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(54) **Title**: SYSTEMS AND METHODS FOR CLASSIFYING IN-SITU SENSOR RESPONSE DATA PATTERNS REPRESENTATIVE OF GRID PATHOLOGY SEVERITY

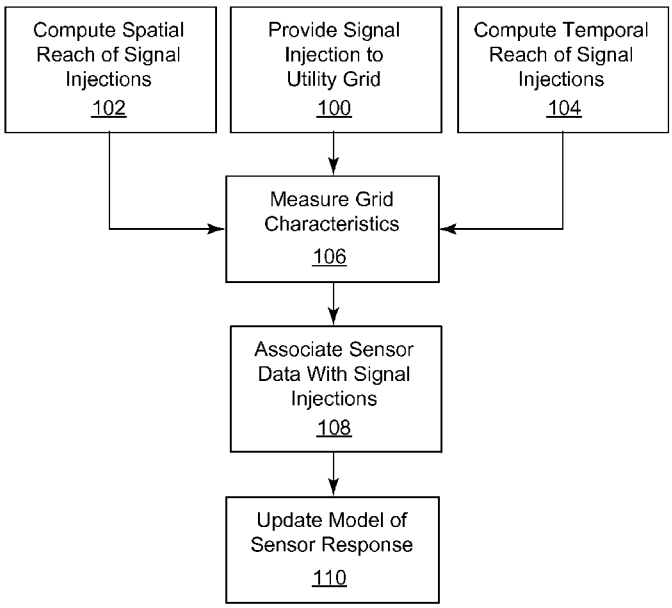

Fig. 1

(57) **Abstract**: The present invention is directed towards methods and systems for characterizing sensors and developing classifiers for sensor responses on a utility grid. Experiments are conducted by selectively varying utility grid parameters and observing the responses of utility grid to the variation. Methods and systems of this invention then associate the particular responses of the utility grid sensors with specific variations in the grid parameters, based on knowledge of the areas of space and periods of time where the variation in grid parameters may affect the sensor response. This associated data is then used to updating a model of grid response.

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SYSTEMS AND METHODS FOR CLASSIFYING IN-SITU SENSOR RESPONSE DATA PATTERNS REPRESENTATIVE OF GRID PATHOLOGY SEVERITY

BACKGROUND

The performance of utilities grids – their reliability, safety, and efficiency – can be drastically improved through sensing key parameters and using those results to direct the operations and maintenance of the grid, by identifying faults, directing appropriate responses, and enabling active management such as incorporating renewable sources into electrical grids while maintaining power quality.

Sensor networks are often used to monitor utilities grids. These sensor networks may include smart meters located at the ends of the grid, sensors at grid nodes, and sensors on or around the utilities lines, these sensors measuring grid parameters such as flow rates in water grids, power quality in electrical grids, or pressures in utilities grids. These sensors are transducers, usually outputting analog signals representative of the measured properties. These outputs need to be characterized to map to specific values of those properties, and/or classified so that they may represent particular states of the world, such as a potential leak that requires investigation, or identification of a difference in phases when incorporating a renewable resource into an electrical grid. Characterization of sensors is usually done through bench testing, while the sensors may have various interferences in the environment surrounding them; in-situ characterization of sensors on a utility grid monitoring network would be preferred, but is difficult for the large numbers of sensors used to monitor a utilities grid.

The trend in analyzing sensor data and directing responses is "big data," which uses large amounts of grid historical data to build models used for classification and direction of responses. These big data models, however, are limited to correlations, as they mine historical data to build the models, limiting their effectiveness for actively directing treatments or making fine adjustments. Further, these big data models typically require large volumes of data that prevent highly granular understandings of grid conditions at particular grid nodes or locations or that can only achieve such granularity after long operations; some have applied machine learning techniques and improved models to increase speed and granularity, but even these approaches continue to rely on correlations from passively collected historical data.

Signal injections have been used to highlight grid faults, such as discovering nodes where power is being illegally drawn from an AC power grid; these techniques rely on already-characterized high-quality sensors such as "smart meters" and are occasional, grid-wide individual actions, not coordinated to be conducted concurrently or sequentially. Signal injections have also been used to test grid-wide response to large changes in high levels of the grid, such as at the HVDC

distribution level. Those signal injections have been large, individual, and human mediated, not susceptible to automation, smaller-scale local testing or concurrent or sequential implementation of tests. Occasional, grid wide, and almost necessarily human-directed signal injections are poorly suited for characterizing extensive networks of diverse sensors placed along the grid in a wide variety of contexts, since they can only generate small sample sizes and cannot vary widely enough to be tailored to individual conditions and idiosyncrasies of the sensor locations.

Utilities grid management would benefit greatly from real-time cause-and-effect understanding of sensor responses to overcome the issues with big data smart grid approaches and allow for real-time, granular, and fine-tuned grid monitoring and management to more fully capitalize on the potential of smart grid to optimize grid parameters and responses, by enabling such optimization to be done at more local levels across these highly variant systems.

SUMMARY OF THE INVENTION

The present invention is directed towards characterizing sensors and developing classifiers for sensor responses on a utility grid, by implementing changes to grid parameters, computing the spatial and temporal reach of those changes to grid parameters, observing the responses at grid sensors, associating the responses at grid sensors with implemented changes to grid parameters based on the time and location of the responses, and updating a model of grid response based on the implemented changes and their associated responses.

Systems of the invention include signal injection directors, signal injection controllers, a plurality of sensors collecting grid data, an association module, an analysis module, and a model memory.

BRIEF DESCRIPTION OF THE DRAWINGS

Fig. 1 is a flow diagram of the steps of a method of the invention.

Fig. 2 is a map of a utility grid, its associated network of sensors, and the spatial reaches of signal injections on an example of the invention.

Fig. 3 is a system diagram of a system of the invention.

Fig. 4 is a data flow diagram of the flows of information among various components of a system of the invention.

Fig. 5 is a flow diagram of an example method for associating sensor responses with signal injections.

Fig. 6 is a flow diagram of an example method for updating a model of sensor response.

Fig. 7 is a diagram depicting the architecture of system embodiments and their interactions with a utility grid.

DETAILED DESCRIPTION OF VARIOUS EMBODIMENTS

Automated testing of sensor responses to specific inputs, and the resulting causal-knowledge based characterization of sensors requires an automated means of associating sensor data with particular signal injections which have been made concurrently and sequentially, and in close spatial proximity to one another, especially on large networks where it is desirable to increase potential sample size and quickly learn sensor and grid responses to the injected signals. These responses to signal injections may be representative of grid events which are useful for management of the utility grid, automation of grid response to particular conditions, improving efficiency, identifying and remedying grid faults, or optimally scheduling required maintenance and reconditioning actions. This association is needed to properly use sensor data collected in response to a signal injection to improve models of sensor response used to convert raw sensor outputs into levels of a physical variable or classifications of potential statuses at the sensor and thus improve the sensitivity and discriminability of utility grid sensors, and to provide in-situ classification or characterization of the sensor outputs based on highly temporally and spatially granular models of sensor response and grid behavior.

Fig. 1 is a flow chart depicting an example of a method of the invention. One or more signal injection are provided to the grid in step **100**. The signal injections each have a spatial reach, computed in step **102** and a temporal reach computed in step **104**. Measurements of grid characteristics are made in step **106**. Some of these steps may be taken independent of one another or be performed continuously, such as the measurements of step **106**. The sensor data from step **106** is associated with particular signal injections in step **108**, using spatial and temporal reaches computed in steps **102** and **104**. Data associated with signal injection in step **108** may be used to characterize sensor responses or may be used to characterize the effects of the controls used to implement signal injections into the grid. In embodiments characterizing sensor responses, the associated data from step **108** then is used to update one or more models of sensor response in step **110**. The updated models of sensor response may be used to detect and classify events at the sensors based on their raw readings, leading to more accurate sensing and calibrating the sensors to detect events of interest to grid operators against the baseline of their normal readings in the field. These methods may be done iteratively to refine and regularly update the models of sensor response, allowing regular in-situ calibration of grid sensors and accounting for changes in baseline conditions or sensor response characteristics.

The signal injection **100** is a change effected on grid components to introduce a particular condition into a utility grid, such as a water distribution grid, an electrical grid, or a gas distribution grid. This may be done by manipulating existing grid controls, and selecting and implementing one particular state within the range of permissible states for that grid control, for example selecting a particular position for a load tap changer at a transformer, or the switch state of a capacitor bank in a power distribution network. This signal injection **100** may be simple, manipulating one variable at

one location, or complex and involving multiple variables and/or be implemented at multiple locations. An example of a simple signal injection **100** in a water grid may be increasing flow through a valve at a location. An example of a complex signal injection of step **100** in a gas grid may be increasing the pressure at one point while closing a valve immediately following that point to direct most of the pressure increase down one particular path. An example of a complex signal injection of step **100** in an electrical grid may be bringing on multiple renewable sources on line in a particular order and with specific timing, such as connecting the inverters for distributed photovoltaic generation sources and adjusting load tap changers at nearby substations minutes later.

