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(71) Applicant: GENERAL ELECTRIC COMPANY [US/US]; 1 River Road, Schnectady, NY 12345 (US).

(72) Inventors: WANG, Honggang; One Research Circle, Niskayuna, NY 12309 (US). **YAN, Weizhong**; One Research Circle, Niskayuna, NY 12309 (US).

(74) Agent: STABLER, Nicholas, M. et al.; Buckley, Maschoff & Talwalkar LLC, 50 Locust Avenue, New Canaan, CT 06840 (US).

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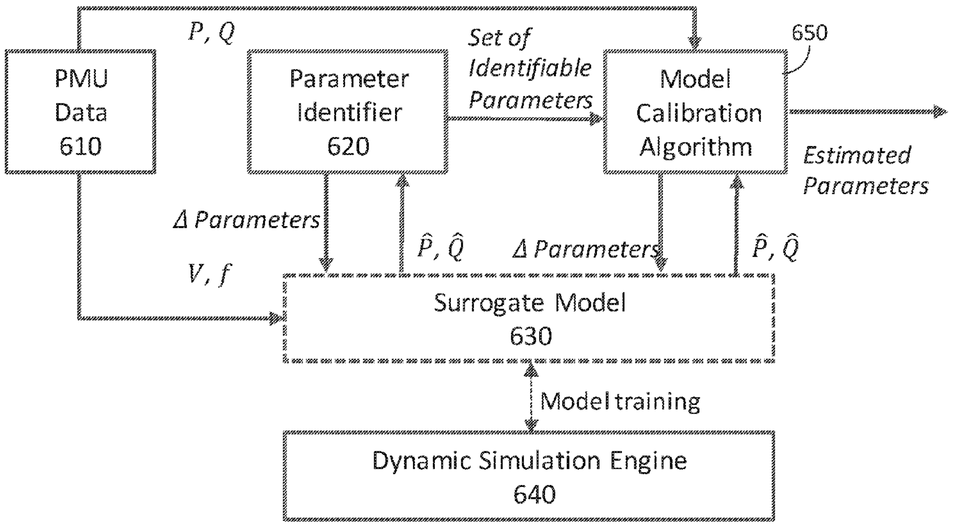
FIG. 6A



(57) Abstract: The example embodiments are directed to a system and method of a surrogate model that emulates the behavior of a dynamic simulation engine without using the differential algebraic equations (DAE) that is used for model calibration. In one example, the method may include receiving a set of parameters of a power system model based on events that are detected from an electrical power grid, identifying a subset of parameters to be calibrated from among the set of parameters of the power system model, predicting calibration values of the subset of parameters via execution of a predictive model which identifies optimal parameter values based on input and output relationships learned from a dynamic simulation engine, and storing the predicted calibration of values for the subset of parameters.

WO 2020/197533 A1

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SURROGATE OF A SIMULATION ENGINE FOR POWER SYSTEM MODEL CALIBRATION

BACKGROUND

[0001] Power system modeling is the process of building a computer model of the electric grid including its components and their characteristics so that studies of the system can be performed. An electric grid's components include generators, power lines, substations, reclosers, voltage regulators, transformers, loads, and several other components. These components have impedances, power ratings, start-up time, capacities, etc. which can be inputted into the computer model. Power system models are useful in providing critical analysis of power system stability.

[0002] Model construction and validation are important tasks that form the foundation of all power system studies. Periodic system model validation is necessary to ensure that the power system models are accurate and up-to-date. These tasks need to be performed regularly in order to keep up with ongoing changes and additions to the power system. Disturbances present great opportunities for model verification and identification of necessary model improvements.

[0003] Traditional power system model calibration involves multiple playback simulations using a commercial dynamic simulation software. The purpose of the simulation is to test all possible parameters of a power system model to determine which parameters should be calibrated. The whole optimization process is characterized by a large number of decision variables or tunable parameters (*e.g.*, hundreds, etc.), absence of analytical gradient information, highly non-linear system responses, and computationally expensive function evaluations resulting in a limited function evaluation budget.

[0004] The simulation (testing of different parameters of the model) can take a great deal of time. For example, a typical playback simulation may take 0.6 seconds for one parameter to be tested. An average power system model may have an optimization problem with 100 tunable parameters. In this case, one Jacobian matrix calculation may take about 60 seconds (100 parameters x 0.6 seconds). An average optimization can take 200 iterations. As a result, the total time of the simulation takes 200 min. Furthermore, if there are multiple events (such as N events) available for model calibration, then it may take 200*N min. Accordingly, what is needed is a mechanism for significantly reducing the calculation time for power system model calibration. There is also a need for a technical solution to have a good balance between calculation speed and quality of solution.

SUMMARY

[0005] The example embodiments improve upon the prior art through the use of a surrogate model (*e.g.*, a predictive model such as a neural network) which can be used to accurately perform the function of a simulation engine when determining model parameters for calibration. The surrogate model can be trained based on the data generated by running a dynamic simulation engine. In this way, the surrogate model can identify patterns in the parameter data of a power system model and predict which parameters to use for calibration rather than having to perform a simulation/test of each parameter using a simulation engine. As a result, the model calibration system can operate at significantly faster speeds (*e.g.*, 20-30 times faster, etc.) than using a dynamic simulation engine to test for each of the parameters.

[0006] In an example embodiment, provided is a method may include at least one of receiving a set of parameters of a power system model based on events that are detected from an electrical power grid, identifying a subset of parameters to be calibrated from among the set of parameters of the power system model, predicting calibration values of the subset of parameters via execution of a predictive model which identifies optimal parameter values based on input and output relationships learned from a dynamic simulation engine, and storing the predicted calibration of values for the subset of parameters.

[0007] In another example embodiment, provided is a system may include a processor configured to at least one of receive a set of parameters of a power system model based on events that are detected from an electrical power grid, identify a subset of parameters to be calibrated from among the set of parameters of the power system model, and predict calibration values of the subset of parameters via execution of a predictive model which identifies optimal parameter values based on input and output relationships learned from a dynamic simulation engine, and a storage configured to store the predicted calibration of values for the subset of parameters.

[0008] In another example embodiment, provided is a non-transitory computer-readable medium storing instructions which when executed by a processor cause a computer to perform a method including at least one of receiving a set of parameters of a power system model based on events that are detected from an electrical power grid, identifying a subset of parameters to be calibrated from among the set of parameters of the power system model, predicting calibration values of the subset of parameters via execution of a predictive model which identifies optimal parameter values based on input and output relationships learned from a dynamic simulation engine, and storing the predicted calibration of values for the subset of parameters.

BRIEF DESCRIPTION OF THE DRAWINGS

[0009] FIG. 1 is a diagram illustrating a power distribution grid.

[0010] FIG. 2 is a high-level block diagram of a system in accordance with some embodiments.

[0011] FIG. 3 is a diagram illustrating a method in accordance with some embodiments.

[0012] FIG. 4 is a block diagram of a system for power disturbance based model calibration in accordance with some embodiments.

[0013] FIG. 5 is a general framework for power system model parameter conditioning in accordance with some embodiments.

[0014] FIG. 6A is a diagram illustrating a model calibration system using a surrogate in accordance with some embodiments.

[0015] FIG. 6B is a diagram illustrating an alternative model calibration system using a surrogate in accordance with some embodiments.

[0016] FIG. 6C is a diagram illustrating a model calibration algorithm in accordance with some embodiments.

[0017] FIG. 7 is a diagram illustrating a generator network capable of being represented by a surrogate model in accordance with some embodiments.

[0018] FIG. 8 is a diagram illustrating an offline training environment for a surrogate model in accordance with some embodiments.

[0019] FIG. 9 is a diagram illustrating a process of generating training data for a surrogate model in accordance with some embodiments.

[0020] FIG. 10A is a diagram illustrating a continuous learning process of a surrogate model in accordance with some embodiments.

[0021] FIG. 10B are diagrams illustrating timelines of calibration operations by a simulation engine and a surrogate model, respectively, in accordance with some embodiments.

[0022] FIG. 11 is a diagram illustrating candidate parameter estimation algorithms in accordance with some embodiments.

[0023] FIG. 12 is a diagram illustrating model calibration algorithms in accordance with some embodiments.

[0024] FIG. 13 is a diagram illustrating an apparatus or platform according to some embodiments.

[0025] FIG. 14 is a diagram illustrating a method of performing model calibration using a surrogate model in accordance with some embodiments.

[0026] Throughout the drawings and the detailed description, unless otherwise described, the same drawing reference numerals will be understood to refer to the same elements, features, and structures. The relative size and depiction of these elements may be exaggerated or adjusted for clarity, illustration, and/or convenience.

DETAILED DESCRIPTION

[0027] In the following detailed description, numerous specific details are set forth in order to provide a thorough understanding of embodiments. However, it will be understood by those of ordinary skill in the art that the embodiments may be practiced without these specific details. In other instances, well-known methods, procedures, components and circuits have not been described in detail so as not to obscure the embodiments.

[0028] One or more specific embodiments are described below. In an effort to provide a concise description of these embodiments, all features of an actual implementation may not be described in the specification. It should be appreciated that in the development of any such actual implementation, as in any engineering or design project, numerous implementation-specific decisions must be made to achieve the developers’ specific goals, such as compliance with system-related and business-related constraints, which may vary from one implementation to another. Moreover, it should be appreciated that such a development effort might be complex and time consuming, but would nevertheless be a routine undertaking of design, fabrication, and manufacture for those of ordinary skill having the benefit of this disclosure.

[0029] A traditional simulation engine relies on differential algebraic equations (DAEs) therein to perform simulations. For example, the simulation engine may include dozens, hundreds, and the like, for a single component on the power grid. Because of the amount of different equations in the simulation engine software to represent the power system (generator, transformer, load), performance of a simulation is slow. Furthermore, the simulation engine has a non-linear response, it is not easy to automatically extract analytical gradient information which is what is needed for optimization. One simulation is the equivalent of a Jacobian Matrix Calculation which can include 200 iterations or more. Each iteration can take a minute or more. Meaning that for one simulation, the simulation engine can require at least 200 minutes of time.

[0030] Typically a dynamic simulation engine is used to facilitate both identifiability of parameters (in total) and determination of parameters for calibration. Given field data with time stamped voltage (V) and frequency (f), the simulation engine will provide the simulated active power ($\hat{P}$) and reactive ($\hat{Q}$) with the same timestamp. Parameter identification involves multiple calls of simulation engines with parameter perturbation to determine the best choice of a subset of the parameters for tuning (calibration). Calibration involves multiple calls of the simulation engine to search for the best value for the given subset of parameters determined in the identifiability step.

[0031] The example embodiments provide a surrogate (*e.g.*, predictive model) which can be used to replace the dynamic simulation engine when performing the parameter identification and the parameter calibration. The surrogate model can be trained based on historical behavior of a dynamic simulation engine thereby learning patterns between inputs and outputs of the dynamic simulation engine. The surrogate model can emulate the functionality performed by the dynamic simulation engine without having to perform numerous rounds of simulation. Instead, the model can predict (*e.g.*, via a neural network, or the like) a subset of parameters for model calibration and also predict / estimate optimal parameter values for the subset of parameters in association with a power system model that is being calibrated.

[0032] According to the examples herein, a surrogate model may be used to capture both input–output function and first derivative of a dynamic simulation engine used for model calibration. The surrogate model may be updated based on its confidence level and prediction deviation against the original simulation engine. Here, the surrogate model may be a surrogate for a dynamic simulation engine and may be used to perform model calibration without using DAE equations. The system described herein may be a model parameter tuning engine, which is configured to receive the power system data and model calibration command, and search for the optimal model parameters using the surrogate model until the closeness between simulated response and the real response from the power system data meet a predefined threshold.

[0033] In some of the examples described herein, the surrogate model may operate on disturbance event data that includes one or more of device terminal real power, reactive power, voltage magnitude, and phase angle data. The model calibration may be triggered by user or by automatic model validation step. In some aspects, the surrogate model may be trained offline when there is no grid event calibration task. The surrogate model may represent a set of different models used for different kinds of events. In some embodiments, the surrogate model's input may include at least one of voltage, frequency and other model tunable parameters. The surrogate model may be a neural network model, fuzzy logic, a polynomial function, and the like. Other model tunable parameters may include a parameter affecting dynamic behavior of machine, exciter, stabilizer and governor. Also, the surrogate model's output may include active power, reactive power or both. In some cases, the optimizer may be gradient based method including Newton-like methods. For example, the optimizer may be gradient free method including pattern search, genetic algorithm, simulated annealing, particle swarm optimizer, differential evolution, and the like.

[0034] FIG. 1 illustrates a power distribution grid 100. The grid 100 includes a number of components, such as power generators 110. In some cases, planning studies conducted using dynamic models predict stable grid 100 operation, but the actual grid 100 may become unstable in a few minutes with severe swings (resulting in a massive blackout). To ensure that the models represent the real system accurately, the North American Electric Reliability Coordinator ("NERC") requires generators 110 above 10 MVA to be tested every five years to check the accuracy of dynamic models and let the power plant dynamic models be updated as necessary.

[0035] In a typical staged test, a generator 110 is first taken offline from normal operation. While the generator 110 is offline, testing equipment is connected to the generator 110 and its controllers to perform a series of pre-designed tests to derive the desired model parameters. Recently, PMUs 120 and Digital Fault Recorders ("DFRs") 130 have seen dramatic increasing installation in recent years, which may allow for non-invasive model validation by using the sub-second-resolution dynamic data. Varying types of disturbances across locations in the grid 100 along with the large installed base of PMUs 120 may, according to some embodiments, make it possible to validate the dynamic models of the generators 110 frequently at different operating conditions. There is a need for a production-grade software tool generic enough to be applicable to wide variety of models (traditional generating plant, wind, solar, dynamic load, etc. with minimal changes to existing simulation engines. Note that model calibration is a process that seek multiple (dozens or hundreds) of model parameters, which could suffer from local minimum and multiple solutions. There is need for an algorithm to enhance the quality of a solution within a reasonable amount time and computation burdens.

[0036] To achieve such results, FIG. 2 is a high-level block diagram of a system 200 in accordance with some embodiments. The system 200 includes one or more measurement units 210 (*e.g.*, PMUs, DFRs, or other devices to measure frequency, voltage, current, or power phasors) that store information into a measurement data store 220. As used herein, the term "PMU" might refer to, for example, a device used to estimate the magnitude and phase angle of an electrical phasor quantity like voltage or current in an electricity grid using a common time source for synchronization. The term "DFR" might refer to, for example, an Intelligent Electronic Device ("IED") that can be installed in a remote location, and acts as a termination point for field contacts. According to some embodiments, the measurement data might be associated with disturbance event data and/or data from deliberately performed unit tests. According to some embodiments, a model parameter tuning engine 250 may access this data and use it to tune parameters for a dynamic system model 260. The process might be performed automatically or be initiated via a calibration command from a remote operator interface device 290. As used herein, the term "automatically" may refer to, for example, actions that can be performed with little or no human intervention.

[0037] Note that power systems may be designed and operated using mathematical models (power system models) that characterize the expected behavior of power plants, grid elements, and the grid as a whole. These models support decisions about what types of equipment to invest in, where to put it, and how to use it in second-to-second, minute-to-minute, hourly, daily, and long-term operations. When a generator, load, or other element of the system does not act in the way that its model predicts, the mismatch between reality and model-based expectations can degrade reliability and efficiency. Inaccurate models have contributed to a number of major North American power outages.

