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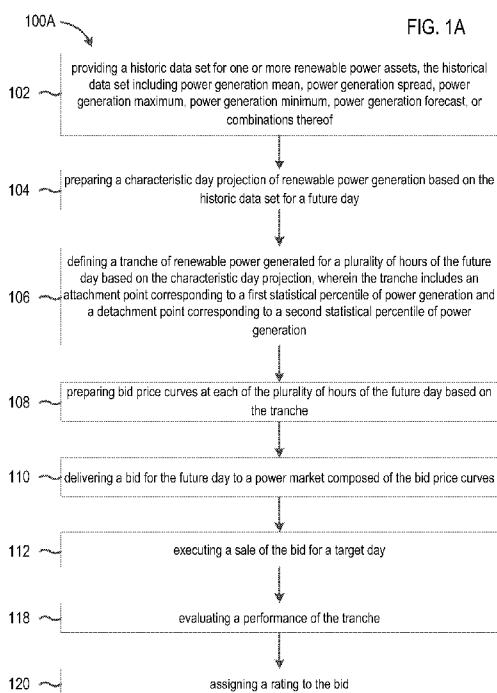
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(54) Title: SYSTEMS AND METHODS FOR RISK-RESPONSIVE BIDDING FOR RENEWABLE POWER GENERATION



(57) Abstract: Financial engineering asset securitization principles are employed to carve out "risk-free" power generation capability from renewable assets, e.g., wind and solar. Dynamically evolving tranches of renewable power are defined that allow renewable power generators to participate in day-ahead power markets with bids competitive with those for conventionally-derived power. Historical data sets containing, e.g., renewable power generation mean, spread, maximum, minimum, and forecast, are used to define a characteristic day projection. A tranche of renewable power generated during each hour is prepared based on the characteristic day projection, using the 4th percentile of generated power as the attachment point and the 5th-7th percentile as detachment point, corresponding to a 96% likelihood of successfully fulfilling a bid contract, competitive with conventionally-derived power. Bid price curves are prepared for each hour, and a bid for the day-ahead market composed of the bid price curves is prepared. A rating indicating how likely a renewable generator will fulfill a contract's obligations can be provided as well.

SYSTEMS AND METHODS FOR RISK-RESPONSIVE BIDDING FOR RENEWABLE POWER GENERATION

CROSS-REFERENCE TO RELATED APPLICATIONS

5 [0001] This application claims the benefit of U.S. Provisional Patent Application Nos. 63/526,076, filed July 11, 2023, and 63/662,085, filed June 20, 2024, which are incorporated by reference as if disclosed herein in their entireties.

STATEMENT REGARDING FEDERALLY SPONSORED RESEARCH AND DEVELOPMENT

10 [0002] This invention was made with government support under grant number DE-AR0001276, awarded by the Advanced Research Projects Agency-Energy (ARPA). The government has certain rights in the invention.

BACKGROUND

[0003] Environmental concerns are playing a role in pushing towards higher adoption and
15 utilization of renewable energy. In all world geographies, renewable energy investment is viewed as a useful component of the solution to meet the global energy demand. Renewable generation has been the fastest growing resource in the United States, supported by federal tax credits and state-level renewable targets. Renewable generation participating as equal peers in power markets is desirable for meeting future energy demand in all geographies. This is
20 desirable for enterprises investing in renewable generation with a goal of being profitable without relying on government subsidies. It is also desirable for the benefits of lower cost of renewable generation to translate to lower cost of energy for consumers. Therefore, renewable generation investment and power market participation of renewable generators is a desired component of future sustainability goals.

25 [0004] However, renewable energy resources such as wind and solar generate power stochastically, and thus, pose risk and reliability challenges for power grids and the renewable energy producers alike, which impedes their competitive participation in the power markets. The fundamental risk arising from the variation in weather conditions prevents an accurate prediction of generation throughput from these power generation resources, especially when compared to
30 traditional coal, natural gas or nuclear-based power generation. Accurate prediction would allow for advanced planning of demand and supply matching on power grids by the grid operators, often termed as the unit commitment problem.

[0005] Renewable generators can bid a conservative segment of the forecasted power generated into the day-ahead market with the aim of generating greater risk-adjusted profitability. However, these bids and their underlying risks may vary across renewable generators, and be calibrated for a reliable clearing of the day-ahead power market.

- 5 [0006] Various risk management solutions have emerged for the management of risk of intermittence in renewable power production using wind or solar assets. Energy storage technologies based on different principles pose as very promising mechanism for reducing the intermittence risk of renewable generation. While storage technologies can help mitigate the intermittence risk, cost constraints are likely to prevent entirely eliminating the intermittence.
- 10 [0007] Deregulation of power markets in the past decades has merited borrowing risk management principles from the financial domain to benefit the power markets. In the credit markets, securitization has been used for decades for risk pooling and carving out securities to match investors' risk-reward appetite. Bidding strategies for renewable integrated micro-grids have been developed by modeling uncertainties in renewable energy production. However, in
- 15 the larger scale power grids, existing renewable risk management solutions and bidding strategies assume renewable generators to be price takers, which limits their competitiveness and revenue generation capability, and further subjects them to high degrees of curtailment. These traits are not supportive of sustainable growth and investment in renewable energy. Existing literature has also not developed risk-responsive pricing strategies to support the stochastic
- 20 renewable generators' bidding in the day-ahead power markets.
- [0008] A rigorous third-party performance risk scoring of these risk-free bids is a valuable input and validation in support of a robust day-ahead market clearing framework. For a reliable and trusted incorporation of these risk-responsive contracts in the market clearing in a unit commitment/economic dispatch framework, a third-party validation and affirmation of these
- 25 contracts is desired.

SUMMARY

- [0009] Aspects of the present disclosure are directed to the application of financial engineering asset securitization principles to carve out "risk-free" generation capability from renewable assets, e.g., wind and solar. Dynamically evolving tranches of renewable power are defined that
- 30 allow renewable power generators to participate in day-ahead power markets with bids competitive with those of conventionally-derived power generators.

[0010] Aspects of the present disclosure are directed to a method including providing a historic data set for one or more renewable power assets, the historical data set including power generation mean, power generation spread, power generation maximum, power generation minimum, power generation forecast, or combinations thereof. In some embodiments, the

5 method includes preparing a characteristic day projection of renewable power generation based on the historic data set for a future day. In some embodiments, the method includes defining a tranche of renewable power generated for a plurality of hours of the future day based on the characteristic day projection, where the tranche includes an attachment point corresponding to a first statistical percentile of power generation and a detachment point corresponding to a second
10 statistical percentile of power generation. In some embodiments, the method includes preparing bid price curves at each of the plurality of hours of the future day based on the tranche. In some embodiments, the method includes delivering a bid for the future day to a power market composed of the bid price curves; and executing a sale of the bid for a target day. In some embodiments, the method includes identifying a shortfall amount between the bid and delivered
15 renewable power during the target day; and supplementing the delivered renewable power with delivered conventionally derived power at least equal to the shortfall amount. In some embodiments, the method includes evaluating a performance of the tranche, where the step of evaluating the performance of the tranche includes: identifying an average daily return of the tranche and a standard deviation of the daily return of the tranche; identifying the return of a
20 risk-free benchmark; and estimating a Sharpe ratio of the tranche to the risk-free benchmark, where the risk-free benchmark is defined in terms of a combined cycle natural gas generator.

[0011] In some embodiments, the method includes assigning a rating to the bid, wherein assigning a rating to the bid includes a first supervised learning process and at least a second supervised machine learning process. In some embodiments, the method includes predicting
25 with the first supervised learning process a rate of a power shortfall for each of the plurality of hours of the future day based on a first set of variables and a first training data set. In some embodiments, the method includes predicting with a second supervised learning process an occurrence of a power shortfall based on a predicted rate of a power shortfall, a second set of variables, and the first training data set. In some embodiments, the method includes applying the
30 first supervised learning process and the second supervised training process on a second training data set. In some embodiments, the method includes preparing a confusion matrix of the second supervised training process for the second training data set including off-diagonal entries. In some embodiments, the method includes defining off-diagonal entries as non-zero power shortfalls. In some embodiments, the method includes predicting with a third supervised

learning process a level of shortfall for each of the plurality of hours of the future day based on the non-zero power shortfalls of the second training data set and a third set of variables. In some embodiments, the method includes predicting with a fourth supervised learning process a level of shortfall for each of the plurality of hours of the future day based on a predicted level of shortfall from the third supervised learning process and a fourth set of variables. In some embodiments, the method includes mapping the level of shortfall predicted for the future day by the fourth supervised learning process to a rating scale.

[0012] In some embodiments, the first supervised learning process and third supervised learning process are random forest models and the second supervised learning process and fourth supervised learning process are neural network models. In some embodiments, the variables in the first set of variables, second set of variables, third set of variables, and fourth set of variables include average power generation, standard deviation of power generation, minimum power generation, power generation forecast ($F(t)$), differences between 2PM and 10PM power generation forecast, power generation forecast error, maximum power generation forecast error in a 24 hour window, minimum power generation forecast error in a 24 hour window, difference between midnight and noon power generation forecast error, predicted power contracted ($Q(t)$), predicted day-ahead market price, predicted real-time market price, natural gas futures price, or combinations thereof. In some embodiments, the first set of variables includes power generation forecast ($F(t)$) and predicted power contracted ($Q(t)$); the second set of variables includes power generation forecast ($F(t)$), differences between 2PM and 10PM power generation forecast, the third set of variables includes power generation forecast ($F(t)$) and predicted power contracted ($Q(t)$); and the fourth set of variables includes differences between 2PM and 10PM power generation forecast and average power generation.

