases. The stochastic model uncovered more varied system conditions not observed in the deterministic model that represent the potential for more significant supply shortfalls or more significant over-generation curtailment risk than the deterministic results. The stochastic model provides us the likelihood of outcomes based on the 500 draws in the simulations using the more expanded projections of load, generation, wind generation and solar generation. It provides the possible range of scenarios and context which can be used to evaluate the findings in the deterministic runs. The deterministic model is unable to capture the range of possible system conditions.

III. STOCHASTIC VARIABLES

Q. Please describe the four stochastic variables modeled in the CAISO's study.

A. The CAISO's model has stochastic variables for load, solar generation, wind generation and forced outages. The load variable is the aggregated load of the CAISO, excluding the California Department of Water Resources (CDWR) pump load. The solar variable is the aggregated solar generation of RPS solar resources, distributed generation photo-voltaic generation inside the CAISO and the RPS solar resources from out-of-state. The wind variable is the aggregate wind generation by RPS wind resources inside the CAISO and out-of-state. In simulations, the generated stochastic values of load, solar and wind generation are distributed to the five zones - PG&E_BAY, PG&E_VALLY, SCE, SDG&E, and the external zone by ratios calculated based on the 2024 deterministic load, solar and wind generation profiles. Lastly, forced outages are generated for each generation resource inside the CAISO.

Of the four stochastic variables, forced outage is independent of all other variables. Load, solar and wind generation are assumed to follow mean reversion stochastic process, which is auto-correlated. In other words, the next hour load depends on the current hour load. The correlations among the three are derived from the process of developing the stochastic variables. For details please see Appendix A, Section III.G.

Q. What are the factors specifically considered in developing the load, solar generation and wind generation stochastic variables.

A. Load, solar generation and wind generation are assumed to follow a mean reversion stochastic process. However each of these is defined specifically based on historical data. The repetitive patterns as well as the volatilities of the variables decide how each of is defined in the model. Load and solar generation have repetitive daily patterns that are preserved in the developed stochastic variables, but wind does not. Also solar generation is more volatile than load due to its intermittency as reflect actual historical data. Therefore, the three stochastic variables are developed differently. For a detailed description of the mean reversion stochastic process, please see Appendix A.

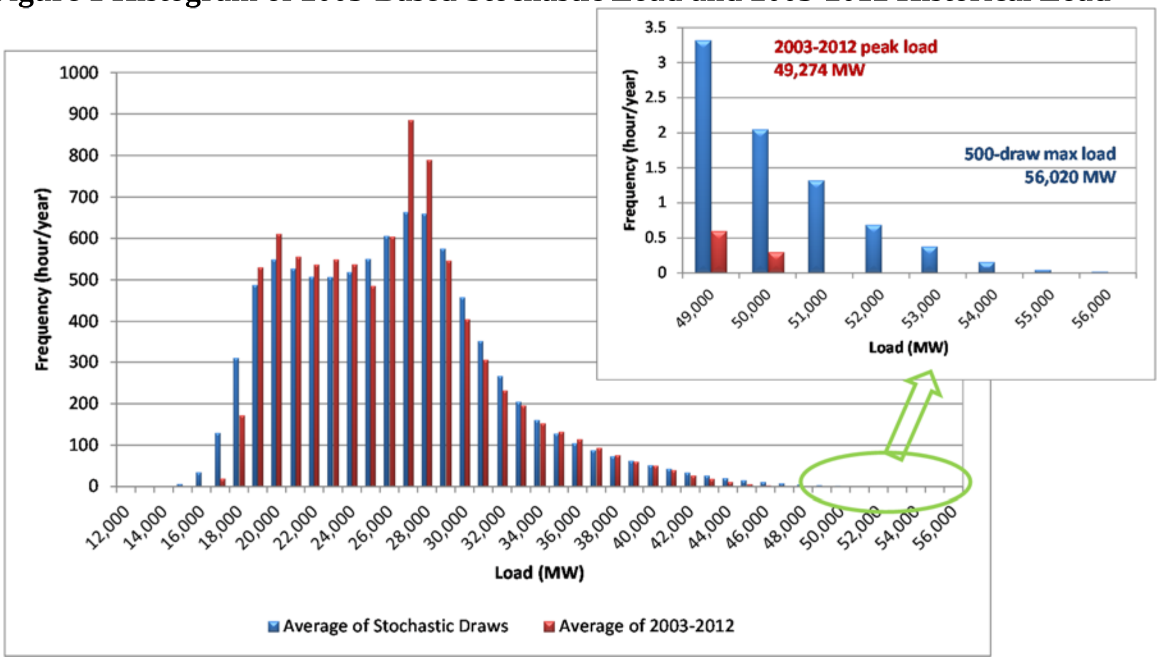
Q. Please explain the CAISO's development of the load stochastic variable.

A. Load stochastic variable is developed based on the CAISO 2003-2012 historical hourly load data. This was the most recent complete 10-year data set available when these studies were commenced. This period of available load data also matches the solar historical data obtained by the CAISO and used to develop the solar stochastic variable. The load data does not include the CWDR pump load because the pump load depends on the hydro condition of the year, which does not vary within the year. Instead, pump load is modeled as a deterministic input.

The stochastic study assumes that the hourly historical load ratio follows a mean reversion stochastic process. The hourly historical load ratio is calculated by dividing 2003-2012 historical load values by the 2005 load values by matching date and hour. The 2005 load value is used as the denominator of the ratio because the 2024 deterministic load profile is developed based on the 2005 historical load profile. This approach preserves the daily load patterns in the stochastic variable. The parameters of the stochastic process are estimated through regression based on the historical load ratios. The CAISO then generated 500-iteration stochastic values of the load ratio and multiplied these by the 2024 deterministic load profile to get the 500-iteration stochastic values of the load variable.

The CAISO benchmarked the load stochastic variable with the historical data, by generating 500-iteration stochastic load values based on the 2005 load profile. The CAISO used these 2005-load based stochastic values to compare the 2003-2012 historical load data in a frequency distribution. As can be seen in Figure 1, the stochastic variable generated values match well with the actual 2003-2012 historical load data.

Figure 1 Histogram of 2005-Based Stochastic Load and 2003-2012 Historical Load



The stochastic variable values extend below the minimum historical load and above the maximum historical load, as one would expect from a 500-iteration simulation. These points represent the load conditions that did not happen in the historical period, but were possible. Capturing these extreme conditions with the stochastic load variable improves the representation of possible load conditions in the simulations for 2024. These possible outcomes, while less likely, are rooted in the historical patterns contained in the historical data set. It is important to include the full range of possible outcomes in the study so that the Commission can make informed decisions about the determination of need and how to fill those needs.

In order to validate the generated 2024 stochastic load values, the CAISO compared the results m with the 2024 deterministic load profile using a full-sample histogram, a one-week chronological profile plot, and the distribution of the 500 stochastic load values at the deterministic model peak load hour. These comparisons show the stochastic load values are relatively evenly distributed around the deterministic load profile. This indicates that the 500 stochastic load profiles include the deterministic load.

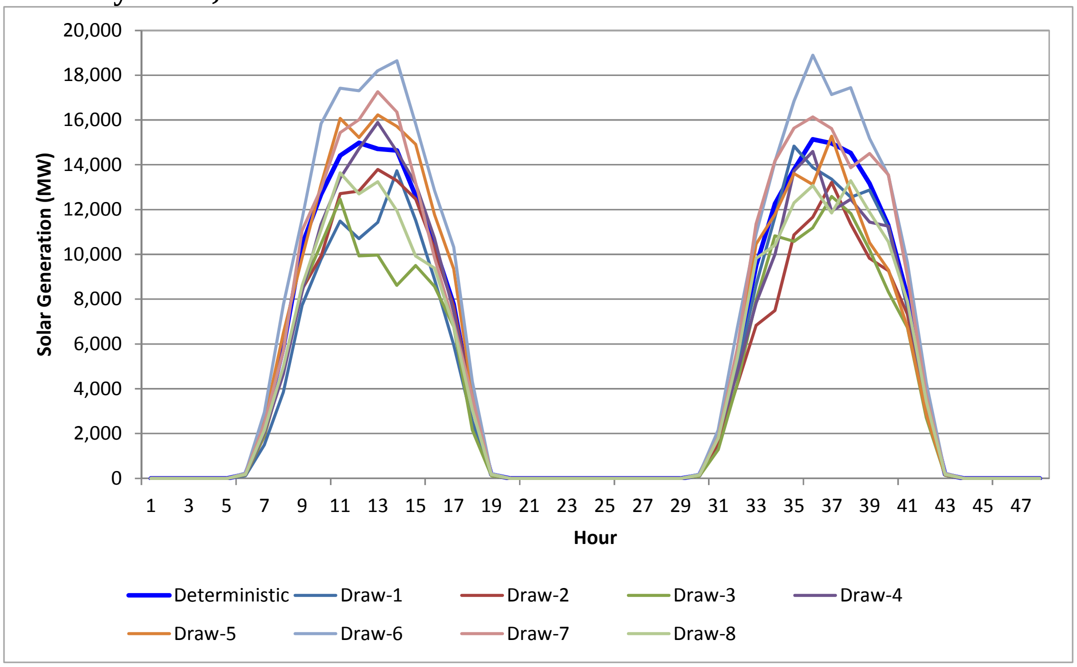
The CAISO's process for validating the stochastic load variable results is described in detail in Appendix A, Section III.D

Q. Please explain the CAISO's development of the solar stochastic variable.

A. Solar stochastic variable is developed based on the Clean Power Research 2003-2012 historical hourly "Global Horizontal Irradiance (GHI) W/m2" data of 11 sites inside the CAISO. The CAISO used these historical irradiance values to approximate relative solar generation. As with the deterministic model, the solar generation values in the stochastic model include distributed generation photovoltaic solar. The CAISO developed both hourly and daily solar generation ratios and used the weighted average to develop the final 500-iteration solar generation ratio stochastic values. This approach was based on the CAISO's analysis of the volatilities of the historical and the 2024 deterministic solar generation profiles.

The CAISO validated the solar stochastic variable in a similar manner as the load stochastic variable. The 2005-data based benchmarking was not conducted because the solar historical data is based on irradiance, as opposed to actual generation data. As expected, the solar stochastic variable shows more volatility than load, but as Figure 2 below shows, the stochastic generated solar generation values are comparable to the 2024 deterministic solar generation results. Figure 2 represents the first eight stochastic solar generation profiles plotted against the deterministic solar generation profiles for July 18 and 19, 2024, the peak load days in the deterministic model.

Figure 2 July 18-19, 2024 Deterministic and Stochastic Solar Profiles



Additional information regarding the development of the solar generation stochastic variable can be found in Appendix A, Section III.E.

Q. Please explain the CAISO's development of the wind stochastic variable.

A. The CAISO developed the wind stochastic variable based on the NREL 2004-2012 hourly simulated wind generation data for 60 California sites based on historical weather data. The NREL simulation assumes 30 MW of installed capacity at each site. Unlike load and solar generation, wind generation does not have a repetitive daily pattern. The CAISO's stochastic model assumes that the sum of 60 sites simulated wind generation follows a mean reversion stochastic process. Similar to the solar generation variable, the CAISO developed hourly and daily stochastic processes based on the historical data and used the weighted average of the two to generate 500-iteration simulated wind generation values. The CAISO then normalized the simulated wind generation values with the estimated seasonal long-term mean and multiplied the ratios by the 2024 deterministic wind generation profile to produce the 500-iteration stochastic values for the wind variable.

The CAISO validated the wind stochastic variable in the same manner as the solar stochastic variable. Additional details regarding the development of validation of the wind generation stochastic variable can be found in Appendix A, Section III.F.

Q. Please explain the CAISO's development of the forced outage stochastic variable.

A. The forced outages are generated using the converged Monte Carlo method, as is used in the deterministic model. Forced outages are created independently for each generation resource in the CAISO in each iteration of the Monte Carlo simulations. The bases for the forced outage stochastic variable are the forced outage rates of the resources based on CAISO 2006-2010 actual outage data, as was used in the deterministic model. Forced outages are independent of any other variables in the model.

IV. MONTE CARLO SIMULATION AND RESULTS

Q. Describe how the stochastic model was prepared to run the simulations.

A. The stochastic model was first benchmarked with the deterministic model. The 2024 deterministic load, solar and wind generating profiles were used as the input of the stochastic model. Forced outages were also fixed to that in the deterministic model. Ran one iteration of the stochastic model with the deterministic inputs and compared the results with that of the deterministic model. The comparison focused on capacity shortfall and renewable generation curtailment. The stochastic model results are very close to the deterministic model results.

Q. Pleases describe the Monte Carlo simulations.

A. With the generated stochastic values of the load, solar and wind generation variables, 500-iteration Monte Carlo simulations were run. Each iteration of the simulations took one set of generated values of load, solar and wind generation stochastic variables as input. The 500-iteration 12-month hourly chronological simulations were split on multiple computers running in parallel.

