METHOD AND SYSTEM FOR CHILLER PERFORMANCE ANOMALY DIAGNOSIS

TECHNICAL FIELD

[0001] The present invention generally relates to a computer-implemented method and a system for chiller performance anomaly diagnosis, and more particularly, to chiller performance anomaly diagnosis based on root cause analysis (RCA).

BACKGROUND

[0002] As the core cooling equipment, chiller has wide applications in comfort cooling and industry process cooling plants. Root cause analysis (RCA) method based on Theory of Constraint was developed for the diagnosis of chiller's performance anomaly, such as chilled water supply capacity deterioration, chilled water supply temperature spike, and so on. In performance anomaly diagnosis, RCA may analyze the correlation between chiller's performance, such as chilled water supply (CHW) and main constraints, such as cooling water flow rate, chilled water return temperature, and so on. The constraint with the strongest correlation with chiller performance during the anomaly is identified as the bottleneck or root cause of chiller performance anomaly. RCA diagnosis is helpful in lowering chiller's maintenance cost and has been applied in different types of chillers, including steam absorption chiller (SAC) and electric chiller (EC).

[0003] However, various low quality problems have been found in conventional RCA-based performance anomaly diagnosis. For example, there are instances where conventional RCA-based performance anomaly diagnosis fail to capture an anomaly in chiller's performance and identify the root cause of the anomaly.

[0004] A need therefore exists to provide a method and a system for chiller performance anomaly diagnosis, and more particularly, to RCA-based performance anomaly diagnosis, that seek to overcome, or at least ameliorate, one or more of the deficiencies of conventional chiller performance anomaly diagnosis methods. It is against this background that the present invention has been developed.

SUMMARY

[0005] According to a first aspect of the present invention, there is provided a computer-implemented method for chiller performance anomaly diagnosis, the method comprising:

setting a first correlation model between a performance parameter of a chiller and a first plurality of operational parameters;

determining an optimal window size for performing a root cause analysis diagnosis based on the first correlation model with respect to an anomaly identified in the performance parameter; and

performing the root cause analysis diagnosis based on the first correlation model and the optimal window size with respect to the anomaly for determining a root cause of the anomaly identified in the performance parameter of the chiller, the root cause analysis diagnosis being performed on a dataset comprising measurement data relating to the performance parameter and the first plurality of operational parameters collected over a period of time, including anomaly measurement data having an anomaly period associated with the anomaly.

[0006] According to a second aspect of the present invention, there is provided a system for chiller performance anomaly diagnosis, the system comprising:

a memory; and

at least one processor communicatively coupled to the memory and configured to perform the method for chiller performance anomaly diagnosis according to the first aspect of the present invention.

[0007] According to a third aspect of the present invention, there is provided a computer program product, embodied in one or more non-transitory computer-readable storage mediums, comprising instructions executable by at least one processor to perform a method for chiller performance anomaly diagnosis according to the first aspect of the present invention.

BRIEF DESCRIPTION OF THE DRAWINGS

[0008] Embodiments of the present invention will be better understood and readily apparent to one of ordinary skill in the art from the following written description, by way of example only, and in conjunction with the drawings, in which:

FIG. 1 depicts a schematic flow diagram of a method for chiller performance anomaly diagnosis according to various embodiments of the present invention;

FIG. 2 depicts a schematic block diagram of a system for chiller performance anomaly diagnosis according to various embodiments of the present invention according to various embodiments of the present invention;

FIG. 3 depicts a schematic drawing of a window size optimizer for performing root cause analysis diagnosis according to various embodiments of the present invention;

FIG. 4 depicts a schematic drawing of an example system architecture for RCA diagnosis on a chiller, including window size calculation, according to various example embodiments of the present invention;

FIG. 5 illustrates an example graphical user interface (GUI) which may be presented on and utilized by an operator (e.g., operator device) to define an RCA model (correlation model) and an anomaly period for performing root cause analysis diagnosis according to various example embodiments of the present invention;

FIG. 6 depicts a schematic flow diagram of a method of chiller anomaly diagnosis based on a RCA model (with multi-layer RCA model capability) according to various example embodiments of the present invention;

FIG. 7 illustrates a double-layer RCA model, including an upper layer and a lower layer, according to various example embodiments of the present invention;

FIG. 8 depicts a schematic flow diagram of a method of determining an optimal window size for performing a RCA diagnosis with respect to an anomaly according to various example embodiments of the present invention; and

FIG. 9 illustrates an example sliding window technique across the anomaly period according to various example embodiments of the present invention.

DETAILED DESCRIPTION

[0009] Various embodiments of the present invention provide a method (computer-implemented method) and a system for chiller performance anomaly diagnosis, and more particularly, to a root cause analysis (RCA)-based chiller performance anomaly diagnosis, that seek to overcome, or at least ameliorate, one or more of the deficiencies associated with conventional chiller performance anomaly diagnosis methods. In the context of various embodiments, it will be appreciated by a person skilled in the art that a chiller may refer to any apparatus or system configured to cool or chill fluids (e.g., to produce chilled water) so as to provide cooling effects for various purposes, and is not limited to any particular types of chillers. For example, embodiments of the present invention may be applied or implemented to carry out performance anomaly diagnosis on various types of chillers, such as in a cooling plant or a heating, ventilation, and air conditioning (HVAC) system, including but not limited to, steam absorption chiller (SAC), electric chiller (EC), centrifugal chiller (CC), screw chiller (SC), and so on.

[0010] Various embodiments of the present invention identified that various low quality problems have been found in conventional RCA-based chiller performance anomaly diagnosis. For example, there are instances where conventional RCA-based chiller performance anomaly diagnosis fail to capture an anomaly in chiller's performance and identify the root cause of the anomaly.

[0011] By way of example only and for better understanding, a conventional RCA-based chiller performance anomaly diagnosis will now be described.

[0012] For example, as described in Okitsu et al., "Root Cause Analysis on Changes in Chiller Performance using Linear Regression", International Conference on Computer and Information Sciences, Kuala Lumpur, June 2014, pages 298-303 (hereinafter referred to as the Okitsu document), and Zhang et al., "A Case Study of Electric Chiller Performance Bottleneck Diagnosis by Root Cause Analysis", IEEE International Conferences on Information Technology, Information Systems and Electrical Engineering (ICITISEE 2016), Yogyakarta, Indonesia, 23-24 August 2016 (hereinafter referred to as the Zhang document), the contents of both the Okitsu and Zhang documents which are hereby incorporated by reference in their entirety for all purposes, a conventional RCA diagnosis method was developed based on Theory of Constraints,

which has been applied on performance anomaly diagnosis for chillers, including SAC and EC. During the conventional RCA diagnosis, RCA may construct a correlation model (RCA model) between a chiller performance parameter (e.g. chilled water supply (CHW)) and its operational parameters (which may also interchangeably be referred to as "constraints") (e.g. cooling water supply temperature, cooling water flow rate, and chilled water return temperature) through multiple linear regression. Each constraint's contribution rate to the performance parameter is calculated based on the correlation coefficients associated with the correlation model. The constraint with the largest contribution rate may then be selected as the bottleneck or anomaly root cause in the chiller's performance.

[0013] By way of an example only and for better understanding, the conventional method for RCA diagnosis for an air cooled EC's CHW performance (performance parameter) may include the following basic steps.

[0014] Step 1: construct a multiple linear correlation model for EC's CHW performance and associated constraints:

$$CHW'(t) = C_R(t) \times CHW_r(t) + C_T(t) \times TMP(t) + C_E(t) \times ELE(t), \quad \text{(Equation 1)}$$

where,

$CHW'(t)$ denotes calculated chilled water supply performance at time t, estimated by the correlation model;

$CHW_r(t)$ denotes a constraint of chilled water return temperature at time t;

$TMP(t)$ denotes a constraint of ambient air temperature at time t;

$ELE(t)$ denotes a constraint of chiller's electricity consumption at time t;

$C_R(t)$ denotes a correlation coefficient of $CHW_r(t)$ at time t, generated from multiple linear regression;

$C_T(t)$ denotes a correlation coefficient of $TMP(t)$ at time t, generated from multiple linear regression; and

$C_E(t)$ denotes a correlation coefficient of $ELE(t)$ at time t, generated from multiple linear regression.

[0015] Step 2: calculate each constraint's contribution ratio to the CHW performance. For example, for the constraint $ELE(t)$, the contribution ratio $R_E(t)$ may be calculated as follows:

$$R_E(t) = |C_E(t)| \,/\, P(t) \qquad \text{(Equation 2)}$$

$$P(t) = |C_E(t)| + |C_R(t)| + |C_T(t)| \qquad \text{(Equation 3)}$$

[0016] The constraint $TMP(t)$'s contribution ratio $R_T(t)$ and constraint $CHW_r(t)$'s contribution ratio $R_R(t)$ may be calculated in the same or similar manner.

[0017] Step 3: select the constraint with the highest contribution ratio as the bottleneck of the CHW performance. During the performance anomaly period, the bottleneck is regarded as the root cause of the anomaly.