[0013] Aspects of the present disclosure are directed to a non-transitory computer-readable medium including one or more instructions that, when executed by one or more processors of a device, cause the device to provide a historic data set for one or more renewable power assets, the historical data set including power generation mean, power generation spread, power generation maximum, power generation minimum, power generation forecast, or combinations thereof; prepare a characteristic day projection of renewable power generation based on the historic data set for a future day; define a tranche of renewable power generated for a plurality of hours of the future day based on the characteristic day projection, where the tranche includes an attachment point corresponding to a first statistical percentile of power generation and a detachment point corresponding to a second statistical percentile of power generation; prepare bid price curves at each of the plurality of hours of the future day based on the tranche; provide a

bid for the future day to a power market composed of the bid price curves; and execute a sale of the bid for a target day.

BRIEF DESCRIPTION OF THE DRAWINGS

[0014] The drawings show embodiments of the disclosed subject matter for the purpose of illustrating the invention. However, it should be understood that the present application is not limited to the precise arrangements and instrumentalities shown in the drawings, wherein:

[0015] FIGs. 1A-1B are charts of methods of making a “risk-free” bid based on renewable energy in power markets according to some embodiments of the present disclosure;

[0016] FIG. 1C is a graph showing hourly generation risk profiles for characteristic days according to some embodiments of the present disclosure;

[0017] FIG. 2 is a schematic representation of a system including a non-transitory computer-readable medium storing a set of instructions for making a risk-free bid based on renewable energy in power markets according to some embodiments of the present disclosure;

[0018] FIG. 3 are graphs showing hourly generation profiles of wind and solar power assets during high characteristic days and low characteristic days; and

[0019] FIG. 4 is a graph showing bid curves for solar and wind power assets according to some embodiments of the present disclosure.

DETAILED DESCRIPTION

[0020] Referring now to FIG. 1A, some embodiments of the present disclosure are directed to a method 100A of making a “risk-free” power supply bid based on renewable energy in power markets. As used herein, the term “risk-free” is used to refer to assuming an amount of risk equal to or lesser than a bid in a power market based on power generated by a conventional energy source, e.g., natural gas, coal, etc., or combinations thereof. The term “risk-free” is also used to refer to bids that include supplementing renewable energy delivery shortfalls with power derived from conventional sources, e.g., at the power generator’s expense, in order to supply the contracted amount of power, as will be described in greater detail below. As used herein, the term “renewable energy” refers to solar, wind, other forms of renewable energy, and combinations thereof. In some embodiments, the power markets are convention power markets, i.e., the bid produced by method 100A can be provided alongside bids composed entirely of conventionally-derived power.

[0021] Still referring to FIG. 1A, at 102, a historic data set for one or more renewable power assets is provided. In some embodiments, the renewable power assets include solar power generators, wind power generators, etc., or combinations thereof. In some embodiments, the renewable power assets are all positioned within the same geographical area. In some

embodiments, the renewable power assets are positioned across two or more geographic areas. In some embodiments, the historical data set includes power generation mean, power generation spread, power generation maximum, power generation minimum, power generation forecast, or combinations thereof, for the renewable power assets.

[0022] In some embodiments, at 104, a characteristic day projection of renewable power

generation based on the historic data set for a future day is prepared. In some embodiments, the future day is the day D+1 for a bid provided to power markets on day D, i.e., provided to a day-ahead market. Power generation of renewable assets, such as solar and wind farms, is highly dependent on variations in the weather patterns. Although no two days are identical by their exact generation levels, several days can be identified as similar by the above-identified

historical data regarding generation and forecast of generation characteristics, i.e., a “characteristic day.” These similar days of a type can be treated as independent and identically distributed observations to allow percentile estimates for each hour’s generation distribution for that characteristic day. For example, as seen in FIG. 1C, similar days defining a characteristic day for a sample solar farm are used to identify an empirical distribution of generation profile of each hour and corresponding percentile estimates are obtained for the characteristic day.

In FIG. 1C, mean, confidence interval of the mean, 25th percentile of generation, and 75th percentile of generation, and attachment points (light dots) and detachment points (dark dots) for each hour are displayed. Each hour’s generation profile is displayed by vertical scatter plot of generation levels for the hour. In some embodiments, the historical data is used to conduct a clustering analysis using a k-means clustering algorithm to identify days having similar risk profiles. A choice of “k” is identified for each of the one or more renewable power assets based on the inflection points in the k-means elbow curve. The centroid of each cluster typifies each characteristic day type.

[0023] At 106, at least a first tranche of renewable power is generated. In some embodiments,

the tranche is generated for a plurality of hours of the future day, e.g., D+1, based on the characteristic day projection. In some embodiments, the plurality of hours includes about all hours of the future day. In some embodiments, the plurality of hours includes all 24 hours of the future day. In some embodiments, the tranche includes an attachment point corresponding to a first statistical percentile of power generation and a detachment point corresponding to a second

statistical percentile of power generation. In some embodiments, the first statistical percentile corresponds to the typical reliability rate of conventionally-derived power. In some embodiments, the first statistical percentile is the 4th percentile. This implies that the tranche will exhibit a power delivery reliability of 96%, matching an average reliability rate for

5 conventionally-derived power asset, e.g., a combined cycle natural gas generator. In some embodiments, the second statistical percentile is defined with the aim of matching risk-return characteristics of the renewable power assets with conventionally-derived power assets. In some embodiments, the second statistical percentile is between the 5th percentile and the 10th percentile. In some embodiments, the second statistical percentile is between the 5th percentile and the 9th percentile. In some embodiments, the second statistical percentile is between the 5th percentile and the 8th percentile. In some embodiments, the second statistical percentile is between the 5th percentile and the 7th percentile. In some embodiments, the second statistical percentile is between the 5th percentile and the 6th percentile. In some embodiments, the second statistical percentile is between the 6th percentile and the 7th percentile. In some embodiments, the second statistical percentile is the 5th percentile. In some embodiments, the second statistical percentile is the 6th percentile. In some embodiments, the second statistical percentile is the 7th percentile.

[0024] Still referring to FIG. 1A, at 108, bid price curves are prepared at each of the plurality of hours of the future day based on the tranche. In some embodiments, bid price curves are prepared for all 24 hours of D+1, i.e., for bidding in the day-ahead market. In some embodiments, the bid price curve is calculated according to Formula I:

$$f_{rf}(C_x) = \begin{cases} P_{rfj} & C_x = C_j; j = 1, \dots, J \\ P_{rfj} + \frac{P_{rfj+1} - P_{rfj}}{C_{j+1} - C_j} (C_x - C_j) & C_{j+1} > C_x > C_j, \end{cases} \quad (\text{Formula I}).$$

In some embodiments, C_x is the power generation of the renewable power assets corresponding to the xth percentile of power generation. In some embodiments, P_{rfj} is the bid price at the percentile bid points. In some embodiments, C_1 is the first statistical percentile. In some embodiments, C_J is the second statistical percentile.

[0025] In some embodiments, bid price P_{rfj} is calculated according to Formula II:

$$P_{r,f,x} = \eta_{rf} * E[D_t | Y_{t+1} \geq C_j] * P(Y_{t+1} \geq C_j) + E[E[D_t] | E^Q[\frac{R_{t+1}}{E[D_t]}] + \lambda_{rf} * \sigma^Q[\frac{R_{t+1}}{E[D_t]}] | Y_{t+1} < C_j] * P(Y_{t+1} < C_j)] \quad (\text{Formula II}).$$

In some embodiments, D_t is the forward price of electricity at market clearing time t , Y_{t+1} is the actual generation of the renewable asset at a time $t+1$; and R_{t+1} is the real-time price when the generated renewable power is delivered. In some embodiments, η_{rf} is a discount loading for allowing competitive bids. In some embodiments, $E[D_t | Y_{t+1} \geq C_j] * P(Y_{t+1} \geq C_j)$ is the expected day ahead price. In some embodiments,

$E[E[D_t] | E^Q[\frac{R_{t+1}}{E[D_t]}] + \lambda_{rf} * \sigma^Q[\frac{R_{t+1}}{E[D_t]}] | Y_{t+1} < C_j] * P(Y_{t+1} < C_j)]$ corresponds to the scenario when the renewable power generation fails to exceed the obligation of the bid.

[0026] Still referring to FIG. 1A, in some embodiments of method 100A, at 110, a bid for a future day, composed of the bid price curves, is delivered to a power market. As discussed above, in some embodiments the power market is the day-ahead market. At 112, a sale of the bid is executed for a target day, e.g., the day that the renewable power is contracted to be delivered, such as day D+1 in the day-ahead market.

[0027] Referring now to FIG. 1B, some embodiments of the present disclosure are directed to a method 100B in which, at 114, a shortfall amount between the bid and delivered renewable power during the target day is identified. At 116, the delivered renewable power is supplemented with delivered conventionally derived power at least equal to the shortfall amount to address the shortfall.

[0028] In some embodiments, the market prices of the conventionally derived power to address the shortfall is calculated according to Formulas III-V:

$$D_t = \alpha L_{t-1} + \beta N_{t-1} + \epsilon \quad (\text{Formula III})$$

$$E[D_t] = \alpha L_{t-1} + \beta N_{t-1} \quad (\text{Formula IV})$$

$$R_{t+1} = \gamma E[D_t] + \delta L_{t-1} + \theta N_{t-1} + \epsilon' \quad (\text{Formula V}).$$

In some embodiments, α , β , γ , δ , and θ are estimated regression coefficients and ϵ' is the residual error for a real-time market price of electricity; L_{t-1} is the lagged regional load; N_{t-1} is the lagged

natural gas price. In some embodiments, $E[D_t]$ is the estimated forward price of electricity at market clearing time t .

[0029] Referring again to FIG. 1A, in some embodiments of method 100A, a performance of the tranche is evaluated at 118. In some embodiments, evaluating 118 is performed relative to a benchmark, e.g., a “risk-free” benchmark such as the performance of a combined cycle natural gas generator. In some embodiments, evaluating 118 includes identifying an average daily return of the tranche and a standard deviation of the daily return of the tranche. In some embodiments, the return of a risk-free benchmark is identified. A Sharpe ratio of the tranche to the risk-free benchmark is then estimated.