Q. Generally describe the capacity shortfall results observed in the stochastic modeling.

A. The capacity shortfalls include shortfalls in load following-up, non-spinning, spinning, regulation-up and unserved energy. The 500-iteration Monte Carlo simulations identified an average of 19.9 hours per year with a capacity shortfall. The maximum capacity shortfall observed was 16,745 MW. In contrast, the CAISO's deterministic model indicated a total of five hours with capacity shortfall with the maximum shortfall equal to 1,489 MW. The differences between the stochastic and deterministic results are based on the various possible system supply and demand variations presented in the stochastic inputs. The most frequent capacity shortfalls occurred in July from hours 18 to 20. These results reinforce the findings of the deterministic study, which found capacity shortfalls in similar time frames. The CAISO notes that in both the stochastic and deterministic studies, these shortfalls occurred after the peak load hour when solar generation production drops prior to the evening reduction in load. Traditionally planning focused only on peak load hour. With the increase in renewable generation, the traditional planning reserve margin approach focusing on peak load hour has become insufficient and outdated. The results of the CAISO's study confirm that planning to meet peak load hour requirements is not necessarily sufficient to maintain reliability.

Q. How can the capacity shortfalls observed in the CAISO's stochastic model be used to determine system capacity needs?

A. Prior to making a determination of need, one must set a level of system reliability to be achieved. Once the desired level of system reliability is set, the stochastic study results may be used determine whether there is a need to reach that level. The CAISO used the 1 day-in-10 years standard to determine the system capacity needs based on the results.

Q. Explain the 1-day-in-10-years standard applied by the CAISO.

A. The CAISO used the 1 day-in-10 years reliability standard to determine the amount of additional capacity needed to provide system reliability. The 1 day-in-10 years standard is an industry standard that is widely used in determining system capacity needs. On a more granular level, the CAISO's application of the 1 day-in-10 years standard provides that the system must have seven or fewer hours of capacity shortfall in 10 years.[1] Because the CAISO's stochastic study results produce 500 hourly year-long iterations, up to 350 hours with capacity shortfall are allowed in order to meet the reliability standard.[2] The results can be easily arranged to determine any capacity shortfalls in excess of 350 hours for the 500 years represented by the stochastic model results. One can sort the observed capacity shortfalls by MW and determine the MW of capacity needed to eliminate all but the highest 350 hourly shortfalls. Table 1 below presents this analysis.

Table 1 Sorted Capacity Shortfalls

Order #	Capacity Shortfall (MW)
1	16,745
2	16,408
3	15,879
…	
350	8,297
351	**8,292**

Based on this analysis, 8,292 MW of capacity shortfall should be eliminated in order to meet the 1 day-in-10 years reliability standard.

However, this analysis does not take into account any offsets from the authorized 2,315 MW Track 1 and Track 4 capacity, which are not modeled in the CAISO's stochastic or deterministic studies.

[1] See Appendix B.
[2] 7 Hours/10 Years = 350 hours/500 years.

Q. How should the Commission use the stochastic study results in determining whether procurement should be authorized in this proceeding?

A. The stochastic study provides context and support to interpret the deterministic study results. This is because the stochastic model uncovers system conditions not observed in the deterministic study. Presenting this range of system conditions allows the Commission to plan for contingencies and make procurement decisions based on its own interpretation of service level reliability criteria. The CAISO presented the results of the 1 day-in-10 years reliability standard because it is directly applicable to the stochastic model results. Based on the CAISO's interpretation of the 1 day-in-10 years standard, the identified capacity need is 8,292 MW, before accounting for Track 1 and Track 4 resources. The Commission should use this data to inform its decision as to whether new procurement is needed only after the CAISO conducts additional deterministic studies to identify any flexible capacity need.

Q. Describe the renewable generation curtailment observed in the stochastic modeling.

A. Renewable generation curtailment observed in the CAISO's stochastic study was more than double the amounts observed in the deterministic study. The number of hours with curtailment increased from 96 to an average of 209 hours per year, the maximum single hour curtailment jumped from 5,927 MW to 12,393 MW, and the total energy curtailed increased from 153 gigawatt-hours (GWh) to an average of 407 GWh. Table 2 summarizes the observed differences in renewable curtailment between the CAISO's deterministic and stochastic studies.

Table 2 Summary of Renewable Curtailment

Month	1	2	3	4	5	6	7	8	9	10	11	12	Annual
500-Iteration Average													
Number of Hours	10.6	12.5	40.9	61.5	34.9	15.6	2.3	0.3	3.8	5.2	8.7	12.7	209
Max Curtailment (MW)	8,303	8,178	12,393	11,022	10,244	8,808	5,529	3,937	8,045	7,379	7,240	9,436	12,393
Curtailment (GWh)	16.9	19.4	93.4	135.7	71.6	24.8	2.7	0.2	4.0	6.1	10.8	21.4	407
Deterministic													
Number of Hours		2	26	47	16	5							96
Max Curtailment (MW)		243	5,927	5,410	2,984	2,025							5,927
Curtailment (GWh)		0.5	48.4	76.7	21.7	6.2							153

The CAISO notes that in 69 of the 209 hours with curtailment either solar or wind generation, or both, are capped at the installed capacity. Curtailment could be higher in the stochastic study if there were no installed capacity limit or a higher limit.

Q. How should Commission used the results of the CAISO's stochastic study in determining capacity needs in this proceeding?

A. The CAISO's stochastic study results provide context and support for the deterministic studies conducted to date. The results reveal a more comprehensive range of possible outcomes. Dr. Meeusen's concurrently served testimony discusses the reliability implications of the data presented herein and the need for important policy decisions regarding the level of service reliability to be maintained. The Commission can use the stochastic study data to make informed decisions to balance the costs of additional procurement against the appropriate level of service reliability for customers.

Q. Does this conclude your testimony?

A. Yes, it does.

APPENDIX A

The CAISO Stochastic Production Simulation Model & Results

Appendix A –
The CAISO Stochastic Production Simulation Model and Results

I. Introduction

This document describes the technical details of the California Independent System Operator (CAISO) stochastic production simulation model and the results of the Trajectory scenario using the 2014 long-term procurement plan (LTPP) assumptions adopted in the Assigned Commissioner's Ruling dated May 12, 2014.[1]

This model was developed to evaluate the system capacity and flexibility sufficiency in order to integrate renewable generation to meet the California state renewable portfolio standard (RPS) goal. It was based on the Trajectory scenario deterministic zonal production simulation model the CAISO developed for the 2014 LTPP system flexibility studies. The model includes stochastic variables for generation resource forced outages, load, solar and wind generation. For the stochastic model, the CAISO ran a 500-iteration Monte Carlo simulation. Each iteration was a full-year hourly chronological simulation. The stochastic model results complement the deterministic model results that the CAISO served on August 13, 2014. The stochastic results show:

- Significantly higher capacity shortfalls than the deterministic run;
- Capacity shortfalls measured against the 1 day-in-10 years reliability standard; and
- More than double the renewable curtailment in number of hours, the maximum curtailment (MW), and total curtailment energy (GWh) compared to the deterministic run results.

II. Modeling Assumptions

A. The Base Model

The base of the stochastic simulation model is a streamlined version of the deterministic zonal production simulation model using the Trajectory scenario assumptions. Because it takes a significant amount of time to run and complete a sufficient number of iterations it was necessary to scale down the base model to a size that allowed the Monte Carlo simulations to be completed in a reasonable time to present the results in this proceeding. The deterministic model includes individual generation resources and load modeled throughout the Western Electricity

1 The study is for year 2024.

Coordinating Council (WECC).[2] The stochastic model only maintains a detailed representation of individual generation resources and load only inside the CAISO. The remainder of the WECC resources and load are aggregated into a single market zone to capture all resources and loads located outside the CAISO.

Inside the CAISO the stochastic model is essentially the same as the deterministic model. There are four zones inside the CAISO: PG&E_BAY, PG&E_VALLEY, SCE, and SDG&E. Both the stochastic and deterministic models have the same generation resources and inter-zonal transmission capabilities. Both models enforce the same operational constraints, such as minimum up and down time, start-up and shut-down profiles, ramp rate and energy usage limit. As with the deterministic model, the 25% regional generation requirement for the CAISO, SCE and SDG&E as well as the CAISO zero net export constraint are enforced in the stochastic model. The two models also share the same deterministic inputs for regulation and load-following requirements, hydro generation and California Department of Water Resources (CDWR) pump load, and maintenance outage schedules.

A single set of deterministic regulation and load following requirements are used for all the iterations in the Monte Carlo simulations.[3] Recalculating regulation and load following requirements for each of the 500 iterations in the Monte Carlo simulations would take an inordinate amount of time and would be impossible to provide this testimony within the timeframe of this proceeding. Spinning and non-spinning reserves are held at 3% of load as in the deterministic model. Because load is a stochastic variable, the hourly values of spinning and non-spinning reserve requirements vary in each iteration.

Hydro generation and CDWR pump load are deterministic inputs in the stochastic model based on 2005 actual data, as was used in the deterministic model. Hydro generation and CDWR pump load depend on the hydro condition of the year. The hydro condition is determined in the winter months and does not change throughout the year.

In practice, maintenance outage schedules are planned events, unlike the stochastic variables. Uncertainty should not have an impact on planning maintenance outages. Therefore deterministic model maintenance outage schedules are used in all the iterations of the Monte Carlo simulations.

[2] For details of the CAISO 2014 LTPP deterministic model, see Dr. Liu's initial and reply testimony at http://www.caiso.com/Documents/Aug13_2014_InitialTestimony_ShuchengLiu_Phase1A_LTPP_R13-12-010.pdf and http://www.caiso.com/Documents/Oct22_2014_ReplyTestimony_ShuchengLiu_Phase1ALong-TermProcurementPlans_R13-12-010.pdf.

[3] The load-following and regulation requirements are from the Trajectory scenario Production Cost Run deterministic model.

The stochastic model uses the exact same unit commitment and economic dispatch methodologies as the deterministic model. The two models, therefore, should produce comparable results.

B. The External Zone

All generation resources and load in WECC and outside of the CAISO, are aggregated into a single external zone. The external zone is connected to the CAISO directly and provides the CAISO with dedicated and economic imports. It also takes CAISO exports when economic, subject to the export constraints. The external zone contains the California out-of-state RPS resources, the CAISO non-RPS dedicated imports, the ancillary services and load following provided by out-of-state resources, and a "market station" for economic import and export.

1) Transmission connections

The external zone is connected to PG&E_VALLEY, SCE, and SDG&E zones directly. The ratings of the paths are 7,800 MW, 13,502 MW, and 4,223 MW respectively, each of which are derived from the deterministic model. The CAISO total net import limit is 12,594 MW, which is the maximum net import on July 19, 2024, the peak load day in the deterministic run.[4] All dedicated imports, economic imports, and ancillary services and load-following provided by outside resources are subject to the maximum net import limit.

The paths from the external zone to the three CAISO zones have an import wheeling rate equal to $11.25/MWh. The import wheeling rate is calculated as the average of wheeling rates (including the CO2 cost adders) for the four major CAISO import paths in the deterministic model. Table 1 summarizes the wheeling rates for the four major CAISO import paths and the average rate used in the stochastic model:

Table 1 Import Wheeling Rates ($/MWh)

Import Path	Wheeling Rate	CO2 Cost Adder	Total
NW-PG&E_VALLEY	1.87	2.02	3.89
NEVP-SCE	6.81	10.12	16.93
SRP-SCE	1.97	10.12	12.09
SRP-SDG&E	1.97	10.12	12.09
Average	**3.15**	**8.10**	**11.25**

The CAISO export wheeling rate used in the stochastic model is $9.96/MWh, as was used in the deterministic model.

4 The CAISO annual maximum net import is 12,992 MW in the Trajectory scenario deterministic run. The deterministic model does not have a CAISO total net import limit, but has a 14,142 MW California total net import limit that is shared by the CAISO, IID, LADWP, SMUD, and TIDC.

2) Import from out-of-state RPS resources

RPS solar and wind resources located outside of California are a part of the aggregated solar and wind stochastic variables in the model (see discussion in Section III below). Based on its load and internal RPS generation, CAISO market participants own or have contracted for 31% of total out-of-state RPS generation. As assumed in the deterministic model, the CAISO takes 70% of its share of the out-of-state RPS generation as dedicated (must-take) import. As a result, 21.7% of the total out-of-state RPS generation is modeled as dedicated import to the CAISO. The remainder of the out-of-state RPS generation may come into the CAISO as economic import.

3) Non-RPS dedicated import, ancillary services and load following provided by out-of-state resources

Because out-of-state non-RPS generation resources are not modeled individually in the stochastic model, the dedicated import from Hoover, Palo Verde and similar resources cannot be optimized in the Monte Carlo simulations. In order to model hourly dedicated import values from the non-RPS resources in the stochastic model, the hourly deterministic model dedicated import profile is used as an input. Similarly, the hourly values for ancillary services and load following provided by out-of-state resources in the deterministic model run are also used as inputs to the stochastic model.

4) Market station for economic import and export

The market station in the external zone represents all other generation resources and load in the rest of the WECC. The market station handles the CAISO's economic import and export. To enable the economic import and export capability, a 4-block price curve was developed for the market station. The CAISO derived the price curve based on the market clearing prices (MCPs) in the deterministic model run according to the following steps:

- Calculate hourly average MCPs of three major import zones—NW, NEVP, and SRP—over the course of the 8,784 hours in the deterministic run;
- Sort the hourly average MCPs from low to high and divide into 4 equal groups of 2,196 hours;
- Calculate the average of MCPs of each group to get 4 prices;
- Each block of the curve has a size about 3,149 MW, which is about one fourth of the 12,594 MW CAISO total net import limit. The last block is extended to 15,000 MW.