[0018] From the above-mentioned steps 1 to 3, it can be seen that the RCA diagnosis result heavily depends on the correlation coefficients $C_R(t)$, $C_T(t)$ and $C_E(t)$, which are generated through multiple linear regression with Gaussian model family and identity link function. At time t, the regression process is conducted on data sample during a period of $[t\text{-}w,\ t]$, where w is window size (which may also interchangeably be referred to as the "sample size" or the like). According to the Okitsu document and the Zhang document, the conventional RCA method utilizes uniform (fixed predetermined) window size for the regression process. In this regard, embodiments of the present invention found that such a conventional RCA-based performance anomaly diagnosis method suffers from various low quality problems, and identified an attributing factor as the lack of window (sample) size management. For example, the conventional RCA-based performance anomaly diagnosis method uses uniform window size for time dependent correlation analysis, which has been found according to embodiments of the present invention to be not effective for anomalies with different sizes (e.g., different period lengths). For example and without limitation, embodiments of the present invention identified that when the RCA window size is much larger than the anomaly size, the anomaly data may be buried by the normal data (i.e., portion(s) of the data without the anomaly), causing the RCA diagnosis to fail to capture one or more anomalies in chiller's performance and identify the root cause of the anomaly. On the

other hand, if the window size is too small, the RCA diagnosis may become unstable because of correlation overfit issue, which may be caused by, e.g., too small amount of sample data and too many constraints.

[0019] Accordingly, various embodiments of the present invention advantageously provide a method (computer-implemented method) and a system for chiller performance anomaly diagnosis, and more particularly, to a RCA-based chiller performance anomaly diagnosis, that seek to overcome, or at least ameliorate, one or more of the deficiencies associated with conventional chiller performance anomaly diagnosis methods, such as the above-mentioned conventional chiller performance anomaly diagnosis method, by improving the quality or effectiveness of chiller performance anomaly diagnosis (e.g., stability, accuracy and/or precision). In particular, various embodiments of the present invention advantageously include a RCA window size management technique in chiller performance anomaly diagnosis to accommodate for variable time dependent anomalies, and more particularly, for determining an optimal window size for performing the RCA diagnosis with respect to an anomaly identified in a performance parameter of a chiller.

[0020] FIG. 1 depicts a schematic flow diagram of a method (computer-implemented method) 100 for chiller performance anomaly diagnosis according to various embodiments of the present invention. The method 100 comprises, at 102, setting a first correlation model between a performance parameter of a chiller and a first plurality of operational parameters; at 104, determining an optimal window size for performing a root cause analysis (RCA) diagnosis based on the first correlation model with respect to an anomaly identified in the performance parameter; and at 106, performing the RCA diagnosis based on the first correlation model and the optimal window size with respect to the anomaly for determining a root cause of the anomaly identified in the performance parameter of the chiller. In this regard, the RCA diagnosis is performed on a dataset comprising measurement data relating to the performance parameter and the first plurality of operational parameters collected over a period of time, including anomaly measurement data having an anomaly period associated with the anomaly.

[0021] Accordingly, various embodiments of the present invention provide a method for chiller performance anomaly diagnosis that advantageously includes a RCA window size management technique, and more particularly, that determines an optimal window

size for performing the RCA diagnosis with respect to an anomaly identified in a performance parameter of a chiller. As a result, the quality or effectiveness of the chiller performance anomaly diagnosis according to embodiments of the present invention can be significantly improved, such as stability, accuracy and/or precision, thereby enabling better and more efficient identification/detection of the root cause of an anomaly in a performance of a chiller.

[0022] It will be appreciated by a person skilled in the art that the performance parameter of a chiller may be any type of performance related to the chiller that is desired or appropriate to be considered or measured, such as but not limited, chilled water supply (CHW), coefficient of performance (COP), or chilled water supply temperature (CHWs).

[0023] It will also be appreciated by a person skilled in the art that the operational parameter may be any type of operational parameter that is selected or determined to be associated or related to the performance parameter being considered or measured, for example, a plurality of operational parameters that is selected or determined as affecting or impacting the performance parameter being considered or measured. By way of example only and without limitation, the operational parameters may be selected from a group consisting of chilled water return temperature, chilled water flow rate, cooling water supply temperature, cooling water flow rate, steam flow rate, steam pressure, cooling water return temperature, electricity consumption, and ambient air temperature.

[0024] In various embodiments, the first correlation model may be a multiple linear correlation model between a performance parameter of a chiller and a plurality of operational parameters.

[0025] In various embodiments, it will be appreciated by a person skilled in the art that the performance parameter(s) and the operational parameter(s) may be measured by one or more appropriate sensors known in the art. For example and without limitation, in a cooling plant, it can be appreciated by a person skilled in the art that various sensors as desired or as appropriate may be installed therein or thereabout to measure or monitor various performance parameters and operational parameters, and the associated sensor data (or measurement data) may thus be collected over time and stored in one or more data storage mediums in a manner known in the art and thus need not be described herein for conciseness. For example, the above-mentioned dataset comprising measurement data

relating to the performance parameter and the first plurality of operational parameters collected over a period of time may be obtained from such sensor data collected over time.

[0026] In various embodiments, the above-mentioned determining an optimal window size comprises obtaining a plurality of candidate window sizes; and assessing each of the plurality of candidate window sizes with respect to the first correlation model for determining a candidate window size amongst the plurality of candidate window sizes that is optimal for performing the RCA diagnosis based on the first correlation model with respect to the anomaly. For example, a set or range of candidate window sizes may be determined and each candidate window size in the set or range is then subjected to an assessment (or evaluation) to determine how well the RCA diagnosis performs using the candidate window size based on the first correlation model.

[0027] In various embodiments, the above-mentioned assessing each of the plurality of candidate window sizes comprises: for each candidate window size, generating a set of anomaly data samples from the dataset, each anomaly data sample generated based on the candidate window size and includes at least an anomaly data point belonging to the anomaly measurement data; performing a multiple linear regression analysis on the set of anomaly data samples based on the first correlation model; and determining an overall quality measure of fit of the first correlation model to the set of anomaly data samples generated. Accordingly, for each candidate window size being assessed, a set of anomaly data samples is generated from the above-mentioned dataset. In this regard, each anomaly data sample in the set is generated based on the candidate window size and includes at least an anomaly data point belonging to the anomaly measurement data (e.g., hence referred to as anomaly data sample). For example, each anomaly data sample in the set may have a same size (same period length) determined based on the candidate window size, such as but not limited to, being equal to the candidate window size × the data sampling time interval of the dataset. For example, each anomaly data sample in the set may cover a different amount or different portion/part of the anomaly measurement data. A multiple linear regression analysis may then be performed on each anomaly data sample in the set based on the first correlation model to obtain respective first quality measure of fit (e.g., square of multiple correlation coefficients (R^2)) of the first

correlation model to the anomaly data sample. An overall quality measure of fit (e.g., confidence interval (CI)) of the first correlation model to the set of anomaly data samples obtained may then be determined. As a result, the suitability or performance of each candidate window size amongst the plurality of candidate window sizes is assessed, and an optimal candidate window size may then be determined for performing the root cause analysis diagnosis based on the first correlation model with respect to the anomaly.

[0028] In various embodiments, the set of anomaly data samples (for each candidate window size) is generated based on a sliding window technique performed across the anomaly period.

[0029] In various embodiments, the sliding window technique comprises generating a first anomaly data sample comprising a starting data point of the anomaly measurement data and generating a subsequent anomaly data sample for each subsequent time interval until a last anomaly data sample comprising a last data point of the anomaly measurement data to generate the set of anomaly data samples. For example, if the time interval (e.g., data sampling time interval) of the dataset is five minutes, then a subsequent anomaly data sample may be generated for each subsequent five minutes until the last anomaly data sample.

[0030] In various embodiments, the first anomaly data sample has an anomaly sample period ending at the starting data point of the anomaly measurement data, and the last anomaly data sample has an anomaly sample period starting at the last data point of the anomaly measurement data. In other words, the window (e.g., anomaly sample period) may slide from a starting point or leftmost side of the anomaly measurement data to an ending point or rightmost side of the anomaly measurement data.

[0031] In various embodiments, each anomaly data sample of the set of anomaly data samples has an anomaly sample period length determined based on the candidate window size. For example, as described above, each anomaly data sample in the set may have the same anomaly sample period length determined based on the candidate window size, such as but not limited to, being equal to the candidate window size × the data sampling time interval of the dataset.

[0032] In various embodiments, the above-mentioned performing a multiple linear regression analysis comprises: performing, for each anomaly data sample of the set of

anomaly data samples, a multiple linear regression analysis on the anomaly data sample based on the first correlation model; and determining, for each anomaly data sample of the set of anomaly data samples, a first quality measure of fit of the first correlation model to the anomaly data sample to generate a set of first quality measures for the set of anomaly data samples. In this regard, the above-mentioned overall quality measure of fit of the first correlation model to the set of anomaly data samples may then be determined based on the set of first quality measures. As mentioned hereinbefore, the first quality measure may comprise a square of multiple correlation coefficients (R^2) of the first correlation model to the anomaly data sample, and the overall quality measure may comprise a confidence interval (CI) of the set of first quality measures determined. In this regard, the multiple linear regression analysis on the anomaly data sample based on the first correlation model may produce the correlation coefficients of the operational parameters, respectively, included in the first correlation model. The first quality measure may then be determined based on the correlation coefficients obtained.