[0030] Still referring to FIG. 1A, in some embodiments of method 100A, a rating is assigned to the bid at 120. In some embodiments, assigning a rating 120 includes a first supervised learning process and at least a second supervised machine learning process. In some embodiments, the supervised learning processes include random forest models, neural network models, or combinations thereof. In some embodiments, rating 120 is performed utilizing in at least two stages. In some embodiments, rating 120 is performed utilizing a first training data set and at least a second training data set. In some embodiments, the training data sets include historical renewable power generation and power generation shortfall data for one or more renewable power assets, e.g., those producing power for inclusion in the bid. In some embodiments, the rating 120 is performed utilizing one or more sets of variables. In some embodiments, the rating 120 is performed utilizing a plurality of sets of variables. In some embodiments, the sets of variables include average power generation, standard deviation of power generation, minimum power generation, power generation forecast ($F(t)$), differences between 2PM and 10PM power generation forecast, power generation forecast error, maximum power generation forecast error in a 24 hour window, minimum power generation forecast error in a 24 hour window, difference between midnight and noon power generation forecast error, predicted power contracted ($Q(t)$), predicted day-ahead market price, predicted real-time market price, natural gas futures price, or combinations thereof.

[0031] In some embodiments of rating 120, the first supervised learning process predicts a rate of a power shortfall for each of the plurality of hours of the future day based on a first set of variables and the first training data set. In some embodiments, a second supervised learning process predicts an occurrence of a power shortfall based on a predicted rate of a power shortfall, a second set of variables, and the first training data set. In some embodiments, the first supervised learning process and the second supervised training process are applied on a second

training data set. In some embodiments, a confusion matrix of the second supervised training process for the second training data set including off-diagonal entries is prepared. The off-diagonal entries are defined as non-zero power shortfalls. In some embodiments, a third supervised learning process predicts a level of shortfall for each of the plurality of hours of the future day based on the non-zero power shortfalls of the second training data set and a third set of variables. In some embodiments, a fourth supervised learning process predicts a level of shortfall for each of the plurality of hours of the future day based on a predicted level of shortfall from the third supervised learning process and a fourth set of variables. In some embodiments, the level of shortfall predicted for the future day by the fourth supervised learning process is mapped to a rating scale. Similar to credit rating of debt issuance and securities issued based on debt securitization, the performance risk scoring demonstrated at 120 provides an indication of how likely a renewable generator will fulfill a contract's obligations. By way of example, when a bid is rated 120 to meet its obligation, it can earn a "AAA" rating, and any drop from the target level can be given a rating of "AAA-," "AA+," "AA," "AA-," etc., depending on the predicted level of shortfall.

[0032] In some embodiments, the first supervised learning process is a random forest model. In some embodiments, the third supervised learning process is a random forest model. In some embodiments, the first supervised learning process and the third supervised learning process are random forest models. In some embodiments, the second supervised learning process is a neural network model. In some embodiments, the fourth supervised learning process is a neural network model. In some embodiments, the second supervised learning process and fourth supervised learning process are neural network models. In some embodiments, the variables in the first set of variables, second set of variables, third set of variables, and fourth set of variables include average power generation, standard deviation of power generation, minimum power generation, power generation forecast ($F(t)$), differences between 2PM and 10PM power generation forecast, power generation forecast error, maximum power generation forecast error in a 24 hour window, minimum power generation forecast error in a 24 hour window, difference between midnight and noon power generation forecast error, predicted power contracted ($Q(t)$), predicted day-ahead market price, predicted real-time market price, natural gas futures price, or combinations thereof.

[0033] In some embodiments, the first set of variables includes power generation forecast ($F(t)$) and predicted power contracted ($Q(t)$). In some embodiments, the second set of variables includes power generation forecast ($F(t)$), differences between 2PM and 10PM power generation forecast. In some embodiments, the third set of variables includes power generation

forecast ($F(t)$) and predicted power contracted ($Q(t)$). In some embodiments, the fourth set of variables includes differences between 2PM and 10PM power generation forecast and average power generation.

[0034] Referring now to FIG. 2, some embodiments of the present disclosure are directed to a system 200 including a computing device 202. In some embodiments, computing device 202 includes a non-transitory computer-readable medium 204 storing a set of instructions 206 for making a risk-free bid 208 based on renewable energy in power markets. In some embodiments, computing device 202 includes any suitable hardware to receive, store, analyze, process, transmit, etc. data to generate bid 208. Some embodiments of computing device 202 include one or more processors. The processor may include, for example, a processing unit and/or programmable circuitry. The processing units or circuits can include hardwired circuitry, e.g., programmable logic devices, programmable array logic, field programmable gate arrays, etc., programmable circuitry, e.g., computer processors including one or more individual instruction processing cores, microcontrollers, etc., state machine circuitry, and/or firmware that stores instructions executed by programmable circuitry. Some embodiments of computing device 202 include a machine-readable storage device 204 including any type of tangible, non-transitory storage device, e.g., compact disk read-only memories (CD-ROMs), semiconductor devices such as read-only memories (ROMs), random access memories (RAMs) such as dynamic and static RAMs, erasable programmable read-only memories (EPROMs), electrically erasable programmable read-only memories (EEPROMs), flash memories, magnetic or optical cards, etc.

[0035] In some embodiments, medium 204 includes one or more instructions 206A that, when executed by one or more processors of device 202, cause the device to provide a historic data set for one or more renewable power assets, the historical data set including power generation mean, power generation spread, power generation maximum, power generation minimum, power generation forecast, or combinations thereof. In some embodiments, medium 204 includes one or more instructions 206B that, when executed by one or more processors of device 202, cause the device to prepare a characteristic day projection of renewable power generation based on the historic data set for a future day. In some embodiments, medium 204 includes one or more instructions 206C that, when executed by one or more processors of device 202, cause the device to define a tranche of renewable power generated for a plurality of hours of the future day based on the characteristic day projection, wherein the tranche includes an attachment point corresponding to a first statistical percentile of power generation and a detachment point corresponding to a second statistical percentile of power generation. In some embodiments, medium 204 includes one or more instructions 206D that, when executed by one or more

processors of device 202, cause the device to prepare bid price curves at each of the plurality of hours of the future day based on the tranche. In some embodiments, medium 204 includes one or more instructions 206E that, when executed by one or more processors of device 202, cause the device to provide a bid for the future day to a power market composed of the bid price

5 curves. In some embodiments, medium 204 includes one or more instructions 206F that, when executed by one or more processors of device 202, cause the device to execute a sale of the bid for a target day.

[0036] As discussed above, in some embodiments, the first statistical percentile is the 4th percentile. In some embodiments, the second statistical percentile is between the 5th percentile and the 10th percentile. In some embodiments, the second statistical percentile is between the 5th percentile and the 9th percentile. In some embodiments, the second statistical percentile is between the 5th percentile and the 8th percentile. In some embodiments, the second statistical percentile is between the 5th percentile and the 7th percentile. In some embodiments, the second statistical percentile is between the 5th percentile and the 6th percentile. In some embodiments,

15 the second statistical percentile is between the 6th percentile and the 7th percentile. In some embodiments, the second statistical percentile is the 5th percentile. In some embodiments, the second statistical percentile is 6th percentile. In some embodiments, the second statistical percentile is the 7th percentile. In some embodiments, the bid price curve is calculated according to Formula I above. In some embodiments, the bid price $P_{rf,j}$ is calculated according

20 to Formula II above.

EXAMPLES

[0037] A renewable power bid composed of a plurality of bid curves consistent with embodiments of the present disclosure was prepared. Days of similar power generation and forecast risk profile were identified for a plurality of renewable power assets using clustering

25 analysis conducted on 11 daily statistics. Table 1 and Table 2 below show the 11 summary statistics features used for clustering defined in terms of hourly generation and forecast time series for the day. The centroid coordinates summarized in the two tables describe the nature of each characteristic day, where 6 was used as the number of clusters chosen based on k-means elbow curves.

Chr Day	Mean Gen	Std of Gen	Hour of Max Gen	Hour of Max Error	Hour of Min Error	Man Gen	Max Forecast Error	Min Forecast Error	Post- noon / Pre- noon Mean Gen	2pm – 10pm Gen	# of days
L0	1.52	2.4	11.9	7.49	11.67	7.23	1.65	-5.58	1.77	5.00	217
L1	5.96	8.45	12.37	12.05	11.62	24.39	8.99	-4.61	2.08	17.08	165
L2	6.05	7.99	12.9	9.88	13.86	23.42	5.72	-11.6	2.05	47.47	42
L3	12.4	16.86	12.44	11.34	13.23	46.63	17.32	-9.63	2.06	15.66	61
L4	12.73	15.68	12.62	11.77	12.69	40.85	9.47	-4.21	1.84	36.87	146
L5	15.59	19.41	12.68	10.63	14.86	51.07	13.34	-13.65	2.14	46.25	98

Table 1: Centroid coordinates of 6 characteristic days for solar renewable power assets.

Chr Day	Mean Gen	Std of Gen	Hour of Min Gen	Hour of Max Gen	Hour of Min Error	Hour of Max Error	Max Error	Min Error	12AM – Noon Gen	Min Gen	Max Gen	# of days
L0	7.87	6.39	9.65	11.02	11.60	10.73	13.21	-9.79	4.53	0.81	21.76	419
L1	19.34	12.82	10.31	10.83	10.82	12.11	20.09	-15.97	-41.60	3.78	45.46	150
L2	25.09	16.83	11.51	12.14	11.68	12.18	24.24	-19.50	6.50	4.53	58.09	293
L3	46.75	21.47	12.59	11.16	11.32	12.67	-5.38	-78.17	3.92	15.22	81.22	63
L4	46.88	25.01	10.34	11.75	12.07	11.03	35.24	-19.70	39.82	11.55	89.80	169
L5	57.29	24.42	11.50	11.88	12.96	12.56	32.37	-17.98	-19.79	0.59	95.33	245

Table 2: Centroid coordinates of 6 characteristic days for wind renewable power assets.