The signal injection of step **100** may be implemented through automatic or human-mediated means. The signal injections are controlled changes in grid parameters, for example, electrical signal injections in electrical grids such as increases or decreases in current, voltage, or power factor caused by actuating grid controls. The signal injections may be coordinated to be separated in their spatial and temporal reaches. In gas grids, the signals may be injected through, for example, changing the routing of gas through pipes to increase or decrease the pressure at certain points. The responses to these signals may be the increase or decrease in the number and/or severity of leaks detected by a sensor network surrounding the grid pipes, or changes in downstream pressures connected to the areas being driven to high or low pressure. These signal injections may be accomplished in human-mediated cases through the manual adjustment of various valves and switches at the direction of a schedule distributed to maintenance personnel who perform these adjustment; these schedules may take various forms, such as maintenance queues, additional tasks, and may be distributed through a variety of electronic means such as email, text message, calendar reminders on a computer, tablet, smart phone or other portable computing device. In these human-mediated cases, the times of these adjustments may be audited by having the maintenance personnel check in using a networked device to record the time the changes are actually implemented, for use in the processing of subsequent data generated as a result of these signal injections. In fully machine-to-machine implemented embodiments of signal injection on gas grids, the switches and valves are operated by actuators coupled to the system through a wired or wireless communications network, and responding to signals sent by the system or acting in accordance with instructions or schedules distributed to the controllers for those actuators by the system. Machine-to-machine implementations allow for more closely coordinated tests as there will be less variance in the time of implementation, and the improved timing allows more sophisticated trials to be conducted. In these implementations, monitoring of the sensor conditions and actuator states may be constantly correlated to create a real-time understanding of relationships among spatially and temporally distributed influences, enabling changes in relationships as well as local sensor states to be detected and characterized, for example through factorial isolation of detected changes.

In electrical grids, human-mediated methods involve manual switching of power flow, activating or deactivating power sources connected to the grid, changing load tap changer positions,

switching capacitor banks on and off, activating or deactivating heavy industrial equipment (such as arc furnaces) or other major manually-controlled power loads on the grid. In these examples, the changes are made by the maintenance personnel at the direction of a schedule distributed to them; these schedules may take various forms, such as maintenance queues, additional tasks, and may be distributed through a variety of electronic means such as email, text message, calendar reminders on a computer, tablet, smart phone or other portable computing device. In these human-mediated cases, the times of these adjustments may be audited by having the maintenance personnel check in using a networked device to record the time the changes are actually implemented, for use in the processing of subsequent data generated as a result of these signal injections. These human-mediated methods may alter measurable factors such as power quality, line temperature, line sag, available power levels, and other factors, which may be captured by sensor networks observing those measurable grid factors.

In electrical grids, machine-to-machine methods offer a greater measure of control, and can inject signals through a variety of automated means. This includes automation of the types of switching and maintenance behaviors that may be used in human-mediated examples such as changing the position of load tap changers, or switching capacitor banks, and additionally M2M methods of signal injection may capitalize on greater precision and breadth of control to include actions such as coordinating use of devices such as appliances at end locations to create coordinated demand and loading at consumer locations, or to implement complex coordination of combinations of multiple types of grid-influencing actions to generate more complex conditions, or introducing changes into the automatic power factor correction units. These combinatoric possibilities are very difficult to address through big-data approaches, since even large volumes of data may only have limited sample sizes reflecting particular combinations, and the sheer number of combinatoric possibilities makes big data solutions to these problems nearly intractable. These may be initiated through automatic control of the associated grid components and networked devices, including power generation, switches, voltage regulation equipment, smart meters and smart appliances receiving power from the grid, and other grid components susceptible to remote control by the system. These may take advantage of millisecond-level control capabilities to manipulate power quality variables such as the integration of new sources or immediate responses to new loads or the specific operation of automatic power factor correction units, as well as further increasing the ability to test combinatorics of grid actions or conditions involving those highly time-sensitive variables.

The injected signals may be simple, directing one individual grid action such as opening a valve in a water or gas grid, or bringing one particular renewable source online or altering the output voltage from one substation in electrical grid examples to change the grid conditions, or they may be complex, composed of multiple grid actions coordinated such that their individual spatial and temporal reaches overlap to produce a multi-factor treatment at areas within the overlapping reaches. One example of a complex grid action may be to vary both load tap changer positions and capacitor

bank switching simultaneously to provide more fine-grained control over reactive power in an electrical grid. This multi-factor treatment may include variances of multiple different grid parameters, for example to explore combinatoric effects of those parameters, or may be used to produce multiple instances of similar variations of a particular grid parameter, for example to use additive effects to increase the magnitude of a particular variance of a grid parameter at one or more specific locations on the grid while protecting more sensitive neighboring parts of the grid by keeping them within narrower or different operational ranges by exposing those parts to only a component of the overall signal injection; for example, the power levels at sensitive nodes around a more robust node may each be given an increase that has a predicted spatial reach that includes the more robust node, but not other sensitive nodes, and these multiple sensitive nodes may each provide a power increase within their narrower operational ranges to produce a combined increase in power at the robust node that exceeds the individual increases at each sensitive node.

For complex signals, the temporal and spatial reaches are predicted based on treating the complex signal's effects on the system as a whole, composed set. For those complex signals, while individual grid actions will have overlapping spatial and temporal reaches, the defined set of grid actions that make up the complex signal is instead treated as one signal injection, with the overall spatial and temporal reach of the combination of the defined set of grid actions used to determine the areas of space and periods of time where no other signals may be injected into the grid, to maintain the orthogonality of the complex signal injection from other grid signal injections.

Complex signals may be input into the system having already been defined as the set of grid actions to be done together and the times and locations of those grid actions, after being derived by other systems or selected by grid personnel, or may be derived by systems selecting multiple grid actions from the set of grid actions as directed by, for example, a Partially Observable Markov Decision Process (POMDP) model exploring combinatorics or operating within constraints on operational conditions that vary from location to location across the grid.

Signal injections exploring grid responses may be composed by searching for waveforms that have a spatial-temporal regularity with any controlled grid activity, which are co-occurring in immediate or regular delayed fashion, through for example, Principal Component or Fourier analysis. These statistical regularities in waveforms or component waveforms (for example, the frequency, voltage, and/or current) link grid actions with changes in grid conditions to provide the set of available options for manipulating grid conditions based on active control of grid actions and data on the observed times and locations of these waveform components relative to the grid actions may be used to determine spatial and temporal reaches for particular signal injections.

A processor is used to compute the signal injection's spatial reach in step **102** and the signal injection's temporal reach in step **104**. The spatial reach is the area over which sensors will show response to that signal based on the location and nature of that injected signal. The spatial reach can be computed by predicting, to a high confidence interval, the furthest sensor that would show a

response to the injected signal and preventing any other trial from being conducted if it is likely to produce a response in the region of spatial uncertainty during the period of spatial uncertainty for the current trial. Temporal reach is the period over which the sensor network will be observing events related to the injected signal. This includes the duration of the signal itself, and the duration of the expected sensor response to the signal, for example a prediction based on historical data associating waveform components with particular grid actions that implement the signal injection. This temporal reach may be determined by using the expected time at a high confidence interval of the sensor response being completed, and using that as the duration for relevant data and a period from which to exclude other trials having a common spatial reach. The spatial and temporal reaches for these injected signals may be based on current models of the grid based on the nature and magnitude of the injected signal, the components and connections and/or the current data on grid responses to perturbations. For example, for a signal injection made by switching a capacitor bank on a distribution network, the spatial reach may be the downstream portion of the distribution network, and an example of the temporal reach may be the time it takes for transients introduced by the switching of the capacitor bank to settle. One particular method for calculating these reaches is a Bayesian Causal Network, which starts by discovering correlations through data mining then directly tests causality and directionality within those identified correlations. In gas grids, for example, the spatial reach of a pressure increase may be determined based on a map of the grid components, such as the branches of pipes and the volumes of the pipes and the behavior of the gas under pressure, particularly the segments of the grid downstream from the increased pressure and the magnitude of the pressure increase; the temporal reach may be the duration at which the increased pressure is maintained, plus a time lag for the effects of the pressure increase to fade at the furthest-out points at which the pressure is expected to have observable effects, again relying on the known characteristics of the utility and the grid, such as the branches and volumes of pipes and pressure characteristics of a gas grid. Historical data for the spatial and temporal reaches may be generated actively generated by conducting consistent signal injections while varying the temporal and spatial reaches over which data is associated with the signal injection, and finding the temporal and spatial reaches that capture the fullest extent of the signal injection without growing so large as to become confounded; this may be determined by finding the spatial and temporal reach values that produce the peak measured response to the signal injection.

Measurements are taken at a plurality of sensors distributed across the utility grid **106**. The sensor measurements are typically continuous. The sensors may be, for example, for water grids flow meters whose response is based on the speed of water flow through a pipe, for gas grids methane detectors whose response is based on methane concentration, and for electrical grids cabled sensor terminations providing voltage and current wave forms at the termination. The sensor data also includes metadata or other indications of the time at which the data was collected and the specific sensor or the location where the data was collected.

The measurements taken across the grid in step **106** are then associated with a signal injection in step **108**. The association made in step **108** is based on the spatial and temporal reaches computed in steps **102** and **104**, which describe the time and space over which signal injections are likely to have effects captured by the sensors. The sensor data collected in step **106** is parsed by the time of the sensor measurements and the location of the sensors or of the data, using metadata accompanying the sensor data to provide the time and location information. The parsing assigns the sensor data to specific signal injections that could influence the readings at a particular time and location; some sensor data may be collected that lies outside the temporal or spatial reaches of the signal injections to the grid; this data is not associated with a particular signal injection. This allows multiple signal injections to be made concurrently along the grid while still attributing particular sensor responses with specific signal injections, improving the efficiency of automated signal injection methods for characterizing grid sensors.