[0033] In various embodiments, the above-mentioned assessing each of the plurality of candidate window sizes further comprises determining one of the plurality of candidate window sizes as the optimal window size based on the respective overall quality measures determined for the plurality of candidate window sizes. For example, the candidate window size resulting in the best overall quality measure determined may be determined to be the optimal window size for performing the RCA diagnosis based on the first correlation model with respect to the anomaly identified in the performance parameter.

[0034] In various embodiments, the method 100 further comprises determining whether the root cause determined from the RCA diagnosis with respect to the anomaly based on the first correlation model and the optimal window size is a synthesized operational parameter synthesized from a second plurality of operational parameters. In other words, the RCA diagnosis (e.g., first root cause analysis diagnosis) may output the root cause (e.g., first root cause) determined with respect to the anomaly, and it is determined whether such a root cause determined is a synthesized operational parameter synthesized from (based on a combination of) a second plurality of operational parameters. By way of example only and without limitation, the synthesized operational

parameter may be chilled water return quality (CHW_q), cooling water supply quality (COW_q), or steam supply quality (STM_q). As an example, the CHW_q may be synthesized from CHW_r and CHW_f (e.g., $CHW_r(t) \times CHW_f(t)$).

[0035] In various embodiments, the method 100 further comprises: determining the root cause to be a synthesized operational parameter (e.g., if the root cause (the first root cause) is determined to be a synthesized operational parameter); setting a second correlation model between the performance parameter and the second plurality of operational parameters associated with the synthesized operational parameter; and determining a second optimal window size for performing a second RCA diagnosis with respect to the anomaly based on the second correlation model; and performing the second RCA diagnosis based on the second correlation model and the second optimal window size with respect to the anomaly for determining a second root cause of the anomaly identified in the performance parameter of the chiller. In this regard, the second RCA diagnosis is performed on a second dataset comprising measurement data relating to the performance parameter and the second plurality of operational parameters collected over a period of time (e.g., the above-mentioned period of time), including the anomaly measurement data.

[0036] The second optimal window size may be determined in the same or similar manner as the first optimal window size, and thus need not be repeated herein for conciseness and clarity. The second RCA diagnosis may also be performed in the same or similar manner as the first RCA diagnosis, and thus need not be repeated herein for conciseness and clarity.

[0037] Accordingly, in various embodiments, if a root cause determined RCA diagnosis with respect to an anomaly is a synthesized operational parameter, the above-mentioned steps may be repeated (e.g., including setting a further correlation model, determining a further optimal window size, and performing a further RCA diagnosis based on the further correlation model) to determine a further root cause of the anomaly, until the further root cause determined is a non-synthesized operational parameter (which may also be interchangeably referred to as a raw operational parameter). As a result, a raw or primary operational parameter may be identified as the bottleneck or root cause of

the anomaly, which has been found to further improve the quality or effectiveness of chiller performance anomaly diagnosis.

[0038] Accordingly, various embodiments of the present invention advantageously provide a method for chiller performance anomaly diagnosis, and more particularly, to a RCA-based chiller performance anomaly diagnosis, with improved quality or effectiveness, resulting in more effective and efficient maintenance of the chiller.

[0039] FIG. 2 depicts a schematic block diagram of a system 200 for chiller performance anomaly diagnosis according to various embodiments of the present invention, such as corresponding to the method 100 for chiller performance anomaly diagnosis as described hereinbefore with reference to FIG. 1 according to various embodiments of the present invention. It will be appreciated by a person skilled in the art that the system 200 may be configured primarily for perform chiller performance anomaly diagnosis or may be configured to perform chiller performance anomaly diagnosis as one function amongst a plurality of other functions capable of being performed by the system 200.

[0040] The system 200 comprises a memory 202 and at least one processor 204 communicatively coupled to the memory 202 and configured to perform the method for chiller performance anomaly diagnosis according to the method 100 for chiller performance anomaly diagnosis as described hereinbefore with reference to FIG. 1 according to various embodiments of the present invention.

[0041] It will be appreciated by a person skilled in the art that the at least one processor 204 may be configured to perform the required functions or operations through set(s) of instructions (e.g., software modules) executable by the at least one processor 204 to perform the required functions or operations. Accordingly, as shown in FIG. 2, the system 200 may further comprise a first correlation model setting module or circuit 206 configured to set a first correlation model between a performance parameter of a chiller and a first plurality of operational parameters; an optimal window size determining module or circuit (or referred to as a window size optimizer) 208 configured to determine an optimal window size for performing a RCA diagnosis based on the first correlation model with respect to an anomaly identified in the performance parameter; and a RCA module or circuit (or referred to as a RCA engine) 210 configured to perform the RCA

diagnosis based on the first correlation model and the optimal window size with respect to the anomaly for determining a root cause of the anomaly identified in the performance parameter of the chiller. In this regard, the RCA diagnosis is performed on a dataset (e.g., stored in the memory 202) comprising measurement data relating to the performance parameter and the first plurality of operational parameters collected over a period of time, including anomaly measurement data having an anomaly period associated with the anomaly.

[0042] It will be appreciated by a person skilled in the art that the above-mentioned modules are not necessarily separate modules, and one or more modules may be realized by or compiled as one functional module (e.g., a circuit or a software program) as desired or as appropriate without deviating from the scope of the present invention. For example, the first correlation model setting module 206, the optimal window size determining module 208 and the RCA module 210 may be realized (e.g., compiled together) as one executable software program (e.g., software application or simply referred to as an "app"), which for example may be stored in the memory 202 and executable by the at least one processor 204 to perform the functions/operations as described herein according to various embodiments.

[0043] In various embodiments, the system 200 corresponds to the method 100 as described hereinbefore with reference to FIG. 1, and therefore, various functions or operations configured to be performed by the least one processor 204 may correspond to various steps or operations of the method 100 described hereinbefore according to various embodiments, and thus need not be repeated with respect to the system 200 for clarity and conciseness. In other words, various embodiments described herein in context of the method(s) are analogously valid for the respective system(s) or device(s), and vice versa. For example, in various embodiments, the memory 202 may have stored therein the first correlation model setting module 206, the optimal window size determining module 208 and/or the RCA module 210, which respectively correspond to various steps or parts of the method 100 as described hereinbefore, which are executable by the at least one processor 204 to perform the corresponding functions/operations as described herein.

[0044] A computing system, a controller, a microcontroller or any other system providing a processing capability may be provided according to various embodiments in

the present disclosure. Such a system may be taken to include one or more processors and one or more computer-readable storage mediums. For example, the system 200 described hereinbefore may include a processor (or controller) 204 and a computer-readable storage medium (or memory) 202 which are for example used in various processing carried out therein as described herein. A memory or computer-readable storage medium used in various embodiments may be a volatile memory, for example a DRAM (Dynamic Random Access Memory) or a non-volatile memory, for example a PROM (Programmable Read Only Memory), an EPROM (Erasable PROM), EEPROM (Electrically Erasable PROM), or a flash memory, e.g., a floating gate memory, a charge trapping memory, an MRAM (Magnetoresistive Random Access Memory) or a PCRAM (Phase Change Random Access Memory).

[0045] In various embodiments, a "circuit" may be understood as any kind of a logic implementing entity, which may be special purpose circuitry or a processor executing software stored in a memory, firmware, or any combination thereof. Thus, in an embodiment, a "circuit" may be a hard-wired logic circuit or a programmable logic circuit such as a programmable processor, e.g., a microprocessor (e.g., a Complex Instruction Set Computer (CISC) processor or a Reduced Instruction Set Computer (RISC) processor). A "circuit" may also be a processor executing software, e.g., any kind of computer program, e.g., a computer program using a virtual machine code, e.g., Java. Any other kind of implementation of the respective functions which will be described in more detail below may also be understood as a "circuit" in accordance with various alternative embodiments. Similarly, a "module" may be a portion of a system according to various embodiments in the present invention and may encompass a "circuit" as above, or may be understood to be any kind of a logic-implementing entity therefrom.

[0046] Some portions of the present disclosure are explicitly or implicitly presented in terms of algorithms and functional or symbolic representations of operations on data within a computer memory. These algorithmic descriptions and functional or symbolic representations are the means used by those skilled in the data processing arts to convey most effectively the substance of their work to others skilled in the art. An algorithm is here, and generally, conceived to be a self-consistent sequence of steps leading to a

desired result. The steps are those requiring physical manipulations of physical quantities, such as electrical, magnetic or optical signals capable of being stored, transferred, combined, compared, and otherwise manipulated.