[0038] Table 1 shows that the solar assets' L0 cluster has the lowest mean generation and L4 cluster has the second highest mean generation level, each containing 217 days and 146 days respectively, from among the total number of days in the historical data set. The highest mean generation cluster, L5 also displays higher maximum and minimum forecast error than the L4 cluster, while containing fewer days in the cluster. L4 days have higher forecast error compared to L0 days, implying that when the amount of generation is high the accuracy of forecasting shows greater variability, which is seen for other high mean generation clusters, L3 and L5. Among the remaining low generation clusters, namely L1 and L2, the coefficient of variation of generation of L2 cluster is lower than that of the L0 and L1 clusters, while maximum forecast error in L2 is lower than that in L1 cluster. Therefore, the L2 cluster is a more cohesive cluster, even if it only has 42 days in it.

[0039] Table 2 indicates that wind generation has overall high mean generation as well as higher standard deviation of generation, although the coefficient of variation in all characteristic days is below 1. Among specific clusters, L0 has the lowest mean generation and L4 and L5 are among the highest mean generation clusters. L4 and L5 days have similar standard deviation of generation, even though L5 has a higher mean generation level, suggesting the L5 cluster with 245 days is a fairly productive cluster of days. As before, increasing mean generation among these clusters corresponds to higher maximum and minimum forecast error, with cluster L3 showing the property of the maximum forecast error also being negative. This feature and the midnight-noon generation feature offer two distinctions between L3 and L4 days, with all other cluster characteristics being quite comparable.

[0040] Referring now to FIG. 3, the 24-hour generation profile of specific characteristic days, high and low, is shown to highlight how the generation level changes by the hour of the day for the wind (top panel) and solar (bottom panel) asset. These plots show the raw generation levels for each hour for days in that cluster, the hourly mean generation, 95% confidence interval for the mean, and hourly 25th and 75th percentiles of generation. The plots show that each characteristic day exhibits a risk profile with differences between high and low generation characteristic days. Besides the difference in the generation level, the generation profile of high wind days shows a decreasing trend in the 24-hour period, whereas low wind days exhibit a steady low level of generation with ever so slight upward trend. The high solar generation cluster shows sharp rise as the sun rises in the morning with a much smaller inter-quartile range throughout the day, while the low solar generation cluster rises very gradually, settles at a lower peak with a relatively large inter-quartile range.

[0041] Treating the data points in a characteristic day as independent and identically distributed, the percentiles by which risk-free tranche's hourly attachment and detachment points were estimated. Tables 3A-3B below list the hourly attachment point of the tranche for two characteristic days each for wind and solar assets at the 4th percentile of their respective power generation distribution. The detachment point was set at 7th and 9th percentiles, respectively, for the solar and the wind assets. For these definitions of the tranche, the bid price point for each percentile from the attachment to the detachment point of the tranche was computed.

Asset	Wind Unit			
MW capacity	135.5 MW			
Characteristic day type	High Wind Days (L5)		Medium Wind Days (L4)	
Hour /Day Type	Attachment Point (4th Percentile)	Detachment Point (9th Percentile)	Attachment Point (4th Percentile)	Detachment Point (9th Percentile)
0	3.88	12.60	5.25	13.67
1	2.78	9.06	7.44	14.27
2	2.24	6.73	8.42	14.92
3	0.74	6.99	6.44	16.01
4	0.18	4.90	2.40	14.17
5	0.68	5.50	4.91	10.07
6	0.18	3.80	5.56	10.56
7	0.20	1.98	4.04	7.11
8	0.28	3.48	3.00	7.11
9	0.10	3.49	1.40	4.71
10	0.08	2.89	0.20	3.84
11	0.00	1.70	0.37	3.21
12	0.08	5.26	0.10	3.55
13	0.28	4.49	0.00	3.00
14	0.58	5.90	0.00	1.12
15	0.55	7.16	0.00	1.20
16	1.08	5.87	0.00	0.77
17	0.86	3.80	0.07	0.77
18	0.50	3.18	0.00	0.40
19	0.38	2.80	0.00	0.41
20	0.50	3.78	0.07	0.71
21	0.00	2.17	0.00	0.42
22	0.17	1.59	0.00	0.40
23	0.17	1.96	0.00	1.21

Table 3A: Attachment and detachment points for the risk-free tranche for the wind units corresponding to two different characteristic days.

Asset	Solar Unit			
MW capacity	68.5 MW			
Characteristic day type	High Solar Days (L4)		Low Solar Days (L0)	
Hour /Day Type	Attachment Point (4th Percentile)	Detachment Point (7th Percentile)	Attachment Point (4th Percentile)	Detachment Point (7th Percentile)
0	0.00	0.00	0.00	0.00
1	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00
7	0.12	0.42	0.00	0.00
8	3.71	4.19	0.03	0.04
9	9.68	11.31	0.25	0.43
10	14.04	18.12	0.46	0.67
11	19.65	24.63	0.59	0.74
12	25.98	28.03	0.60	0.91
13	26.58	29.71	0.55	0.78
14	25.80	28.24	0.43	0.61
15	19.43	20.70	0.15	0.31
16	9.25	11.18	0.00	0.00
17	2.14	4.70	0.00	0.00
18	0.01	0.37	0.00	0.00
19	0.00	0.00	0.00	0.00
20	0.00	0.00	0.00	0.00
21	0.00	0.00	0.00	0.00
22	0.00	0.00	0.00	0.00
23	0.00	0.00	0.00	0.00

Table 3B: Attachment and detachment points for the risk-free tranche for the solar units corresponding to two different characteristic days.

- 5 [0042] Referring now to FIG. 4, based on the day-ahead and real-time market prices and estimated risk-neutral probabilities, bid points were prepared, e.g., according to Formula II above, for the range of percentile points between the tranche's attachment and detachment points. Bid curves were prepared for the two times points shown in Table 4 below, which are peak load and off-peak load hours for the wind and solar assets for their respective high
- 10 generation characteristic days.

Geography	Resource	Peak Time	Off-Peak Time
NY (Zone A)	Solar	2PM	7AM
	Wind	2PM	12AM

Table 4: Sample peak and off-peak load hours on a high generation characteristic day

FIG. 4 shows the bid curves for wind and solar assets in New York state for high generation characteristic days at these time points, with bid prices in \$/MW aligning for each bid-point of power offered. The bid curve starts from the attachment point of the tranche and ends at the detachment point, linearly interpolated for all points in the middle and reflective of the incremental risk with increasing bid point.

[0043] It was observed that the tranche bid curves are responsive to the risk-profile of different characteristic days and the hour for the day. They had different bid-point (MW) levels for different hours of the day, based on the hourly risk generation risk. The day-ahead market prices are typically higher for peak load times than the off-peak load times. This is reflected in the bid price points of \$/MW level of the renewable asset's risk-free tranche bid curve. These hourly bid curves determine when a renewable asset's risk-free offer is accepted by the day-ahead market and in doing so, determines the revenue and the return time-series of the renewable asset's risk-free tranche.

[0044] To determine the performance of the tranche in this embodiment, its performance was evaluated relative to a benchmark of a plurality of combined cycle natural gas generators selected from different locations in New York state. The power sold by the representative combined cycle natural gas generators in the day-ahead market was determined by its bid curve posts and the day-ahead market clearing price for the particular hour. Using a historic simulation of day-ahead market prices, a representative combined cycle natural gas generator return time series was generated. The Sharpe ratio for this benchmark was 0.43. For solar assets, the returns for the high (L4) and low (L0) characteristic day types were computed. The Sharpe ratio for this tranche was 0.40, within 5% of the Sharpe ratio of the combined cycle natural gas generator benchmark. For wind assets, the returns for high (L5) and medium (L4) characteristic days were computed. The Sharpe ratio for this tranche is 0.28. However, tail-risk analysis shows that even though the Sharpe ratio of the wind power tranche was lower than that of the benchmark, there is only minimal tail risk and "risk-free" contracting is better than not contracting on 98.8% of the days studied.

[0045] Systems and methods of the present disclosure advantageously utilize securitization principles to define a market bid based on stochastic renewable generation resources, which can be priced, offered, and fulfilled by renewable generators comparable to their non-stochastic conventional generation counterparts. The tranche definition of securitization utilizes an assessment of a power generation risk profile of an individual renewable asset and dynamically adapts the attachment and detachment points of the specific asset's risk-free tranche to its risk profile. A minimum entropy risk-neutral pricing framework helps determine the market-based bid curves for the risk-free tranche. The performance of the tranche in defining bids for the day-ahead power markets was evaluated relative to a defined risk-free benchmark. It was demonstrated that the bids comprised of power generated by renewable assets, e.g., solar and wind, were comparable to those of conventional combined cycle natural gas generators.

[0046] A performance risk scoring methodology provides third-party input for a robust and reliable functioning of power markets. A comparably and reliably performing risk-free tranche offered by renewable generators can provide assurance to power grid system operators to incorporate the renewable assets based risk-free tranche in the typical day-ahead unit commitment and economic dispatch decisions.

[0047] Although the invention has been described and illustrated with respect to exemplary embodiments thereof, it should be understood by those skilled in the art that the foregoing and various other changes, omissions and additions may be made therein and thereto, without parting from the spirit and scope of the present invention.

CLAIMS

What is claimed is:

1. A method of making a power supply bid based on renewable energy in power markets, comprising:

5 providing a historic data set for one or more renewable power assets, the
 historical data set including power generation mean, power generation spread,
 power generation maximum, power generation minimum, power generation
 forecast, or combinations thereof;

10 preparing a characteristic day projection of renewable power generation based on
 the historic data set for a future day;

 defining a tranche of renewable power generated for a plurality of hours of the
 future day based on the characteristic day projection, wherein the tranche includes
 an attachment point corresponding to a first statistical percentile of power
 generation and a detachment point corresponding to a second statistical percentile
15 of power generation; and

 preparing bid price curves at each of the plurality of hours of the future day based
 on the tranche.

2. The method according to claim 1, further comprising:

20 delivering a bid for the future day to a power market composed of the bid price
 curves; and

 executing a sale of the bid for a target day.