[0038] The behavior of power plants and electric grids may change over time and should be checked and updated to assure that they remain accurate. Engineers use the processes of validation and calibration to make sure that a model can accurately predict the behavior of the modeled object. Validation assures that the model accurately represents the operation of the real system – including model structure, correct assumptions, and that the output matches actual events. Once the model is validated, a calibration process may be used to make minor adjustments to the model and its parameters so that the model continues to provide accurate outputs. High-speed, time-synchronized data, collected using PMUs may facilitate model validation of the dynamic response to grid events. Grid operators may use, for example, PMU data recorded during normal plant operations and grid events to validate grid and power plant models quickly and at lower cost.

[0039] The transmission operators or Regional reliability coordinators, or Independent System Operators, like MISO, ISO-New England, PG&E, can use this calibrated generator or power system model for power system stability study based on N-k contingencies, in every 5 to 10 minutes. If there is stability issue (transient stability) for some specific contingency, the power flow will be redirected to relieve the stress-limiting factors. For example, the output of some power generators will be adjusted to redirect the power flow. Alternatively, adding more capacity (more power lines) to the existing system can be used to increase the transmission capacity.

[0040] With a model that accurately reflects oscillations and their causes, the grid operator can also diagnose the causes of operating events, such as wind-driven oscillations, and identify appropriate corrective measures before those oscillations spread to harm other assets or cause a loss of load.

[0041] As used herein, devices, including those associated with the system 200 and any other device described herein, may exchange information via any communication network which may be one or more of a Local Area Network ("LAN"), a Metropolitan Area Network ("MAN"), a Wide Area Network ("WAN"), a proprietary network, a Public

Switched Telephone Network ("PSTN"), a Wireless Application Protocol ("WAP") network, a Bluetooth network, a wireless LAN network, and/or an Internet Protocol ("IP") network such as the Internet, an intranet, or an extranet. Note that any devices described herein may communicate via one or more such communication networks.

[0042] The model parameter tuning engine 250 may store information into and/or retrieve information from various data stores, which may be locally stored or reside remote from the model parameter tuning engine 250. Although a single model parameter tuning engine 250 is shown in FIG. 2, any number of such devices may be included. Moreover, various devices described herein might be combined according to embodiments of the present invention. For example, in some embodiments, the measurement data store 220 and the model parameter tuning engine 250 might comprise a single apparatus. The system 200 functions may be performed by a constellation of networked apparatuses, such as in a distributed processing or cloud-based architecture.

[0043] A user may access the system 200 via the device 290 (*e.g.*, a Personal Computer ("PC"), tablet, or smartphone) to view information about and/or manage operational information in accordance with any of the embodiments described herein. In some cases, an interactive graphical user interface display may let an operator or administrator define and/or adjust certain parameters (*e.g.*, when a new electrical power grid component is calibrated) and/or provide or receive automatically generated recommendations or results from the system 200.

[0044] FIG. 3 is a method that might performed by some or all of the elements of the system 200 described with respect to FIG. 2. The flow charts described herein do not imply a fixed order to the steps, and embodiments of the present invention may be practiced in any order that is practicable. Note that any of the methods described herein may be performed by hardware, software, or any combination of these approaches. For example, a computer-readable storage medium may store thereon instructions that when executed by a machine result in performance according to any of the embodiments described herein.

[0045] At S310, a model parameter turning engine may receive, from a measurement data store, measurement data measured by an electrical power system measurement unit (*e.g.*, a PMU, DFR, or other means of measuring frequency, voltage, current, or power phasors). The measurement data might be associated with, for example, disturbance event data, and/or data from deliberately performed unit tests. The disturbance data may be associated with a power grid electrical component. The electrical component might be associated with, for example, a generator, a wind turbine, a solar panel, a dynamic load, *etc*. The measurement data might include, according to some embodiments, device terminal real power ("P"), reactive power ("Q"), voltage magnitude ("V"), frequency ("f"), and/or phase angle data ("θ").

[0046] At S320, the system may receive a model calibration command. According to some embodiments, the calibration command is received via an automated process. According to other embodiments, the calibration command is received via a user console interface display. The interface display might, according to some embodiments (as described with respect to FIG. 9), provide for event data selection, simulation engine selection, and/or calibration algorithm configuration.

[0047] At S330, the system may pre-condition the measurement data. The pre-conditioning might include, for example, normalization of parameter and model output. The pre-conditioning might also include an identifiability assessment providing sensitivity and dependency. According to some embodiments, the pre-conditioning further includes a feature transformation on model output data. At S340, the system may set-up an optimization problem based on a result of the pre-conditioning.

[0048] At S350, the system may determine system parameters, of a dynamic simulation engine for the component of the electrical power system, by solving the optimization problem (set up at S340) with an iterative method until at least one convergence criteria is met. According to some embodiments, the optimization problem set-up includes a weight set-up on an objective function based on a feature transformation result. Note that solving the optimization problem might include sending model input and model parameters into the dynamic simulation engine and obtaining predicted model output for calculation of residual. Moreover, solving the optimization problem could include a Jacobian approximation (and the Jacobian approximation might not call the dynamic simulation engine if an improvement of residual meets a pre-defined criteria).

[0049] FIG. 4 is a block diagram of a system 400 for power disturbance based model calibration in accordance with some embodiments. The system 400 includes a parameter identifiability analysis 452 that provides a set of identifiable parameters to a model calibration engine 454. The parameter identifiability analysis provides Δ parameters to a dynamic simulation engine 460 and receives back $\hat{P}, \hat{Q}$. The model calibration engine 454 also receives PMU data from disturbance events 410 (specifically, for example, P and Q). The model calibration algorithm 454, according to some embodiments, provides Δ parameters to the dynamic simulation engine 460 and receives back $\hat{P}$, $\hat{Q}$ along with auxiliary quantities. As will be described, this architecture may let disturbance events in a power grid be used to calibrate a power system model (*e.g.*, the dynamic simulation engine) in a non-invasive way.

[0050] FIG. 5 is a general framework for power system model parameter conditioning according to some embodiments. At S510, disturbance data may be obtained (*e.g.*, from a PMU or DFR) to obtain, for example, V, f, P, and Q measurement data at a Point Of Interest ("POI"). At S520, a playback simulation may run load model benchmarking using default model parameters (*e.g.*, associated with a Positive Sequence Load Flow ("PSLF") or Transient Security Assessment Tool ("TSAT")). At S530, model validation may compare measurements to default model response. If the response matches the measurements, the framework may end (*e.g.*, the existing model is sufficiently correct and does not need to be updated). At S540, an event analysis algorithm may determine if event is qualitatively different from previous events. At S550, a parameter identifiability analysis algorithm may determine most identifiable set of parameters across all events of interest. Finally, at S560 an Unscented Kalman Filter ("UKF")/optimization-based parameter estimation process may be performed. As a result, the estimated parameter values, confidence metrics, and error in model response (aa compared to measurements) may be reported.

[0051] Disturbance data may be monitored by one or more PMUs coupled to an electrical power distribution grid may be received. The disturbance data can include voltage ("V"), frequency ("f"), and/or active and nonactive reactive ("P" and "Q") power measurements from one or more points of interest (POI) on the electrical power grid. A power system model may include model parameters. These model parameters can be the current parameters incorporated in the power system model. The current parameters can be stored in a model parameter record. Model calibration involves identifying a subset of parameters that can be "tuned" and modifying / adjusting the parameters such that the power system model behaves identically or almost identically to the actual power component being represented by the power system model.

[0052] In accordance with some embodiments, the model calibration can implement model calibration with three functionalities. The first functionality is an event screening tool to select characteristics of a disturbance event from a library of recorded event data. This functionality can simulate the power system responses when the power system is subjected to different disturbances. The second functionality is a parameter identifiability study. When implementing this functionality, the can simulate the response(s) of a power system model. The third functionality is simultaneous tuning of models using event data to adjust the identified model parameters. According to various embodiments, the second functionality (parameter identifiability) and the third functionality (tuning of model parameters) may be done using a surrogate model in place of a dynamic simulation engine.

[0053] Event screening can be implemented during the simulation to provide computational efficiency. If hundreds of events are stitched together and fed into the calibration algorithm unselectively, the algorithm may not be able to converge. To maintain the number of events manageable and still keep an acceptable representation of all the events, a screening procedure may be performed to select the most characteristic events among all. Depending on the type of events, the measurement data could have different characteristics. For example, if an event is a local oscillation, the oscillation frequency in the measurement data would be much faster as compared to an inter-area oscillation event. In some implementations, a K-medoids clustering algorithm can be utilized to group events with similar characteristic together, thus reducing the number of events to be calibrated.

[0054] Instead of using the time consuming simulation engine, the surrogate model or models (such as Neural Networks) with equivalent function of dynamic simulation engine, may be used for both identifiability and calibration. The surrogate model may be built offline while there is no request for model calibration. Once built, the surrogate model comprising a set of weights and bias in learned structure of network will be used to predict the active power ($\hat{P}$) and reactive ($\hat{Q}$) given different set of parameters together with time stamped voltage (V) and frequency (f).

[0055] The parameter identifiability analysis addresses two aspects: (a) magnitude of sensitivity of output to parameter change; and (b) dependencies among different parameter sensitivities. For example, if the sensitivity magnitude of a particular parameter is low, the parameter would appear in a row being close to zero in the parameter estimation problem's Jacobian matrix. Also, if some of the parameter sensitivities have dependencies, it reflects that there is a linear dependence among the corresponding rows of the Jacobian. Both these scenarios lead to singularity of the Jacobian matrix, making the estimation problem infeasible. Therefore, it may be important to select a subset of parameters which are highly sensitive as well as result in no dependencies among parameter sensitivities. Once the subset of parameters is identified, values in the active power system model for the parameters may be updated, and the system may generate a report and/or display of the estimated parameter values(s), confidence metrics, and the model error response as compared to measured data.

[0056] FIG. 6A illustrates a model calibration system 600A using a surrogate model 630 in accordance with some embodiments. In this example, the surrogate model 630 may be a neural network, fuzzy logic, a polynomial function, and the like. The surrogate model 630 may be trained (*e.g.*, offline) based on historical operating behavior of a dynamic simulation engine 640. In the example of FIG. 6A, the surrogate model 630 may emulate the functionality of the dynamic simulation (online) and thereby replace the dynamic simulation engine with the power system model calibration process. For example, the surrogate model 630 may represent overall system dynamics including several different model types and controllers. An example of the features represented by the surrogate model 630 are shown in FIG. 7. Furthermore, the training of the surrogate model 630 may be performed based on inputs and outputs of the dynamic simulation engine 640. An example of offline training of the surrogate model 60 is described in the example of FIG. 8.

[0057] Referring to FIG. 6A, disturbance event data sensed by one or more PMUs may be collected by a PMU data component 610. For example, the disturbance event data may include device terminal real power, reactive power, voltage magnitude, phase angle data, and the like, detected of components on the power grid. Here, the voltage and frequency components of the disturbance event data may be fed to the surrogate model 630. Furthermore, the active power (P) and the reactive power (Q) may be fed to a model calibration algorithm component 650.

[0058] To perform calibration of a power system model of a component on the power grid based on the disturbance event data, multiple steps are performed including identifying parameters for calibration and tuning those parameters. For example, a power system model can include around 100 parameters (or more) in the model. A traditional model calibration performed by a dynamic simulation engine tries to tune the 100 parameters to make sure the calculated P bar and Q bar are as close as possible to the measured P and Q. Traditionally, the system must call the simulation engine for each parameter (100 times). For each parameter the system is trying to figure out how it affects the output. If the parameter has a lot of effect on the calibration, it is chosen to be in the subset of identified parameters. However, if it does not have much effect, it will not be called on. Here, the system must check each parameter and determine whether it is needed for model calibration. The system is trying to figure out which parameters (out of the 100) that can be tuned by the model calibration algorithm to align the simulated active power ($\hat{P}$) and reactive power ($\hat{Q}$) with generated by the power system model to the actual P and Q generated by the component at the same time.

[0059] According to various embodiments, the surrogate model 630 can be called by a parameter identification component 620 in place of the dynamic simulation engine to assist in identifying a subset of parameters. Once built, the surrogate model 630 may include a set of weights and bias in a learned structure of the network which can be used to predict the simulated active power ($\hat{P}$) and the simulated reactive power ($\hat{Q}$) given different set of parameters together with time stamped voltage (V) and frequency (f). In this way, the surrogate model 630 can help identify the subset parameters based on the impact they have on the simulated active power ($\hat{P}$) and the simulated reactive ($\hat{Q}$). In particular, the surrogate model 630 may identify patterns between inputs (V) and (f) with respect to outputs of the predicted simulated active power ($\hat{P}$) and the simulated reactive power ($\hat{Q}$), and identify which parameters are most optimal for tuning the power system model.

[0060] The subset of parameters of the power system model that are selected for tuning (calibration) may be forwarded to a model calibration algorithm component 650 which can call the surrogate model 630 to determine optimal parameter values which can represent the power system model. Here, the optimal parameter values may be determined based on a comparison of the simulated active power ($\hat{P}$) and the simulated reactive power ($\hat{Q}$)with respect to the actual active power and actual reactive power of the component on the electrical grid. The model parameter calibration performed by the model calibration algorithm component 650 may include calling a derivative of output of the surrogate model 630 with respect to the parameters. Accordingly, the surrogate model 630 may have a good balance of learning both the input-output function of the simulation engine and their derivative relationship.

[0061] As further described in the example of FIG. 8, a combined function and derivative approximation (CFDA) performance index may be used as a cost function of neural network training to ensure that an accurate relationship between power output to the voltage/frequency input is captured by the surrogate model 630, and also the derivative relationship between power output and the parameter inputs (like generator inertia) are captured in the surrogate model 630.

[0062] The estimated parameters generated by the model calibration algorithm component 650 and the surrogate model 630 can be reported to a user interface (such as an operator) and/or transmitted to another entity associated with the power system model. The estimated parameter values may be output with confidence metrics and error information regarding model responses versus measurements.

[0063] FIG. 6B illustrates an alternative model calibration system 600B using the surrogate model 630 in accordance with some embodiments. Referring to FIG. 6B, the alternative model calibration system 600B includes the same components as the model calibration system 600A, except in FIG. 6B, the dynamic simulation engine 640 is included in the online operation of the model calibration system 600B. In particular, the dynamic simulation engine 640 may help the parameter identification component 620 identify the subset of parameters to be tuned during calibration. Meanwhile, the surrogate model 630 may help the model calibration algorithm component 650 predict/determine optimal parameter values for the subset of parameters.

[0064] In the example of FIG. 6B, the parameter identification does not involve much time in comparison to the parameter tuning. Therefore, the dynamic simulation engine 640 can be used to identify the subset of parameters without accruing much additional time. However, the longer process of parameter estimation/simulation may still be performed by the surrogate model 630 instead of the dynamic simulation engine 640 thereby realizing significant time savings.