[0047] Unless specifically stated otherwise, and as apparent from the following, it will be appreciated that throughout the present specification, discussions utilizing terms such as "setting", "determining", "performing", "obtaining", "assessing", "generating", or the like, refer to the actions and processes of a computer system, or similar electronic device, that manipulates and transforms data represented as physical quantities within the computer system into other data similarly represented as physical quantities within the computer system or other information storage, transmission or display devices.

[0048] The present specification also discloses a system, a device or an apparatus for performing the operations/functions of the methods described herein. Such a system, device or apparatus may be specially constructed for the required purposes, or may comprise a general purpose computer or other device selectively activated or reconfigured by a computer program stored in the computer. The algorithms presented herein are not inherently related to any particular computer or other apparatus. Various general-purpose machines may be used with computer programs in accordance with the teachings herein. Alternatively, the construction of more specialized apparatus to perform the required method steps may be appropriate.

[0049] In addition, the present specification also at least implicitly discloses a computer program or software/functional module, in that it would be apparent to the person skilled in the art that the individual steps of the methods described herein may be put into effect by computer code. The computer program is not intended to be limited to any particular programming language and implementation thereof. It will be appreciated that a variety of programming languages and coding thereof may be used to implement the teachings of the disclosure contained herein. Moreover, the computer program is not intended to be limited to any particular control flow. There are many other variants of the computer program, which can use different control flows without departing from the spirit or scope of the invention. It will be appreciated by a person skilled in the art that various modules described herein (e.g., the first correlation model setting module 206, the optimal window size determining module 208 and/or the RCA module 210) may be

software module(s) realized by computer program(s) or set(s) of instructions executable by a computer processor to perform the required functions, or may be hardware module(s) being functional hardware unit(s) designed to perform the required functions. It will also be appreciated that a combination of hardware and software modules may be implemented.

[0050] Furthermore, one or more of the steps of a computer program/module or method described herein may be performed in parallel rather than sequentially. Such a computer program may be stored on any computer readable medium. The computer readable medium may include storage devices such as magnetic or optical disks, memory chips, or other storage devices suitable for interfacing with a general purpose computer. The computer program when loaded and executed on such a general-purpose computer effectively results in an apparatus that implements the steps of the methods described herein.

[0051] In various embodiments, there is provided a computer program product, embodied in one or more computer-readable storage mediums (non-transitory computer-readable storage medium), comprising instructions (e.g., the first correlation model setting module 206, the optimal window size determining module 208 and/or the RCA module 210) executable by one or more computer processors to perform a method 100 for chiller performance anomaly diagnosis as described hereinbefore with reference to FIG. 2. Accordingly, various computer programs or modules described herein may be stored in a computer program product receivable by a computer system or an electronic device therein for execution by at least one processor of the system or device to perform the required or desired functions.

[0052] The software or functional modules described herein may also be implemented as hardware modules. More particularly, in the hardware sense, a module is a functional hardware unit designed for use with other components or modules. For example, a module may be implemented using discrete electronic components, or it can form a portion of an entire electronic circuit such as an Application Specific Integrated Circuit (ASIC). Numerous other possibilities exist. Those skilled in the art will appreciate that the software or functional module(s) described herein can also be implemented as a combination of hardware and software modules.

[0053] It will be appreciated by a person skilled in the art that the terminology used herein is for the purpose of describing various embodiments only and is not intended to be limiting of the present invention. As used herein, the singular forms "a", "an" and "the" are intended to include the plural forms as well, unless the context clearly indicates otherwise. It will be further understood that the terms "comprises" and/or "comprising," when used in this specification, specify the presence of stated features, integers, steps, operations, elements, and/or components, but do not preclude the presence or addition of one or more other features, integers, steps, operations, elements, components, and/or groups thereof.

[0054] FIG. 3 depicts a schematic drawing of a window size optimizer 208 for performing RCA diagnosis according to various embodiments of the present invention, such as corresponding to the above-mentioned determining an optimal window size described with respect to the method 100. The window size optimizer 208 comprises a candidate obtaining module or circuit 302 configured to obtain a plurality of candidate window sizes; a candidate assessment module or circuit 304 configured to assess each of the plurality of candidate window sizes with respect to the first correlation model for determining a candidate window size amongst the plurality of candidate window sizes that is optimal for performing the RCA diagnosis based on the first correlation model with respect to the anomaly; and an output module or circuit 306 configured to output the optimal window size determined.

[0055] In various embodiments, the window size optimizer 208 corresponds to the above-mentioned determining an optimal window size described with respect to the method 100, and thus various functions or operations configured to be performed by the window size optimizer 208 when executed by a processor (e.g., processor 204) may correspond to various steps or parts of the above-mentioned determining an optimal window size described with respect to the method 100, and thus need not be repeated with respect to the window size optimizer 208 for clarity and conciseness. It will be appreciated that the window size optimizer 208 may be implemented as a software module (e.g., a computer program) executable by a processor to, or a hardware module (e.g., a circuit) configured to, or a combination of hardware and software modules

configured to, perform the method of determining an optimal window size described hereinbefore according to various embodiments of the present invention.

[0056] In order that the present invention may be readily understood and put into practical effect, various example embodiments of the present invention will be described hereinafter by way of examples only and not limitations. It will be appreciated by a person skilled in the art that the present invention may, however, be embodied in various different forms or configurations and should not be construed as limited to the example embodiments set forth hereinafter. Rather, these example embodiments are provided so that this disclosure will be thorough and complete, and will fully convey the scope of the present invention to those skilled in the art.

[0057] Various example embodiments of the present invention provide a RCA window size management method in chiller diagnosis for accommodating variable time dependent anomalies. In various example embodiments, the method builds a double-layer (or multi-layer if more than two layers) diagnosis model (RCA or correlation model) to address, for example, possible unstable diagnosis issue caused by small RCA window size. For example, for a double-layer RCA model, on an upper layer (or a first layer) of the RCA model, synthesized chiller constraints may be constructed by combining related raw sensor constraints (non-synthesized constraints) on a lower layer (or a second layer) of the RCA model, through which the number of constraints used in RCA correlation analysis is effectively reduced, thus better matching small window size in correlation analysis and providing more stable diagnosis. The method may further determine an optimal RCA window size for performing RCA diagnosis based on the RCA model with respect to an anomaly, for example, based on correlation coefficients (determined with respect the correlation model) and confidence interval (CI). The method has been found to increase diagnosis accuracy by, for example, rejecting window sizes and anomaly samples with low correlation to the performance of the chiller being considered, and raises diagnosis precision through selecting an optimal window size with the narrowest CI.

[0058] Accordingly, various example embodiments of the present invention provides a quantitative window size management method for RCA diagnosis, including a multi-layer (e.g., double-layer) diagnosis model and a window size estimation or optimization

method. Various example embodiments of the present invention address low quality of chiller anomaly diagnosis based on RCA, and provide a method and a computer system for managing RCA window size based on correlation coefficients and a multi-layer (e.g., double-layer) diagnosis model.

[0059] FIG. 4 depicts a schematic drawing of an example system architecture 400 for RCA diagnosis on a chiller, including window size calculation/optimization, according to various example embodiments of the present invention. The system architecture 400 may comprise an operator (e.g., an operator device) 401, a chiller 402, a server 403 and workstations 411 to 412, all of which may be connected via a network 415, such as but not limited to, a local area network (LAN) or a wide area network (WAN). The operator 401 may be one or more terminals utilized by a chiller operator (e.g., a maintenance personnel) to estimate an optimal window size and start the RCA diagnosis, which may for example be a computing device, such as a personal computer, a tablet, a smartphone, and so on. The chiller 402 may provide chiller's operational data for use on the network 415 through, for example, a sensor data collection system, such as OSIsoft PI System. The server 403 may be implemented by a computer system (e.g., corresponding to the system 200 described hereinbefore with reference to FIG. 2 according to various embodiments) having stored therein instructions executable by a processor in the server 403 to determine an optimal window size (e.g., a software module (program logic) 404) and to perform RCA diagnosis based on the optimal window size (e.g., RCA engine 405). The server 403 may also have stored therein chiller operational data 406 (e.g., corresponding to the "dataset comprises measurement data" described hereinbefore according to various embodiments) and instructions executable by a processor in the server 403 to provide a graphic user interface (GUI) to the operator 401.

[0060] The operator 401 may display various chiller operational data from the server 403 through the GUI presented on the operator 401, on which the chiller operator may define a RCA model (a correlation model), identify an anomaly period, and submit window size estimation and RCA diagnosis requests to the server 403. In various example embodiment of the present invention, the operator 401 may include multiple terminals over the network 415, thereby allowing remote access to the server 403 from different locations.

[0061] For example, the chiller 402 may represent an SAC or EC in a cooling plant, and may utilize a sensor data collection system, such as but not limited to, an OSIsoft PI System to provide uniform data access interface to the server 403 and other components over network 415. It will be appreciated by a person skilled in the art that more than one chiller (i.e., multiple chillers) may be operating in the cooling plant, and the server 403 may thus be configured to provide window size estimation or optimization and RCA diagnosis for each of the chillers. In other words, it will be appreciated by a person skilled in the art that the method and system for chiller performance anomaly diagnosis according to various embodiments of the present invention may be applied respectively to any one or more chillers as desired or as appropriate.