3. The method according to claim 2, further comprising:

 identifying a shortfall amount between the bid and delivered renewable power
 during the target day; and

25 supplementing the delivered renewable power with delivered conventionally
 derived power at least equal to the shortfall amount.

4. The method according to claim 1, further comprising evaluating a performance of the
 tranche, wherein the step of evaluating the performance of the tranche includes:

identifying an average daily return of the tranche and a standard deviation of the daily return of the tranche;

identifying the return of a benchmark; and

estimating a Sharpe ratio of the tranche to the benchmark,

5 wherein the benchmark is defined in terms of a combined cycle natural gas generator.

5. The method according to claim 2, wherein the target day is the day-ahead.

6. The method according to claim 2, wherein the plurality of hours includes all 24 hours.

7. The method according to claim 2, wherein the first statistical percentile is the 4th
10 percentile and the second statistical percentile is between the 5th and the 7th percentile.

8. The method according to claim 2, wherein the bid price curve is calculated according to Formula I:

$$f_{rf}(C_x) = \begin{cases} P_{rf,j} & C_x = C_j, j = 1, \dots, J \\ P_{rf,j} + \frac{P_{rf,j+1} - P_{rf,j}}{C_{j+1} - C_j} (C_x - C_j) & C_{j+1} > C_x > C_j. \end{cases} \quad (\text{Formula I})$$

15 wherein C is the power generation of the renewable power assets corresponding to the xth percentile of power generation, P_{rf,j} is the bid price at the percentile bid points, C₁ is the first statistical percentile, and C_J is the second statistical percentile.

9. The method according to claim 8, wherein the bid price P_{rf,j} is calculated according to Formula II:

$$P_{rf,j,x} = \eta_{rf} * E[D_t | Y_{t+1} \geq C_j] * P(Y_{t+1} \geq C_j) + E[E[D_t] | E^Q[\frac{R_{t+1}}{E[D_t]}]] + \lambda_{rf} * \sigma^Q[\frac{R_{t+1}}{E[D_t]}] | Y_{t+1} < C_j] * P(Y_{t+1} < C_j) \quad (\text{Formula II}).$$

20

10. The method according to claim 10, further comprising assigning a rating to the bid, wherein assigning a rating to the bid includes a first supervised learning process and at least a second supervised machine learning process, further comprising:

predicting with the first supervised learning process a rate of a power shortfall for each of the plurality of hours of the future day based on a first set of variables and a first training data set;

predicting with a second supervised learning process an occurrence of a power shortfall based on a predicted rate of a power shortfall, a second set of variables, and the first training data set;

applying the first supervised learning process and the second supervised training process on a second training data set;

preparing a confusion matrix of the second supervised training process for the second training data set including off-diagonal entries;

defining off-diagonal entries as non-zero power shortfalls;

predicting with a third supervised learning process a level of shortfall for each of the plurality of hours of the future day based on the non-zero power shortfalls of the second training data set and a third set of variables;

predicting with a fourth supervised learning process a level of shortfall for each of the plurality of hours of the future day based on a predicted level of shortfall from the third supervised learning process and a fourth set of variables; and

mapping the level of shortfall predicted for the future day by the fourth supervised learning process to a rating scale.

11. The method according to claim 10, wherein the first supervised learning process and third supervised learning process are random forest models and the second supervised learning process and fourth supervised learning process are neural network models.

12. The method according to claim 10, wherein variables in the first set of variables, second set of variables, third set of variables, and fourth set of variables include average power generation, standard deviation of power generation, minimum power generation, power generation forecast ($F(t)$), differences between 2PM and 10PM power generation forecast, power generation forecast error, maximum power generation forecast error in a 24 hour window, minimum power generation forecast error in a 24 hour window, difference between midnight and noon power generation forecast error, predicted power

contracted ($Q(t)$), predicted day-ahead market price, predicted real-time market price, natural gas futures price, or combinations thereof.

13. The method according to claim 12, wherein:

the first set of variables includes power generation forecast ($F(t)$) and predicted power contracted ($Q(t)$);

the second set of variables includes power generation forecast ($F(t)$), differences between 2PM and 10PM power generation forecast,

the third set of variables includes power generation forecast ($F(t)$) and predicted power contracted ($Q(t)$); and

the fourth set of variables includes differences between 2PM and 10PM power generation forecast and average power generation.

14. A non-transitory computer-readable medium storing a set of instructions for making a power supply bid based on renewable energy in power markets, comprising:

one or more instructions that, when executed by one or more processors of a device, cause the device to:

provide a historic data set for one or more renewable power assets, the historical data set including power generation mean, power generation spread, power generation maximum, power generation minimum, power generation forecast, or combinations thereof;

prepare a characteristic day projection of renewable power generation based on the historic data set for a future day;

define a tranche of renewable power generated for a plurality of hours of the future day based on the characteristic day projection, wherein the tranche includes an attachment point corresponding to a first statistical percentile of power generation and a detachment point corresponding to a second statistical percentile of power generation; and

prepare bid price curves at each of the plurality of hours of the future day based on the tranche.

15. The non-transitory computer-readable medium of claim 14, wherein the one or more instructions further cause the device to:

provide a bid for the future day to a power market composed of the bid price curves; and

5 execute a sale of the bid for a target day.

16. The non-transitory computer-readable medium of claim 15, wherein the first statistical percentile is the 4th percentile and the second statistical percentile is between the 5th and the 7th percentile.

10 17. The non-transitory computer-readable medium of claim 15, wherein the bid price curve is calculated according to Formula I:

$$f_{rf}(C_x) = \begin{cases} P_{rfj} & C_x = C_j; j = 1, \dots, J \\ P_{rfj} + \frac{P_{rfj+1} - P_{rfj}}{C_{j+1} - C_j} (C_x - C_j) & C_{j+1} > C_x > C_j. \end{cases} \quad (\text{Formula I})$$

wherein C_x is the power generation of the renewable power assets corresponding to the x^{th} percentile of power generation, P_{rfj} is the bid price at the percentile bid points, C_1 is the first statistical percentile, and C_J is the second statistical percentile.

15

18. The non-transitory computer-readable medium of claim 17, wherein the bid price P_{rfj} is calculated according to Formula II:

$$P_{rf,x} = \eta_{rf} * E[D_t | Y_{t+1} \geq C_j] * P(Y_{t+1} \geq C_j) + E[E[D_t] [E^Q[\frac{R_{t+1}}{E[D_t]}]] + \lambda_{rf} * \sigma^Q[\frac{R_{t+1}}{E[D_t]}]] | Y_{t+1} < C_j] * P(Y_{t+1} < C_j) \quad (\text{Formula II}).$$

20

19. A method of making a power supply bid based on renewable energy in power markets, comprising:

providing a historic data set for one or more renewable power assets, the historical data set including power generation mean, power generation spread, power generation maximum, power generation minimum, power generation forecast, or combinations thereof;

preparing a characteristic day projection of renewable power generation for a target day based on the historic data set for sale in a day-ahead market;

defining a tranche of renewable power generated for each hour of the target day based on the characteristic day projection, wherein the tranche includes an attachment point corresponding to a first statistical percentile of power generation and a detachment point corresponding to a second statistical percentile of power generation, wherein the first statistical percentile is the 4th percentile and the second statistical percentile is between the 5th and the 7th percentile;

preparing bid price curves at each hour of the target day based on the tranche;

delivering a bid for the day-ahead market composed of the bid price curves; and

executing a sale of the bid in the day-ahead market,

wherein the bid price curves are calculated according to Formula I:

$$f_{rf}(C_x) = \begin{cases} P_{rfj} & C_x = C_j; j = 1, \dots, J \\ P_{rfj} + \frac{P_{rfj+1} - P_{rfj}}{C_{j+1} - C_j} (C_x - C_j) & C_{j+1} > C_x > C_j. \end{cases} \quad (\text{Formula I})$$

wherein C_x is the power generation of the renewable power assets corresponding to the x^{th} percentile of power generation, P_{rfj} is the bid price at the percentile bid points, C_1 is the first statistical percentile, and C_J is the second statistical percentile, and

the bid price P_{rfj} is calculated according to Formula II:

$$P_{rfj,x} = \eta_{rf} * E[D_t | Y_{t+1} \geq C_j] * P(Y_{t+1} \geq C_j) + E[E[D_t] | E^Q[\frac{R_{t+1}}{E[D_t]}] + \lambda_{rf} * \sigma^Q[\frac{R_{t+1}}{E[D_t]}]] | Y_{t+1} < C_j] * P(Y_{t+1} < C_j) \quad (\text{Formula II}).$$

20. The method according to claim 19, further comprising assigning a rating to the bid, wherein assigning a rating to the bid includes:

predicting with the first random forest model a rate of a power shortfall for each hour of the target day based on a first set of variables and a first training data set;

predicting with a first neural network an occurrence of a power shortfall based on a predicted rate of a power shortfall, a second set of variables, and the first training data set;

5 applying the first random forest model and the first neural network on a second training data set;

 preparing a confusion matrix of the first neural network for the second training data set including off-diagonal entries;

 defining off-diagonal entries as non-zero power shortfalls;

10 predicting with a second random forest model a level of shortfall for each hour of the target day based on the non-zero power shortfalls of the second training data set and a third set of variables;

 predicting with a second neural network a level of shortfall for each hour of the target day based on a predicted level of shortfall from the second random forest model and a fourth set of variables; and

15 mapping the level of shortfall predicted for the target day by the second neural network to a rating scale,

 wherein:

 the first set of variables includes power generation forecast ($F(t)$) and predicted power contracted ($Q(t)$);

20 the second set of variables includes power generation forecast ($F(t)$), differences between 2PM and 10PM power generation forecast,

 the third set of variables includes power generation forecast ($F(t)$) and predicted power contracted ($Q(t)$); and

25 the fourth set of variables includes differences between 2PM and 10PM power generation forecast and average power generation.