An example method for the association of signal injections and sensor data of step **108** is detailed in Fig. 5. A signal injection is selected in step **500**, reach data for that signal injection is received in step **502**, sensor data is parsed by time in step **504**, sensor data is then parsed by location in step **506**, sensor data identified in the parsing steps is associated with the signal injection in step **508**, and additional signal injections are checked for and the process iterated for those signal injections in step **510**.

A signal injection is selected in step **500**. The signal injection is selected from the set of signal injections that have not yet had grid sensor data associated with them. Then, the reach data for that signal injection is received in step **502**. The reach data is the particular spatial and temporal reach of the selected signal injection, which is computed based on the nature of the signal injection and stored in memory. Combined with the actual time and location of the signal injection, this data defines a region of space and period of time where the signal injection was likely to have an effect on a utility grid, detected by sensors on or near the grid.

The sensor data is parsed by time in step **504**. Sensor data has timestamps associated with samples or ranges of time from which continuous measurements are taken. For individual, time-stamped samples, the parsing by time is a comparison of the time at which the sample was taken against a range of times during which sensor data could be associated with the signal injection, based on the time of the signal injection and the temporal reach of the signal injection, creating a span starting at the time of the signal injection and having a duration of the temporal reach, during which data may be associated with the signal injection.

The sensor data is parsed by location in step **506**. Sensor data also includes the location of the sensor, either directly as coordinates or indirectly, such as an identifier of the sensor that collected the data, which has a known location. The data is parsed by location by determining the area over which sensor data is associated with the signal injection, by using the spatial reach of the signal injection and the location of that signal injection. Coordinates or sensor locations are

compared against that area and sensor data within that area may be associated with the signal injection. In this example, the parsing by location is done on data already parsed by time and determined to possibly be associated with the signal injection, meaning that data that may still be associated with the signal injection following this step will be associated with the signal injection in step **508**. While this example has the data first being parsed by time and then location, the parsing steps may be done in reverse order, or done simultaneously and the results combined; in these examples, data is to be associated with a signal injection where the data was collected at a sensor within the spatial reach of the signal injection, and at a time within the temporal reach of the signal inection.

The parsed data is then associated with the signal injection in step **508**. The data within the spatial and temporal reaches of the time and location of the signal injection, identified in the parsing steps is associated with the signal injection. This association may be done by adding the association to the sensor data as metadata, tags, a segment of the data itself, or other means of identifying that the data is associated with a particular signal injection. Optionally, during this association stage, confounded data may be identified if it already is associated with another signal injection, but was identified as being associable with the current signal injection based on the parsing by time and location. In these situations, the data point may be flagged, discarded, or its associations may be cleared so that it is not associated with any data point due to uncertainty about the signal injection or injections that influenced that data point.

Additional signal injections that have not yet had data associated with them are checked for in step **510** and these steps may be iterated for any signal injections that have not yet had data associated with them, for example by having each signal injection include a category of metadata indicating whether or not it has already been associated with data and changing that metadata from a 0 to a 1 during the association step. In that example, the metadata is checked for the signal injections, determining whether any signal injections still have a 0 representing their association with sensor data. When all current signal injections have been associated with sensor data, the association process ends.

Returning to Fig. 1, updating a model of sensor response is done in step **110** based on the associated sensor data from step **108** and data concerning the signal injection and the sensors, as well as the currently-existing model of sensor response. The model of sensor response may be one of a variety of models that map the sensor output to levels of a variable or the presence or likelihood of a particular grid condition at the sensor; it may also be a plurality of alternative models that link the sensor outputs to particular values of a variable or states surrounding the sensor. The particular updating process depends on the particular model or models selected to assign meaning to sensor outputs.

Updating the model may be used to improve the characterization of a sensor response. In these embodiments, the sensor response data may be used to falsify belief states in a Partially

Observable Markov Decision Process or similar technique, where the belief states are a number of alternative models that characterize the sensor data; the falsification of belief states eliminates poor models, converging on the use of the best models as the method for mapping the sensor response to a level of a measured variable or the presence of a condition of interest at or near the sensor and improving the sensitivity and accuracy of the sensor by using updated models based on data from signal injections reaching that sensor, to process its outputs.

The updating of a model of sensor response may be the refinements of classifiers or probability estimates used to identify when sensor outputs are indicative of particular conditions. Classifiers determine that a state of the world or event is indicated by particular sensor output, because they map that sensor output data to a category. Probability estimates similarly map the sensor output to a state of the world or event, but do so as a range of probabilities of states or events that are possible for the given sensor output. An example of a classifier for a gas grid condition may be, for example, that signals indicative of methane levels elevated to twice the baseline level from 3 adjacent sensors on a sensor network is a high-priority potential leak event. An example of a classifier for an electrical grid condition is discovery of an association between a particular power source or load and a specific observable impact on power quality, found, for example through Fourier or wavelet transform analysis. One specific example of updating a classifier may be, in the grid example, identifying a signal that degrades power quality within the impact of integrating a solar source into the grid through Fourier analysis of the waveform data associated with bringing the solar source on-line, and identifying that component as a result of that renewable source integration.

The model of sensor response may be based on data from a particular window of time, which may be adjusted when the model is updated, and may be a pre-defined period, or one determined dynamically. For an example of a pre-defined period, models of sensor response may be based on data only from the past 30 days, in which case the updating process includes removing data that is older than that, in addition to incorporating the newly collected data. The period from which data is used in the model of sensor response may also be adjusted dynamically. For example, a trigger may be set so that where the addition of the current sensor data causes a shift in the mean values or confidence intervals for established relationships of signal injections and sensor outputs that are greater than a certain threshold indicative of a change in system response behavior, historical data may be discarded and data collection for determining relationships between signal injections and sensor outputs started over to accurately discover and reflect this change in system response behavior.

One particular example method for updating a model of sensor response using sensor data associated with particular signal injections is detailed in Fig. 6. In this example, the associated sensor data is used to update a database of knowledge regarding the effects of the signal injection **600**. This process includes receiving data associated with a signal injection **602**, updating signal injection response data **604**, and updating means and confidence intervals for the signal injection

response data **606**. The knowledge database updated in **600** is used to validate models of sensor response **608**. This process includes selecting a model of sensor response **610**, using the model of sensor response to compute a predicted response to the signal injection **612**, comparing the prediction to the means and confidence intervals for the effects of the signal injection **614**, and if the predicted response lies outside the confidence intervals, invalid models are discarded **616**. This is iterated for additional models of sensor response until all sensor models have been tested against the updated knowledge of the effects of the signal injection **618**, and when the models have been tested, the process ends **620**.

Data associated with a signal injection is received in step **602**. The data is sensor data, which has been associated with a signal injection made into a utility grid, and associated based on the time and location of the data collection and the time, location and spatial and temporal reaches of the signal injection.

The data received in step **602** is used to update a signal injection response data in step **604**. The signal injection response data may be stored as a table of inferential statistics relating the effect of the signal injection on the response of the sensor. This table describes the relationship between a particular signal injection and its effects on sensor responses. Sensor data associated with the signal injection described in the table is selected and added to the database. In step **606** this updated database is then used to compute an updated mean and updated confidence intervals for the relationship between the signal injection and the sensor response.

The now-updated knowledge of the relationship between the signal injection and the sensor response is used to test and validate models of sensor response **608**. First, a model of sensor response is selected **610** from the set of models of sensor response. The selection may be random, or progressing through a set list, or selected based on estimates of its validity, for example through a Bayesian Causal Network where the model of sensor response is a belief state. The selected model of sensor response is used to compute the expected response to the signal injection **612**. This computation uses the time, location, and nature of the signal injection and the model of sensor response to create an estimate of the sensor response to that particular signal injection. This expected response is compared to the current means and confidence intervals in step **614**. In this step, the expected response according to the model of sensor response is compared to the sensor response data associated with the signal injection. If the expected response is within the confidence intervals of the current signal injection response data, the model remains valid. If the expected response falls outside the confidence intervals for the response of the sensor to the signal injection, the model is determined to be invalid and the model is discarded **616**. The valid models are used to evaluate incoming sensor data.

The process is iterated by checking for models of sensor response that have not yet been tested against the current database of sensor response to signal injections in step **618**. This may be determined, for example, by having a time-stamp for both the last time the database was updated and

the last time the model was updated, and checking the model update timestamps against the database update timestamp. When all models are current, the process ends **620**.]

The updated sensor model or models may then be used to interpret sensor results, improving the capability of the sensor to detect and report various states of the world or events through the falsification of incorrect aspects of the sensor response model or models. This updated sensor model can be used to trigger responses such as alarms for particular leak severities on gas grids, or deviations in power quality or drops in voltage requiring remedial actions on electrical grids. The updated sensor model is generated with the sensor already placed in the field, allowing automatic calibration of the sensor and adjustment to its local environment and baseline conditions, improving the accuracy and reliability of sensor readings and refining its ability to inform grid operators of particular grid conditions.