[0062] In various example embodiments, upon receiving the RCA window size estimation request from the operator 401, the server 403 may execute the program logic 404 and return the optimal window size determined to the operator 401. If the request from the operator 401 is for chiller anomaly diagnosis, the server 403 may proceed to perform RCA diagnosis based on the correlation model (RCA model) defined and the optimal window size determined by executing the RCA engine 405. The RCA engine 405 may be configured to perform the RCA diagnosis in a manner known in the art, such as described in the Okitsu document or the Zhang document, but using the optimal window size determined according to various example embodiments for improving the quality of the RCA diagnosis. It will be appreciated by a person skilled in the art that the server 403 may host (stored therein) chiller operational data 406 locally, which can be automatically or manually collected from the chiller 402, or may retrieve chiller operational data 406 stored remotely (e.g., in a storage server).

[0063] In various example embodiments, the server 403 and the operator 401 may be implemented on different computers over the network 415, wherein the requests and results transmission therebetween may be implemented through RESTful web services or remote procedure call (RPC). In case of heavy computation load, the server 403 may distribute some window size calculation tasks to one or more workstations 411 to 412. In various example embodiments, various distributed, parallel or cloud computing systems, such as Hadoop, may be utilized among the server 403 and the workstations 411 to 412 to shorten the window size estimation time and facilitate real-time diagnosis. In various

other example embodiments, both the operator 401 and the server 403 may be implemented on a same computer, e.g., for smaller applications.

[0064] In various example embodiments, the program logic 404 configured to calculate the optimal window size for RCA diagnosis may be implemented by any appropriate computer language known in the art, such as a compilation language or an interpretation language. In various example embodiments, the program logic 404 may be stored in and executed on the server 403. In various example embodiments, the program logic 404 may be distributed among the server 403 and one or more of the workstations 411 to 412 in a distributed computing schema for speeding up calculation. In such a case, the server 403 and the one or more workstations 411 to 412 together may then correspond to the system 200 described hereinbefore with reference to FIG. 2 according to various embodiments.

[0065] FIG. 5 illustrates an example GUI 500 which may be presented on and utilized by the operator 401 to define an RCA model 502 and an anomaly period for the RCA window size estimation according to various example embodiments of the present invention. For example, the operator 401 may define or select a chiller performance desired to be considered for a chiller and the related constraints in the RCA model 502. By way of an example only and without limitation, the chiller performance and sensors for the constraints may be selected through respective pull-down menus 503. For example, for the chiller performance, a performance parameter may be selected from three possible options, including chilled water supply (CHW), coefficient of performance (COP) and chilled water supply temperature (CHWs). For the constraints, the operator 401 may define a plurality of constraints (e.g., corresponding to the "first plurality of operational parameters" described hereinbefore according to various embodiments), such as but not limited to, two or three constraints through the respective columns of the constraints (e.g., denoted as "Constraint 1", "Constraint 2", and "Constraint 3" in FIG. 5), and each of the constraints may be defined by one or more sensors in the respective column. For example, if a constraint's column includes only one sensor, the constraint may be represented by that sensor's data (operational parameter) in the RCA model. If a constraint's column includes two or more sensors, the constraint may be defined as a synthesized constraint based on a combination of the two or more sensors' data (two or

more operational parameters) (e.g., corresponding to the "second plurality of operational parameters" described hereinbefore according to various embodiments), such as a multiplication of the two or more sensors' data. By way of an example only, FIG. 5 illustrates that Constraint 1 and Constraint 3 are synthesized constraints, which are each based on two sensors.

[0066] In various example embodiments, one or more appropriate weightings or offsets may be applied to one or more sensors' data obtained respectively, for example, to take into account various measurement factors, data compatibility and so on. For example, a text field 506 may be provided next to each sensor for allowing the measurement/sensor data obtained from the respective sensor to be adjusted/modified as desired or as appropriate, such as to build a more complex model. As an illustrative example, an offset of "50" may be applied to the sensor data from Sensor 1 such that Constraint 1 will be constructed through a combination of (50 – sensed value of Sensor 1) and sensed value of Sensor 2.

[0067] As shown in FIG. 5, the GUI 500 may also display a plot in a performance field 510 showing the selected chiller's time series performance based on the chiller's raw data (measurement/sensor data) obtained by the operator 401. The GUI 500 may automatically update the chiller's time series performance according to the type of performance selected in the RCA model 502. In various example embodiments, the operator 401 may select or identify a portion 512 of the measurement data relating to an anomaly, which such a portion 512 may be referred to as an anomaly measurement data having an anomaly period associated with the anomaly. The selection may be manually performed by a user based on a user input (e.g., via a mouse device) or may be automatically identified/detected by the operator 401 or the server 403. The time period of the anomaly may then be displayed in an anomaly time table 514. The operator 401 may also directly change/adjust time indicated in time table 514 as appropriate, whereby T_1 represents an anomaly starting time and T_2 represents an anomaly ending time. Any anomaly period changes in time table 514 may also be automatically synchronized in the display of the period of the anomaly measurement data 512 in the GUI 500.

[0068] As shown in FIG. 5, a Start RCA button 520 may also be provided for allowing the operator 401 to send a RCA request to the server 403, when triggered, for

starting the RCA diagnosis. The RCA request may include information on the RCA model 502 defined and the anomaly time information from the anomaly period identified. For example, upon receiving the RCA request, the server 403 may initiate the RCA engine 405 using the information on the RCA model 502 defined and the anomaly time information to perform RCA diagnosis with respect to the anomaly 512 identified in the selected performance parameter. In this regard, the server 403 receiving the information of the RCA model 502 may thus set the RCA model to be used in subsequent processing as defined in the information of the RCA model 502 received.

[0069] As shown in FIG. 5, in a diagnosis result field 522, various diagnosis outputs/results received from the server 403 may be displayed, including the optimal window sizes for two layers of the RCA model (double-layer RCA model) 502 (e.g., an upper or first layer model corresponding to the "first correlation model" and a lower or second layer model corresponding to the "second correlation model" as described hereinbefore according to various embodiments of the present invention) and the bottleneck (root cause) for chiller anomaly 512. The diagnosis result may include a window size for upper model field 516 for displaying an optimal window size determined by the server 403 for the upper layer model, and a window size for lower model field 517 for displaying an optimal window size determined by the server 403 for the lower layer model of the double-layer RCA model 502. For example, the window size for lower model field 517 may display not applicable or 0 hour if no synthesized constraint is identified as a bottleneck. The diagnosis result may further include a bottleneck field 519 indicating the sensor (e.g., sensor's ID or name) which has been determined by the server 403 as the root cause for chiller anomaly 512.

[0070] Accordingly, in various example embodiments, a method of chiller anomaly diagnosis based on a double-layer RCA model is provided, which may be performed by the program logic 404. FIG. 6 depicts a schematic flow diagram of a method 600 of chiller anomaly diagnosis based on a RCA model (with multi-layer RCA model capability) according to various example embodiments of the present invention.

[0071] In step 604, the method 600 builds or sets an upper or first layer (e.g., corresponding to the "first correlation model" described hereinbefore according to various embodiments) of a RCA model according to the RCA model 502 (e.g., multi-

layer RCA model, such as double-layer RCA model) defined. For illustration purpose only and without limitation, FIG. 7 illustrates a double-layer RCA model 700, including an upper or first layer 704 and a lower or second layer 706. At the lower layer 706, there are a plurality of "raw" operational parameters (non-synthesized operational parameters (constraints)) (e.g., corresponding to respective sensors) related to the chiller, such as chilled water return temperature (CHW_r), chilled water flow (CHW_f), cooling water supply temperature (COW_s), cooling water flow rate (COW_f), steam flow rate (STM_f), steam pressure (STM_p), cooling water return temperature (COW_r), electricity consumption (ELE), ambient temperature (AMB_t), and so on. At the upper layer 704, one or more synthesized operational parameters may be constructed by combining related operational parameters from the lower layer 706. It will be appreciated by a person skilled in the art that if each operational parameter (constraint) selected in the RCA model 502 is a non-synthesized operational parameter (e.g., includes only one sensor), the multi-layer (e.g., double-layer) RCA model may thus be reduced to a single-layer RCA model.

[0072] The multi-layer (e.g., double-layer) RCA model is advantageous over the conventional single-layer RCA model disclosed in the Okitsu document and the Zhang document. For example, the conventional RCA model may require constraints be chosen from too many raw sensors, which may miss important sensors if not enough of them are selected, or cause correlation result to be unstable (e.g., may also be referred to as an overfit issue) if too many constraints are included in the RCA model, especially in case of small window size. By replacing the raw sensor constraints in the RCA model with related synthesized constraints, the multi-layer RCA model effectively reduces the number of constraints in the correlation analysis without losing the coverage of sensors' information, thus advantageously maintaining correlation analysis and diagnosis stability.