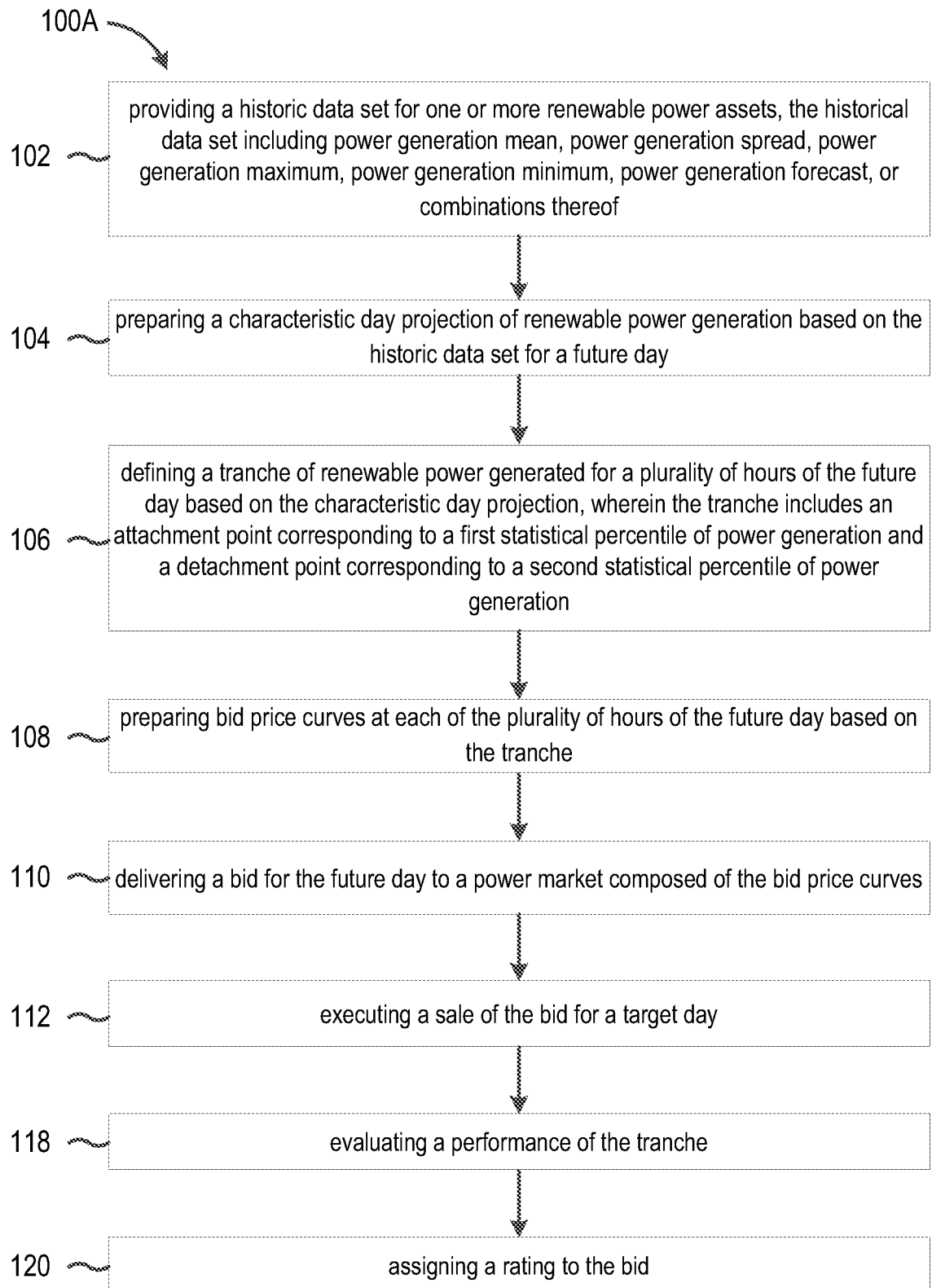


FIG. 1A

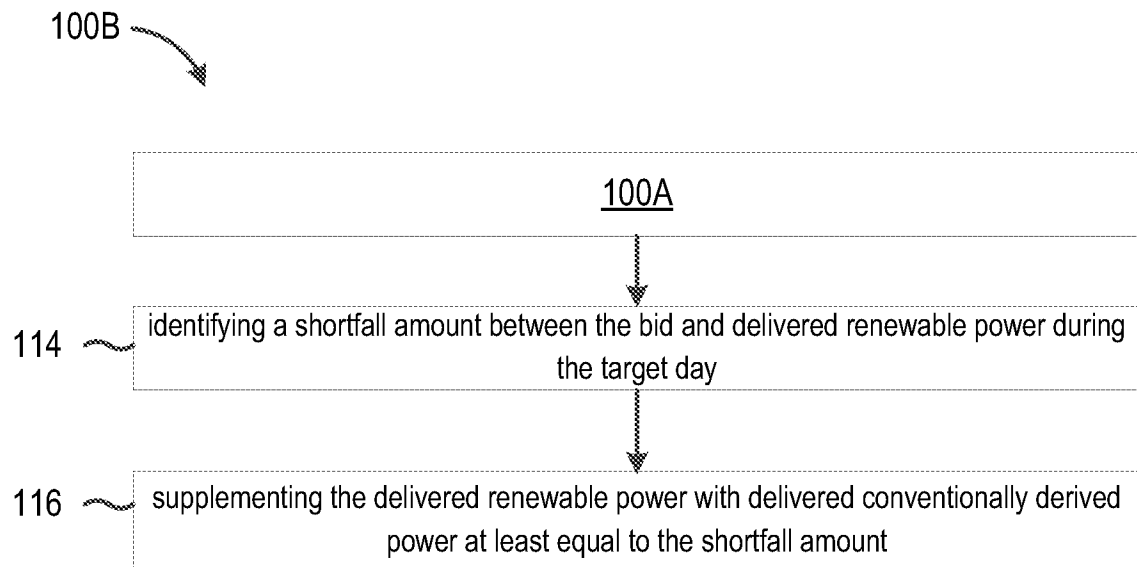


FIG. 1B

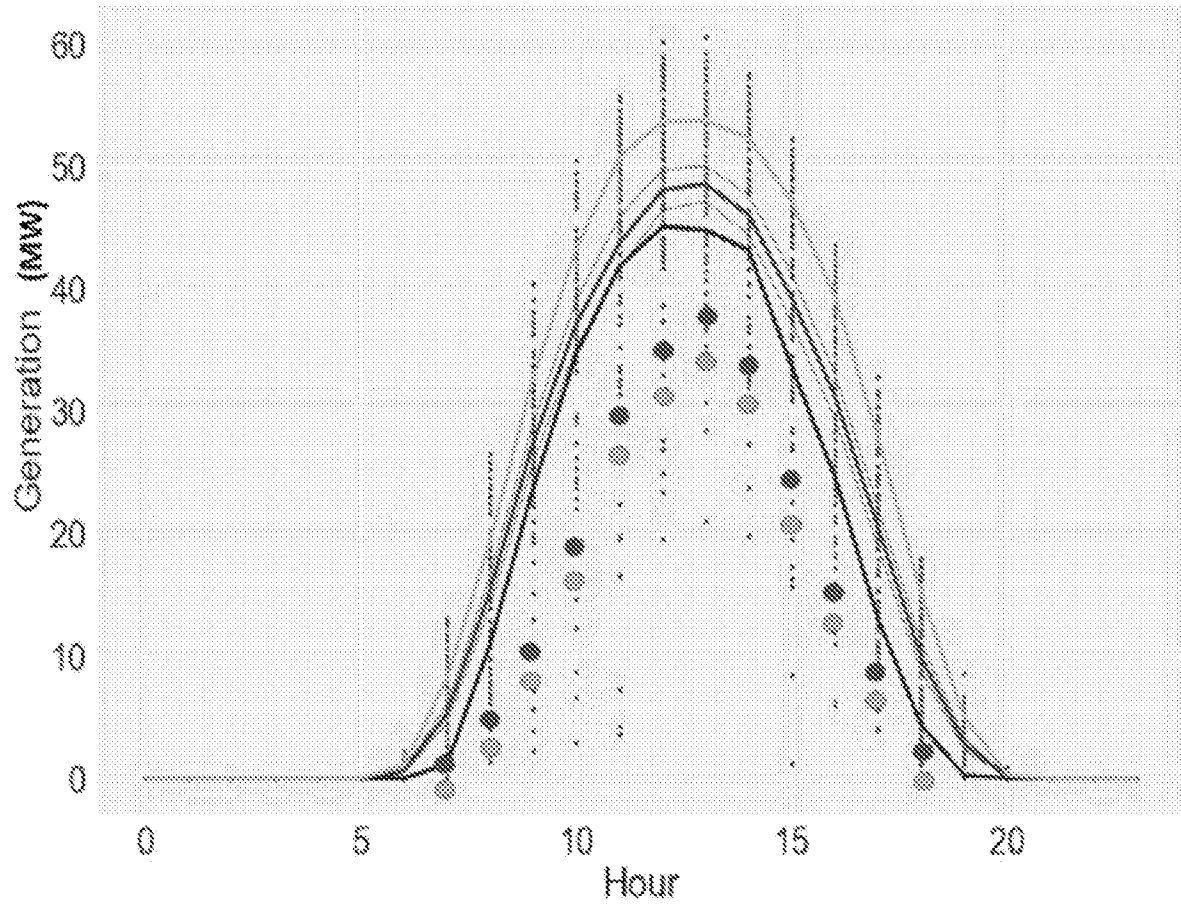


FIG. 1C