[0065] FIG. 6C illustrates a model calibration algorithm that can be used by the model calibration algorithm component 650 in accordance with some embodiments. Here, the model calibration algorithm attempts to find a parameter value (θ^*) for a parameter (or parameters) of the power system model that creates a matching output between the simulated active power ($\hat{P}$) and the simulated reactive power ($\hat{Q}$) predicted by the surrogate model 630 with respect to the actual active power (P) and actual reactive power (Q) of the component on the electrical grid.

[0066] FIG. 7 illustrates a generator network 700 capable of being represented by a surrogate model in accordance with some embodiments. Referring to FIG. 7, generators can have several classes of models (with controllers) including machine models 720, exciter models 730, governor models 740, stabilizer models 750, and the like. A network model 710 such as a neural network (such as Radial Basis Network, Support Vector Machine, Deep Learning Neural Network, Long Short Term Memory, etc.) can be used to represent the overall system dynamics. As another example, multiple neural networks can be used such as one neural network for each model component, or the like. As a third example, the overall system model can be represented by a mixture of surrogate model for some components (such as Machine Model 720 and Governor Model 740) and DAE model for other components (such as Exciter Model 730 and Stabilizer Model 750). In the case of using a surrogate model to represent a component model, the surrogate model input shall include both the component model input (such as governor control setpoint, electrical power and rotor speed for Governor Component) and the related tunable parameters (such as tunable parameters inside of a governor model). The selection of which type of model to be used for a certain component is based on the difficulty of building surrogate models. For example, Stabilizer model 750 is comprised of a series of multiple dynamic transfer functions for lead-lap compensations, which may be quite challenging to be represented by a surrogated model which can still maintain the system stability. In this case, a DAE model with control structure may be preferred compared to a surrogate model.

[0067] The example embodiments implement a surrogate model (simple model) to replace and represent the components of a dynamic simulation engine. An example of a common dynamic simulation engine is PSLF, PSS/E, TSAT. The models are dynamic models meaning that they have time variables included in the equations. In other words, these models are dynamic so that over time the models change. The models are also interconnected with each other. So a change in one model can cause a change in another model. The surrogate model (network model 710) that can be used may represent the input/output relationships of the different models of the dynamic simulation engine. There is an input/output mapping that is learned.

[0068] FIG. 8 illustrates an offline training environment 800 for a surrogate model 630 in accordance with some embodiments. In this example, the surrogate model 630 may learn from the input and output relationships of the dynamic simulation engine 640. Since the model parameter calibration involves calling a derivate of the output with respect to the parameters, the model may learn a good balance of both the input/output relationship and their derivative relationship. A cost function module 810 may use a combined function and derivative approximation (CFDA) performance index as a cost function of surrogate model 630 such as a neural network that is trained to ensure relationship between power output to the voltage/frequency input is captured, and also the derivative relationship between power output and the parameter inputs (like inertia) are captured in the surrogate model 630.

[0069] In the example of the training in FIG. 8, the surrogate model 630 is observing the simulation engine 640 over time and become a duplicate by learning how the simulation engine 640 react to inputs. The surrogate model 630 is trying to emulate the behavior of the simulation engine 640. In this case, a large amount of training data (inputs and outputs) of the simulation engine 640 may be observed and used for learning. Then the surrogate model 630 can be trained by learning input/output relationships. This can be an offline training. The cost function can be determined using the error between the actual power (P) and/or the actual reactive power (Q) determined by the simulation engine 640 with respect to the simulated active power ($\hat{P}$) and the simulated reactive power ($\hat{Q}$) predicted by the surrogate model 630. In other words, the cost function can be used to determine a confidence level of the predictive model based on a deviation of predictions made by the surrogate model in comparison to determinations made by simulations performed by the dynamic simulation engine for the identified subset of parameters.

[0070] The cost function generated by the cost function module 810 indicates whether the surrogate model 630 is performing well or not. The cost function allows the system/operator to tune weight and bias attributes of the surrogate model 630 through a surrogate model optimizer 820. For example, the weight and bias of the surrogate model 630 may be adjusted by the surrogate model optimizer 820 until the cost function 810 is at an acceptable level. Accordingly, the cost function can minimize the error between the actual and simulated outputs and also help learn a derivative relationship thereof.

[0071] The training data design space may comprise of different events, model tunable parameters for each of the components and various voltage and frequency profile as a time series. The event data may come from Design Of Experiment (DOE) based on the grid network model, such as the Western Electricity Coordinating Council (WECC) generic models. The DOE may comprise of different grid disturbance scenarios such as generator trip, load trip, line trip, asset failure and line fault, etc. The data generation may also consider the statistical distribution of the existing database for real world grid disturbance, so that more experiments may be generated for the more frequent event category in the database.

Each event may be represented by the voltage and frequency time series or by the features extracted from the voltage and frequency time series. The DOE may further comprise of the different parameter combination, and the parameter space may be designed based on the available parameter space in the WECC, Eastern Interconnections. Full factorial, Taguchi screening, central composite and Box-Behnken are some of the known design methodologies used to create the event space and tunable parameter space.

[0072] The model may take the voltage and frequency time series as input with proper conditioning (like the length of the time series) and extract the event feature inside the model. Or the model may take the feature of the voltage and frequency time series directly. As used herein, the term “feature” may refer to, for example, mathematical characterizations of data. Examples of features as applied to data might include the maximum, minimum, mean, standard deviation, variance, range, current value, settling time, Fast Fourier Transform (“FFT”) spectral components, linear and non-linear principal components, independent components, sparse coding features, deep learning features, etc.

[0073] Note that many different types of features may be utilized in accordance with any of the embodiments described herein, including principal components (weights constructed with natural basis sets) and statistical features (e.g., mean, variance, skewness, kurtosis, maximum, minimum values of time series signals, location of maximum and minimum values, independent components, etc.). Other examples include deep learning features (e.g., generated by mining experimental and/or historical data sets) and frequency domain features (e.g., associated with coefficients of Fourier or wavelet transforms). Note that a deep learning technique might be associated with, for example, an auto-encoder, a de-noising auto-encoder, a restricted Boltzmann machine, etc. Embodiments may also be associated with time series analysis features, such as cross-correlations, auto-correlations, orders of the autoregressive, moving average model, parameters of the model, derivatives and integrals of signals, rise time, settling time, neural networks, etc. Still other examples include logical features (with semantic abstractions such as “yes” and “no”), geographic/position locations, and interaction features (mathematical combinations of signals from multiple data source nodes and specific locations).According to some embodiments, dissimilar values from data source nodes may be normalized to unit-less space, which may allow for a simple way to compare outputs and strength of outputs.

[0074] The surrogate model may be a feedforward neural network models, including a Time delay neural network (TDNN), convolutional neural network, NLARX (Non Linear Auto Regressive with eXogenous inputs) models. The surrogate model may also use recurrent neural networks such as Long short-term memory (LSTM), Elman networks, Jordan networks and echo state network. The surrogate model may also use an ensemble model which is a combination of multiple models with the same type or different type of neural network models. Each model in the ensemble may represent one specific event type, operating range, or a subspace of parameter space.

[0075] FIG. 9 illustrates a process 900 of generating training data for a surrogate model in accordance with some embodiments. Referring to FIG. 9, in 902 the system may receive data sets for various event categories of data such as different types of disturbances detected from the power grid. The data may include voltage, frequency, current, power, and the like. In 904, the system may receive a predefined parameter range associated with the event data, the parameter range may define a parameter space spanned by either a simple high/low limit or combination with some inequality or non-linear constraints. In 906, the system may identify predefined working points which are predefined for each event category. The working points may indicate the grid network condition and/or generator working condition based on the use of subspace spanned by the principal feature from the operating data. Based on the data sets, the parameter range and the working points, in 908 the system may generate a parameter design space for each event category and working point.

[0076] In 910, the system may determine data sampling in the parameter design space for each event category and working point. In 912, a simulation engine may determine whether the data converges normally or whether the data does not converge. If the data does not converge, in 916, the data is added to the training data. For example, data pairs with event, parameter, response and derivative over parameter may be added to the training data. If the data does converge, in 914 the parameter set can be updated and the process can be repeated with the updated parameter set.

[0077] FIG. 10A illustrates a continuous learning process 1000 for a surrogate model in accordance with some embodiments. When the surrogate model has been learned/trained it is added to an online application where the model may generated prediction given necessary model inputs. However, over time the model may deviate from the real plant behavior due to various reasons and the operators may want to improve accuracy. Referring to the example of FIG. 10A, the surrogate model can continue to learn. This may be performed by post-event model evaluation, as illustrated in FIG. 10B.

[0078] Referring to FIG. 10B, the top timeline 1020 shows the calibration activity using DAE based simulation engine (such as GE's PSLF software). It shows three model calibration activities (1022, 1024, 1026) over predetermined time frame (*e.g.*, 1 year, etc.) for example. The rectangular blocks (1022, 1024, 1026) indicate occurrence of model calibration activity, and the length of the rectangular block indicates an amount of time spent for one model calibration activity. The bottom timeline 1030 shows the calibration behavior may be changed based on the use of surrogate model. It also shows the continuous learning process. As shown, three rectangular blocks 1032, 1034, and 1036 represent the model calibration activity performed by a surrogate model instead of the simulation engine. Compared to the top figure 1020, the time spent by the surrogate model performing model calibration (1032, 1034, 1036) is significantly reduced with the use of surrogate model compared to those with use of DAE based simulation engine (1022,1024,1026). Also, during the time where there is no model calibration activity, four round corner rectangular areas (1042, 1044, 1046, 1048) are added which represents periods of time where the continuous learning is occurring. The first area (1042) indicates the first surrogate model training process before the first use of surrogate model for model calibration. It takes the longest time because it is the first time to build the model from scratch. After the first surrogate model training, the surrogate model may be used during the first model calibration activity (1032). After that, the surrogate model may be improved based on the information from the activity 1032. This continuous learning process will go on in 1044, 1046 and 1048 until the surrogate achieved satisfactory performance, such as an equivalent performance as the DAE based simulation engine. The benefit of the continuous model learning is fast deployment of the model calibration system and also a significant reduced time for model calibration activity with reasonable model quality.

[0079] In this example, the simulation engine may do the same job as the surrogate model and results of each may be used to compare the performance of the simulation engine to the surrogate network to verify / train the surrogate model. This training may be performed offline and post-event evaluation by the surrogate model.

[0080] Referring again to FIG. 10A, in 1002 pre-event model training is performed on the surrogate model (such as a ANN) before the system/user triggers model calibration. In

1004, the trained surrogate model (*e.g.*, ANN, etc.) may be used for event based model calibration and the results may be output in 1005. In 1006, the system may perform a post-event model evaluation against dynamic simulation engine results over the same data. For example, in 1006, the system may perform a cost function evaluation such as shown in the cost function analysis of example of FIG. 8. In 1008, the system may determine whether the surrogate model needs to be updated. For example, the system may be determined to update the model if the relative error between the surrogate model (ANN) and the simulation engine is above a predefined threshold. In response, in 1010, the system may use the new event data and parameter space to generate a new model (*e.g.*, retrain ANN, etc.

[0081] FIG. 11 illustrates candidate parameter estimation algorithms 1100 according to some embodiments. In one approach 1120, measured input/output data 1110 (u, y^m) may be used by a power system component model 1122 and an UKF based approach 1124 to create an estimation parameter (p^*) 1140.

[0082] In particular, the system may compute sigma points based on covariance and standard deviation information. The Kalman Gain matrix K may be computed based on Ŷ and the parameters may be updated based on:

$$p_k = p_{k-1} + K(y^m - \hat{y})$$

until p_k converges. According to another approach 1130, the measured input/output data 1110 (u, y^m) may be used by a power system component model 1132 and an optimization-based approach 1134 to create the estimation parameter (p^*) 1140. In this case, the following optimization problem may be solved:

$$\min_{p} \left\| y^m - \hat{Y}(p) \right\|^2$$

The system may then compute output as compared to parameter Jacobian information and iteratively solve the above optimization problem by moving parameters in directions indicated by the Jacobian information.

[0083] FIG. 12 illustrates 1200 model calibration algorithms in accordance with some embodiments. In particular, a first power system component model 1210 may receive θ and generate $P(\theta)$, $Q(\theta)$ as illustrated by graph 1220 showing P_{PMU}, Q_{PMU}. A second power system component model 1230 may receive θ^* and generate $P(\theta^*)$, $Q(\theta^*)$ as illustrated by graph 1240 showing P_{PMU}, Q_{PMU}. The system may utilize the following model:

$$\text{Model: } y(\theta) = \begin{bmatrix} P(\theta) \\ Q(\theta) \end{bmatrix}, \text{Measurement: } y^m = \begin{bmatrix} P_{PMU} \\ Q_{PMU} \end{bmatrix},$$

where, $P(\theta)$, $Q(\theta)$ are model outputs as a function of parameters θ and P_{PMU} and Q_{PMY} are time series PMU measurements. The goal of the model calibration may be to find θ^* such that model output matches measurements: $y(\theta) \approx y^m$. According to some embodiments, a two-stage approach may include:

- Stage 1 including a parameter identifiability analysis; and
- Stage 2 including a parameter estimation.

[0084] Note that the embodiments described herein may also be implemented using any number of different hardware configurations. For example, FIG. 13 is a block diagram of an apparatus or platform 1300 that may be, for example, associated with the system 200 of FIG. 2 and/or any other system described herein. The platform 1300 comprises a processor 1310, such as one or more commercially available Central Processing Units ("CPUs") in the form of one-chip microprocessors, coupled to a communication device 1320 configured to communicate via a communication network (not shown in FIG. 13). The communication device 1320 may be used to communicate, for example, with one or more remote measurement units, components, user interfaces, *etc*. The platform 1300 further includes an input device 1340 (*e.g.*, a computer mouse and/or keyboard to input power grid and/or modeling information) and/an output device 1350 (*e.g.*, a computer monitor to render a display, provide alerts, transmit recommendations, and/or create reports). According to some embodiments, a mobile device, monitoring physical system, and/or PC may be used to exchange information with the platform 1300.

[0085] The processor 1310 also communicates with a storage device 1330. The storage device 1330 may comprise any appropriate information storage device, including combinations of magnetic storage devices (*e.g.*, a hard disk drive), optical storage devices, mobile telephones, and/or semiconductor memory devices. The storage device 1330 stores a program 1312 and/or a power system disturbance based model calibration engine 1314 for controlling the processor 1310. The processor 1310 performs instructions of the programs 1312, 1314, and thereby operates in accordance with any of the embodiments described herein. For example, the processor 1310 may calibrate a dynamic simulation engine, having system parameters, associated with a component of an electrical power system (*e.g.*, a generator, wind turbine, *etc.*). The processor 1310 may receive, from a measurement data store, measurement data measured by an electrical power system measurement unit (*e.g.*, a phasor measurement unit, digital fault recorder, or other means of measuring frequency, voltage, current, or power phasors). The processor 1310 may then pre-condition the measurement data and set-up an optimization problem based on a result of the pre-conditioning. The system parameters of the dynamic simulation engine may be determined by solving the optimization problem with an iterative method until at least one convergence criteria is met. According to some embodiments, solving the optimization problem includes a Jacobian approximation that does not call the dynamic simulation engine if an improvement of residual meets a pre-defined criteria.

[0086] The programs 1312, 1314 may be stored in a compressed, uncompiled and/or encrypted format. The programs 1312, 1314 may furthermore include other program elements, such as an operating system, clipboard application, a database management system, and/or device drivers used by the processor 1310 to interface with peripheral devices.