[0073] By way of examples only and without limitations, three example synthesized constraints may be defined as shown in Equation 4, Equation 5 and Equation 6 to diagnose most frequently reported anomalies.

$$CHW_q(t) = CHW_r(t) \times CHW_f(t) \qquad \text{(Equation 4)}$$

where,

$CHW_q(t)$ denotes a synthesized constraint, representing chilled water return quality;

$CHW_r(t)$ denotes a raw sensor constraint, representing chilled water return temperature at time t; and

$CHW_f(t)$ denotes a raw sensor constraint, representing chilled water flow rate at time t.

[0074] In Equation 4, $CHW_q(t)$ is defined as the product of $CHW_r(t)$ and $CHW_f(t)$, which may for example mean that higher chilled water return temperature or chilled water flow brings higher chilled water return quality. In RCA diagnosis, if CHW_q is selected as one of the constraints in the RCA model and identified as the bottleneck of chiller performance, then a further RCA diagnosis is conducted on a lower or further layer of the RCA model with constraints of CHW_r and CHW_f, to determine which one of the two constraints is the root cause of the chiller performance or anomaly.

$$COW_q(t) = (T_{top} - COW_s(t)) * COW_f(t) \qquad \text{(Equation 5)}$$

where,

$COW_q(t)$ denotes a synthesized constraint, representing cooling water supply quality;

T_{top} denotes a constant, representing a higher temperature than any cooling water supply temperature;

$COW_s(t)$ denotes a raw sensor constraint, representing cooling water supply temperature at time t; and

$COW_f(t)$ denotes a raw sensor constraint, representing cooling water flow rate at time t.

[0075] In Equation 5, $COW_q(t)$ is proportional to $COW_f(t)$, but inversely proportional to $COW_s(t)$, which may for example mean that higher cooling water flow or lower cooling water supply temperature brings higher cooling water supply quality. Similarly, in RCA diagnosis, if COW_q is selected as one of the constraints in RCA model and identified as the bottleneck of chiller performance, then a further RCA diagnosis is conducted on a lower or further layer the RCA model with constraints of COW_s and

COW_f, to determine which one of the two constraints is the root cause of the chiller performance or anomaly.

$$STM_q(t) = STM_f(t) * STM_p(t) \quad \text{(Equation 6)}$$

where,

$STM_q(t)$ denotes a synthesized constraint, representing steam supply quality;

$STM_f(t)$ denotes a raw sensor constraint, representing steam flow rate at time t; and

$STM_p(t)$ denotes a raw sensor constraint, representing steam pressure at time t.

[0076] In Equation 6, $STM_q(t)$ is defined for SAC. It equals to the product of $STM_f(t)$ and $STM_p(t)$, which may for example mean that higher steam flow rate or steam pressure brings higher steam supply quality. Similarly, in RCA diagnosis, if STM_q is selected as one of the constraints in the RCA model and identified as the bottleneck of chiller performance, then a further RCA diagnosis is conducted on a lower layer RCA model with constraints of STM_f and STM_p, to determine which one of the two constraints is the root cause of the chiller performance or anomaly.

[0077] In step 606, the optimal window size is calculated for the RCA model provided by step 604 (e.g., upper or first layer model) or step 612 (e.g., lower or second layer model if produced). Step 606 will be described in further detail later below with reference to FIG. 8.

[0078] In step 608, the method 600 calls an RCA diagnosis program and uses the optimal window size determined from step 606. For example, the RCA diagnosis program may be hosted on the server 403 and implemented according to the RCA diagnosis method as described in the Okitsu document or the Zhang document, but using the optimal window size determined from step 606.

[0079] Step 610 determines whether a further RCA diagnosis is needed for a lower (or further) layer of the RCA model to find the root cause of anomaly. If the bottleneck diagnosed by the RCA diagnosis program is a synthesized constraint, then the method may proceed to step 612 to perform a further RCA diagnosis on a lower (or further) layer

model for the synthesized constraint. Otherwise, if the bottleneck is already a "raw" sensor ("raw" operational parameter), the method may simply proceed to step 614.

[0080] Step 612 constructs a lower (or further) layer of the RCA model according to the definition of synthesized constraint, which is diagnosed as bottleneck in step 608. For example, on the lower layer, only "raw" sensors inside the bottleneck constraint are selected to form the model's new constraints; each constraint including only one "raw" sensor. Then step 612 sends the newly constructed lower layer of the RCA model (e.g., corresponding to the "second correlation model" as described hereinbefore according to various embodiments) to step 606 for window size estimation or optimization.

[0081] In step 614, the bottleneck diagnosed by the RCA diagnosis program is identified as the root cause of the anomaly. The diagnosis result may then be sent to the operator 401 and displayed in the diagnosis result field 522 of the GUI 500.

[0082] FIG. 8 depicts a schematic flow diagram 800 of a method 800 of calculating an optimal window size for performing a RCA diagnosis based on a correlation model with respect to an anomaly according to various example embodiments of the present invention (e.g., corresponding to the step 104 of determining an optimal window size described hereinbefore with reference to FIG. 1 and the step 606 of calculating an optimal window size 606 described hereinbefore with reference to FIG. 6). In the illustrative example shown in FIG. 8 and without limitation, the method 800 of calculating an optimal window size may be based on R^2 (square of multiple correlation coefficient) and CI for more accurate and precise RCA diagnosis.

[0083] In step 804, multiple sets of anomaly data samples are generated from the chiller operational data 406, each set generated for a respective one of a plurality of candidate window sizes. For example, Equation 7 below defines a possible range or set of candidate window sizes (W), whereby the window size may be defined in terms of the number of intervals (Δ).

$$\begin{aligned} &W = i - 1 \\ &4 \times C \leq i \leq 2 \times (A + 1) \\ &\emptyset = \{W\} \end{aligned} \qquad \text{(Equation 7)}$$

where,

i denotes the number of data points in an anomaly data sample;

C denotes the number of constraints in the RCA diagnosis model (e.g., $C \in \{2, 3\}$);

Δ denotes the data sampling's time interval (e.g., 5 minutes);

A denotes the anomaly size, measured in the number of Δ; and

$\emptyset$ denotes the set of W.

[0084] Based on Equation 7, the anomaly sample's time period may be calculated as $W \times \Delta$, and W ranges from $4 \times C$-1 to $2 \times A + 1$ for example. For example, the lower limit of the window size may be determined to ensure that the anomaly sample has minimum data to meet constraints' correlation analysis requirement in the RCA, as otherwise, the RCA may have unstable correlation or diagnosis result. The upper limit of the window size may be determined to avoid the window size from becoming too big, which may then include too many normal data (non-anomaly data) in every anomaly data sample and cause the anomaly data to be insignificant or buried by the normal data. Various example embodiments note that if the upper limit is less than the lower limit, for example, in the case of a very narrow chiller performance spike anomaly, there may only be one window size choice, namely, the lower limit, such as size $4 \times C$-1. It will be appreciated by a person skilled in the art that the lower and upper limits described above are only exemplary and for illustration purpose, and the lower and upper limits may be defined differently as desired or as appropriate, without deviating from the scope of the present invention.

[0085] In various example embodiments, for each window size $W \in \emptyset$, the anomaly samples may be constructed by selecting chiller's operational data through a sliding window (sliding window technique) across the anomaly period. An example sliding window technique is shown in FIG. 9. In various example embodiments, the first anomaly sample 902 may be built by selecting chiller data from T_0 till $T_0 + W \times \Delta$, whereby the data at $T_0 + W \times \Delta$ is the first data point 903 of the anomaly measurement data having an anomaly period. For example, this is to ensure that every anomaly sample includes at least one anomaly data point. Further, anomaly time period may be represented as ranging from $T_0 + W \times \Delta$ to $T_0 + (W + A) \times \Delta$. For illustration purpose only, Table 1 below shows an example data format for data sample at each data point of an anomaly sample,

comprising a plurality of fields. For example, the "Time" field may indicate data sampling time, the "Performance" may indicate the performance parameter selected, and the plurality of constraints including "Constraint_1", "Constraint_2" and "Constraint_3" may indicate the constraints selected for the RCA model. In the example, the chiller's performance selected is CHW with unit of RT; Constraint_1 selected is CHWr with unit of degrees Celsius (°C); Constraint_2 selected is AMBt with unit of °C; and, Constraint_3 selected is ELE with unit of KW.

Table 1 – Example Data Format for Data Sample at Each Data Point of an Anomaly Sample

Time	Performance	Constraint_1	Constraint_2	Constraint_3
yyyy/mm/dd hh:mm	CHW (RT)	Chilled Water Return Temperature (°C)	Ambient Air Temperature (°C)	Chiller Electricity Consumption (KW)

[0086] Subsequently, the window may be slid from $[T_0, T_0+W\times\Delta]$ to $[T_0+\Delta, T_0+(W+1)\times\Delta]$ to construct the second anomaly sample 904. The process may then repeat for each subsequent time interval until the last anomaly sample 908 with window $[T_0+(W+A)\times\Delta, T_0+(2W+A)\times\Delta]$, in which the data point at $T_0+(W+A)\times\Delta$ is the last data point 910 in the anomaly period.