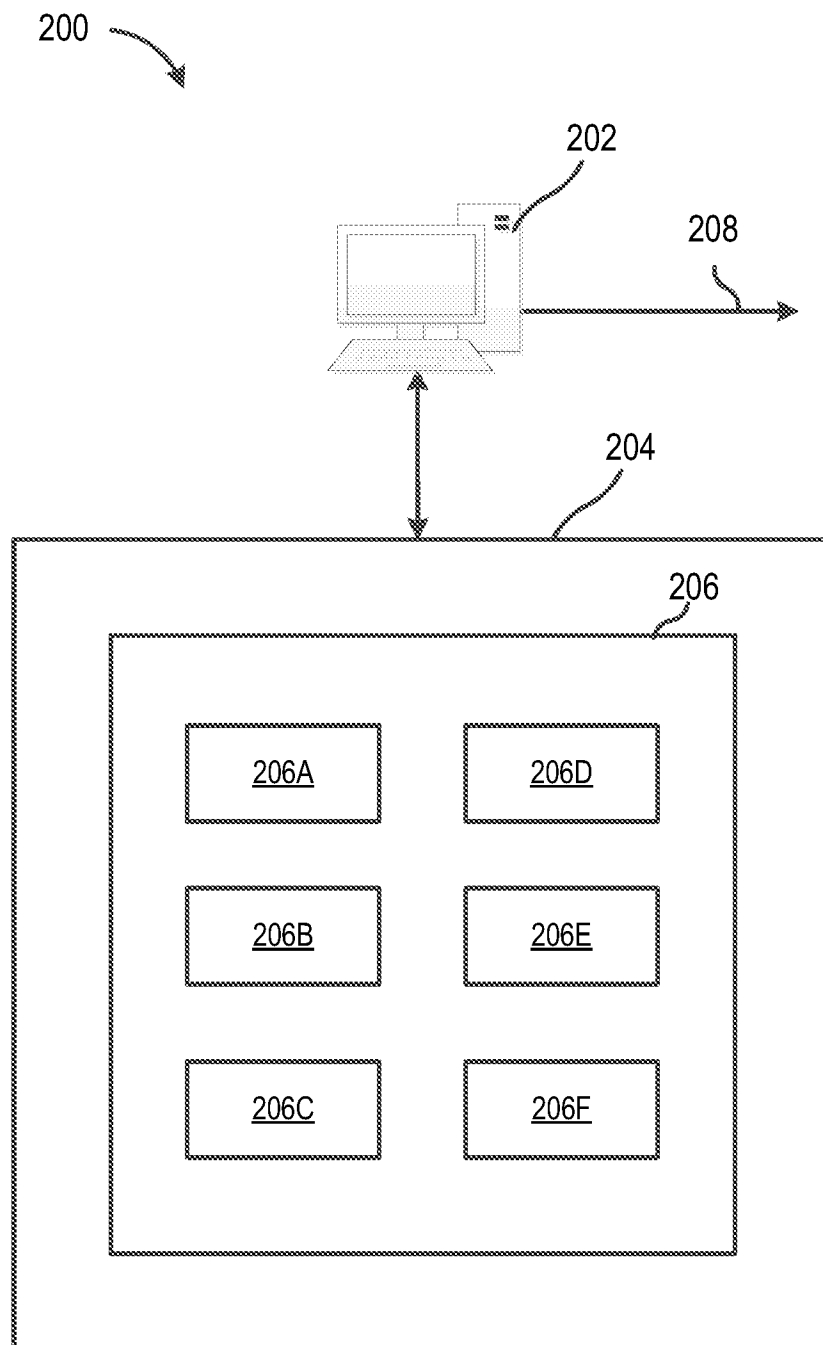


FIG. 2

High generation days

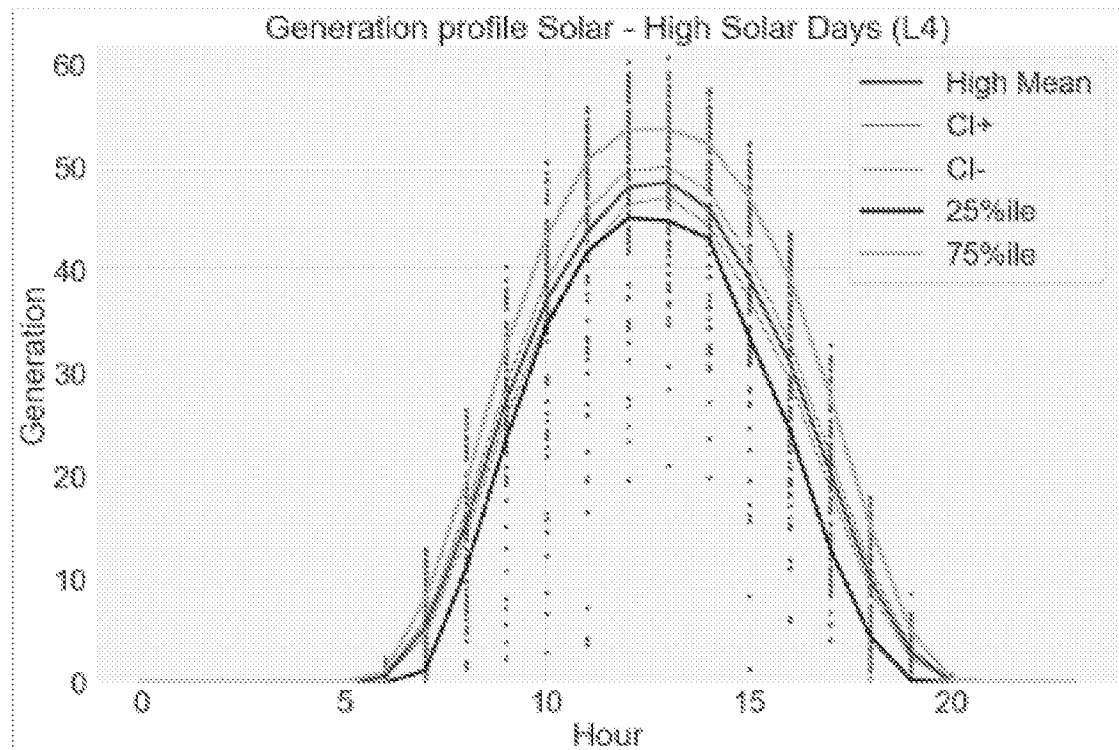
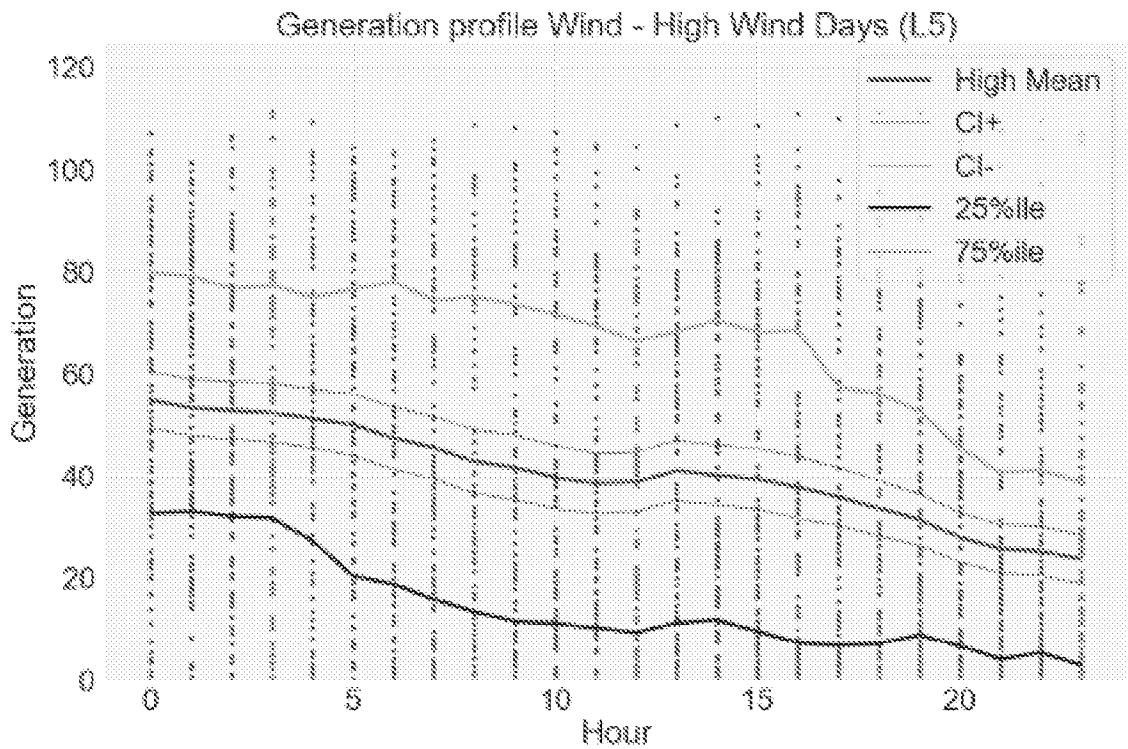