Table 2 represents the price curve for the market station using the method described above. When the CAISO MCP is higher than the price of the curve plus the import wheeling rate, the CAISO imports economically from the market station, subject to the CAISO net import limit. Conversely, when the CAISO MCP plus export wheeling rate is lower than the price of the first block of the curve, the CAISO exports economically to the market station, subject to the CAISO zero net export constraint.

Table 2 Price Curve of the Market Station

	1	2	3	4
Capacity (MW)	0 -3,149	3,149-6,297	6,297-9,446	9,446-15,000
Price ($/MWh)	28.07	29.96	32	48.23

III. Stochastic Variables

A. Overview of Stochastic Variables

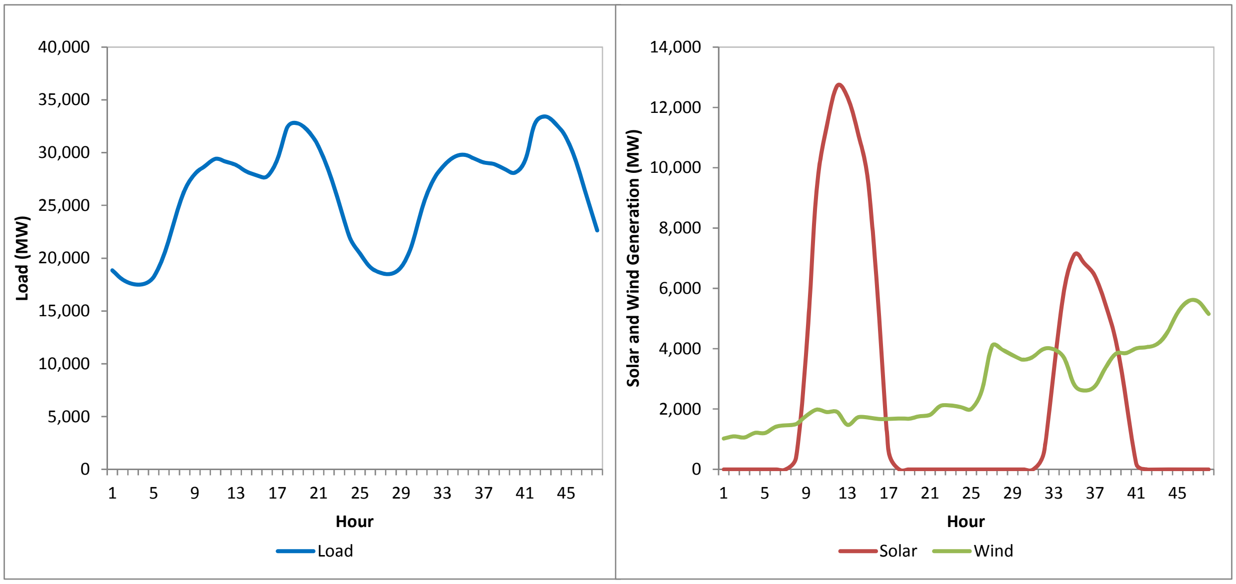
The stochastic variables in CAISO's study were developed based on historical data. The data represent the system conditions that actually occurred in the historical years. To capture a more complete set of possible conditions stochastic variables should also capture system conditions that did not occur, but were possible.

There are different methods of developing stochastic variables. One way is to develop the stochastic variables as stochastic processes or independent random variables in mathematical formulas. The mathematical formulas can generate an unlimited number of samples (draws) for Monte Carlo simulations. The past efforts show that this approach poses a significant challenge in preserving the repeating daily patterns of the variables, such as load and solar generation. As shown in Figure 1, load and solar generation have patterns that repeat every day with small variations. Wind generation does not have such repeating pattern.

Another way to develop stochastic variables is to simply use the scaled historical daily, monthly, or annual profiles for Monte Carlo simulations. In this approach the random variations within the day, month, or year are lost. Such an approach may lead to understatement of the uncertainties of the system. It may especially affect the accuracy of assessing the sufficiency of system flexibility.

The CAISO took a unique approach in developing the stochastic variables for this model. The variables capture the variations of system conditions hour-by-hour chronologically for the whole year and preserve the repetitive daily patterns of the load and solar generation variables. This approach is discussed in detail later in this section.

Figure 1 Hourly Profiles of Load, Solar and Wind Generation



The CAISO's study uses four stochastic variables – forced outage, aggregated load, solar generation and wind generation. The variables are intended to capture the uncertainties that otherwise cannot be explicitly modeled. They do not capture long-term uncertainties such as load growth and installed RPS capacity, or short-term uncertainties such as day-ahead and real-time forecast error. The long-term load growth is taken from the CEC 2013 IEPR forecast. RPS installed capacity is based on the California Public Utilities Commission (CPUC) 2014 LTPP RPS Calculator. The short-term forecast errors are addressed by the calculated regulation and load-following requirements.

Among the stochastic variables, load consists of CAISO total load, excluding the CDWR pump load. Solar generation (including distributed generation photo-voltaic) and wind generation both are the aggregation of the total CAISO internal and out-of-state RPS solar and wind generation. The generated hourly stochastic values of load, solar and wind generation are then allocated to the different zones by the energy ratios of the deterministic model input profiles as provided in Table 3.

Table 3   Load, Solar and Wind Generation Allocation Ratios

	Load	Solar	Wind
PG&E_BAY	20.6%	1.8%	12.9%
DG PV		4.3%	
PG&E_VALLEY	25.5%	18.1%	2.3%
DG PV		6.0%	
SCE	44.4%	47.8%	37.1%
DG PV		6.9%	
SDG&E	9.6%	4.2%	9.3%
DG PV		2.4%	
Out-of-State		8.4%	38.4%
Sum	**100.0%**	**100.0%**	**100.0%**

B. Forced outages

Forced outages are generated for each generation resource over the whole year. The bases for forced outages are the forced outage rates of the resources specified in the model input. The forced outages are generated randomly and independently for each generation resource in each iteration. The converged Monte Carlo method is used in generating the forced outages so that the percent of hours with forced outage is close to the forced outage rates of the resources. The deterministic model also uses the converged Monte Carlo method for generating forced outages.

C. Mean reversion stochastic process

In this model the load, solar generation and wind generation variables are assumed to follow a mean reversion stochastic process.

Equation (1) is a mean reversion stochastic process

$$Y_t = Y_{t-1} + \kappa(\mu - Y_{t-1}) + \varepsilon_t \tag{1}$$

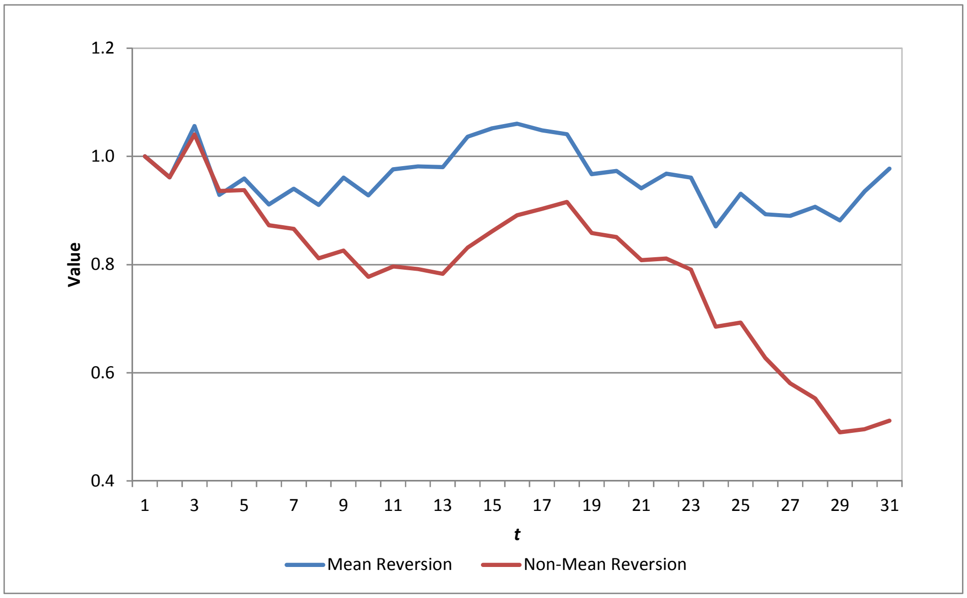
where:

κ – mean reversion rate
μ – long-term mean value
$\varepsilon_t \sim N(0, \sigma)$ – time-independent random error (the drift term) with a zero mean and a constant standard deviation Normal distribution

Equation (1) is basically a random walk with mean reversion. The walk takes one step forward each time. At each step of the walk, there is a random error, ε_t, that affects the direction of the step (the drift). The long-term mean, μ, guides the random walk. When the random walk departs from the long-term mean, a force, the mean reversion, pulls it back toward the mean. The speed of reversion depends on the value of the mean reversion rate, κ (> 0). The larger the value of κ, the faster the reversion. If the value of κ is too large it may cause overcorrection, if it is too small it may result in undercorrection.

Figure 2 demonstrates the differences between two random walks based on the same random error values. The blue line represents a mean reversion random walk and the red line represents a random walk without a mean reversion. The mean reversion walk has a long-term mean of 1.0 and its value varies around the mean as the walk steps forward. The walk without a mean reversion diverges from starting point, thereby is not the correct method for developing the stochastic valuables for this model. The load, solar and wind generation stochastic variables should vary within realistic ranges. A diverged stochastic process does not correctly reflect the realities of these variables.

Figure 2 Mean Reversion vs. Non-Mean Reversion Random Walk



Load, solar and wind generation all have the autocorrelation characteristics built-in the stochastic process. For example, the next hour load is a variation of the current hour load. In other words, the next hour load depends on the current hour load. It is a continuously evolving process. Solar and wind generation, while having natural intermittencies, also demonstrate time dependency relationship for most of the time.

Although load, solar, and wind are all assumed to follow the mean reversion stochastic process, each is defined differently in developing the stochastic variables. Each is based on the overall consideration of their individual daily and weekly patterns (see Figure 1), the volatilities embedded in the historical data, data quality, etc. This is discussed in detail later in this section.

D. Load stochastic variable

The load stochastic variable is developed based on the CAISO 2003-2012 historical hourly load data. The data does not include CDWR pump load.

As discussed above, load has a repetitive daily pattern. A generic mean reversion stochastic process cannot reproduce the daily pattern. Therefore, the CAISO uses a unique approach that combines mean reversion stochastic load ratios and deterministic load profiles to generate stochastic values of the load variable. This is done through the following steps.

1) Align the multi-year historical data with 2024 weekly patterns.

In addition to having a repetitive daily pattern, load also has a repetitive weekly pattern. On weekends load values are usually much lower than on weekdays. In order to calculate hourly load ratios, the weekly patterns of all the data must match correctly. This study is for year 2024, so the weekly pattern of 2024 is used as the basis for aligning historical load data. January 1, 2024 is a Monday. After the alignment, the historical data of each year, from 2003 to 2012, beings with a Monday.

2) Calculate hourly load ratios.

The hourly load ratio is defined as

$$RL_{y,m,d,h} = \frac{L_{y,m,d,h}}{L_{2005,m,d,h}} \qquad (2)$$

where:

$RL_{y,m,d,\text{h}}$ – load ratio of year y month m day d hour h ($y = 2003, 2004, 2006, \ldots, 2012$)
$L_{y,m,d,h}$ – load of year y month m day d hour h

2005 load value is used as the denominator of the ratio because the 2024 deterministic load profile is developed based on the 2005 historical load profile.

3) Estimate mean reversion stochastic process parameters.

Assuming the load ratio, $RL_{y,m,d,\text{h}}$, follows a mean reversion stochastic process

$$RL_t = RL_{t-1} + \kappa(\mu - RL_{t-1}) + \varepsilon_t \qquad (3)$$

where, $\varepsilon_t \sim N(0, \sigma)$

The CAISO ran a regression on the 9 years historical load ratios to estimate the parameters of the stochastic process by season. Table 4 shows the estimated parameters of the load mean reversion stochastic process by season.[5]

[5] Season 1 – December to February; season 2 – March-May; season 3 – June to August; season 4 – September to November

Table 4 Estimated Parameters of the Load Stochastic Variable

	$\hat{\kappa}$	$\hat{\mu}$	$\hat{\sigma}$
Season 1	0.0212	1.0018	0.0105
Season 2	0.0273	1.0011	0.0146
Season 3	0.0074	0.9948	0.0117
Season 4	0.0175	1.0205	0.0153

The estimated parameters suggest the load ratio stochastic process has a long-term mean around 1.0. The standard deviations, σ, are about 1%. The mean reversion rate is also low. That tells us that the load stochastic variable is a relatively smooth and stable process.

4) Generate stochastic values of the load ratios.

Generate 500 iterations (draws) full-year hourly chronological load ratio values, $\widetilde{RL}_{2024,m,d,h,i}$ $(i = 1,2,\cdots,500)$, using equation (3).

5) Calculate stochastic values of the load variable.