[0087] As used herein, information may be “received” by or “transmitted” to, for example: (i) the platform 1300 from another device; or (ii) a software application or module within the platform 1300 from another software application, module, or any other source.

[0088] FIG. 14 illustrates a method 1400 of performing model calibration using a surrogate model in accordance with some embodiments. For example, the method 1400 may be performed by a computing system such as a web server, a user device, a database, an on-premises server, a cloud platform, a desktop PC, a mobile device, and the like. Referring to FIG. 14, in 1410 the method may include receiving a set of parameters associated with a power system model based on events that are detected from an electrical power grid. Here, the events may be grid disturbance events including generator trip, load trip, line trip and fault, etc. The parameters may include inertia (of a generator), control parameters, including gain, integration time, etc. of a power system model which can be tuned through calibration.

[0089] In 1420, the method may include identifying a subset of parameters to be calibrated from among the set of parameters of the power system model. For example, the subset of parameters may be identified based on the influence or the impact they have on a simulated power value created by the power system model in comparison to an actual power value generated by a component on the electrical grid which the power system model is meant to represent. For example, the subset of parameters may be identified from disturbance event data which comprises at least one of real power, reactive power, voltage magnitude, and phase angle data. In 1430, the method may include predicting calibration values of the subset of parameters via execution of a predictive model which identifies optimal parameter values based on input and output relationships learned from a dynamic simulation engine, and in 1440 the method may include storing the predicted calibration of values for the subset of parameters.

[0090] According to various embodiments, the predictive model is a surrogate for a dynamic simulation engine in a calibration system. For example, the predictive model may include at least one of a neural network, fuzzy logic, and a polynomial function. The predicting performed by the surrogate model may determine optimal values for the subset of parameters based on how the subset of parameters effect a simulated performance of the power system model with respect to a real performance of a corresponding power grid component represented by the power system model. In some embodiments, the predicting of the calibration values for the subset of parameters may be performed by the predictive model based on at least one of active power and reactive power output by execution of the predictive model.

[0091] In some embodiments, the predictive model may be least one of a surrogate model and a combination of the surrogate model and a differential algebraic equation (DAE) based model, which are substitutes for the dynamic simulation engine in a calibration system. In some embodiments, the method may further include at least one of updating the surrogate model through continuous learning from the dynamic simulation engine and improving the surrogate model between two model calibration activities.

[0092] In some embodiments, the method may further include determining a confidence level of the predictive model based on a deviation of predictions made by the predictive model with respect to determinations made by the dynamic simulation engine for the identified subset of parameters. In some embodiments, the method may further include updating at least one input/output relationship of the predictive model in response to the determined confidence level falling below a predetermined threshold.

[0093] In some embodiments, the identifying of the subset of parameters may also be performed via execution of the predictive model. As another example, the identifying of the subset of parameters may be performed via simulation by the dynamic simulation engine. The subset of parameters may include tunable parameters of the power system model capable of being adjusted through calibration. In some embodiments, the power system model may be associated with at least one of a generator, a transformer, and a substation on the electrical power grid. In some embodiments, the predicting may be triggered in response to receiving a request for model validation of the power system model. In some embodiments, the predictive model may include a plurality of different generator models such as a governor model, a machine model, an exciter model, a stabilizer model, and the like, which are associated with a plurality of different types of events on the electrical power grid.

[0094] The following illustrates various additional embodiments of the invention. These do not constitute a definition of all possible embodiments, and those skilled in the art will understand that the present invention is applicable to many other embodiments. Further, although the following embodiments are briefly described for clarity, those skilled in the art will understand how to make any changes, if necessary, to the above-described apparatus and methods to accommodate these and other embodiments and applications.

[0095] Although specific hardware and data configurations have been described herein, note that any number of other configurations may be provided in accordance with some embodiments of the present invention (*e.g.*, some of the information associated with the databases described herein may be combined or stored in external systems). Moreover, although some embodiments are focused on particular power grid components, any of the embodiments described herein could be applied to other types of electrical power grid components (including dams, windfarms, batteries, *etc*.).

[0096] The present invention has been described in terms of several embodiments solely for the purpose of illustration. Persons skilled in the art will recognize from this description that the invention is not limited to the embodiments described, but may be practiced with modifications and alterations limited only by the spirit and scope of the appended claims.

THE CLAIMS

1. A method comprising:

receiving a set of parameters associated with a power system model based on events that are detected from an electrical power grid;

identifying a subset of parameters to be calibrated from among the set of parameters of the power system model;

predicting calibration values of the subset of parameters via execution of a predictive model which identifies optimal parameter values based on input and output relationships learned from a dynamic simulation engine; and

storing the predicted calibration of values for the subset of parameters.

2. The method of claim 1, wherein the predictive model is at least one of a surrogate model and a combination of surrogate models and a differential algebraic equation (DAE) based model, for the dynamic simulation engine in a calibration system.

3. The method of claim 2, wherein the method further comprising at least one of updating the surrogate model through continuous learning from the dynamic simulation engine and improving the surrogate model between two model calibration activities.

4. The method of claim 2, wherein the surrogate model's input comprises model tunable parameters and at least two of voltage, frequency, angle, active power, and reactive power.

5. The method of claim 2, wherein the surrogate model comprises at least one of a neural network, fuzzy logic, and a polynomial function without using the differential algebraic equations (DAE).

6. The method of claim 1, wherein the predicting determines optimal values for the subset of parameters based on how the subset of parameters effect a simulated performance of the power system model with respect to a real performance of a corresponding power grid component represented by the power system model.

7. The method of claim 1, wherein the predicting the calibration values for the subset of parameters is performed by the predictive model based on at least one of active power and reactive power output by the by execution of the predictive model.

8. The method of claim 1, further comprising determining a confidence level of the predictive model based on a deviation of predictions made by the predictive model with respect to determinations made by the dynamic simulation engine for the identified subset of parameters.

9. The method of claim 3, further comprising updating at least one input/output relationship of the predictive model in response to the determined confidence level falling below a predetermined threshold.

10. The method of claim 1, wherein the identifying of the subset of parameters is also performed via execution of the predictive model.

11. The method of claim 1, wherein the identifying of the subset of parameters via simulation by the dynamic simulation engine.

12. The method of claim 1, wherein the subset of parameters comprises tunable parameters of the power system model capable of being adjusted through calibration.

13. The method of claim 1, wherein the power system model is associated with at least one of a generator, a transformer, a substation, and a load on the electrical power grid.

14. The method of claim 1, wherein the predictive model comprises a plurality of different generator models associated with a plurality of different types of events on the electrical power grid.

15. The method of claim 1, wherein the identified subset of parameters are identified from disturbance event data which comprises at least one of real power, reactive power, voltage magnitude, and phase angle data.

16. A computing system comprising:

a processor configured to receive a set of parameters associated with a power system model based on events that are detected from an electrical power grid, identify a subset of parameters to be calibrated from among the set of parameters of the power system model, and predict calibration values of the subset of parameters via execution of a predictive model which identifies optimal parameter values based on input and output relationships learned from a dynamic simulation engine; and

a storage configured to store the predicted calibration of values for the subset of parameters.

17. The computing system of claim 15, wherein the processor predicts the calibration values for the subset of parameters based on at least one of active power and reactive power output by execution of the predictive model

18. The computing system of claim 15, wherein the predictive model is a surrogate for the dynamic simulation engine in a calibration system.

19. The computing system of claim 15, wherein the processor identifies the set of parameters via execution of the predictive model.

20. A non-transitory computer-readable medium storing instructions which when executed by a processor cause a computer to perform a method comprising:

receiving a set of parameters associated with a power system model based on events that are detected from an electrical power grid;

identifying a subset of parameters to be calibrated from among the set of parameters of the power system model;

predicting calibration values of the subset of parameters via execution of a predictive model which identifies optimal parameter values based on input and output relationships learned from a dynamic simulation engine; and

storing the predicted calibration of values for the subset of parameters.

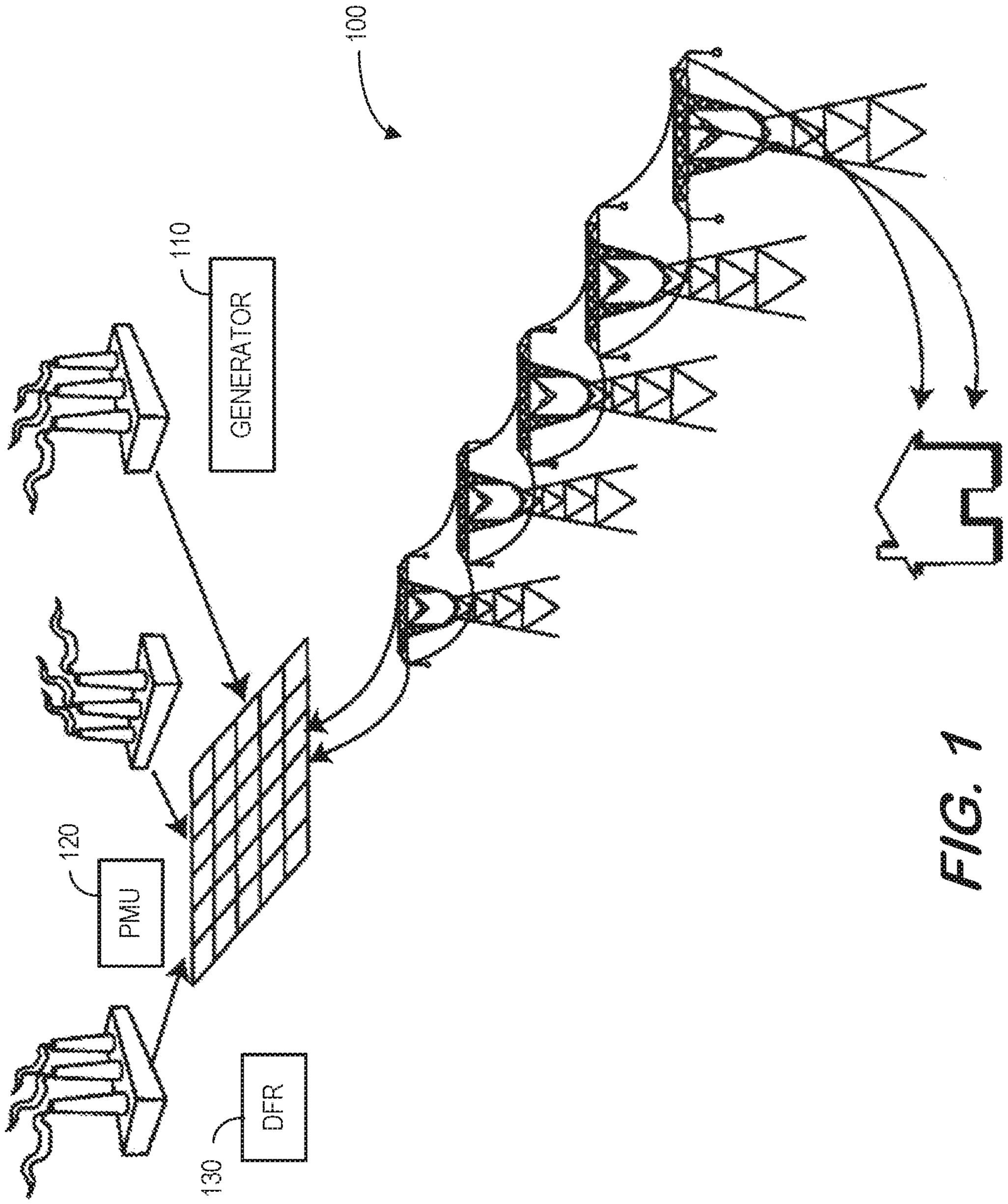


FIG. 1

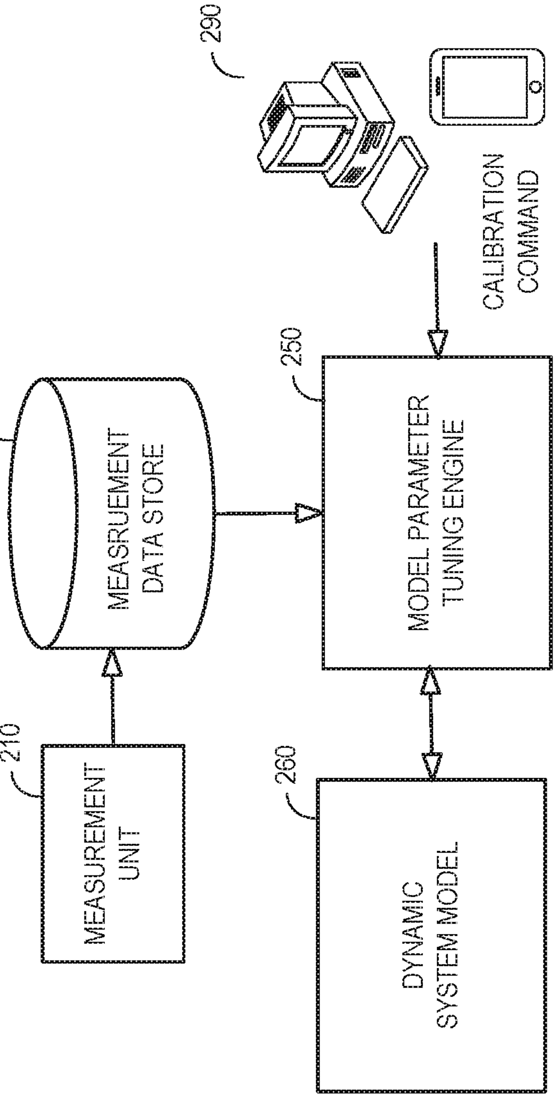

290
CALIBRATION COMMAND
220
MEASRUEMENT DATA STORE
250
MODEL PARAMETER TUNING ENGINE
210
MEASUREMENT UNIT
260
DYNAMIC SYSTEM MODEL