FIG. 3

Low generation days

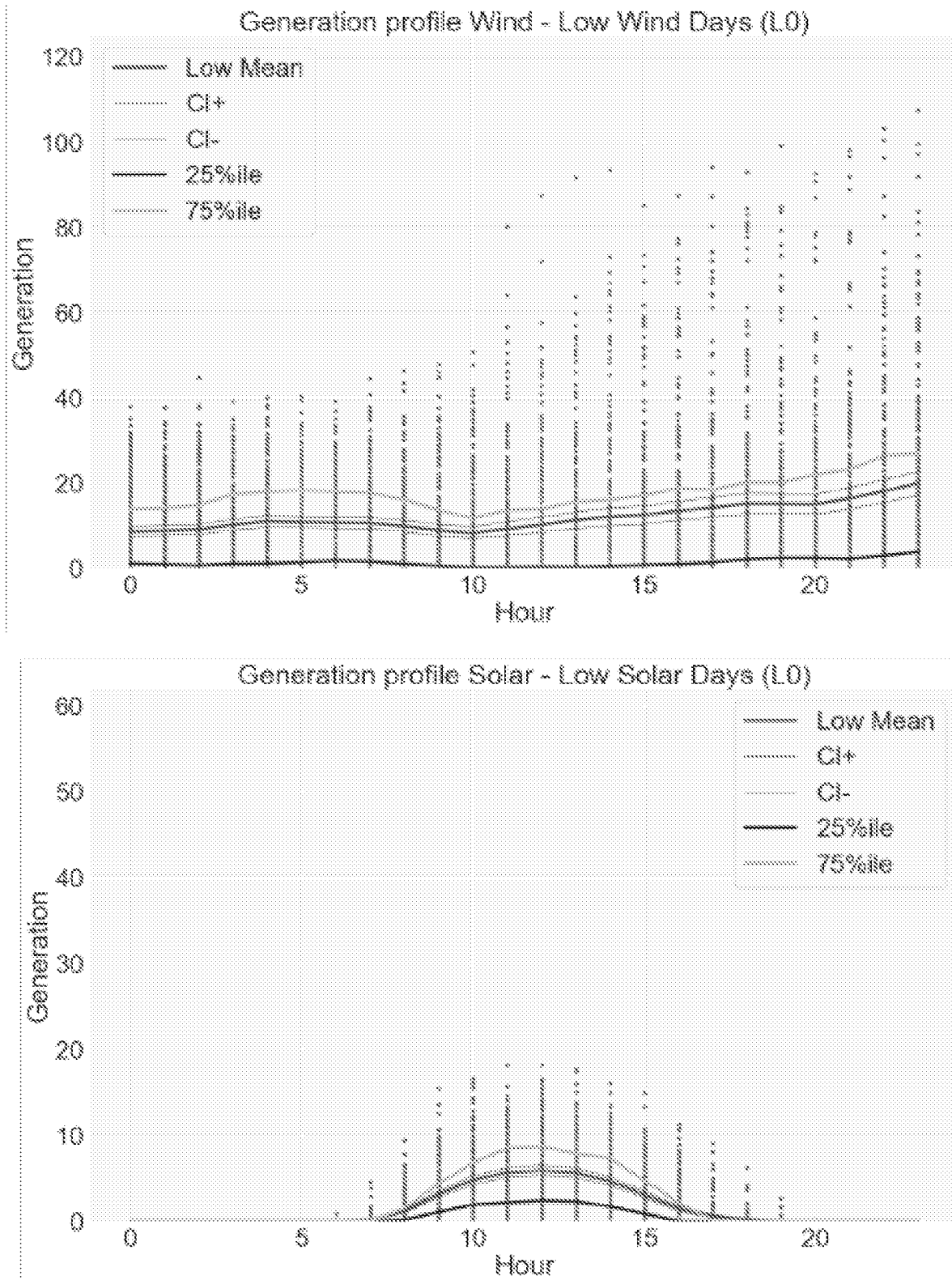


FIG. 3

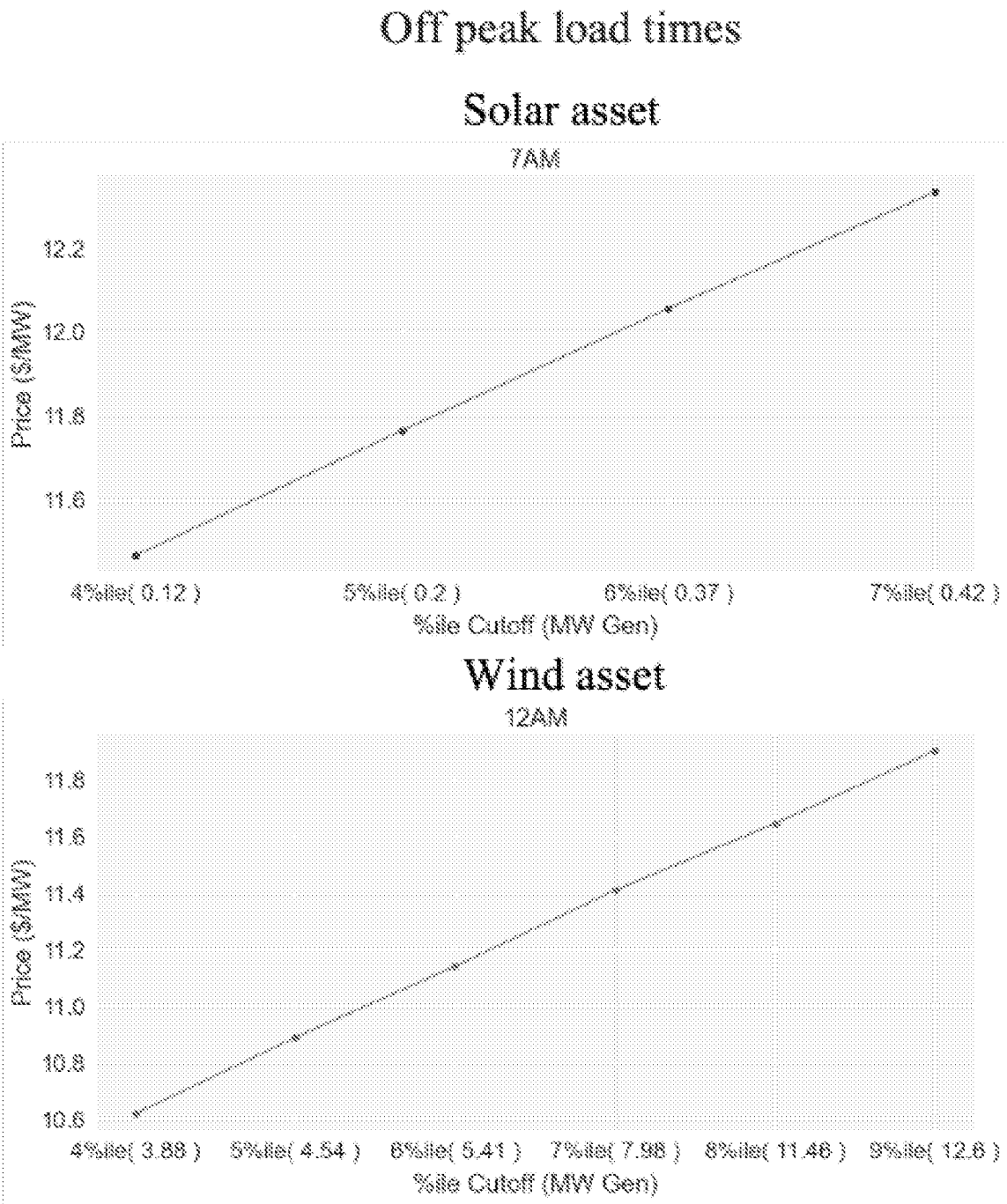


FIG. 4

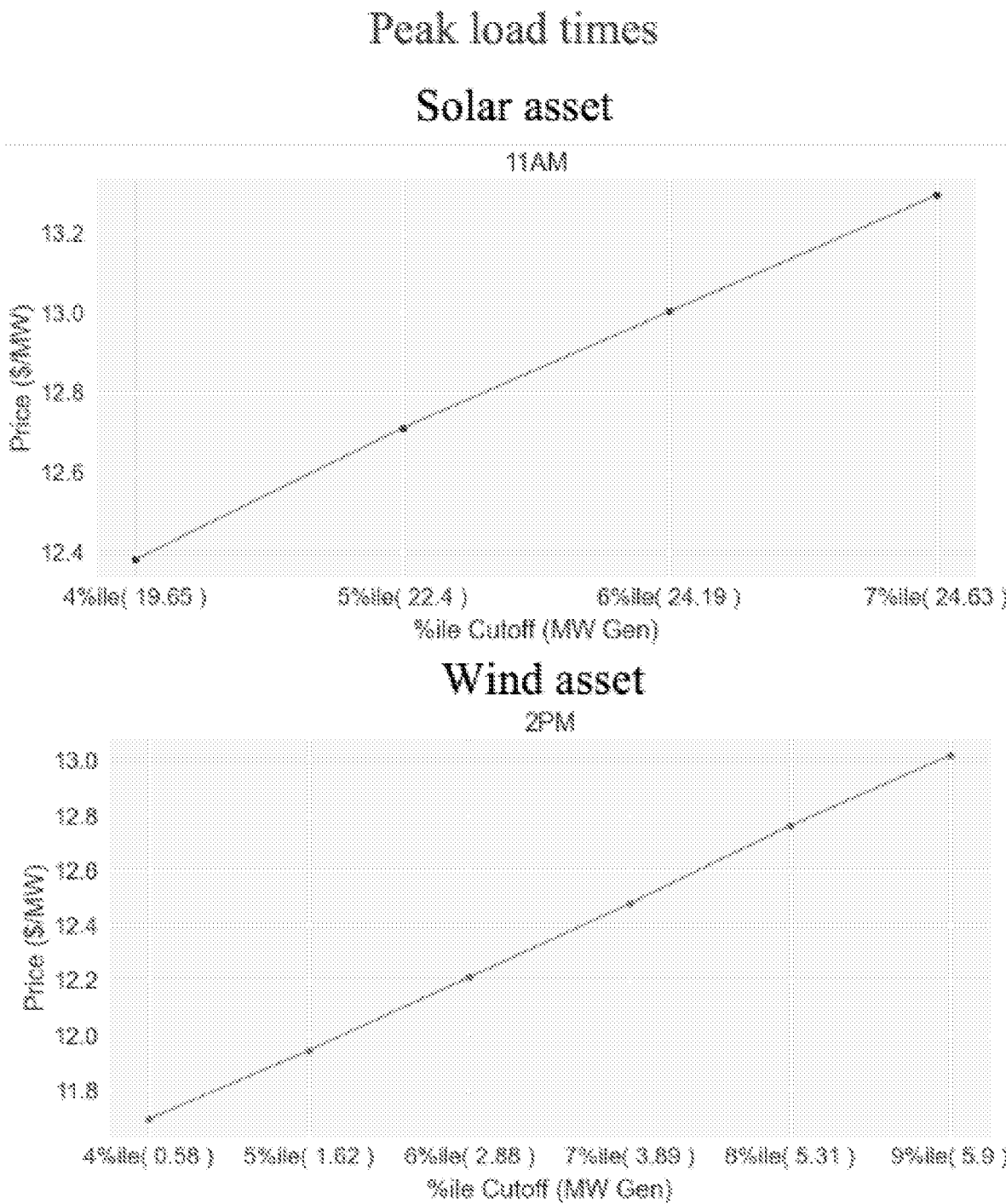


FIG. 4