Multiply the 500-iteration load ratio stochastic values by the value of the 2024 deterministic load profile to generate the 500-iteration stochastic load values.

$$\tilde{L}_{2024,m,d,h,i} = \widetilde{RL}_{2024,m,d,h,i} \times L_{2024,m,d,h} \tag{4}$$

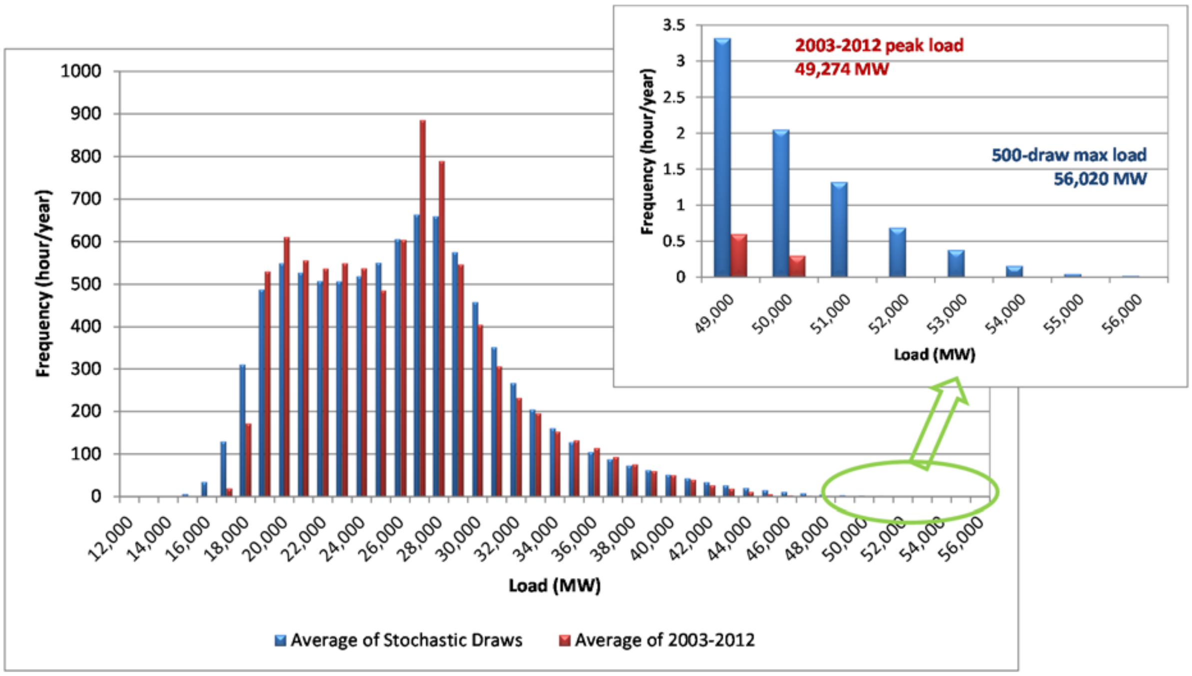
where:

$L_{2024,m,d,h}$ – 2024 deterministic load value of month m day d hour h
$\tilde{L}_{2024,m,d,h,i}$ – 2024 stochastic load value of month m day d hour h iteration i $(i = 1,2,\cdots,500)$

For benchmarking purposes, the CAISO also calculated 500-iteration stochastic load values based on the 2005 historical load profile. That is,

$$\tilde{L}_{2005,m,d,h,i} = \widetilde{RL}_{2024,m,d,h,i} \times L_{2005,m,d,h} \tag{5}$$

Figure 3 Histogram of 2005-Based Stochastic Load and 2003-2012 Historical Load

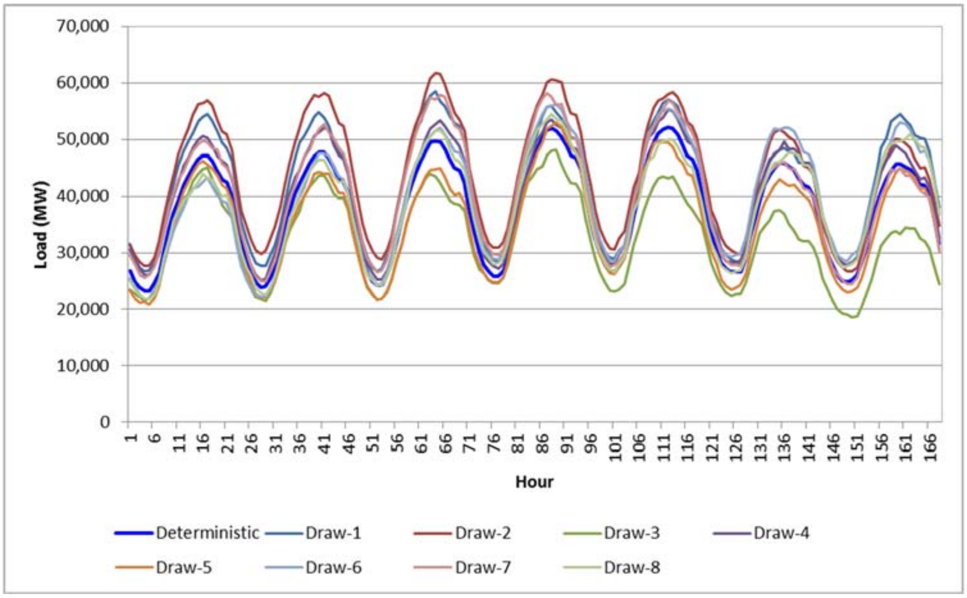


The 2005 based stochastic load values are then benchmarked with the 2003-2012 historical load. Figure 3 shows the histogram comparison of the data. "Average of 2003-2012" represents the frequencies calculated based on the actual observed 2003-2012 hourly load data. The frequencies are then divided by 10, based on the years of observations, and plotted on the histogram. Similarly, "Average of Stochastic Draws" represents the frequencies produced by the 500-iteration hourly 2005-based stochastic load values, divided by 500. In this way the two set of data are on the same scale and directly comparable.

As shown in Figure 3, the two set of data match significantly. As would be expected, the load values from the 500-iteration stochastic draws have a wider distribution range than the range found in the actual 2003-2012 data. On the low end, the stochastic values extended below 16,000 MW, the low end of actual observed hourly loads from 2003-2012 load, to 12,000 MW. On high end, maximum stochastic load values stretched to 56,000 MW, approximately 6,000 MW in excess of actual observed load from 2003-2012. Both the high and low range stochastic results are low probability load conditions that did not actually happen from 2003 to 2012, but were possible, given the parameters of the distribution of the actual data. Capturing these extreme conditions with the stochastic load variable helps to better represent the possible load conditions in the 2024 simulations.

Figure 4 compares the stochastic load profiles with the deterministic load profile for the week of July 15, 2024, the peak load week in the deterministic model. The stochastic load profiles are from the first eight of the 500 draws. Figure 4 shows that the deterministic load profile is within the distribution of the stochastic load profiles. In other words, the deterministic load profile is probably one of the 500 stochastic load profiles.

Figure 4 Week of July 15, 2024 Deterministic and Stochastic Load Profiles



The stochastic load profiles are smooth and have relatively small variations, which is exactly what the estimated parameters indicated. In these stochastic draw values, the peak load is not always on the same day as the deterministic load. This is consistent with the observed 2003-2012 historical load.

Figure 5 Histogram of 2024 Deterministic and Stochastic Load

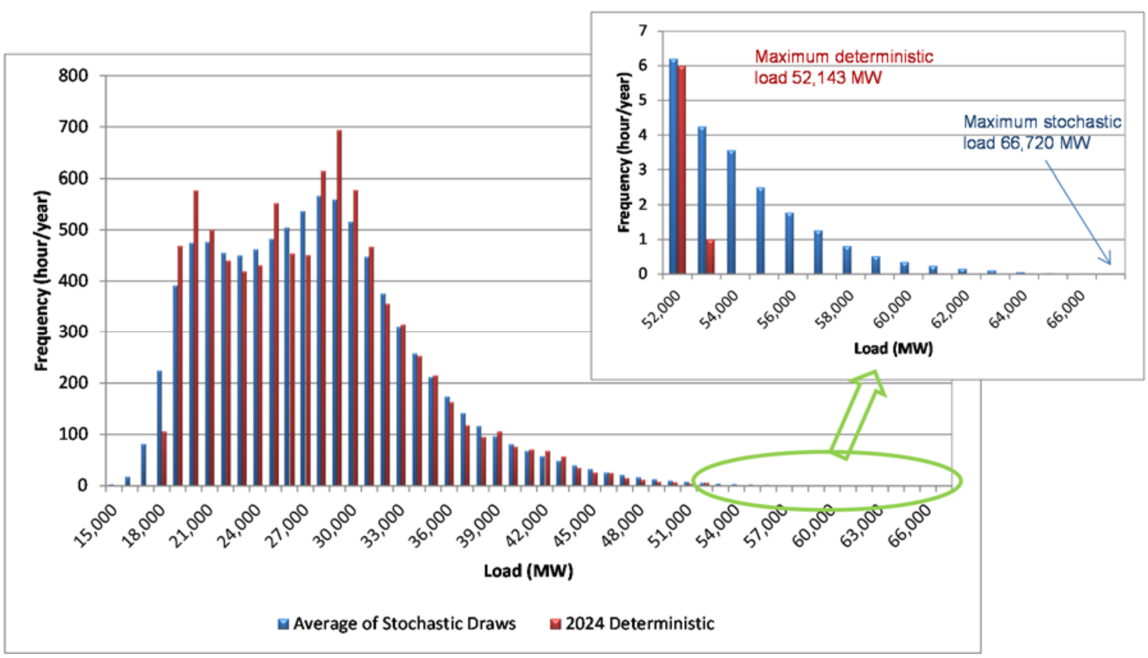


Figure 5 is a histogram of the 2024 deterministic and stochastic load projections, which show that they match significantly. The deterministic load is surrounded by the stochastic load distribution, which indicates that the deterministic load is well represented by the stochastic load. The highest stochastic load value is 66,720 MW, which is 14,577 MW higher than the 52,143 MW highest deterministic load. However, there is a 0.13% per year probability that on average, load will fall in the range of 52,143 and 66,720 MW.

Figure 6 500-Iteration Stochastic Load at July 19, 2024 Hour 16

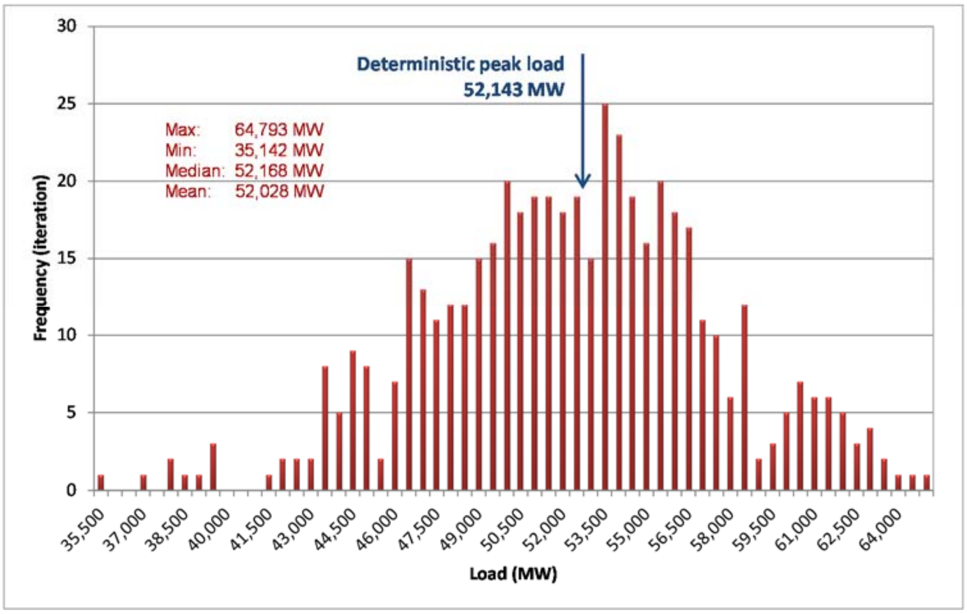


Figure 6 shows the 500 stochastic load values at July 19, 2024, hour 16, the peak load hour in the deterministic model. The values are distributed in the range between 35,142 and 64,793 MW. The median value 52,168 MW is very close to the deterministic peak load, 52,143 MW. This indicates that the deterministic load falls close to the middle of the stochastic load distribution. This is also supported by the information in Figure 4 and Figure 5.

From the above comparison the stochastic load variable demonstrates that it captures the right volatility in the mean reversion stochastic process, covers the small probability but likely load conditions, and preserves the daily and weekly load patterns well.

E. Solar stochastic variable

Solar stochastic variable is developed based on the Clean Power Research 2003-2012 historical hourly "Global Horizontal Irradiance (GHI) W/m2" data. The CAISO obtained the data through Solar Anywhere, which was under contract with the CPUC.

The irradiance is used to approximate relative solar generation. There are 11 sites within the CAISO. The sum of the irradiance of the 11 sites is used to develop the stochastic solar variable. The names of the 11 sites are listed in Table 5.

Table 5 Name of the Sites of Solar Historical Data

Site Name	Site Name	Site Name
Alpine Suntower_PGEVLY	Ivanpah Solar_SCE	SDGE
AV Solar Ranch_PGEVLY	LUZ3_7_SCE	SolarGen2_SDGE
CopperMountain_SCE	LUZ8_9_SCE	TopazSolar_SCE
HighPlains Ranch_PGEVLY	Salton Sea_SDGE	

Similar to load, solar generation also has a repetitive daily pattern. The mean reversion stochastic solar ratios approach is used to generate the stochastic values of the solar variable. Unlike load stochastic variable, which uses only hourly ratios, the solar stochastic variable is built on both hourly and daily solar generation ratios. This is done through the following steps.