Fig. 2 shows one particular example of a utility grid, its associated sensors, and the reach of several signal injections that are made to the grid at close to the same time to illustrate the association of data from different sensors with different signal injections across a grid where there are multiple concurrent signal injections, maximizing the efficiency of such in-situ, automatic calibration without compromising the accuracy of a particular calibration due to confounds from signal injections that overlap in time and space. The utility grid **200** is a set of lines connecting sources of a utility (e.g. electricity, gas, or water) with various utility consumers. The sensor network includes sensors which are situated at locations **202**, **204**, **206**, **208** and **210**. Signal injections are made at locations **212**, **214**, and **216**. The signal injection at **212** has a spatial reach represented by the reach area **218**. The signal injection at **214** has a spatial reach represented by the reach area **220**. The signal injection at **216** has a spatial reach represented by reach area **222**. The spatial reach areas **218**, **220**, and **222** do not overlap, ensuring that the signal injections do not confound one another despite being deployed during the same time. The spatial reach areas **218**, **220**, and **222** all differ in size; this may result from differences in the nature (e.g. bringing a source online vs. switching selection of carrier lines in an electrical grid) or magnitude of the signal injection (e.g. the increase in pressure in psi of a signal injection to a gas grid), or of the predicted reach of the effects based on differences in the grid around the particular location of the signal injection (e.g. the volume of water lines branching from a particular node where flow is being increased in a water grid). The sensor at sensor location **202**, being located in spatial reach area **218**, has its sensor data collected during the temporal reach of signal injection **212** associated with that signal injection **212**. The sensors at sensor locations **204** and **206**, being located in spatial reach area **220**, have the sensor data collected at those sensors during the temporal reach of signal injection **214** associated with that signal injection **214**. The sensor located at sensor location **208**, being located in spatial reach area **222**, has its sensor data collected during the temporal reach of signal injection **216** associated with that signal injection **216**. The sensor located at sensor location **210**, lying outside all of the spatial reach areas during this period, does not have data associated with any of the signal

injections **212**, **214**, or **216**. These associations of data may then be used to update models of sensor response and grid conditions in accordance with step **110** of the method, enabling the sensors to be automatically calibrated in their locations on the grid, and refining the ability of those sensors to detect and report events or world states.

Fig. 3 is a diagram of an embodiment of the invention as a coordinated utility grid system. Memories may be known computer storage means such as flash memory, hard disk drives using magnetic media, or other methods for data storage that can store the data and be accessed frequently and regularly. Processors may be configured to make the calculations through software instructions. Connections among the components may be hard-wired, use of common processors for multiple steps, or networked through wired or wireless means such as the various 802.11 protocols, ZigBee or Bluetooth standards, Ethernet, or other known means for transmitting data among the separate sensors, processors, memories and modules. The sensors, memories, processors, and modules may be distributed across locations, including at the sensors themselves, or co-located in intermediate or central locations.

The signal injection memory **300** is a memory configured to store signal injection characteristics, including the time, location, and nature of signal injections to be made on the grid. The nature of the signal injection is the changes made to the grid conditions to effect the signal injection, such as the particular valves actuated in a water or gas grid, for example. Where the action may have variable magnitude, such as the amount of power supplied to the electrical grid by a turbine, the magnitude is also included in the data stored in this memory. The time and location are the time and location of the particular actions identified in the nature of the injection.

The grid characteristic memory **302** stores data on the grid components and their layout and connections, and the locations of sensors along the utility grid. This data may be stored in a number of forms, such as models of the grid including graphical, stochastic, or Markov chain models of grid component behavior, or databases of components, their locations, connections and/or their basic response characteristics.

The reach processor **304** is a processor configured to compute spatial and temporal reaches using signal injection and grid characteristic data, and optionally may also use historical data on past signal injections to compute these reaches by predicting the space and time where a signal injection is likely to impact sensor readings, by processing variables concerning the signal injection such as its nature, magnitude, and location, and the grid characteristics and past responses. The reach processor **304** preferably applies a Bayesian Causal Network to compute the reaches from signal injection and utility grid properties that are received as inputs.

The sensor network **306** is a plurality of sensors, the network sensors **314**, **316**, and **318**, which are situated at various positions along the utility grid. These sensors may be on, in, or near the utility grid they monitor, and may monitor properties of the grid, the utility itself, or the effects of the utility grid on surrounding conditions. For example, on gas grids, the sensor network may

include pressure sensors inside gas lines and/or methane sensors situated near gas lines. On water grids, sensors may be, for example, flow sensors inside pipes on the line. On electrical grids, the sensors may be, for example, sensored cable terminations, smart meters, voltage meters located at substations, line sag meters, and/or line temperature sensors. The sensors output electrical waveforms based on their transduction of the sensed variable. These sensors may be networked with one another, and are networked with the other components of the system; this may be through a variety of known wired and/or wireless means for communication of signals among devices.

Association processor **308** parses sensor data by the time and location of the sensor outputs and the temporal and spatial reaches of the signal injection. The processor receives information on the time and location of signal injections into the grid, and the temporal and spatial reaches of the signal injection. This data creates periods of time and space which are used to parse sensor output data by time and location of the sensor reading to ensure that the output of sensor network **306** at particular times and locations is associated with the proper signal injections to ensure that models of the sensor response can be accurately and efficiently updated using unconfounded data regarding response to known signal injections.

Model Memory **310** is a memory storing the characterization and/or classification models currently used by the grid to evaluate the sensor outputs. These models may be classifiers, probability estimates, or functions, which may be used to process sensor outputs. Multiple such models may be stored for each characterization or classification of data from sensors on the network, as the system tests and falsifies various models to converge on the best model or models for understanding sensor outputs through the systematic implementation of signal injections to test these models. These models also may be accessed and used to interpret sensor data to detect events or characterize conditions on a utility grid, for example by classifying sensor outputs as indicative or not indicative of a particular event, or using the model to convert a sensor output into measurements of a sensed metric.

Model update processor **312** is a processor configured to receive a current set of characterization and/or classification models and compute and implement updates to those models based on received sensor outputs and conditions associated with those outputs. One example of the model update processor **312**'s function is receiving sensor outputs associated with a signal injection, receiving the nature and magnitude of the signal injection, and the current models of sensor response, predicting sensor responses to the signal injection using the models of sensor response, and comparing the predicted responses with the actual sensor data from the signal injection, and, using a Partially Observable Markov Decision Process, adjusting belief states by, for example, rejecting models whose predictions deviate from the actual measured value by more than an error threshold amount. Updated models may be sent back to the Model Memory **310**, where they may be used to interpret sensor outputs to detect events or characterize conditions along a utility grid.

Fig. 4 is a data flow diagram showing the exchange of information among the components of an embodiment of the invention as a coordinated utility grid system. Signal injection characteristics **400** are the magnitude, nature, and the time and location at which a signal injection is introduced into the utility grid. This data is stored in signal injection memory **402**. The data is transferred from the signal injection memory **402** to the reach processor **404** to be used in computing the reach data **412**, and is transferred from the signal injection memory **402** to the model update processor **406** where it is used to generate predictions in the current models that are subsequently used to falsify some of those models. The signal injection characteristics **400** may optionally be provided to the association processor **408**, which may use the data to parse sensor data **418** and associate it with particular signal injections.

Grid information **410** is the layout of the grid and its components, and may optionally include historical data on grid states and responses to prior signal injections. The grid information **410** is stored in grid memory **412**. The grid information **410** is transferred from the grid memory **412** to the reach processor **404**, where the grid information is used to predict the spatial and temporal reaches **414** of signal injections. The grid information **410** may also be provided to the association processor **408** to match sensors to their locations to enable parsing of sensor data **418**. Grid information **410** may also optionally be provided to the model update processor to be used in predicting responses to signal injections, to validate the models against the collected sensor data **418**.

Reach data **414** is the regions of space and time that are predicted to be impacted by a particular signal injection. The reach data **414** is computed by reach processor **404**, using the signal injection characteristics **400** and the grid information **410** to predict the regions of time and space impacted by the signal injection; the reach data may just be the size of the regions of time and space, or may also incorporate the times and locations of the signal injection to contain concrete areas of space and durations of time that are impacted by the signal injection. The reach data **414** is transmitted used by association processor **408** to establish the periods of time and locations at which sensor data **418** was collected that may be associated with signal injections, the association processor parsing the sensor data **418** to generate the associated sensor data **422** based on when and where the sensor data was collected in comparison to the signal injection and its reach data **414**.

Sensor data **418** is raw outputs from the sensors **420** themselves, typically electrical waveforms output from a transducer; this data is typically generated continuously by the sensors **420**. Alternatively, the sensor data **418** may be taken at discrete sampling periods, or may be stored locally at memories at the sensor or near a cluster of sensors, and pulled down from the sensors at particular times. The sensor data **418** is used by the association processor **408** to produce the associated sensor data **422**.

The associated sensor data **422** is output from the association processor **408**, which generates it by parsing the sensor data **418** by the reach factors **412** to associate the sensor data **418**

with particular signal injections. The associated sensor data **422** output by the association processor **408** is transferred to the model update processor **424** where it is used to update belief states concerning sensor response models **426** that may characterize or classify sensor data.