FIG. 2

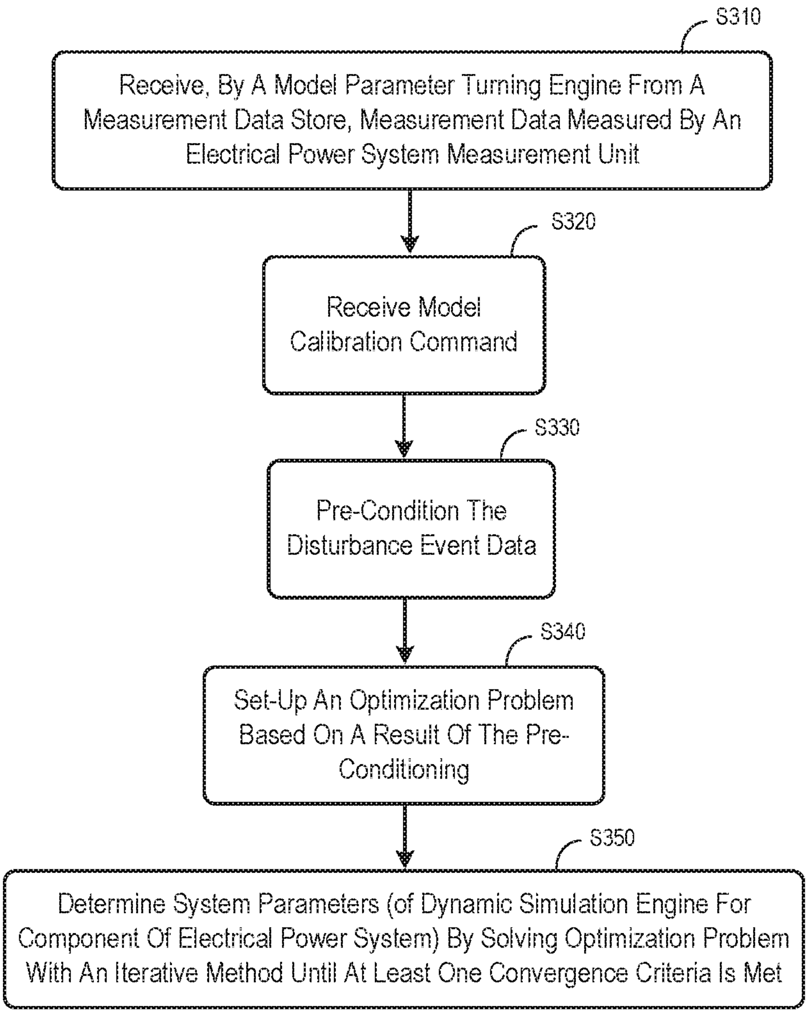

S310
Receive, By A Model Parameter Turning Engine From A Measurement Data Store, Measurement Data Measured By An Electrical Power System Measurement Unit
S320
Receive Model Calibration Command
S330
Pre-Condition The Disturbance Event Data
S340
Set-Up An Optimization Problem Based On A Result Of The Pre-Conditioning
S350
Determine System Parameters (of Dynamic Simulation Engine For Component Of Electrical Power System) By Solving Optimization Problem With An Iterative Method Until At Least One Convergence Criteria Is Met

FIG. 3

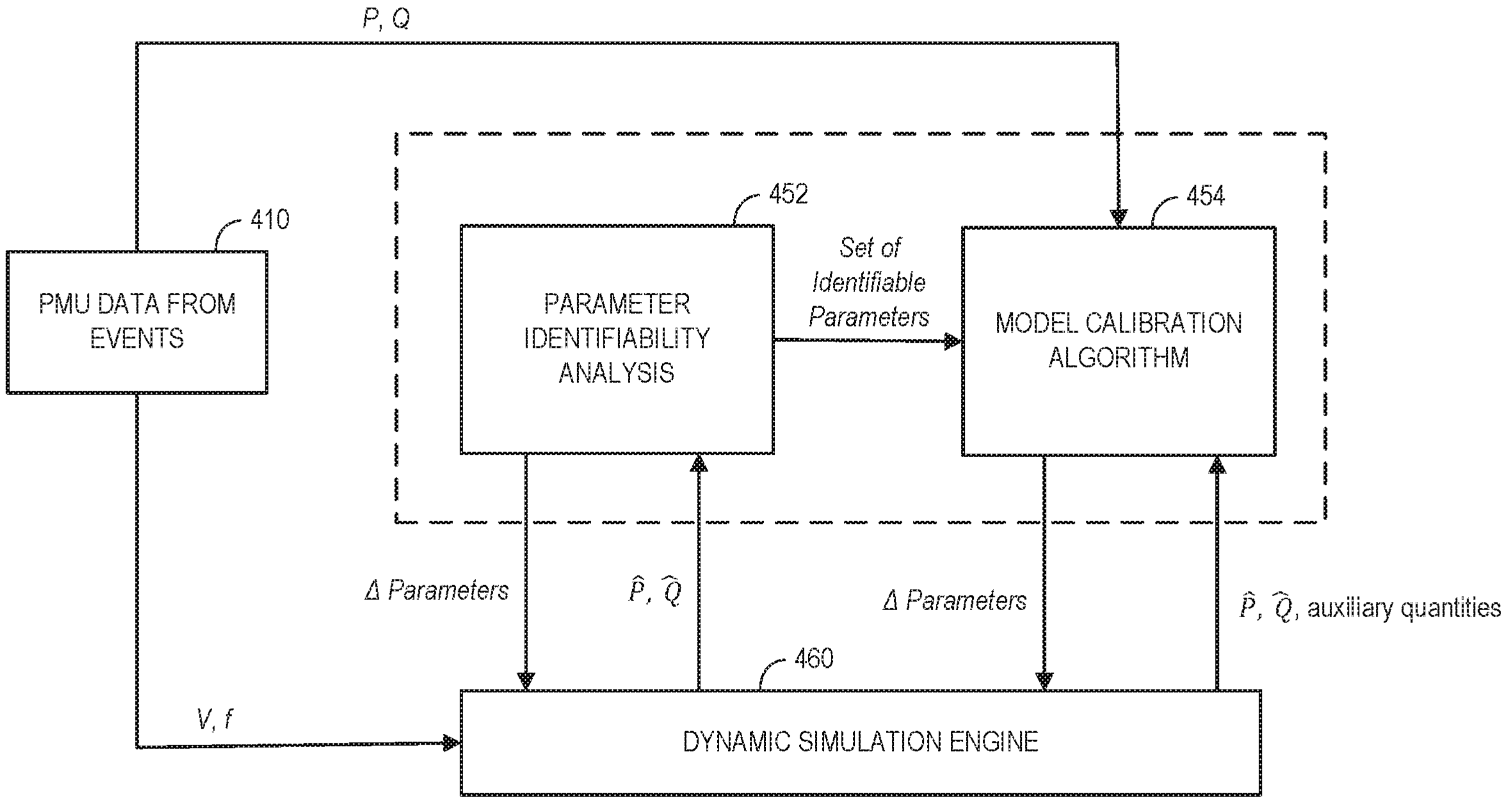

P, Q
410
PMU DATA FROM EVENTS
452
PARAMETER IDENTIFIABILITY ANALYSIS
Set of Identifiable Parameters
454
MODEL CALIBRATION ALGORITHM
Δ Parameters
$\hat{P}$, $\hat{Q}$
Δ Parameters
$\hat{P}$, $\hat{Q}$, auxiliary quantities
460
V, f
DYNAMIC SIMULATION ENGINE

FIG. 4

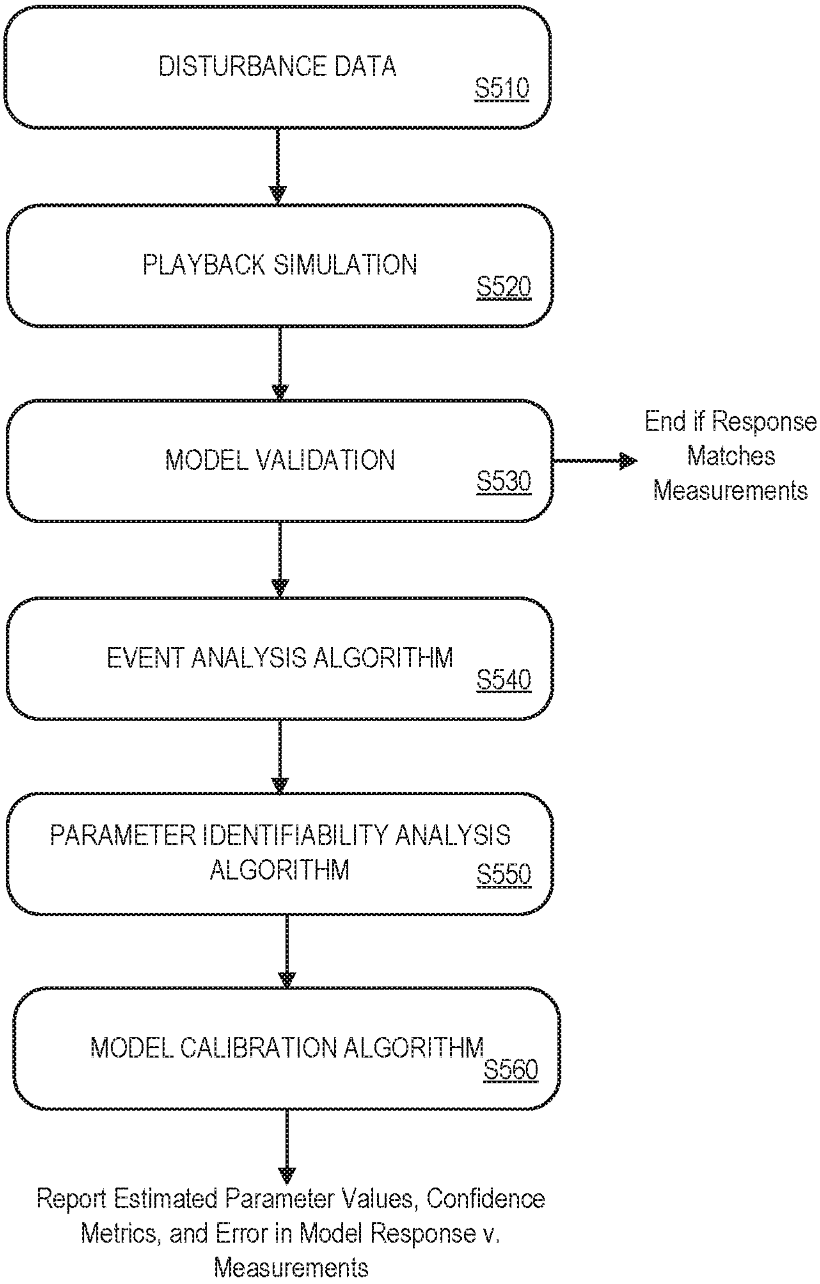
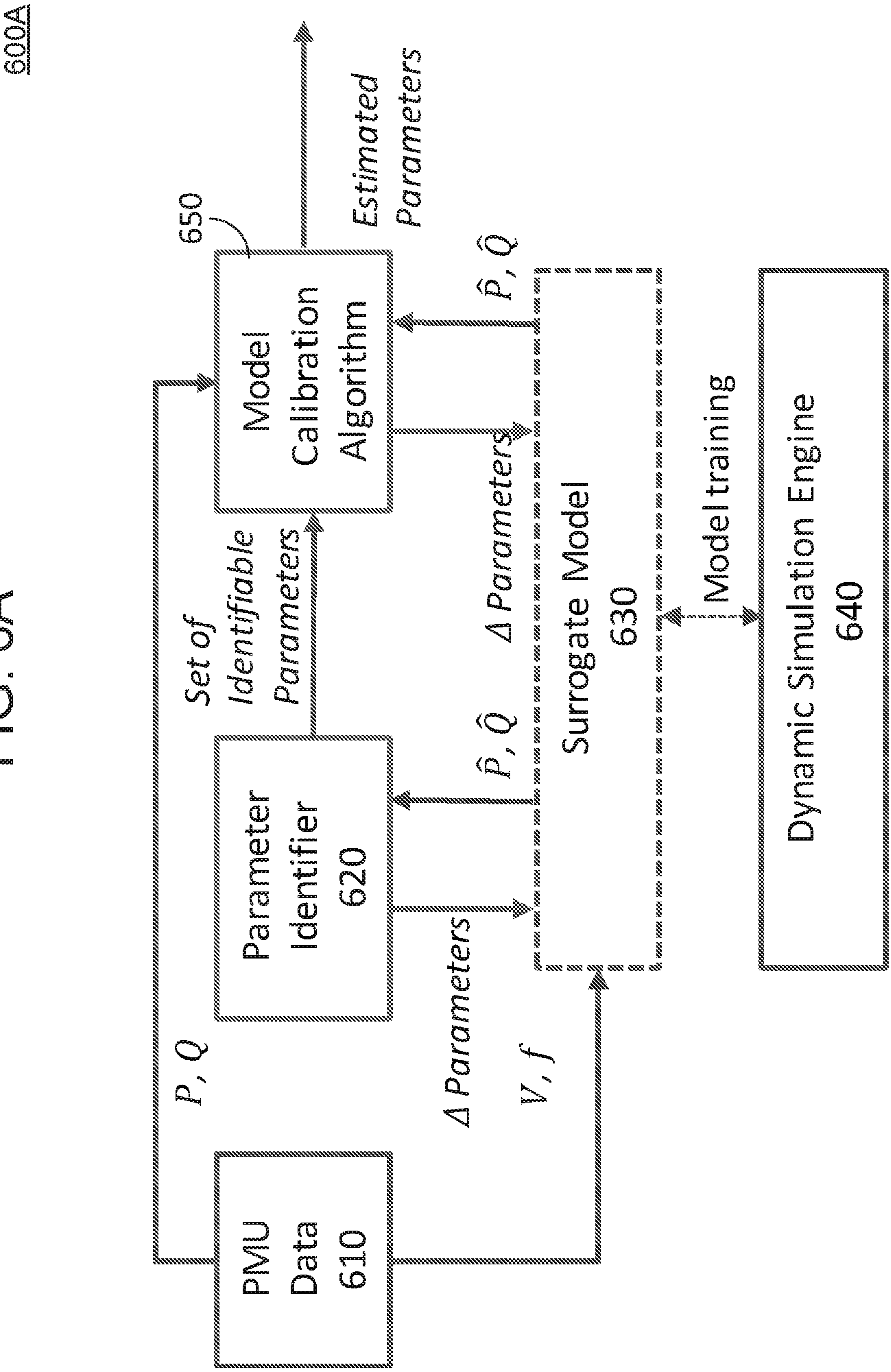

DISTURBANCE DATA
S510
PLAYBACK SIMULATION
S520
MODEL VALIDATION
S530
End if Response Matches Measurements
EVENT ANALYSIS ALGORITHM
S540
PARAMETER IDENTIFIABILITY ANALYSIS ALGORITHM
S550
MODEL CALIBRATION ALGORITHM
S560
Report Estimated Parameter Values, Confidence Metrics, and Error in Model Response v. Measurements

FIG. 5

FIG. 6A


600A
PMU Data 610
P, Q
Δ Parameters
V, f
Parameter Identifier 620
$\hat{P}, \hat{Q}$
Set of Identifiable Parameters
Δ Parameters
$\hat{P}, \hat{Q}$
Surrogate Model 630
Model training
Dynamic Simulation Engine 640
Model Calibration Algorithm
650
Estimated Parameters