1) Align the multi-year historical data with the weekly patterns of 2024

As with the load data, the historical solar data are also aligned with the weekly pattern of 2024. Solar data do not have a weekly pattern. This alignment ensures that the calendar of the solar data match with that of the load data, which is important for enforcing the cross-correlation among load, solar and wind generation.

2) Calculate hourly and daily solar ratios

The hourly and daily solar ratios are defined as

$$RSH_{y,m,d,h} = \frac{SH_{y,m,d,h}}{SH_{2005,m,d,h}} \tag{6}$$

and

$$RSD_{y,m,d} = \frac{SD_{y,m,d}}{SD_{2005,m,d}} \tag{7}$$

where:

$RSH_{y,m,d,\mathrm{h}}$ – solar ratio of year y month m day d hour h ($y \neq 2005$)
$SH_{y,m,d,h}$ – solar irradiance of year y month m day d hour h
$RSD_{\mathrm{y,m,d}}$ – daily solar ratio of year y month m day d ($y \neq 2005$)
$SD_{\mathrm{y,m,d}}$ – average solar irradiance of year y month m day d

The calculated hourly ratios show that for some hours the value of 2005 solar irradiance, $SH_{2005,m,d,h}$ is very small, like the hours at sunrise and sunset. That caused very high hourly solar ratio value, $RSH_{y,m,d,h}$, when the irradiance value of other years, $SH_{y,m,d,h}$, is not so low. That may lead to larger standard deviations in parameter estimation.

3) Estimate mean reversion stochastic process parameters

Assume hourly and daily solar ratios follow mean reversion stochastic processes

$$RSH_t = RSH_{t-1} + \kappa^h(\mu^h - RSH_{t-1}) + \varepsilon_t^h \quad (8)$$

and

$$RSD_t = RSD_{t-1} + \kappa^d(\mu^d - RSD_{t-1}) + \varepsilon_t^d \quad (9)$$

The CAISO ran a regression on the 9 years of historical solar ratios to estimate the parameters of the stochastic process by season. The hours without sunlight are excluded from the regression. Table 6 shows the estimated parameters of the solar mean reversion stochastic process by season.

Table 6 Estimated Parameters of the Solar Stochastic Variable

Hourly	$\hat{\kappa}$	$\hat{\mu}$	$\hat{\sigma}$	Daily	$\hat{\kappa}$	$\hat{\mu}$	$\hat{\sigma}$
1	0.1906	1.2109	0.3749	1	0.5685	1.2120	0.5112
2	0.1852	1.0292	0.2068	2	0.5313	1.0451	0.2788
3	0.4743	1.0453	0.2212	3	0.5365	1.0108	0.1141
4	0.3162	1.1358	0.3346	4	0.6151	1.0671	0.3195

As shown in the table, the solar stochastic processes are more volatile (having larger standard deviation, $\hat{\sigma}$, values) than load. Besides the cause discussed in step 2) above, it also reflects the intermittency of solar generation.

4) Generate stochastic values of the solar ratios

Generate 500 iterations full-year hourly chronological stochastic solar ratio values as

$$\widetilde{RS}_{2024,m,d,h,i} = 0.333 \times \widetilde{RSH}_{y,m,d,h,i} + 0.667 \times \widetilde{RSD}_{y,m,d,i} \quad (10)$$

$(i = 1,2,\cdots,500)$

Using weighted average of hourly and daily ratio is based on the assessment of the volatilities of the final stochastic solar generation values.

5) Calculate stochastic values of the solar variable

Multiply the 500 iterations solar ratio stochastic values by the value of the 2024 deterministic solar profile (including distributed generation photo-voltaic) to generate the 500 iterations stochastic solar values.

$$\tilde{S}_{2024,m,d,h,i} = \widetilde{RS}_{2024,m,d,h,i} \times S_{2024,m,d,h} \quad (11)$$

where:

$S_{2024,m,d,h}$– 2024 deterministic solar generation value of month m day d hour h

$\tilde{S}_{2024,m,d,h,i}$ – 2024 stochastic solar value of month m day d hour h iteration i ($i = 1,2,\cdots,500$)

In calculating the stochastic solar values, the 19,090 MW solar installed capacity is enforced. It sets a maximum limit for the stochastic value. That is $\tilde{S}_{2024,m,d,h,i} \leq 19{,}090$ for all m, d, h, i.

Figure 7 July 18-19, 2024 Deterministic and Stochastic Solar Profiles

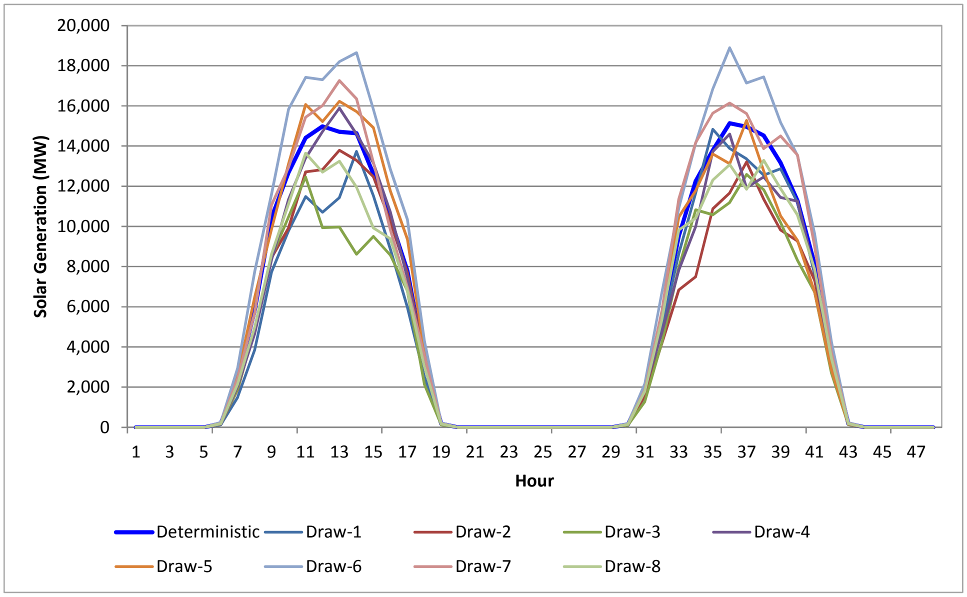
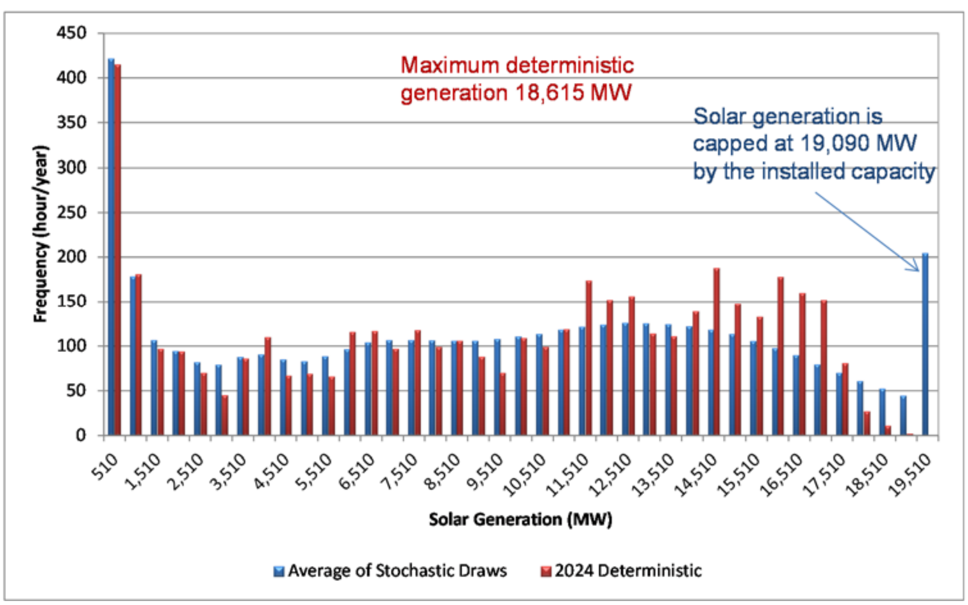


Figure 7 shows the deterministic and stochastic solar profiles of July 18-19, 2024 (the peak load days in the deterministic model) plotted side by side. The stochastic solar profiles are also from the first eight of the 500 draws. Compared to load in Figure 4 solar is more volatile. We discussed the causes of the volatilities earlier in this section. The deterministic solar profile is still within the distribution of the stochastic solar profiles.

Figure 8 Histogram of 2024 Deterministic and Stochastic Solar Generation



As shown in Figure 8 the solar generation has flat histogram. From 1,500 to 18,000 MW the generation in each segment has almost the same number of hours. The stochastic profiles match well with the deterministic, with the exception above 17,500 MW. The stochastic profiles cover more hours in this range. It should be noted that on average there are over 200 hours per year the solar generation is capped by the 19,090 MW installed capacity. The capacity limit certainly has impact on renewable generation curtailment. If there were no installed capacity limit or a higher limit, the renewable generation curtailment could be more.

F. Wind stochastic variable

The wind stochastic variable is developed based on the NREL 2004-2012 hourly simulated wind generation data. The NREL simulation assumes a 30 MW installed capacity at each site. The sum of the simulated generation of 60 sites within the California is used for developing the wind stochastic variable. The locations of the 60 sites are listed in Table 7.

Table 7 Locations of the 60 Sites of Wind Historical Data

Site IDs	Latitude	Longitude	Site IDs	Latitude	Longitude	Site IDs	Latitude	Longitude	Site IDs	Latitude	Longitude
708	32.742	-116.292	2505	34.675	-118.358	3386	35.042	-118.175	9206	37.725	-121.675
709	32.742	-116.275	2506	34.675	-118.342	3387	35.042	-118.158	9207	37.725	-121.658
710	32.742	-116.092	2507	34.675	-118.325	4558	35.342	-118.225	9208	37.725	-121.425
711	32.742	-116.075	2509	34.675	-118.292	4559	35.342	-118.208	9247	37.742	-121.692
712	32.742	-116.058	2572	34.708	-118.325	4560	35.342	-118.192	9248	37.742	-121.675
713	32.742	-115.975	2573	34.708	-118.308	4561	35.342	-118.175	9249	37.742	-121.658
714	32.742	-115.958	2574	34.708	-118.292	4562	35.342	-118.158	9250	37.742	-121.425
715	32.742	-115.942	2575	34.708	-118.275	4563	35.342	-118.142	9251	37.742	-121.408
718	32.758	-116.108	2576	34.708	-118.258	4564	35.342	-118.125	9288	37.758	-121.675
719	32.758	-116.092	3299	35.025	-118.242	4565	35.342	-118.108	9720	38.158	-121.892
720	32.758	-116.075	3381	35.042	-118.258	4566	35.342	-118.092	9721	38.158	-121.875
721	32.758	-116.058	3382	35.042	-118.242	4567	35.342	-118.075	9722	38.158	-121.858
722	32.758	-116.025	3383	35.042	-118.225	4568	35.342	-118.058	9726	38.175	-121.892
723	32.758	-115.975	3384	35.042	-118.208	4569	35.342	-118.042	9727	38.175	-121.875
724	32.758	-115.958	3385	35.042	-118.192	9205	37.725	-121.692	9728	38.175	-121.858

Unlike load and solar generation, wind generation does not have a repetitive daily pattern. The ratio approach used by load and solar is not the best fit for wind. Instead the mean reversion stochastic process is developed directly based on the simulated historical wind generation data. This is done through the following steps.

1) Align the multi-year historical data with the weekly patterns of 2024

The alignment is done for the same reasons as for the solar generation data.

2) Estimate mean reversion stochastic process parameters

Assume hourly and daily simulated wind generation follow mean reversion stochastic processes

$$SWH_t = SWH_{t-1} + \kappa^h(\mu^h - SWH_{t-1}) + \varepsilon_t^h \tag{12}$$

and $$SWD_t = SWD_{t-1} + \kappa^d(\mu^d - SWD_{t-1}) + \varepsilon_t^d \quad (13)$$

where:

$SWH_{y,m,d,\mathrm{h}}$ – simulated wind generation of year y month m day d hour h

$SWD_{y,m,d}$ – average simulated wind generation of year y month m day d

The CAISO ran a regression on the 9 years historical simulated wind generation data to estimate the parameters of the stochastic process by season. In Table 8 are the estimated parameters of the wind mean reversion stochastic process by season.

Table 8 Estimated Parameters of the Wind Stochastic Variable

Hourly	$\hat{\kappa}$	$\hat{\mu}$	$\hat{\sigma}$	Daily	$\hat{\kappa}$	$\hat{\mu}$	$\hat{\sigma}$
Season 1	0.0224	342.88	65.50	Season 1	0.5030	343.88	233.41
Season 2	0.0286	576.38	80.33	Season 2	0.5123	576.90	227.03
Season 3	0.0309	580.59	86.18	Season 3	0.3124	581.35	166.91
Season 4	0.0238	364.69	68.35	Season 4	0.4730	363.42	217.69

The estimated parameters indicate the wind mean reversion stochastic process is volatile. The volatilities mostly come from the intermittency of wind generation.