[0087] For each W in $\emptyset$, step 806 builds chiller performance correlation models through multiple linear correlation regression on W's anomaly samples (set of anomaly data samples) in accordance with Equation 1, then calculates R^2 (square of multiple correlation coefficient) (e.g., corresponding to the "first quality measure" described hereinbefore according to various embodiments) for each anomaly sample in the set. By way of an example only and without limitation, Equation 8 below shows an example R^2 calculation according to various example embodiments for the first anomaly sample s_1 with window $[T_0, T_0+W\times\Delta]$. In this regard, R^2 ranges from 0 to 1, and the closer the value is to 1, the better RCA correlation model fits the anomaly sample.

$$R^2(s_1) = 1 - \frac{SSE(s_1)}{SSTO(s_1)} \qquad \text{(Equation 8)}$$

$$SSE(s_1) = \sum_{i=0}^{W} (CHW(T_0 + i \times \Delta) - CHW'(T_0 + i \times \Delta))^2$$

$$SSTO(s_1) = \sum_{i=0}^{W} (CHW(T_0 + i \times \Delta) - \overline{CHW})^2$$

$$\overline{CHW}(s_1) = \frac{\sum_{i=0}^{W}(CHW(T_0 + i \times \Delta)}{W + 1}$$

where,

i denotes the sequence number of data points in the anomaly sample;

W denotes the window size for the anomaly sample, $W \in \emptyset$;

s_1 denotes the first anomaly sample generated under the window size W;

Δ denotes the time interval between two adjacent data points in the anomaly sample;

T_0 denotes the time stamp of the first data point in the anomaly sample;

SSE denotes the sum of squares of error;

SSTO denotes the total sum of squares;

$CHW(t)$ denotes the observed chilled water supply performance at time t, derived from chilled water flow rate and chilled water temperature difference;

$CHW'(t)$ denotes the calculated chilled water supply performance by the correlation model at time t; and

$\overline{CHW}$ denotes the mean of the anomaly sample's $CHW(t)$, $t = T_0+\Delta \,..\, T_0+W\times\Delta$.

[0088] Similarly, the R^2 value of other anomaly samples generated under the same window size W may be calculated. So, for each window size W, there will be a sampling distribution of R^2 values, and each R^2 corresponding to an anomaly sample generated during the same window sliding process.

[0089] Step 808 calculates the mean value of R^2 for a set of anomaly samples generated for a particular window size W, and may be represented as $\overline{R^2}(W)$.

$$\overline{R^2}(W) = \frac{\sum_{i=1}^{N} R^2(s_i)}{N} \qquad \text{(Equation 9)}$$

where,

N denotes the number of anomaly samples with window size W; and

$R^2(s_i)$ denotes R^2 for the ith anomaly sample with window size W.

[0090] Step 810 determines whether the window size is acceptable according to the performance model's correlation strength. For example, if $\overline{R^2}(W)$ is less than a threshold K, then the related performance model based on the corresponding window size W may be deemed to have a weak liner correlation with the actual anomaly data, which causes poor accuracy in further RCA diagnosis. The corresponding window size W may thus be removed from the current set $\emptyset$ in step 812, and then the method 800 may proceed to step 818. Otherwise, the corresponding window size W may be accepted or maintained in the current set $\emptyset$, and then the method 800 may also proceed to step 818. As a non-limiting example, the default value of the threshold K may be set as 0.5, but which may be adjusted as desired or as appropriate, such as based on specific chiller and anomaly conditions.

[0091] Step 818 determines whether the loop started in step 806 ends or not. For example, if all W in the set $\emptyset$ have been processed by steps 806 to 810, the method 800 may then proceed to step 814; otherwise, the method 800 may return back to step 806.

[0092] For the remaining candidate window sizes W in the current set $\emptyset$, for each window size W, step 814 calculates the confidence interval (CI) of the anomaly samples' R^2 determined for the set of anomaly samples obtained for the corresponding window size W for estimating the quality of the R^2 determined for the set in representing the true value. For example, the 95% CI may be calculated on the anomaly samples' R^2 determined for a set of anomaly samples. The result of 95% CI may be represented as a range of R^2 value, meaning there is a 95% probability that CI contains the true value of R^2 for the whole anomaly population. Accordingly, the narrower 95% CI suggests the higher precision of R^2 and more stable result. By way of an example only and without limitation, the following illustrates an example computation of the 95% CI for R^2.

[0093] In various example embodiments, when the number of anomaly samples (N) in a set is large (e.g., $N \geq 30$), the distribution of R^2 approximates normal, so the 95% CI for R^2 may be calculated as shown in Equation 10 below:

$$CI(W) = \overline{R^2} \pm 1.96 \times \sigma_{R^2} \qquad \text{(Equation 10)}$$

$$\sigma_{R^2} = \sqrt{\frac{\sum_{i=1}^{N}(R_i{}^2 - \overline{R^2})^2}{N}}$$

where,

N denotes the number of anomaly samples with window size W;

$R_i{}^2$ denotes the R^2 for the i-th anomaly sample with window size W;

$\overline{R^2}$ denotes the mean (average) of R^2 for the anomaly samples with window size W;

1.96 denotes a Z-score number corresponding to the 95% CI; and

σ_{R^2} denotes the standard deviation of R^2 for the anomaly samples with window size W.

[0094] When the number of anomaly samples (N) is small (e.g., $N < 30$), the distribution of R^2 will be t distribution, instead of normal distribution, so the calculation for the 95% CI for R^2 may be changed as shown in Equation 11 below:

$$CI(W) = \overline{R^2} \pm t_s \times \sigma_{R^2} \qquad \text{(Equation 11)}$$

where,

t_s denotes a t-score number corresponding to 95% CI. For example, when $N = 20$, $t_s = 2093$.

[0095] From Equations 9, 10 and 11, the value N is widely used in calculation of $\overline{R^2}$ and 95% CI, while $N = W+A+1$ (as shown in FIG. 9), indicating that N is determined by W and A, so it can be appreciated by a person skilled in the art that the window size decision based on 95% CI and $\overline{R^2}$ already takes into account the information of variable anomaly size A.

[0096] Step 816 determines the optimal window size based on anomaly samples' 95% CI. For all window sizes in the current set $\emptyset$ and related anomaly samples, if the width of 95% CI(W) is the narrowest, suggesting that that particular window size W can construct anomaly samples with the highest precision correlation model in terms of coefficient R^2, which in turn brings the most stable diagnosis capability for RCA, so that particular window size W may be selected as optimum.

[0097] Accordingly, various embodiments of the present invention are advantageous over conventional RCA diagnosis methods because they provide a quantitative method to manage the window size in RCA diagnosis for accommodating variable chiller

anomalies. In addition, various embodiments of the present invention further enhance diagnosis stability through a multi-layer (e.g., double-layer) RCA modeling, increase diagnosis accuracy by rejecting window sizes and samples with weak correlation to the anomaly, and increase diagnosis precision through selecting an optimal window size, such as with the narrowest confidence interval.

[0098] The following examples pertain to various embodiments (e.g., including further example embodiments) of the present invention.

[0099] In Example 1, a computer-implemented method for chiller performance anomaly diagnosis is disclosed, the method comprising: setting a first correlation model between a performance parameter of a chiller and a first plurality of operational parameters; determining an optimal window size for performing a root cause analysis diagnosis based on the first correlation model with respect to an anomaly identified in the performance parameter; and performing the root cause analysis diagnosis based on the first correlation model and the optimal window size with respect to the anomaly for determining a root cause of the anomaly identified in the performance parameter of the chiller, the root cause analysis diagnosis being performed on a dataset comprising measurement data relating to the performance parameter and the first plurality of operational parameters collected over a period of time, including anomaly measurement data having an anomaly period associated with the anomaly.

[00100] In Example 2, the method for chiller performance anomaly diagnosis according to Example 1 is disclosed, wherein the above-mentioned determining an optimal window size comprises: obtaining a plurality of candidate window sizes; and assessing each of the plurality of candidate window sizes with respect to the first correlation model for determining a candidate window size amongst the plurality of candidate window sizes that is optimal for performing the root cause analysis diagnosis based on the first correlation model with respect to the anomaly.

[00101] In Example 3, the method for chiller performance anomaly diagnosis according to Example 2 is disclosed, wherein the above-mentioned assessing each of the plurality of candidate window sizes comprises, for each candidate window size: generating a set of anomaly data samples from the dataset, each anomaly data sample generated based on the candidate window size and includes at least an anomaly data point

belonging to the anomaly measurement data; performing a multiple linear regression analysis on the set of anomaly data samples based on the first correlation model; and determining an overall quality measure of fit of the first correlation model to the set of anomaly data samples generated.

[00102] In Example 4, the method for chiller performance anomaly diagnosis according to Example 3 is disclosed, wherein the set of anomaly data samples is generated based on a sliding window technique performed across the anomaly period.