Sensor response models **426** are various models that map the sensor data **418** to particular states, conditions, or events occurring at the sensors **420**. These models may take the form of models that convert the sensor output to a level of a measured variable, or may be classifiers or probability estimates that map the sensor output or combinations of outputs to particular events happening across the grid, either indicating the presence or the likelihood of such an event. These models are stored in the sensor response model memory **428**, and in systems of the invention, the sensor response models **426** are transferred from the model memory **428** to the model update processor **406**, where the response models are updated or falsified based on associated sensor data **422** attributable to particular signal injections; the updated sensor response models **430** are transferred back from the model update processor **406** to the sensor response model memory **428**. Updating the sensor response models allows for calibration of the sensors in-situ and improves the understanding of sensor outputs, improving the event detection and world state monitoring provided by the sensors of the sensor network through iteratively falsifying incorrect models of sensor response to world events of interest to utility operators, such as alerts for various conditions such as leaks and brownouts, or to remove noise from data, such as that used for process optimization efforts such as adjusting flow rates or controlling reactive power levels to support transmission while minimizing waste.

A simple example of an overall architecture involving an example embodiment of the invention is presented in Fig. 7. The control decision layer **700** makes decisions about the states for some or all gird controls. Grid control decisions are made according to methods ensuring that the manipulation of controls creates samples that do not influence one another, and optionally selecting the control decisions to provide high learning value or to improve particular grid parameters such as ensuring certain voltage levels in electrical grids, or flow rates in gas or water grids. The control decisions from the control decision layer **700** are carried out by the controls **702**, **704**, and **706**. Examples of particular controls include capacitor bank switches, load tap changers, switches and storage devices on electrical grids, or valves and sources on water and gas grids. The controls may carry out the control decisions by, for example, actuating switches, moving load tap changer positions, and narrowing or widening valves. The actions of the controls change grid parameters, and those changes propagate through the grid **708**. For example, opening a valve on a gas grid may cause pressures to increase downstream over time, within a certain distance from the valve, or in an electrical grid, power quality and reactive power levels may change based on the switching on or off of a capacitor bank. Sensors **714**, **716**, and **718** placed along the grid measure grid parameters, and detect the propagation of the signal injection through the grid **708**. The signal injections are limited in the extent to which they propagate through the grid **708**, defined as the spatial reach of that signal

injection such as the spatial reach **710** outlining the region affected by the signal injected by control **702** and including the connection of sensor **714** to the grid **708**, and spatial reach **712** outlining the region affected by the signal injected by control **706** and including the connection of sensor **718** to grid **708**. Data processing layer **720** associates the data from sensors **714**, **716**, and **718** with signal injections whose spatial and temporal reaches include the sensor data, for example associating data from sensor **714** with data from a signal injection implemented by control **702** based on spatial reach **710**, and associating data from sensor **718** with a signal injection implemented by control **706** based on spatial reach **712**. The associated sensor data from the data processing layer **720** is then analyzed by the data analysis layer **722** to determine understandings about grid behavior and sensor response. This understanding of grid behavior generated by the data analysis layer **722** may, for example, take the form of sensor response models which are used to interpret the outputs from grid sensors **714**, **716**, and **718** during ordinary operations, for example to set thresholds or alerts for brownout conditions when voltage drops in an electrical line, or setting an alert for methane levels crossing normal operational thresholds. The data analysis layer **722** may interface with the control decision layer **700** to iteratively coordinate and implement signal injections into the grid and provide information that improves the selection of signal injections to implement, for example by predicting the effects of a signal injection on the grid or computing the extent to which learning may be refined by a particular signal injection.

What is claimed is:

1. A method for determining the effects of a signal injection on a sensor response, comprising:
implementing a signal injection on a utility grid
receiving sensor data
receiving a spatial reach for the signal injection
receiving a temporal reach for the signal injection
associating, using a processor, the sensor data within the spatial reach and within the temporal reach with the signal injection.

2. The method of claim 1, further comprising updating a model of sensor response based on the associated sensor data and the signal injection.

3. The method of claim 2, wherein updating a model of sensor response comprises:
predicting the sensor response to the signal injection using models of sensor response
comparing the associated data to the predicted sensor response
falsifying models of sensor response where the predicted sensor response deviates from the associated data.

4. The method of claim 2, wherein updating a model of sensor response comprises:
updating a database of sensor response to signal injections with the associated sensor data
computing, based on the updated database of sensor response to signal injections, relationship between sensor response and a grid parameter affected by the signal injection.

5. The method of claim 2, wherein updating a model of sensor response includes removing data from the model based on the age of the data and an inclusion period.

6. The method of claim 2, wherein the model of sensor response is an alert threshold.

7. The method of claim 2, wherein the model of sensor response is a classifier

8. The method of claim 1, wherein the sensor data are electrical measurements.

9. The method of claim 1, wherein the sensor data are methane concentration measurements.

10. The method of claim 1, wherein the signal injection is a change in state of a grid control.

11. The method of claim 1, further comprising:

implementing a second signal injection on the utility grid

receiving a second spatial reach for a second signal injection

receiving a second temporal reach for a second signal injection

associating sensor data within the second spatial reach and within the second temporal reach with the second signal injection.

12. The method of claim 11, wherein the first signal injection and the second signal injection are implemented concurrently.

13. The method of claim 1, wherein the spatial reach is computed based on a database of grid response to previous signal injections.

14. The method of claim 1, wherein the temporal reach is computed based on a database of grid response to previous signal injections.

15. A system for associating sensor data with particular signal injections into a utility grid, comprising:

a plurality of utility grid controls

a plurality of sensors

a sensor data memory configured to receive and store sensor data

a spatial reach memory configured to receive and store spatial reaches for signal injections

a temporal reach memory configured to receive and store temporal reaches for signal injections

an association processor configured to associate data with signal injections based on the spatial and temporal reaches of the signal injections.

16. The system of claim 15, further comprising:

a memory configured to store a database of previous grid responses to signal injections

a spatial reach processor configured to compute the spatial reach of a signal injection based on the database of previous grid responses to signal injections

a temporal reach processor configured to compute the temporal reach of a signal injection based on the database of previous grid responses to signal injections.

17. The system of claim 15, further comprising:

a memory configured to store models of sensor response

a processor configured to update models of sensor response using associated sensor data.

18. The system of claim 17, wherein the processor is configured to update models of sensor response by comparing the outputs of models of sensor response to data associated with signal injections and falsifying at least some of the models of sensor response.

19. The system of claim 15, wherein the sensors are located along a utility grid.

20. The system of claim 15, wherein the association processor is configured to compare time and location metadata of the sensor data with the spatial and temporal reach of the signal injection.

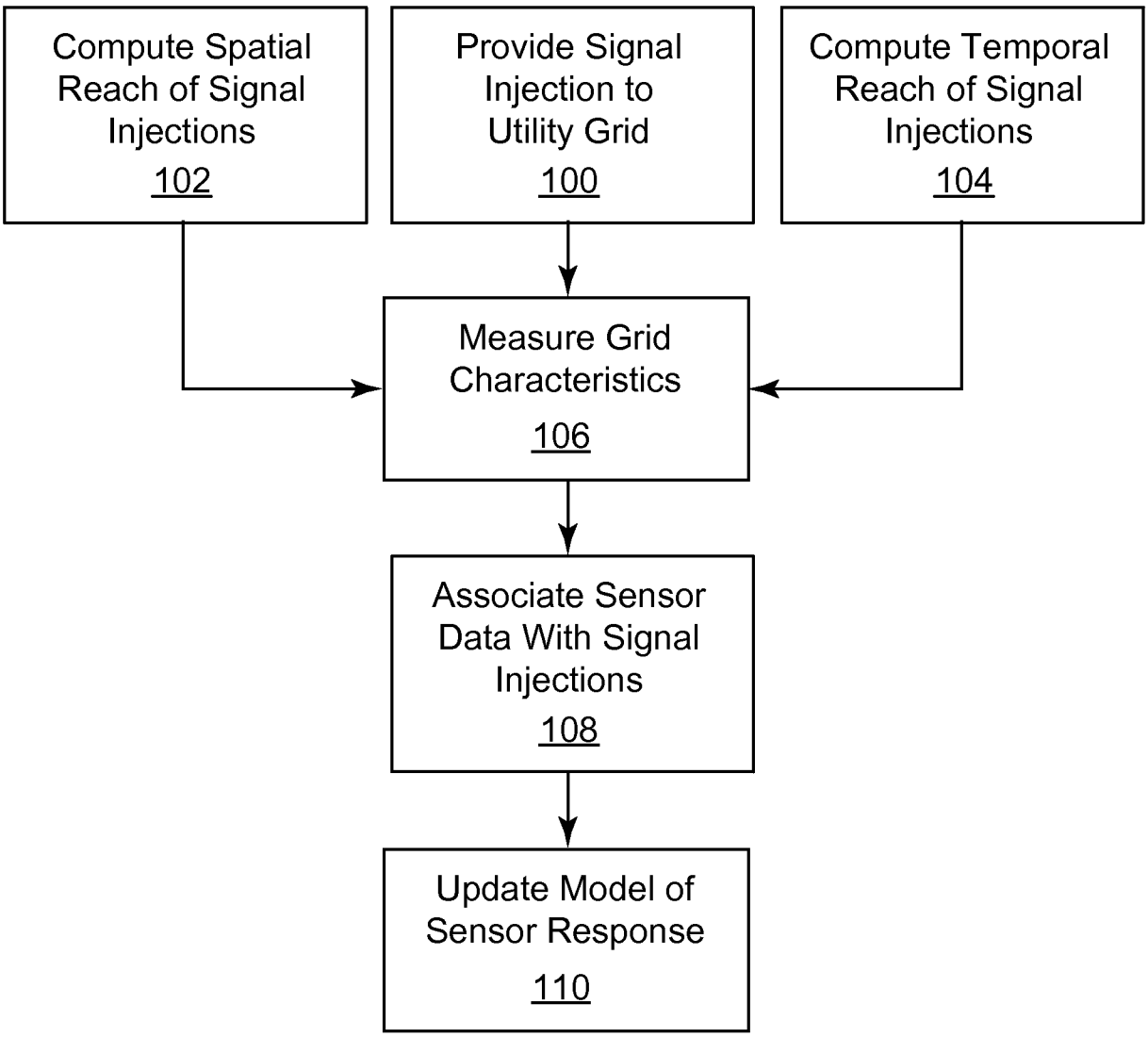
Compute Spatial Reach of Signal Injections
102
Provide Signal Injection to Utility Grid
100
Compute Temporal Reach of Signal Injections
104
Measure Grid Characteristics
106
Associate Sensor Data With Signal Injections
108
Update Model of Sensor Response
110