3) Generate stochastic values of the simulated wind generation

Generate 500 iterations full-year hourly chronological stochastic simulated wind generation values as

$$\widetilde{SW}_{2024,m,d,h,i} = 0.333 \times \widetilde{SWH}_{y,m,d,h,i} + 0.667 \times \widetilde{SWD}_{y,m,d,i} \quad (14)$$

$$(i = 1,2,\cdots,500)$$

The weighted average of hourly and daily ratio is also based on the assessment of the volatilities of the final stochastic wind generation values.

4) Calculate stochastic values of the wind variable

In calculating the stochastic value of wind variable, the 500 iterations stochastic values of the simulated wind generation are normalized by dividing the estimated long-term mean of the season. This normalization is done to ensure that the mean of the stochastic wind values align with the mean of the deterministic wind profile. The normalized stochastic values of simulated wind generation are then multiplied by the value of the 2024 deterministic wind profile to generate the 500 iterations stochastic wind values. That is,

$$\widetilde{W}_{2024,m,d,h,i} = \frac{\widetilde{SW}_{2024,m,d,h,i}}{\hat{\mu}_s} \times W_{2024,m,d,h} \quad (15)$$

where:

$W_{2024,m,d,\mathrm{h}}$ – 2024 deterministic wind generation value of month m day d hour h

$\hat{\mu}_s$ – estimated long-term mean value of season s ($s = 1,2,3,4$)

($i = 1,2,\cdots,500$)

The stochastic wind generation values are also capped the 10,728 MW wind installed capacity.

Figure 9 July 18-19, 2024 Deterministic and Stochastic Wind Profiles

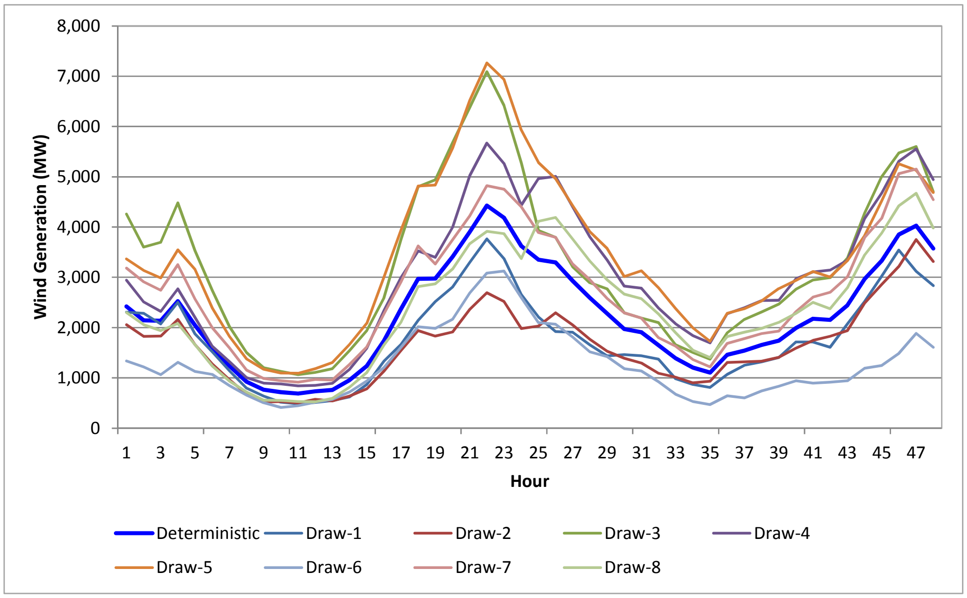
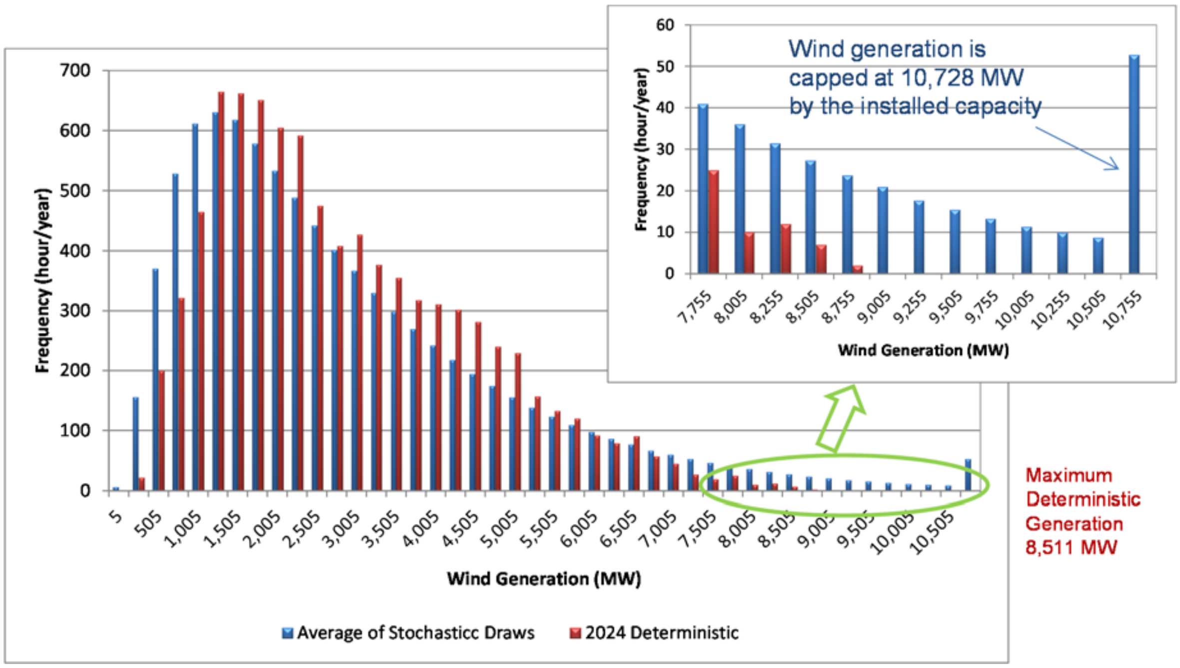


Figure 9 shows the deterministic and stochastic wind profiles of July 18-19, 2024. The stochastic solar profiles are also from the first eight of the 500 draws. The stochastic wind profiles display proper variations around the deterministic profiles.

Figure 10 Histogram of 2024 Deterministic and Stochastic Wind Generation



As shown in Figure 10, the wind generation is distributed toward the low end and concentrated in the range between 5 to 35% of installed capacity. The deterministic profile stretches to the high end, with maximum generation of 8,511 MW. The frequency of wind output diminishes quickly as the output approaches the maximum installed capacity level. The stochastic profiles reach out to the installed capacity limit, 10,728 MW. They have higher probability in the high end than the deterministic profile. On average, there are 53 hours per year the wind generation will reach the cap set by the installed capacity.

G. Correlations

Forced outages are independent of all other stochastic variables. There is no correlation with other variables.

Load, solar and wind generation stochastic variables are developed based on mean reversion stochastic process. The stochastic process is auto-correlated.

Load, solar and wind generation stochastic profiles are all variations of their 2024 deterministic profiles. That can be seen from equation (4), (11), and (15). The cross-correlations among the deterministic load, solar and wind generation profiles are reflected in the stochastic load, solar and wind generation profiles. Therefore there is no need to apply additional cross-correlations.

In Table 9 are the correlation matrixes calculated by season based on the 2024 deterministic load, solar and wind generation profiles. Load and solar are moderately positively correlated in season 2, 3, and 4. Wind is uncorrelated with load and solar.

Table 9 Correlation Matrixes Calculated Based on the 2024 Deterministic Profiles

Season		Load	Solar	Wind	Season	Load	Solar	Wind
1	Load	1			3	1		
	Solar	0.2935	1			0.4445	1	
	Wind	-0.0695	-0.0129	1		-0.0750	-0.1940	1
2	Load	1			4	1		
	Solar	0.4774	1			0.4320	1	
	Wind	0.0034	-0.0722	1		-0.1185	-0.0823	1

IV. Monte Carlo Simulations

In preparing for the Monte Carlo simulations, the stochastic model was first benchmarked with the deterministic model. To do so, the CAISO ran the stochastic model using the 2024 deterministic load, solar and wind generating profiles as inputs, and using the forced outages fixed to the forced outages used in the deterministic model. The CAISO ran one iteration of the stochastic model with these deterministic inputs and compared the results with that of the deterministic model, focusing on the capacity shortfall and renewable generation curtailment. The stochastic model results are very close to the deterministic model results.

The Monte Carlo simulations are 500 iterations of full-year hourly chronological simulations. In order to reduce run time, the simulations were spread onto multiple computers running in parallel. The 500-iteration stochastic values of load, solar and wind generation were generated prior to the simulation so that the inputs on all the computers are consistent. Forced outage schedules were generated randomly during the simulation. Seeds for generating the random forced outages were set up such that the forced outage schedules are unique in each iteration of the Monte Carlo simulations. Using seed control also ensures that the results can be replicated in re-run of the model.

V. Simulation Results

The stochastic model generated significantly more information than the deterministic model. To manage simulation times and to concentrate on answering the key questions, the simulation reported only the capacity shortfall and renewable generation curtailment by hour and by iteration.

Based on the results histograms were created to compare the stochastic results with the deterministic results. The stochastic results were also measured against the 1 day-in-10 years reliability standard.

A. Capacity shortfall

In the deterministic model run there are 5 hours with capacity shortfall, all in July 2024. The maximum shortfall is 1,489 MW. In the stochastic model Monte Carlo simulations in average there are 19.9 hours with capacity shortfall. The capacity shortfall increased significantly, with the maximum shortfall of 16,745 MW.

Table 10 compares the monthly capacity shortfall results of the stochastic and deterministic model runs. In the "500 Iterations Average" section the "Number of Hours" and "Shortfall (GWh)" are average per iteration. "Max Shortfall (MW)" is the maximum shortfall for all iterations in a month. As shown in the table, the 500-iteration average annual number of hours with capacity shortfall almost quadrupled. The stochastic total shortfall (GWh) is more than 15 times higher than the deterministic run. While the expected and maximum shortfalls are shown in Table 10, the entire distribution is provided in Figure 11 below. Any decision about need for capacity should be made based on the distributional results. The numbers in Table 10 are intended for comparison purpose only.

Table 10 Summary of the Stochastic and Deterministic Capacity Shortfall

Month	5	6	7	8	9	10	11	Annual
500-Iteration Average								
Number of Hours	0.0	0.3	16.7	2.5	0.3	0.0	0.0	19.9
Max Shortfall (MW)	0.12	6,462	16,745	9,543	5,164	3,555	1,460	16,745
Shortfall (GWh)	0.00	0.43	46.34	4.34	0.46	0.02	0.01	51.60
Deterministic								
Number of Hours			5					5
Max Shortfall (MW)			1,489					1,489
Shortfall (GWh)			3.22					3.20

The frequency distributions of the capacity shortfall are plotted in Figure 11.[6] The stochastic model yields a much wider range of potential system conditions, including instances with low supply or high load. 11.6 out of the total 19.9 hours per year have capacity shortfalls higher than the 1,489 MW deterministic run maximum shortfall. In total, only one hour of the 500-iteration simulations with a capacity shortfall had solar generation capped at the installed capacity. The installed capacity limit does not have much impact on the volume and frequency of capacity shortfall. Wind generation never reaches the cap during the hours with capacity shortfall.

[6] "Average of 500 Iterations" is the frequencies of all 500-iteration hourly capacity shortfall values divided by 500.

Figure 11 Histogram of Deterministic and Stochastic Capacity Shortfall

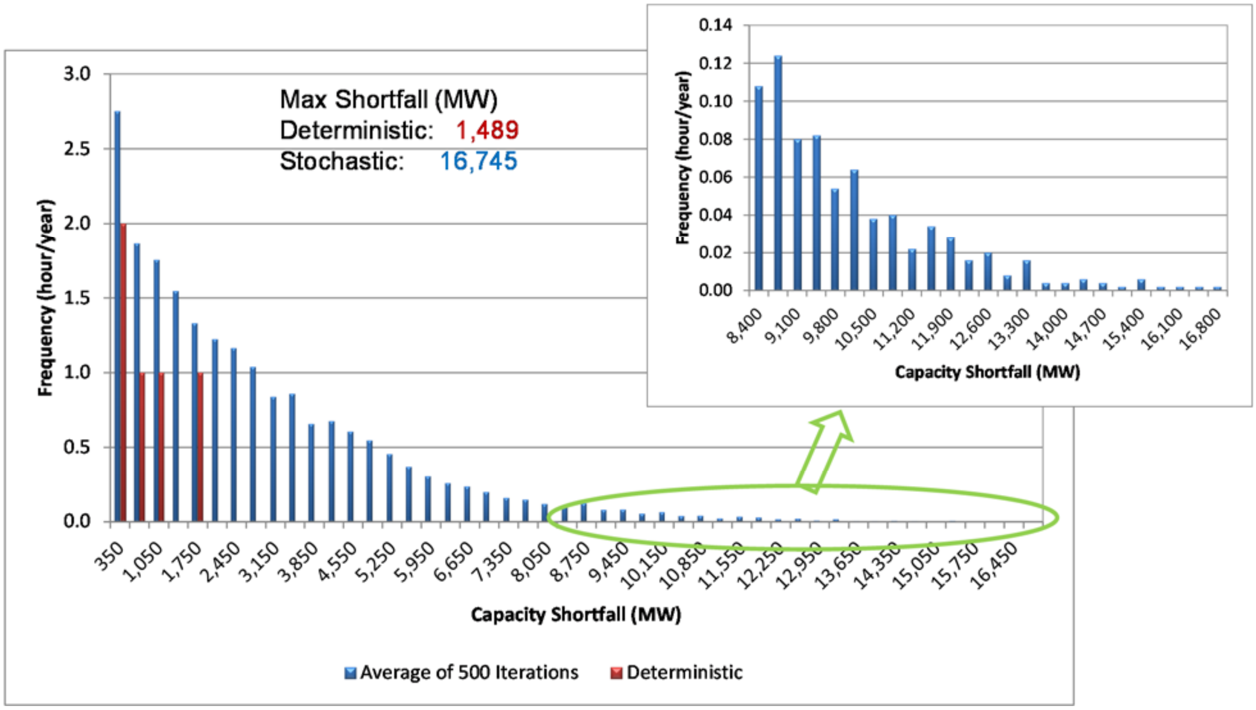


Table 11 shows the frequencies of capacity shortfalls by month and by hour in the stochastic and deterministic model runs. In the deterministic run capacity shortfalls occur only in July. The stochastic model run has capacity shortfalls from May to November, but primarily in July and August. The most frequent capacity shortfalls occur in July, from hour 18 to 21, roughly the same hours capacity shortfalls were found in the deterministic run. The CAISO notes that these shortfalls occur after the peak load hour. The deterministic model results showed the drop-off of solar generation is faster than the load during these hours. The stochastic model simulation results confirmed that finding.