600B

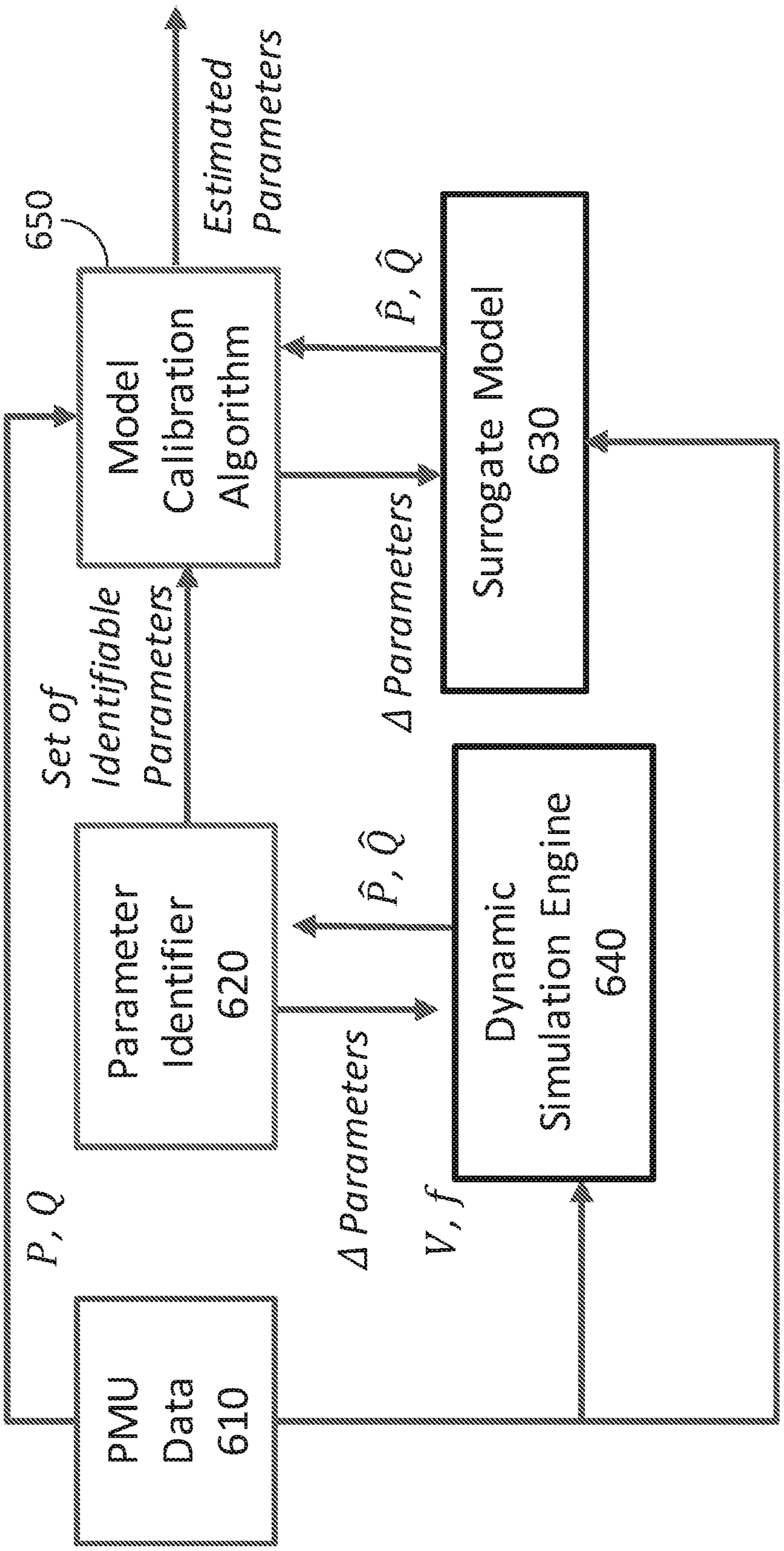

PMU Data 610
P, Q
Parameter Identifier 620
Δ Parameters
$\hat{P}, \hat{Q}$
Dynamic Simulation Engine 640
V, f
Set of Identifiable Parameters
Model Calibration Algorithm
650
Estimated Parameters
Δ Parameters
$\hat{P}, \hat{Q}$
Surrogate Model 630

FIG. 6B

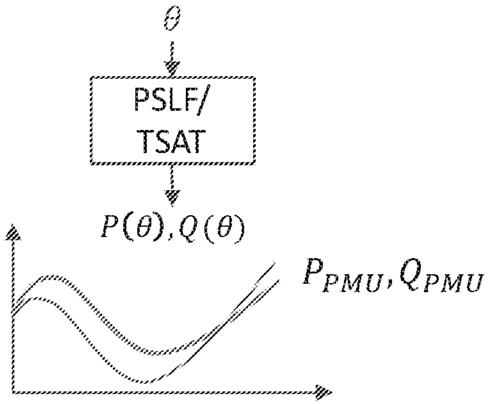
FIG. 6C

Model Calibration Algorithm 650

- Model: $y(\theta) = \begin{bmatrix} P(\theta) \\ Q(\theta) \end{bmatrix}$, Measurement: $y^m = \begin{bmatrix} P_{PMU} \\ Q_{PMU} \end{bmatrix}$,

  where, $P(\theta)$, $Q(\theta)$ are model outputs as a function of parameters θ

  P_{PMU}, Q_{PMU} are time series PMU measurements



- **Goal of Model Calibration: Find $\boldsymbol{\theta}^*$ such that model output matches measurements: $\boldsymbol{y}(\boldsymbol{\theta}^*) \approx \boldsymbol{y}^m$**
- Use a two-stage approach to solve this problem:

  Stage 1: Parameter Identifiability Analysis
  Stage 2: Parameter Estimation

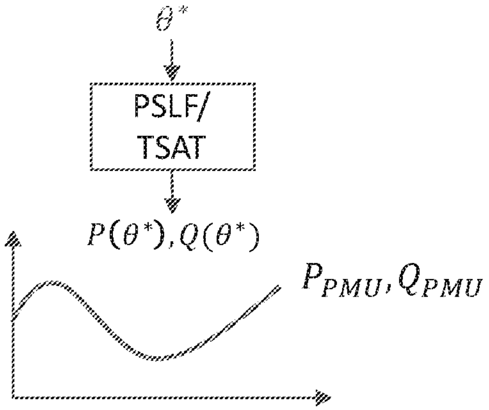
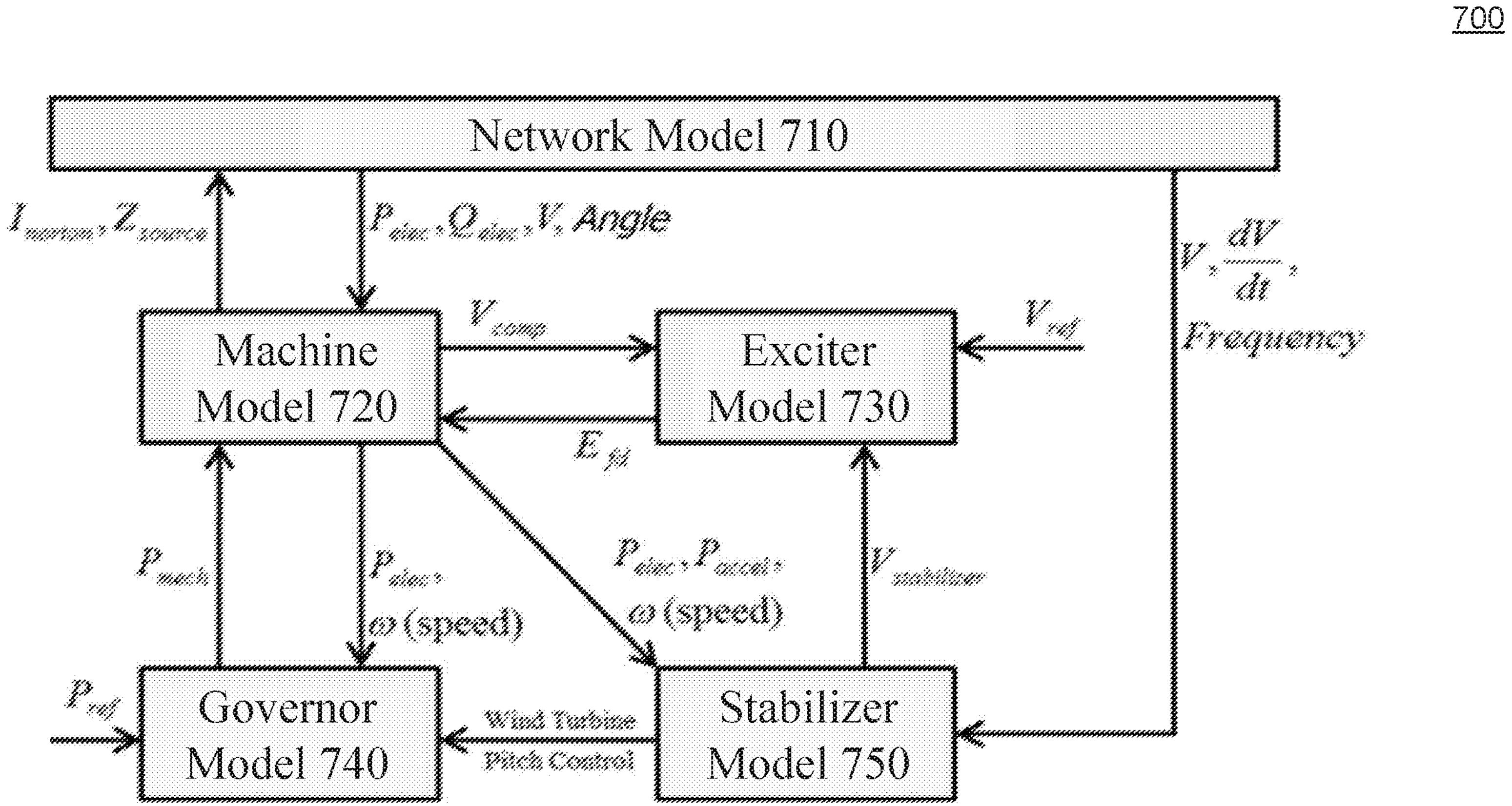


FIG. 7



P_{elec} = Electrical Power
Q_{elec} = Electrical Reactive Power
V = Voltage at Terminal Bus
$\frac{dV}{dt}$ = Derivate of Voltage
V_{comp} = Compensated Voltage

P_{mech} = Mechanical Power
ω (speed) = Rotor Speed (often it's deviation from nominal speed)
P_{accel} = Accelerating Power
$V_{stabilizer}$ = Output of Stabilizer
V_{ref} = Exciter Control Setpoint (determined during initialization)
P_{ref} = Governor Control Setpoint (determined during initialization)

FIG. 8

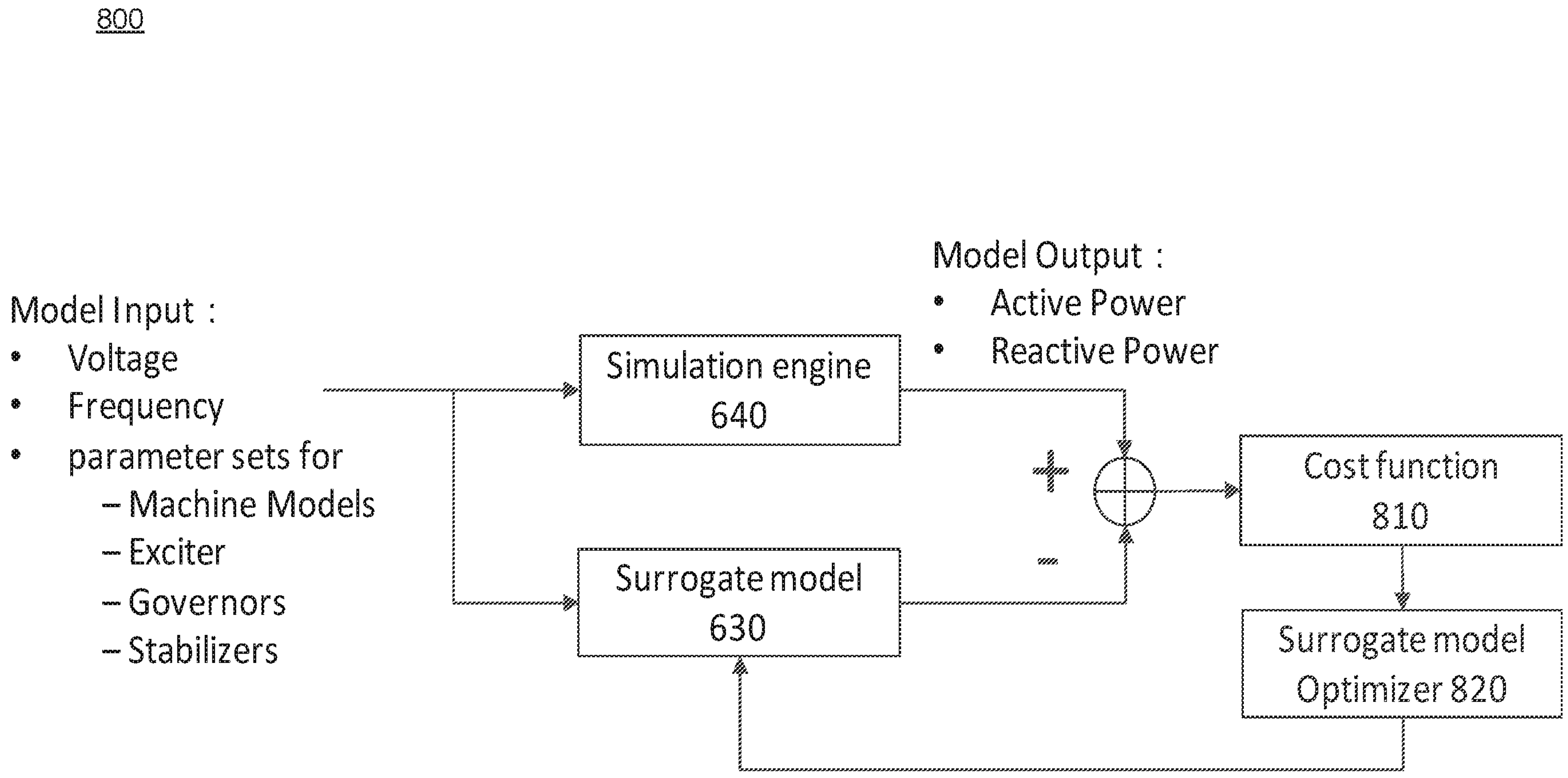

800
Model Input :
• Voltage
• Frequency
• parameter sets for
– Machine Models
– Exciter
– Governors
– Stabilizers
Simulation engine 640
Surrogate model 630
+
-
Model Output :
• Active Power
• Reactive Power
Cost function 810
Surrogate model Optimizer 820