Fig. 1

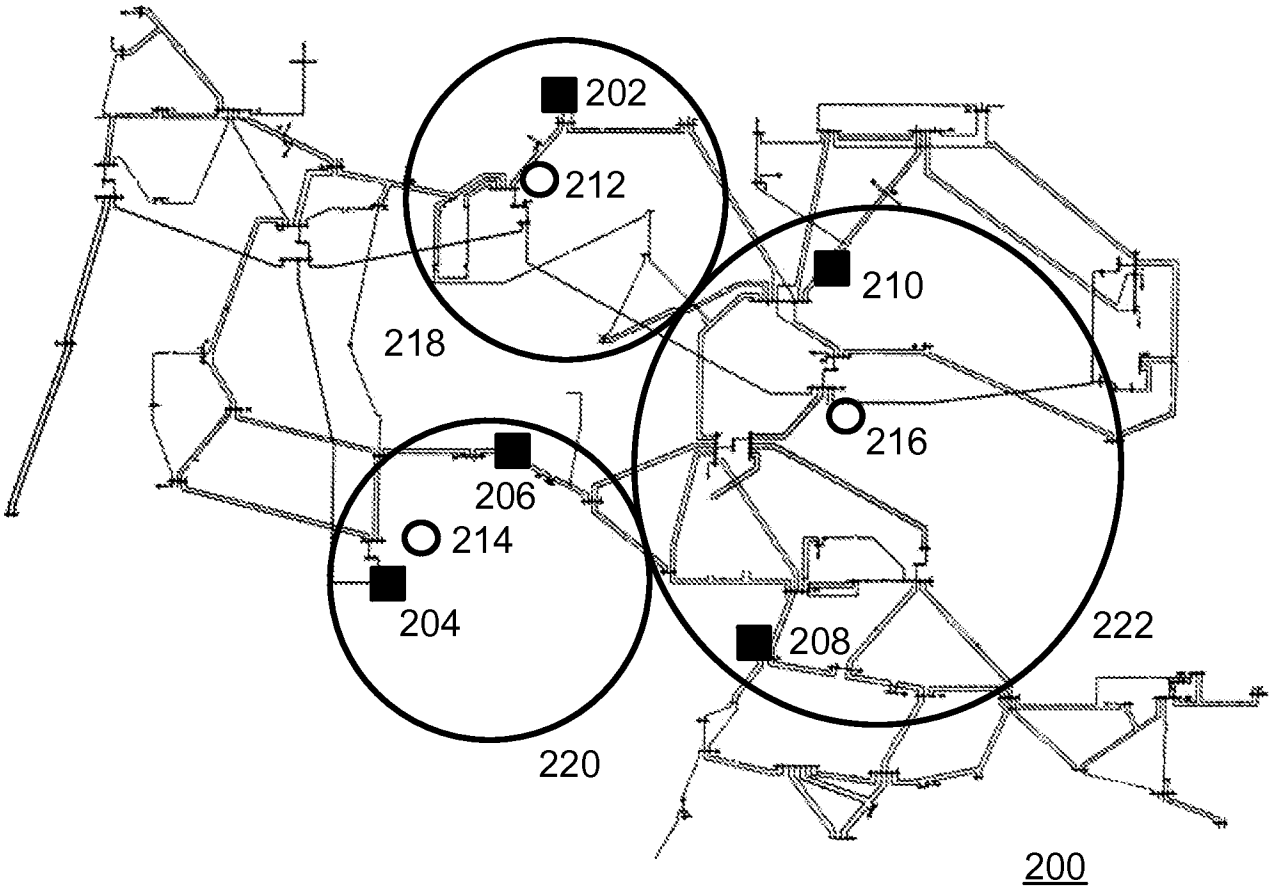

Fig. 2

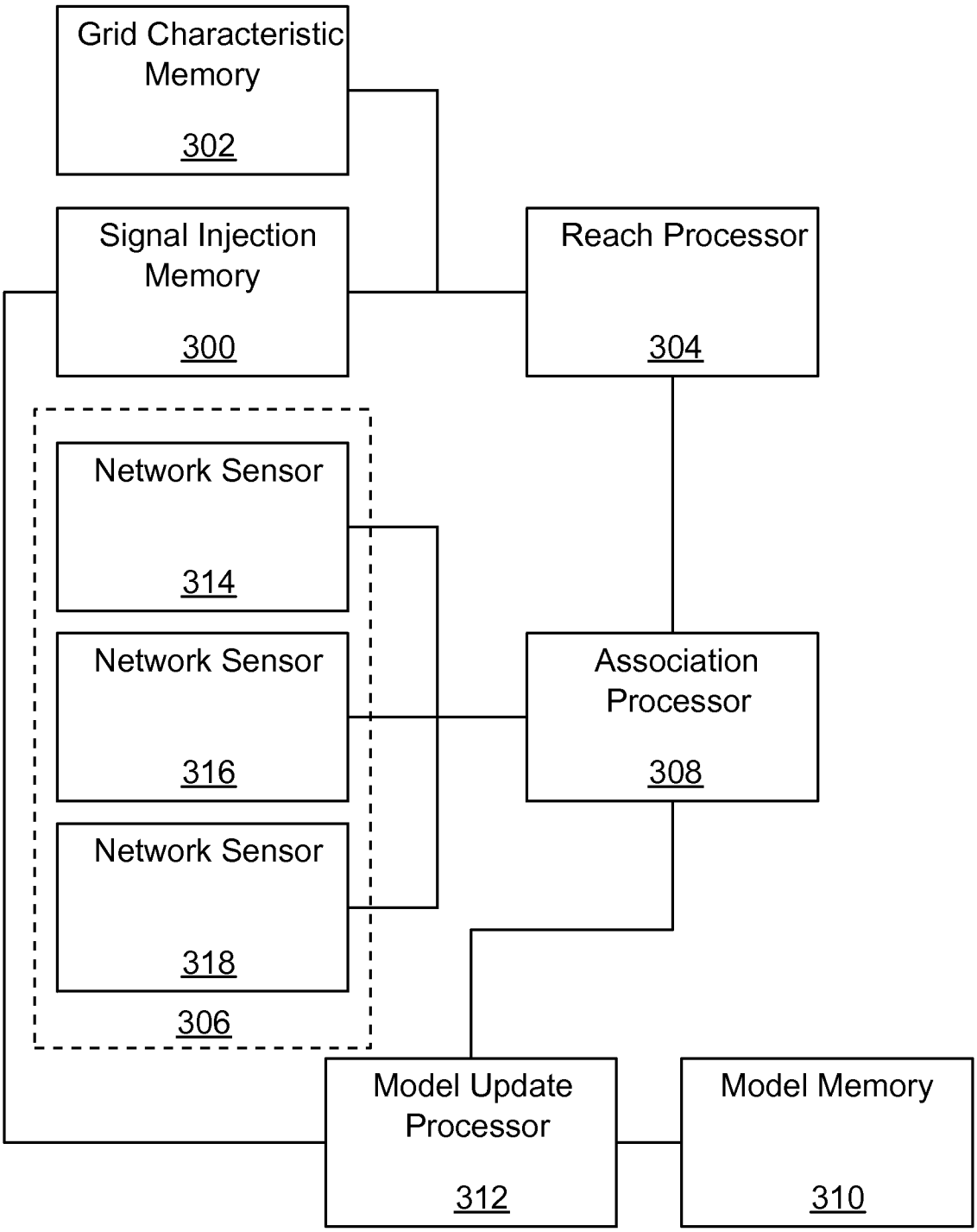
Grid Characteristic Memory
302
Signal Injection Memory
300
Reach Processor
304
Network Sensor
314
Network Sensor
316
Network Sensor
318
306
Association Processor
308
Model Update Processor
312
Model Memory
310