Table 11 Frequency of Capacity Shortfall by Month and Hour of Day

	Stochastic - 500 Iterations Average							Deterministic
Hour of Day/Month	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**7**
11			0.006					
12			0.018					
13			0.058	0.002				
14			0.220	0.004				
15			0.460	0.014				
16			0.956	0.060	0.002			
17		0.026	1.840	0.262	0.018			
18	0.002	0.048	3.054	0.758	0.104	0.004	0.012	2
19		0.098	3.904	0.648	0.054	0.004	0.010	2
20		0.034	2.320	0.334	0.086	0.018	0.002	1
21	0.008	0.034	2.260	0.342	0.052	0.002		
22		0.018	1.336	0.074				
23			0.254	0.012				
24			0.038					
Sum	**0.010**	**0.258**	**16.724**	**2.510**	**0.316**	**0.028**	**0.024**	**5**

The CAISO measured the stochastic simulation results against the 1 day-in-10 years reliability standard to determine if the system has sufficient installed capacity to meet load. The 1 day-in-10 years standard was originally developed based on daily peak load. To apply this standard to hourly simulations, additional studies were conducted to find the equivalent standard. The CAISO used the equivalent of 7 hours-in-10 years, or 0.7 hours-in-1 year in order to determine the capacity shortfalls to be eliminated based on this reliability standard.[7] Using this standard and the hourly by iteration Monte Carlo simulation results, it is easy to find the value of capacity shortfall that needs to be eliminated in order to meet the reliability standard.

In the 500-iteration full-year hourly Monte Carlo simulation, each iteration represents one year. As a result, the CAISO produced Monte Carlo simulations represent a total of 500 years. To meet the reliability standard referenced above, capacity shortfalls are allowed in 0.7 hours per year. Because the CAISO's Monte Carlo results produce 500 years of data, the total hours of allowable capacity shortfall are equal to 0.7 x 500 = 350 hours. As a result, the 351st largest shortfall must be identified and eliminated to meet this reliability standard. The hourly capacity shortfall can be sorted from high to low to find the 351st largest shortfall and thereby determine the value of capacity needed to eliminate all by the 350 greatest hours of shortfall produced by the simulations.

7 See Appendix B – "Probability Fundamentals and Models in Generation and Bulk System Reliability Evaluation," Roy Billinton, NERC Workshop, October 16-18, 2013, Mesa, Arizona

Table 12 shows the sorted capacity shortfalls from the 500-iteration Monte Carlo simulations. The 351st largest shortfall is 8,292 MW. 8,292 MW of capacity shortfall must be eliminated to meet the 1 day-in-10 years reliability standard.

Table 12 Sorted Capacity Shortfalls from Monte Carlo Simulations

Order #	Capacity Shortfall (MW)
1	16,745
2	16,408
3	15,879
…	
350	8,297
351	**8,292**

There are other interpretations of the 1 day-in-10 years standard. The capacity shortfalls reported in the Table 10, Table 11, and Table 12 include deficiencies in load following-up, non-spinning, spinning, regulation-up and unserved energy. Some parties suggest reviewing capacity shortfalls corresponding to the CAISO staged emergencies. According to the CAISO operating procedures, Stage-1 emergency will declared if operating reserves fall below 7% of load.[8] In this study this is equivalent to a shortfall in non-spinning, spinning, regulation-up or unserved energy. Similarly a Stage-3 emergency will be declared if the operating reserves fall below 3% of load. In this study, a Stage-3 emergency is equivalent to a shortfall in spinning, regulation-up, or unserved energy.

As shown in Figure 5, the stochastic load reached values in excess of 60,000 MW based on the characteristics of the stochastic load variable. The CAISO conducted additional analysis to determine the impact these outlier load events had on capacity shortfalls. To do so, the CAISO analyzed the results with maximum stochastic load limit set at the California Energy Commission's (CEC's) projected 1-in-10 peak load forecast for 2024, approximately 58,000 MW.[9] For hours with a capacity shortfall, if the stochastic load value was higher than the limit, the amount in excess of the limit was reduced from the shortfall.

Table 1513 provides a comparison of the total, Stage-1, and Stage-3 capacity shortfalls to be eliminated to meet the standard with different interpretations, with and without the 58,000 MW maximum load limit.

[8] The CAISO Emergency Fact Sheet at http://www.caiso.com/Documents/EmergencyFactSheet.pdf

[9] 58,000 MW approximates the CEC 2013 IEPR High Load (1-in-10) CAISO coincident peak load forecast with AAEE adjustment.

Table 13 Capacity Shortfalls Based on Different Reliability Standards[10]

Reliability Standard (hours-in-1 year)	0.1	0.7	2.4
Without Maximum Load Limit			
Shortfall (MW)	11,822	8,292	5,414
Stage-1 Shortfall (MW)	10,500	6,930	4,050
Stage-3 Shortfall (MW)	9,145	5,521	2,690
With 58,000 MW Maximum Load Limit			
Shortfall (MW)	10,635	7,660	5,158
Stage-1 Shortfall (MW)	9,276	6,370	3,811
Stage-3 Shortfall (MW)	7,948	5,023	2,470

The stochastic model does not include 2,315 MW of Track 1 and Track 4 capacity that the CPUC has authorized. Even assuming that 2,315 MW is "perfect" capacity, a capacity shortfall persists based on the 1-day-in-10 years standard, according to the results in Table 13.

Table 14 provides a different view of the capacity shortfall results to help understand the high-end tail of the capacity shortfall distribution. It sets another reference framework for determining the need for capacity. Table 14 represents the total, Stage-1 and Stage-3 capacity shortfalls, with and without the 58,000 MW maximum load limit, at 100, 97.5, 95, 90, and 75th percentile values. As the results indicate, the capacity shortfalls above 9,000 MW are small probability events. The capacity shortfalls need to be eliminated to meet the 0.7 hours-in-1 year reliability standard in Table 13 fall in the range of 97.5 and 90th percentile values of the capacity shortfalls.

Table 14 Capacity Shortfall by Percentile Values

Percentile	100	97.5	95	90	75
Without Maximum Load Limit					
Shortfall (MW)	16,745	8,924	7,465	5,861	3,782
Stage-1 Shortfall (MW)	15,380	8,529	7,214	5,595	3,534
Stage-3 Shortfall (MW)	14,000	8,087	6,608	5,202	3,095
With 58,000 MW Maximum Load Limit					
Shortfall (MW)	13,150	8,349	6,991	5,589	3,646
Stage-1 Shortfall (MW)	11,820	7,865	6,730	5,365	3,365
Stage-3 Shortfall (MW)	10,405	7,075	6,138	4,810	2,955

B. Renewable generation curtailment

Renewable generation curtailment is unlimited in both the deterministic and stochastic models. The curtailment may mask need for flexibility when a limit on renewable generation curtailment

10 0.1 days-in-1 year standard is an interpretation of the *1 day*-in-10 years, which is not the same as the *1 event*-in-10 years standard.

is established. It is therefore important to understand how much renewable generation is curtailed, how frequently curtailment occurs and at what time it is likely to occur. The next step in this process will be to understand the impact of curtailment on system flexibility need.

Table 15 compares the monthly renewable generation curtailment results of the deterministic and stochastic model runs. In the “500-Iteration Average” section the “Number of Hours” and “Curtailment (GWh)” are average per iteration. “Max Curtailment (MW)” is the maximum shortfall of all iterations of the month. The number of hours, maximum curtailment, and curtailment are more than doubled from the deterministic results. The CAISO also notes that in the 500-iteration average 69 of the 29 hours of curtailment have solar generation, wind generation or both capped at installed capacity. The curtailment could be higher if there was no installed capacity limit or a higher limit.

Table 15 Summary of the Stochastic and Deterministic Renewable Curtailment

Month	1	2	3	4	5	6	7	8	9	10	11	12	Annual
500-Iteration Average													
Number of Hours	10.6	12.5	40.9	61.5	34.9	15.6	2.3	0.3	3.8	5.2	8.7	12.7	209
Max Curtailment (MW)	8,303	8,178	12,393	11,022	10,244	8,808	5,529	3,937	8,045	7,379	7,240	9,436	12,393
Curtailment (GWh)	16.9	19.4	93.4	135.7	71.6	24.8	2.7	0.2	4.0	6.1	10.8	21.4	407
Deterministic													
Number of Hours		2	26	47	16	5							96
Max Curtailment (MW)		243	5,927	5,410	2,984	2,025							5,927
Curtailment (GWh)		0.5	48.4	76.7	21.7	6.2							153

Figure 12 compares the distributions of the deterministic and stochastic model results of renewable generation curtailments. In the stochastic model simulations the renewable generation curtailment is more frequent and has a much higher single-hour curtailment volume.

Figure 12 Histogram of Deterministic and Stochastic Renewable Curtailment

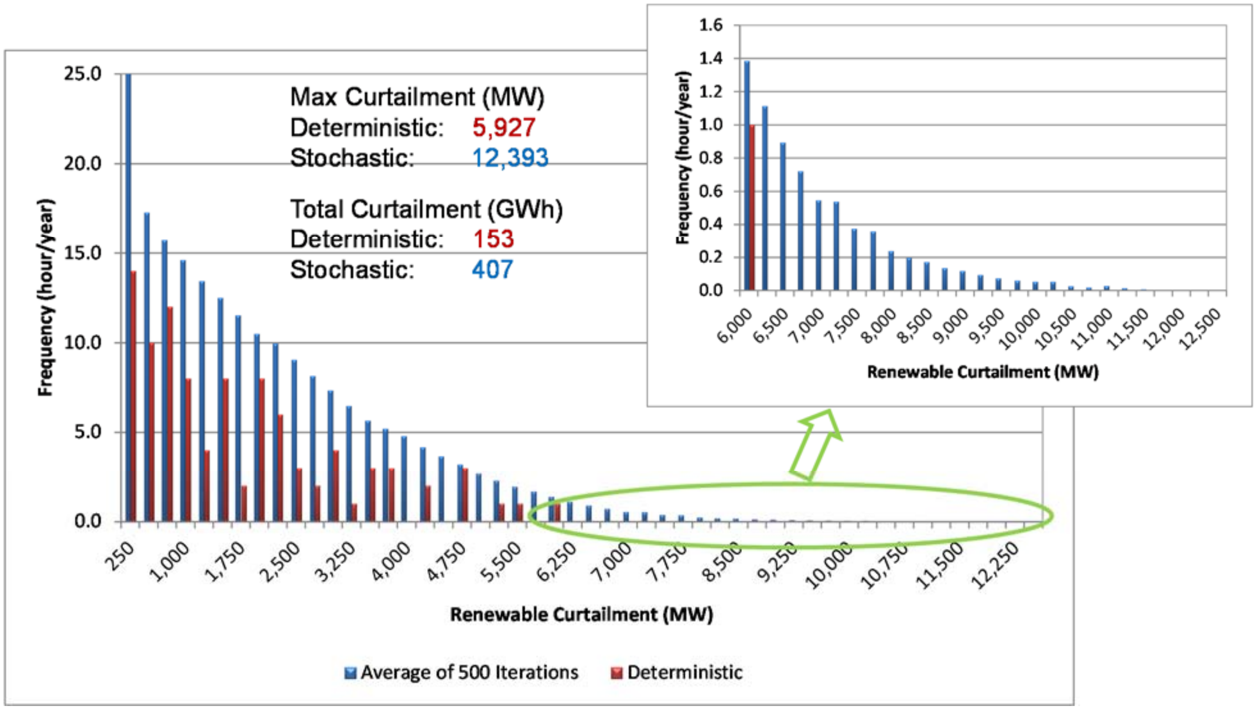


Table 16 shows the frequencies of renewable generation curtailment by month and by hour in the stochastic and deterministic model simulations. In the deterministic run renewable curtailments occur between February and June. The stochastic model simulations show curtailment every month in the year. In both models the highest level of curtailments occur in March and April and in hours 10 to 15.