FIG. 9

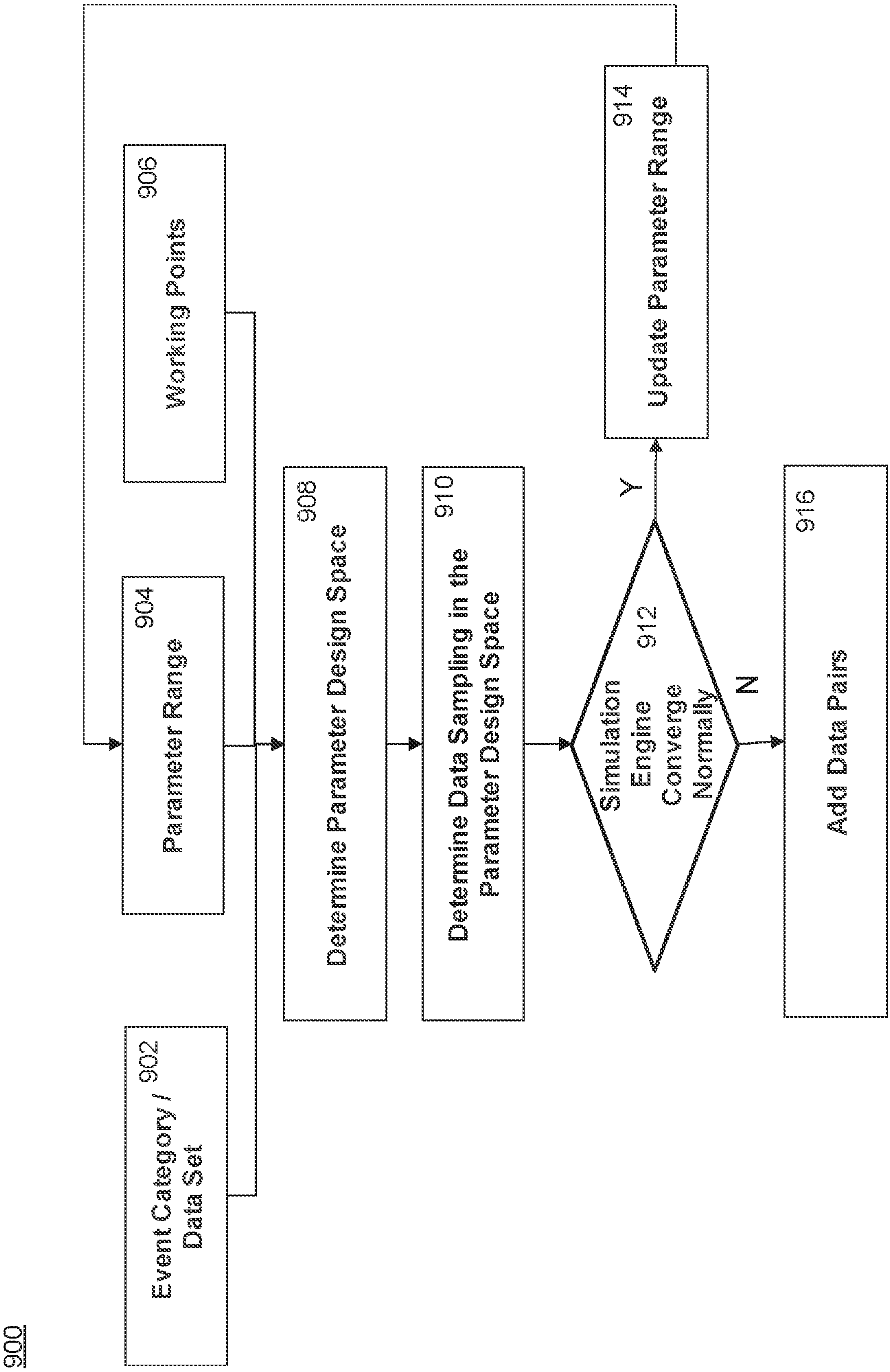

900
Event Category / Data Set
902
Parameter Range
904
Working Points
906
Determine Parameter Design Space
908
Determine Data Sampling in the Parameter Design Space
910
Simulation Engine Converge Normally
912
Y
N
Update Parameter Range
914
Add Data Pairs
916

FIG. 10A

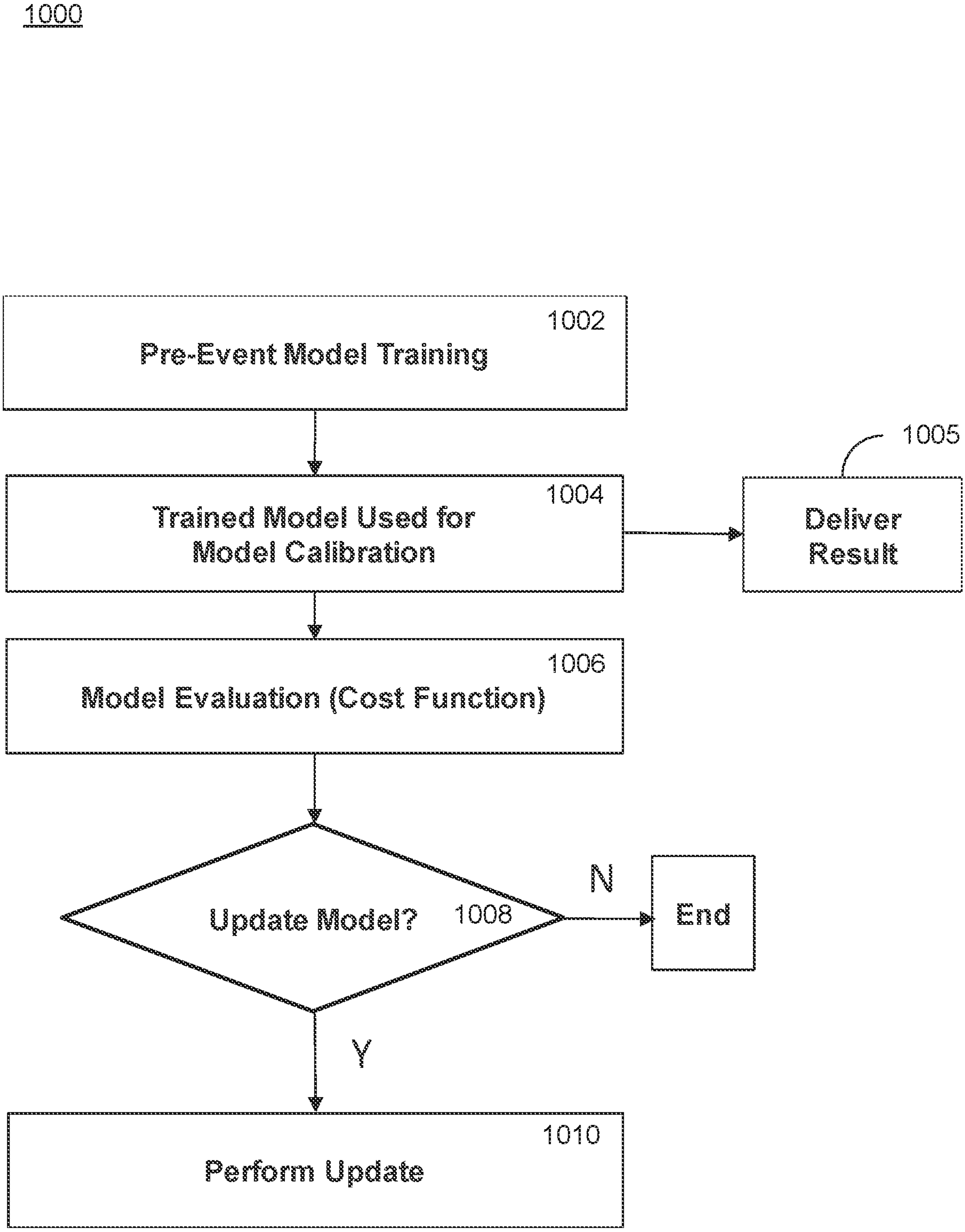
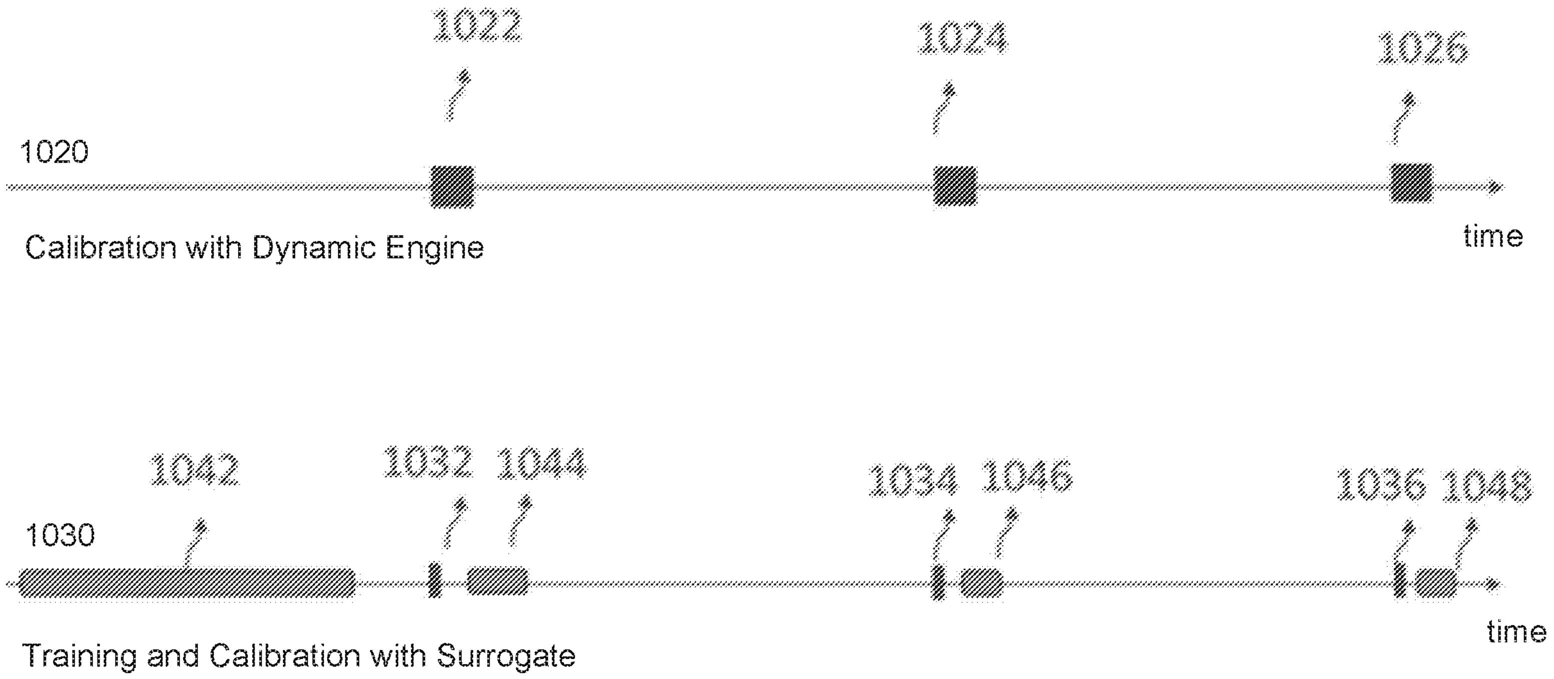

1000
1002
Pre-Event Model Training
1004
Trained Model Used for Model Calibration
1005
Deliver Result
1006
Model Evaluation (Cost Function)
Update Model?
1008
N
End
Y
1010
Perform Update

FIG. 10B


1022
1024
1026
1020
Calibration with Dynamic Engine
time
1042
1032
1044
1034
1046
1036
1048
1030
Training and Calibration with Surrogate
time

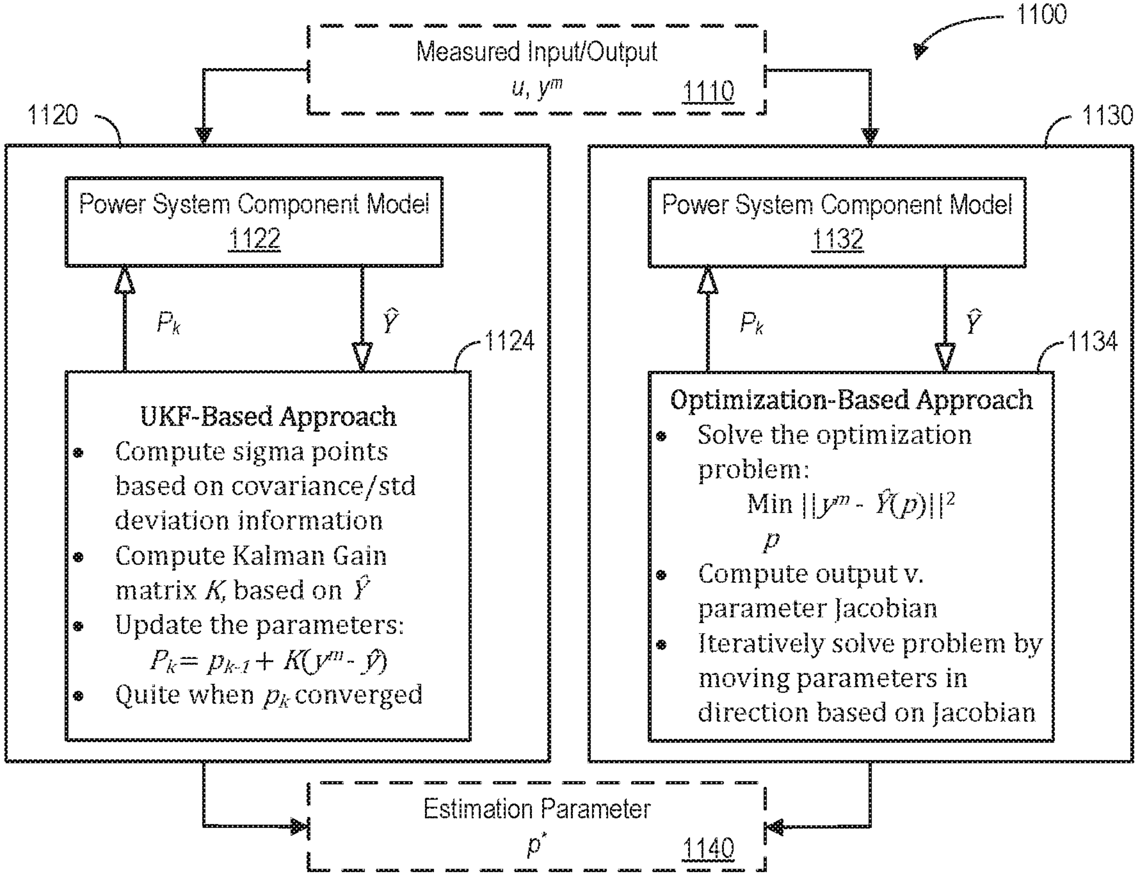

1100
Measured Input/Output
u, y^m
1110
1120
1130
Power System Component Model
1122
P_k
$\hat{Y}$
1124
UKF-Based Approach
Compute sigma points based on covariance/std deviation information
Compute Kalman Gain matrix K, based on $\hat{Y}$
Update the parameters:
$P_k = p_{k-1} + K(y^m - \hat{y})$
Quite when p_k converged
Power System Component Model
1132
P_k
$\hat{Y}$
1134
Optimization-Based Approach
Solve the optimization problem:
$\min_p ||y^m - \hat{Y}(p)||^2$
Compute output v. parameter Jacobian
Iteratively solve problem by moving parameters in direction based on Jacobian
Estimation Parameter
p^*
1140