Fig. 3

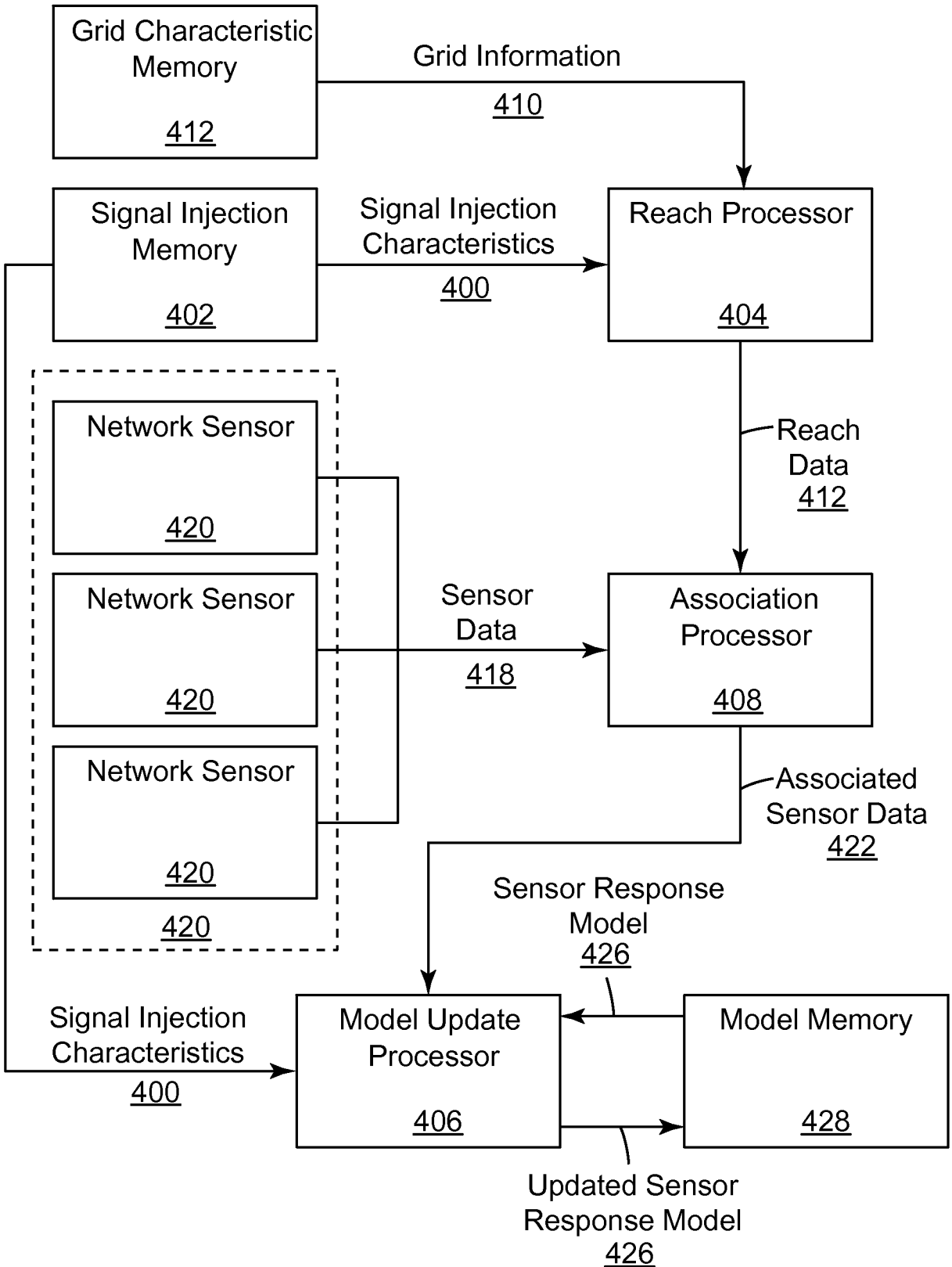
Grid Characteristic Memory
412
Grid Information
410
Signal Injection Memory
402
Signal Injection Characteristics
400
Reach Processor
404
Reach Data
412
Network Sensor
420
Network Sensor
420
Network Sensor
420
420
Sensor Data
418
Association Processor
408
Associated Sensor Data
422
Sensor Response Model
426
Signal Injection Characteristics
400
Model Update Processor
406
Model Memory
428
Updated Sensor Response Model
426

Fig. 4

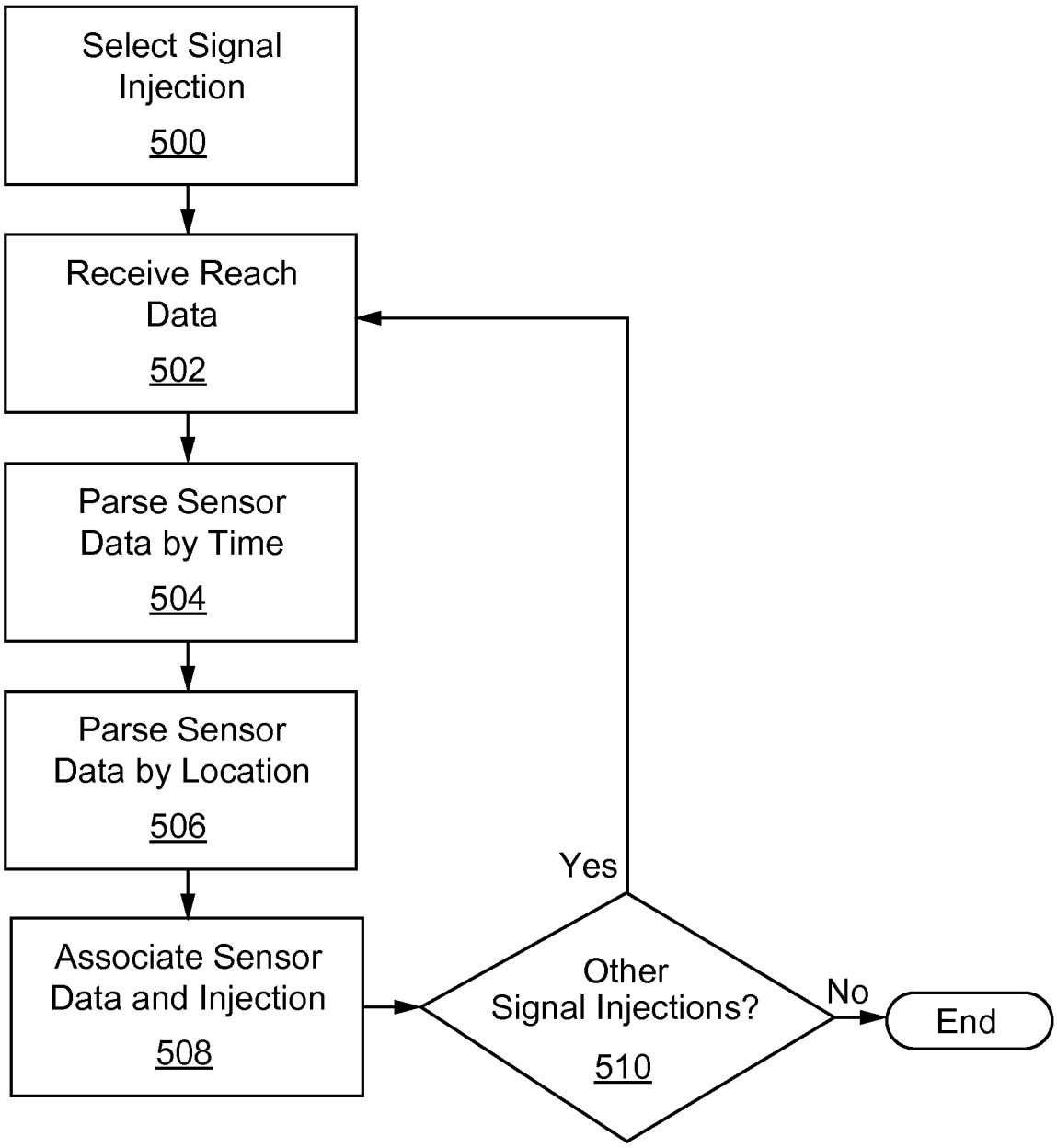
Select Signal Injection
500
Receive Reach Data
502
Parse Sensor Data by Time
504
Parse Sensor Data by Location
506
Associate Sensor Data and Injection
508
Other Signal Injections?
510
Yes
No
End