Table 16 Frequency of Renewable Curtailment by Month and Hour of Day

	Stochastic - 500 Iterations Average												Deterministic				
Hour of Day/Month	1	2	3	4	5	6	7	8	9	10	11	12	2	3	4	5	6
1				0.002													
2					0.002	0.002											
3					0.002	0.004											
4					0.004												
5				0.002	0.002												
6					0.002	0.002											
7					0.016	0.024											
8			0.100	0.352	0.746	0.296	0.054		0.020					1	1		
9	0.002	0.126	2.102	4.430	3.790	1.502	0.382	0.028	0.368	0.216	0.066	0.038		3	5	2	
10	0.604	0.838	4.986	8.076	5.832	2.422	0.530	0.050	1.076	0.676	1.074	1.080		3	8	3	1
11	1.394	1.550	6.166	9.584	5.900	2.698	0.462	0.092	0.676	0.726	1.452	1.872		5	10	4	1
12	1.954	2.190	6.746	10.172	5.564	2.690	0.380	0.058	0.542	0.930	1.864	2.454	1	7	10	3	1
13	2.376	2.648	6.990	10.022	5.352	2.558	0.300	0.044	0.482	1.134	2.052	2.936	1	4	7	2	1
14	2.160	2.536	6.514	8.942	4.142	1.950	0.126	0.018	0.414	0.964	1.524	2.658		2	6	2	1
15	1.600	1.846	5.016	7.116	2.640	1.108	0.016	0.002	0.212	0.478	0.654	1.538		1			
16	0.500	0.722	2.104	2.722	0.888	0.304			0.038	0.064	0.014	0.114					
17			0.148	0.078	0.036	0.026			0.002								
Sum	**10.6**	**12.5**	**40.9**	**61.5**	**34.9**	**15.6**	**2.3**	**0.3**	**3.8**	**5.2**	**8.7**	**12.7**	**2**	**26**	**47**	**16**	**5**

C. Stability of the results

Run time is the obstacle to achieving a larger number of iterations in the Monte Carlo simulation. To understand the stability of the simulation results, a summary of the simulation results with different numbers of iterations is presented in Table 17. As shown in the table the results become relatively stable starting from 300 iterations. The maximum capacity shortfall has a jump from 450 to 500 iterations. That is an indication that 500 iterations are may not be sufficient. Running more iterations would increase capacity shortfall and renewable generation curtailment slightly, but not significantly.

Table 17 Simulation Results with Different Number of Iterations

Number of Iterations	100	150	200	250	300	350	400	450	500
All-Iteration Average - Capacity Shortfall									
Number of Hours	21.7	20.5	20.3	20.1	19.8	19.6	19.5	19.4	19.9
Shortfall (GWh)	56.0	52.8	51.8	50.6	49.6	49.6	49.2	49.4	51.6
All-Iteration Average - Curtailment									
Number of Hours	207.8	210.9	208.2	207.3	208.4	208.3	209.0	209.3	208.9
Curtailment (GWh)	400.8	414.6	408.2	405.7	408.9	407.1	408.6	408.0	406.9
All-Iteration Maximum									
Shortfall (MW)	15,301	15,301	15,301	15,879	15,879	15,879	15,879	15,879	16,745
Curtailment (MW)	10,805	11,174	11,174	11,174	11,174	11,174	12,393	12,393	12,393
Capacity Shortfall To Be Eliminated To Meet 1 day-in-10 years Standard									
Shortfall (MW)	8,322	8,318	8,292	8,212	8,005	8,005	7,948	8,093	8,292

VI. Summary

A. Findings from the simulations

1) The stochastic model run identified a need for capacity based on the 1-day-in-10 years reliability standard.

2) Renewable generation curtailments in the stochastic model run are more than double those found in the deterministic model run.

3) Renewable curtailment was affected by the installed capacity limit. In average, 70 out of the 210 hours per year with curtailment have either solar generation, wind generation, or both, capped by installed capacity. Renewable curtailment could be higher if there were no installed capacity limit or a higher limit.

4) In some of the iterations the 33% RPS goal may not be met even with no curtailment. That is due to the variations of load, solar and wind generation. Iterations in which solar or wind generation is capped by installed capacity are more likely to not meet the 33% RPS goal.

5) The deterministic Trajectory scenario is a relatively mild case compared to the 500 cases the stochastic model simulated. It does not have a high level of capacity shortfall or renewable generation curtailment. The stochastic model uncovered more extreme system conditions

that have either significant supply shortfalls or significant over-generation. These system conditions are not captured by the deterministic model.

6) The stochastic results align well with the deterministic results through benchmarking the model and through developing the stochastic variables that have the deterministic input variable distributions surrounded by the stochastic input variable distributions. The results of the two models support each other.

B. Advantages of the modeling approach

1) The stochastic model is almost identical to the deterministic model that is familiar to the LTPP parties.
2) The approach using mean reversion stochastic process and deterministic input profiles to generate stochastic variables preserves the daily patterns of load and solar generation and their volatilities. It also captures the intra-day volatilities.
3) The stochastic model has auto-correlation and cross-correlation embedded in the stochastic variables. There is no need to apply additional correlation.
4) The stochastic variables capture not only the normal system conditions, but also the extreme conditions that did not happen in the historical data set, but were possible.
5) Any number of independent samples (draws) can be generated to meet the need of Monte Carlo simulations.
6) Full-year hourly chronological sampling aligns the stochastic variables values with other deterministic input, such as the generation profiles for run-of-river hydro, CDWR pump load, maintenance outage schedules, etc. It ensures the model produces results consistent with that of the deterministic model.
7) The full-year hourly chronological Monte Carlo simulations capture every occurrence of capacity shortfall and renewable curtailment. There is no need to approximate results of some time periods of the year with that of other periods.
8) The full-year hourly iteration simulation results can be easily processed to measure against the 1 day-in-10 years reliability standard and to answer different questions about the sufficiency of system capacity and flexibility for renewable integration.

APPENDIX B

Probability Fundamentals & Models in Generation & Bulk System Reliability Evaluation

Roy Billinton
Power System Research Group
University of Saskatchewan

Short Course Agenda: Probability Fundamentals and Models in Generation and Bulk System Reliability Evaluation

October 16, 2013 | 8:00 a.m.-5:00 p.m. MST
October 17, 2013 | 8:00 a.m.-4:30 p.m. MST
October 18, 2013 | 8:00 a.m.-12:00 p.m. MST

Phoenix Marriott Mesa
200 North Centennial Way
Mesa, AZ 85201
(480) 898-8300

Instructor Biography

***Dr. Roy Billinton**, during his 50-year career, has been instrumental in the development of many of the statistical quantities and applications of probability theory methods now considered common in the industry for the planning, design and operation of electric power systems. He currently serves as an emeritus professor in the department of electrical and computer engineering at the University of Saskatchewan (Saskatoon, Saskatchewan) in Canada and has mentored over 130 Master and Ph.D. students.*

Dr. Billinton has authored or co-authored eight books on reliability evaluation and over 940 papers on power system reliability evaluation, economic system operation and power system analysis, and is a Fellow of the IEEE, the EIC, the Canadian Academy of Engineering and the Royal Society of Canada. He is also a Foreign Associate of the US National Academy of Engineering. He was Chair of the Canadian Electrical Association, Consultative Committee on Outage Statistics and is a Professional Engineer in the Province of Saskatchewan.

Dr. Billinton has provided consulting services to virtually all the major Canadian electric power utilities and many other organizations around the world. Over 100 individual utility courses dealing with power system reliability evaluation have been presented.

Probability Fundamentals and Models in Generation and Bulk System Reliability Evaluation

Roy Billinton
Power System Research Group
University of Saskatchewan
CANADA

1

Mission Reliability

Reliability is the **probability** of a device or system performing its **purpose adequately** for the **period of time intended** under the **operating conditions encountered.**

C.R. Knight, E.R. Jervis, G.R. Herd, "Terms of Interest in the Study of Reliability", IRE Transactions on Reliability and Quality Control. Vol. PGRQC-5, April 1955, pp. 34-56.

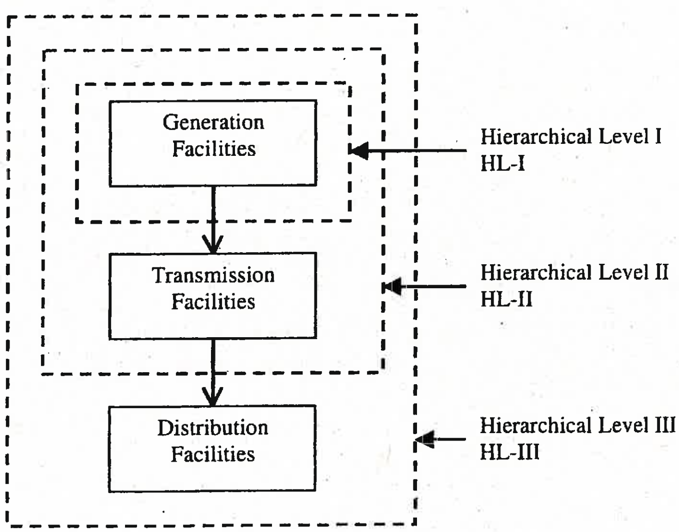
2

Generating Capacity Reliability Evaluation

Roy Billinton
Power System Research Group
University of Saskatchewan
CANADA

1

Functional Zones and Hierarchical Levels



2

Period Analysis

$$LOLE = \sum_{p=1}^{n} LOLE_p$$

$$LOEE = \sum_{p=1}^{n} LOEE_p \quad \text{and} \quad UPM = \frac{LOEE}{\text{Annual Energy Demand}} \times 10^6$$

where, n = number of sub-periods within the total period

$LOLE_p$ = LOLE for sub-period p

$LOEE_p$ = LOEE for sub-period p.

n = 12 in monthly analysis
= 4 in seasonal analysis

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- **Different reliability indices are obtained using different load models.**
- **The LOLE index in hours is obtained using hourly load values.**
- **The LOLE index in days is evaluated using daily peak load values.**
- **It is not valid to obtain the LOLE in hours by multiplying the days/year value by 24. The commonly used index of 0.1 days/year, which is often expressed as one day in ten years, cannot be simply converted to an equivalent index of 2.4 hours/year. This is because the hourly load profile is normally different from that of the daily peak load.**

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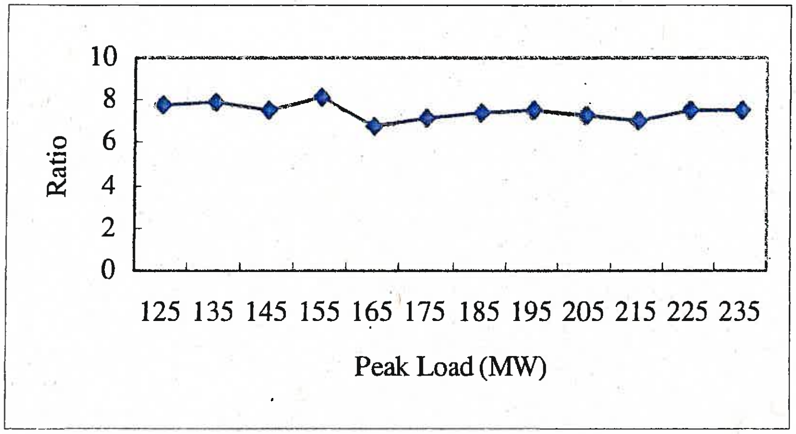
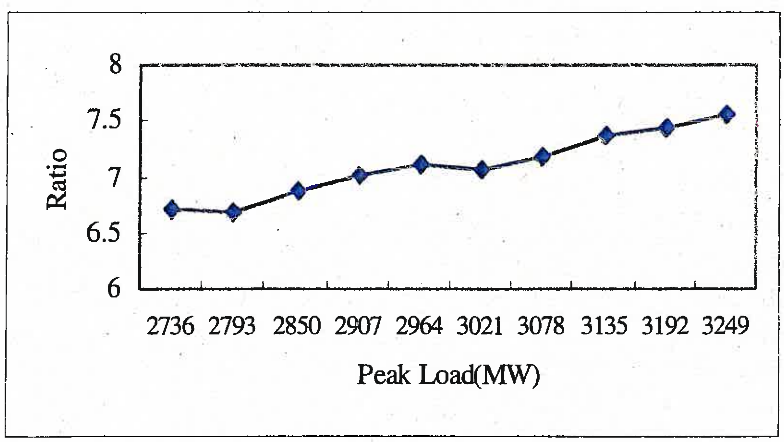
Ratio of the LOLE (hours/year) over the LOLE (days/year) for the RBTS



81

Ratio of the LOLE (hours/year) over the LOLE (days/year) for the IEEE-RTS



82

LOLE(hours/year) and LOLE (days/year)

The LOLE in days/year provides a more pessimistic appraisal than that given by the LOLE in hours/year. The two test systems have the same normalized chronological hourly load model and therefore the same daily and annual load duration curves. The system load factor is 61.44%. The ratio difference in the two test systems is therefore due to the different generation compositions.

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The reciprocal of the LOLE in years per day is often misinterpreted as a frequency index. As an example, the commonly used LOLE index of 0.1 days/year is often expressed as one day in ten years and extended to mean "once in ten years". This is not a valid extension and has a frequency of load loss connotation that is not present in the LOLE index. In order to illustrate this, a comparison of the LOLE (days/year) and LOLF (occ/year) indices was conducted using the two test systems.

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