FIG. 11

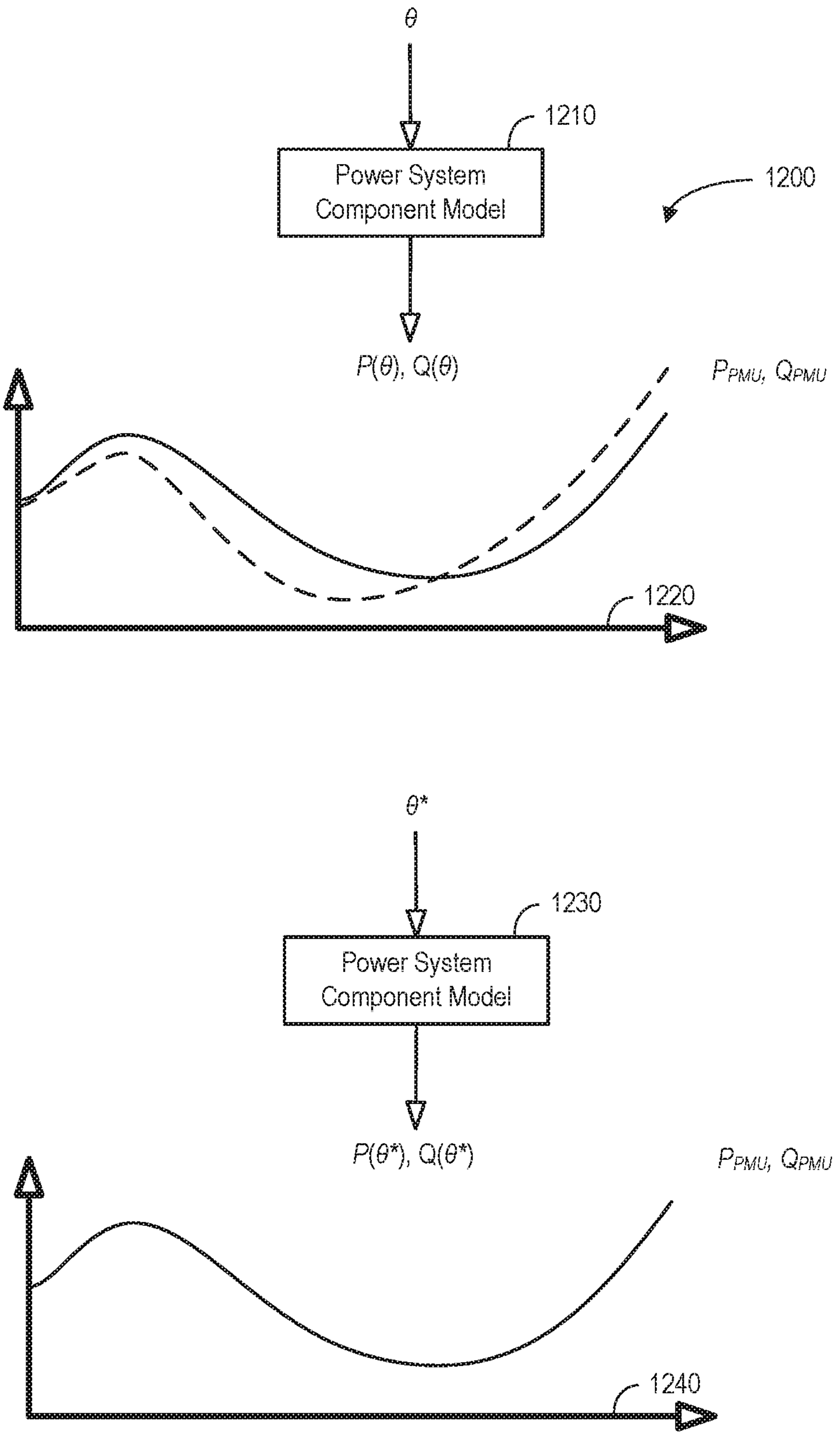

θ
1210
Power System Component Model
1200
P(θ), Q(θ)
P_PMU, Q_PMU
1220
θ*
1230
Power System Component Model
P(θ*), Q(θ*)
P_PMU, Q_PMU
1240

FIG. 12

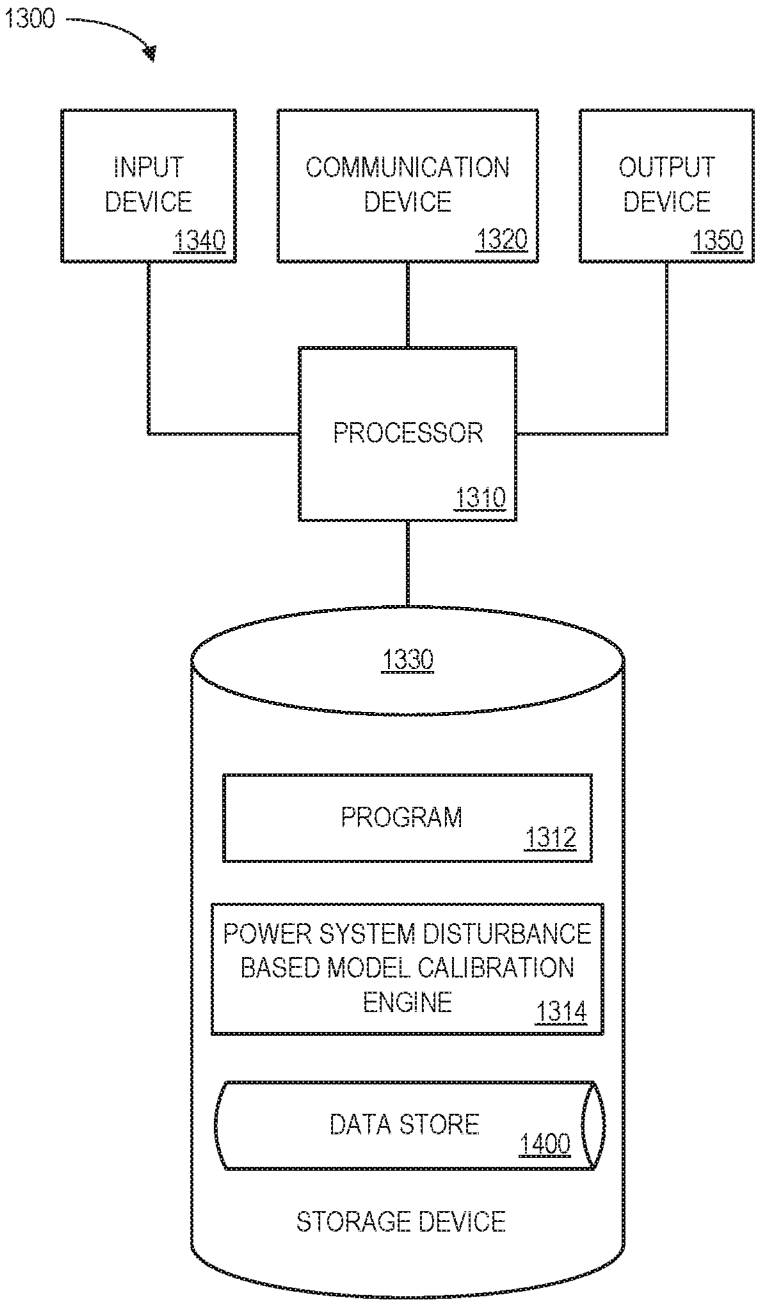
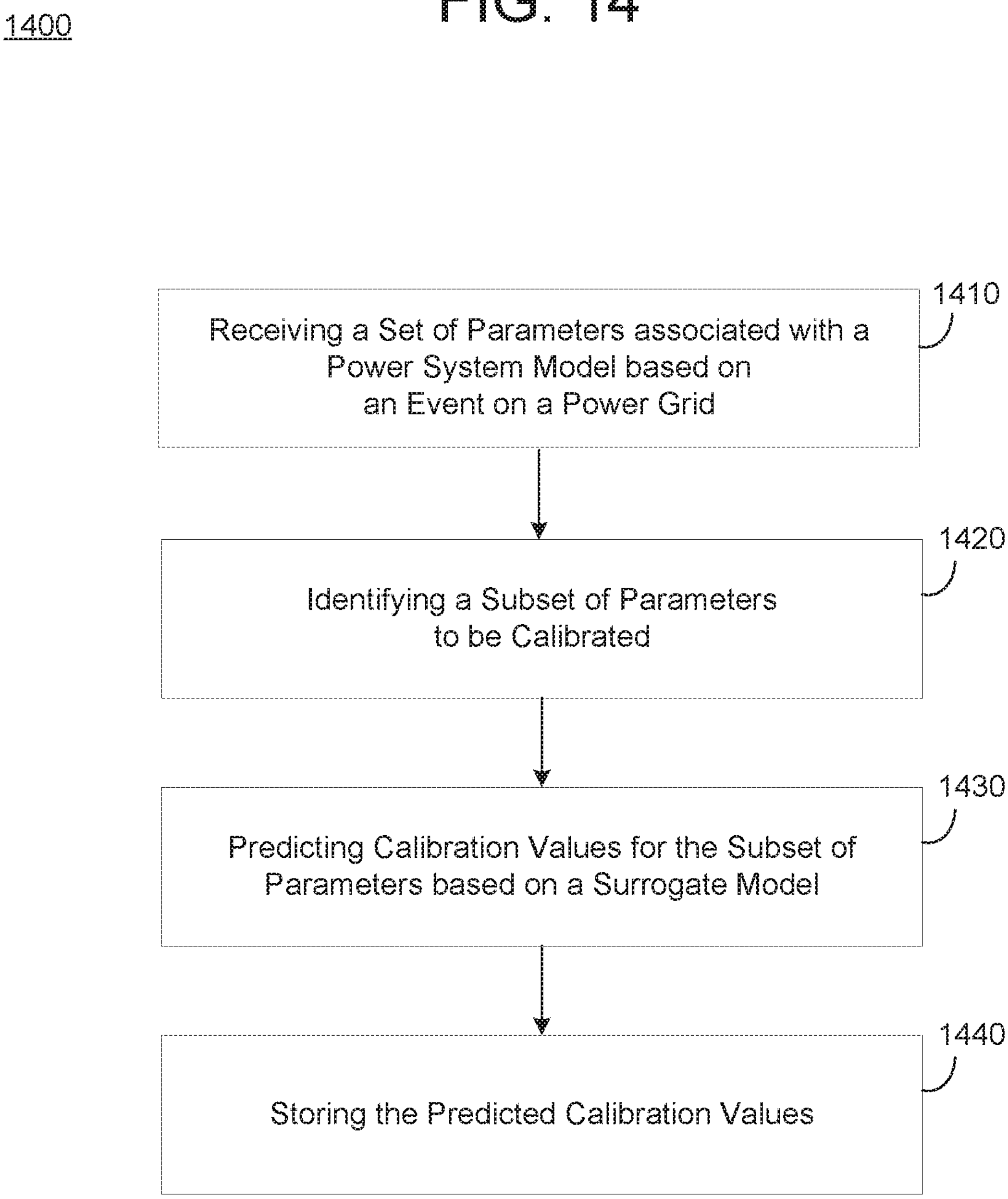

1300
INPUT DEVICE
1340
COMMUNICATION DEVICE
1320
OUTPUT DEVICE
1350
PROCESSOR
1310
1330
PROGRAM
1312
POWER SYSTEM DISTURBANCE BASED MODEL CALIBRATION ENGINE
1314
DATA STORE
1400
STORAGE DEVICE

FIG. 13

FIG. 14


1400
Receiving a Set of Parameters associated with a Power System Model based on an Event on a Power Grid
1410
Identifying a Subset of Parameters to be Calibrated
1420
Predicting Calibration Values for the Subset of Parameters based on a Surrogate Model
1430
Storing the Predicted Calibration Values
1440

INTERNATIONAL SEARCH REPORT

International application No
PCT/US2019/023559

A. CLASSIFICATION OF SUBJECT MATTER
INV. G06F17/50 G01R31/28 H02J3/00 G06N3/08
ADD.

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)
G06F G01R H02J G06N

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)

EPO-Internal, WPI Data

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	YOUSEFI G R: "An application of artificial neural networks in power system load modeling", POWER ENGINEERING SOCIETY GENERAL MEETING, 2005. IEEE SAN FRANCISCO, CA, USA JUNE 12-16, 2005, PISCATAWAY, NJ, USA,IEEE, 12 June 2005 (2005-06-12), pages 1035-1040, XP010821539, DOI: 10.1109/PES.2005.1489294 ISBN: 978-0-7803-9157-4 abstract section II, first and last par. section III, first par.; figures 2-3 section IV the whole document ----- -/--	1-20

☒ Further documents are listed in the continuation of Box C.

☒ See patent family annex.

* Special categories of cited documents :

"A" document defining the general state of the art which is not considered to be of particular relevance

"E" earlier application or patent but published on or after the international filing date

"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)

"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art

"&" document member of the same patent family

Date of the actual completion of the international search 20 November 2019	Date of mailing of the international search report 28/11/2019
Name and mailing address of the ISA/ European Patent Office, P.B. 5818 Patentlaan 2 NL - 2280 HV Rijswijk Tel. (+31-70) 340-2040, Fax: (+31-70) 340-3016	Authorized officer Dapp, Wolfgang

1

C(Continuation). DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	US 2016/371405 A1 (RACZYNSKI CHRISTOPHER MICHAEL [US] ET AL) 22 December 2016 (2016-12-22) paragraphs [0009], [0026]; claim 1 the whole document -----	1,16,20
A	US 2007/168328 A1 (PERALTA RICHARD C [US] ET AL) 19 July 2007 (2007-07-19) paragraph [0007]; claim 21 the whole document -----	1-20

1

INTERNATIONAL SEARCH REPORT

International application No.
PCT/US2019/023559

Box No. II Observations where certain claims were found unsearchable (Continuation of item 2 of first sheet)

This international search report has not been established in respect of certain claims under Article 17(2)(a) for the following reasons:

1. ☒ Claims Nos.: 1-15(partially)
because they relate to subject matter not required to be searched by this Authority, namely:
see FURTHER INFORMATION sheet PCT/ISA/210

2. ☐ Claims Nos.:
because they relate to parts of the international application that do not comply with the prescribed requirements to such an extent that no meaningful international search can be carried out, specifically:

3. ☐ Claims Nos.:
because they are dependent claims and are not drafted in accordance with the second and third sentences of Rule 6.4(a).

Box No. III Observations where unity of invention is lacking (Continuation of item 3 of first sheet)

This International Searching Authority found multiple inventions in this international application, as follows:

1. ☐ As all required additional search fees were timely paid by the applicant, this international search report covers all searchable claims.

2. ☐ As all searchable claims could be searched without effort justifying an additional fees, this Authority did not invite payment of additional fees.

3. ☐ As only some of the required additional search fees were timely paid by the applicant, this international search report covers only those claims for which fees were paid, specifically claims Nos.:

4. ☐ No required additional search fees were timely paid by the applicant. Consequently, this international search report is restricted to the invention first mentioned in the claims; it is covered by claims Nos.:

Remark on Protest

☐ The additional search fees were accompanied by the applicant's protest and, where applicable, the payment of a protest fee.

☐ The additional search fees were accompanied by the applicant's protest but the applicable protest fee was not paid within the time limit specified in the invitation.

☐ No protest accompanied the payment of additional search fees.

FURTHER INFORMATION CONTINUED FROM PCT/ISA/ 210

Continuation of Box II.1

Claims Nos.: 1-15(partially)

Claims 1-15 do not claim any technical means to carry out the method. This allows for the interpretation that the method is carried out as a purely mental act. Such subject matter falls under Rules 39.1(iii) and 67.1(iii) PCT, and no International Search Authority is required to search nor examine it. No embodiment of a purely mental act is searched nor examined.

Continuation of Box II.2

Claims 1-15 do not claim any technical means to carry out the method. This allows for the interpretation that the method is carried out as a purely mental act. Such subject matter falls under Rules 39.1(iii) and 67.1(iii) PCT, and no International Search Authority is required to search nor examine it. No embodiment of a purely mental act is searched nor examined.

INTERNATIONAL SEARCH REPORT

Information on patent family members

International application No
PCT/US2019/023559

Patent document cited in search report	Publication date	Patent family member(s)	Publication date
US 2016371405 A1	22-12-2016	NONE	
US 2007168328 A1	19-07-2007	NONE	