Fig. 5

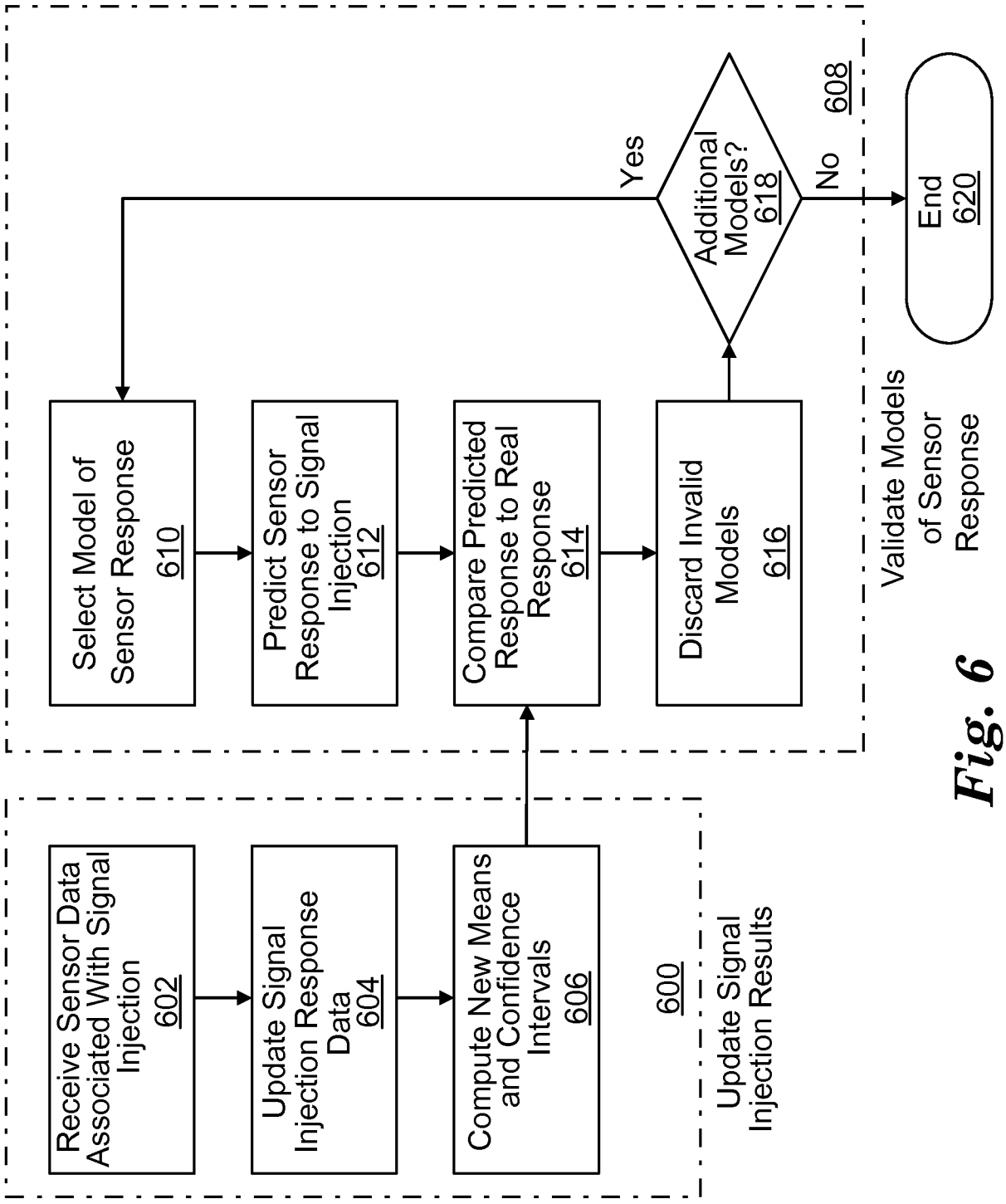
Receive Sensor Data Associated With Signal Injection 602
Update Signal Injection Response Data 604
Compute New Means and Confidence Intervals 606
600
Update Signal Injection Results
Select Model of Sensor Response 610
Predict Sensor Response to Signal Injection 612
Compare Predicted Response to Real Response 614
Discard Invalid Models 616
Validate Models of Sensor Response
Additional Models? 618
Yes
No 608
End 620

Fig. 6

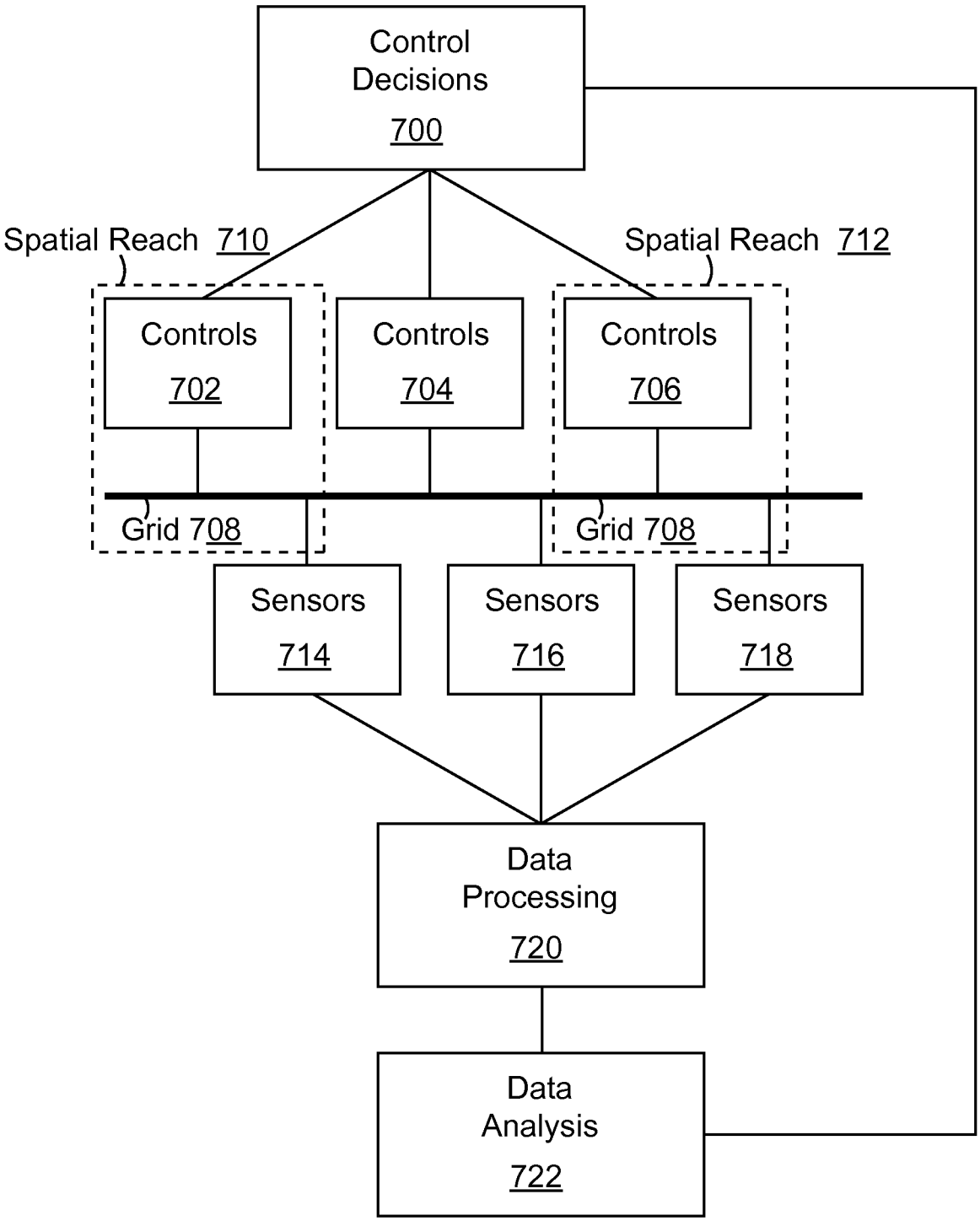
Control Decisions 700
Spatial Reach 710
Spatial Reach 712
Controls 702
Controls 704
Controls 706
Grid 708
Grid 708
Sensors 714
Sensors 716
Sensors 718
Data Processing 720
Data Analysis 722

Fig. 7

INTERNATIONAL SEARCH REPORT

International application No.
PCT/US2015/040359

A. CLASSIFICATION OF SUBJECT MATTER

G06Q 50/06(2012.01)i

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)
G06Q 50/06; G05D 3/12; G05D 5/00; G08B 21/00; G05B 11/01; G01R 31/02; G01R 19/00; G01R 21/00; G01R 19/165

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched
Korean utility models and applications for utility models
Japanese utility models and applications for utility models

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)
eKOMPASS(KIPO internal) & Keywords: grid, sensor, classify, spatial, temporal, signal injection

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	US 8121741 B2 (JEFFREY D. TAFT et al.) 21 February 2012 See abstract, column 4, line 9-column 5, line 57, column 7, lines 3-31, column 12, lines 6-10, claim 9 and figure 3.	1-2,7-10,15,17,19
Y		3-6,11-14,16,18,20
Y	US 2008-0106425 A1 (BRIAN J. DEAVER et al.) 08 May 2008 See abstract, paragraphs [0045], [0081]-[0083], [0109]-[0112], claim 19 and figures 1, 3-5, 12.	3-6,13-14,16,18,20
Y	US 2014-0191746 A1 (ALAN JAMES DAVIE et al.) 10 July 2014 See abstract, paragraphs [0019]-[0020] and claim 4.	11-12
A	US 2012-0041696 A1 (H. BRITTON SANDERFORD, JR. et al.) 16 February 2012 See abstract, claims 1-3, 13-15 and figures 5, 7-8.	1-20
A	US 2010-0102936 A1 (CHRISTOPHER A. WHITE et al.) 29 April 2010 See abstract, claims 1-2, 7-8, 13 and figures 1, 5-6.	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
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"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	Date of mailing of the international search report
16 October 2015 (16.10.2015)	**19 October 2015 (19.10.2015)**

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Telephone No. +82-42-481-8474

INTERNATIONAL SEARCH REPORT

Information on patent family members

International application No.
PCT/US2015/040359

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