[00103] In Example 5, the method for chiller performance anomaly diagnosis according to Example 4 is disclosed, wherein the sliding window technique comprises generating a first anomaly data sample comprising a starting data point of the anomaly measurement data and generating a subsequent anomaly data sample for each subsequent time interval until a last anomaly data sample comprising a last data point of the anomaly measurement data to generate the set of anomaly data samples.

[00104] In Example 6, the method for chiller performance anomaly diagnosis according to Example 5 is disclosed, wherein the first anomaly data sample has an anomaly sample period ending at the starting data point of the anomaly measurement data, and the last anomaly data sample has an anomaly sample period starting at the last data point of the anomaly measurement data.

[00105] In Example 7, the method for chiller performance anomaly diagnosis according to any one of Examples 4 to 6 is disclosed, wherein each anomaly data sample of the set of anomaly data samples has an anomaly sample period length determined based on the candidate window size.

[00106] In Example 8, the method for chiller performance anomaly diagnosis according to any one of Examples 3 to 7 is disclosed, wherein the above-mentioned performing a multiple linear regression analysis comprises: performing, for each anomaly data sample of the set of anomaly data samples, a multiple linear regression analysis on the anomaly data sample based on the first correlation model; and determining, for each anomaly data sample of the set of anomaly data samples, a first quality measure of fit of the first correlation model to the anomaly data sample to generate a set of first quality measures for the set of anomaly data samples, wherein the overall quality measure of fit

of the first correlation model to the set of anomaly data samples is determined based on the set of first quality measures.

[00107] In Example 9, the method for chiller performance anomaly diagnosis according to Example 9 is disclosed the method according to claim 8, wherein the first quality measure comprises a square of multiple correlation coefficients of the first correlation model to the anomaly data sample, and the overall quality measure comprises a confidence interval of the set of first quality measures determined.

[00108] In Example 10, the method for chiller performance anomaly diagnosis according to any one of Examples 3 to 9 is disclosed, wherein the above-mentioned assessing each of the plurality of candidate window sizes further comprises determining one of the plurality of candidate window sizes as the optimal window size based on the respective overall quality measures determined for the plurality of candidate window sizes.

[00109] In Example 11, the method for chiller performance anomaly diagnosis according to any one of Examples 1 to 10 is disclosed, further comprising: determining whether the root cause determined from the root cause analysis diagnosis with respect to the anomaly based on the first correlation model and the optimal window size is a synthesized operational parameter synthesized from a second plurality of operational parameters.

[00110] In Example 12, the method for chiller performance anomaly diagnosis according to Example 11 is disclosed, wherein: determining the root cause to be a synthesized operational parameter; setting a second correlation model between the performance parameter and the second plurality of operational parameters associated with the synthesized operational parameter; determining a second optimal window size for performing a second root cause analysis diagnosis with respect to the anomaly based on the second correlation model; and performing the second root cause analysis diagnosis based on the second correlation model and the second optimal window size with respect to the anomaly for determining a second root cause of the anomaly identified in the performance parameter of the chiller, the second root cause analysis diagnosis being performed on a second dataset comprising measurement data relating to the performance

parameter and the second plurality of operational parameters collected over said period of time, including the anomaly measurement data.

[00111] In Example 13, the method for chiller performance anomaly diagnosis according to Example 11 or 12 is disclosed, wherein: the performance parameter is selected from a group consisting of chilled water supply, coefficient of performance, and chilled water supply temperature; the operational parameters are selected from a group consisting of chilled water return temperature, chilled water flow rate, cooling water supply temperature, cooling water flow rate, steam flow rate, steam pressure, cooling water return temperature, electricity consumption, and ambient air temperature; and the synthesized operational parameter is selected from a group consisting of chilled water return quality, cooling water supply quality, and steam supply quality.

[00112] In Example 14, a system for chiller performance anomaly diagnosis is disclosed, the system comprising: a memory; and at least one processor communicatively coupled to the memory and configured to perform the method for chiller performance anomaly diagnosis according to any one of Examples 1 to 13.

[00113] In Example 15, a computer program product, embodied in one or more non-transitory computer-readable storage mediums, is disclosed, comprising instructions executable by at least one processor to perform a method for chiller performance anomaly diagnosis according to any one of Examples 1 to 13.

[00114] In Example 16, a method for performance diagnosis based on a double-layer RCA model is disclosed, comprising: a method of double-layer RCA modeling; a method of calculating an optimal window size; building an upper layer of the double-layer RCA model based on synthesized constraints; calculating the optimal window size using correlation coefficients and confidence interval; conducting a RCA diagnosis with the optimal window size; and constructing a lower layer of the double-layer RCA model based on raw sensors associated with the constraint determined as a bottleneck.

[00115] In Example 17, the method for performance diagnosis according to Example 16 is disclosed, wherein the method is applied for chiller diagnosis.

[00116] In Example 18, the method for performance diagnosis according to Example 16 or 17 is disclosed, wherein the step of building an upper layer further comprises

building an RCA model via a user interface providing selection of chiller performance, raw sensor constraints and synthesized constraints.

[00117] In Example 19, the method for performance diagnosis according to Example 16 or 17 is disclosed, wherein the step of calculating an optimal window size further comprises: constructing multiple sets of anomaly data samples, each set generated for a respective one of a plurality of candidate window sizes; building a correlation model (RCA model) for the anomaly data samples and calculating correlation coefficients with respect to the correlation model; rejecting candidate window size and samples with weak correlation to chiller performance; calculating confidence interval on anomaly samples' R^2; and determining an optimal window size based on confidence interval of R^2.

[00118] In Example 20, the method for performance diagnosis according to Example 16 or 17 is disclosed, wherein the step of conducting RCA diagnosis further comprises: calling an RCA program to conduct diagnosis with the optimal window size.

[00119] In Example 21, the method for performance diagnosis according to Example 16 or 17 is disclosed, wherein the step of constructing a lower layer further comprises: constructing a lower layer RCA model with chiller performance and raw sensor constraints, the raw sensor constraints which are included in the synthesized constraint determined as a bottleneck.

[00120] In Example 22, the method for performance diagnosis according to Example 19 is disclosed, wherein the step of constructing multiple sets of anomaly data samples comprises constructing each set of anomaly data samples for a corresponding candidate window size based on a sliding window over the anomaly period.

[00121] In Example 23, the method for performance diagnosis according to Example 19 is disclosed, wherein the step of building a correlation model further comprises building a correlation model for each anomaly sample through multiple linear correlation regression, and calculate the correlation coefficient R^2.

[00122] In Example 24, the method for performance diagnosis according to Example 19 is disclosed, wherein the step of rejecting window size further comprises rejecting window size which constructs samples with small mean value of R^2.

[00123] In Example 25, the method for performance diagnosis according to Example 19 is disclosed, wherein the step of calculating confidence interval further comprises

calculating 95% confidence interval on anomaly samples' R^2, according to window size, anomaly size, and so on.

[00124] In Example 26, the method for performance diagnosis according to Example 19 is disclosed, wherein the step of determining an optimal window size further comprises determining an optimal window size based on 95% confidence interval of R^2. The window size with the narrowest width of confidence interval is selected as optimum.

[00125] In Example 27, a computer program product implemented for the method according to Example 16 or 17 is disclosed, including instructions executable by at least one processor to build an upper layer of the double-layer RCA model through synthesized constraints; calculate an optimal window size using correlation coefficients and confidence interval; conduct a RCA diagnosis with the optimal window size; and construct a lower layer of the double-layer RCA model based on raw sensors associated with the constraint determined as a bottleneck.

[00126] In Example 28, the computer program product according to Example 27 is disclosed, wherein the step of building an upper layer comprises building an RCA model via the user interface providing selection of chiller performance, raw sensor constraints and synthesized constraints.

[00127] In Example 29, the computer program product according to Example 27 is disclosed, wherein the step of calculating an optimal window size further comprises: constructing multiple sets of anomaly data samples, each set generated for a respective one of a plurality of candidate window sizes; building a correlation model for the anomaly data samples and calculating correlation coefficients with respect to the correlation model; rejecting window size and samples with weak correlation to chiller performance; calculating confidence interval on anomaly samples' R^2; and determining an optimal window size based on confidence interval of R^2.

[00128] In Example 30, the computer program product according to Example 27 is disclosed, wherein the step of conducting a RCA diagnosis further comprises calling an RCA program to conduct diagnosis with optimal window size.

[00129] In Example 31, the computer program product according to Example 27 is disclosed, wherein the step of constructing an RCA model comprises: constructing an lower layer of the RCA model with chiller performance and raw sensor constraints, the

raw sensor constraints which are included in the synthesized constraint determined as a bottleneck.

[00130] In Example 32, the computer program product according to Example 29 is disclosed, wherein the step of constructing multiple sets fo anomaly data samples comprises constructing each set of anomaly data samples for a corresponding candidate window size based on a sliding window over the anomaly period.

[00131] In Example 33, the computer program product according to Example 29 is disclosed, wherein the step of building a correlation model comprises building a correlation model for each anomaly sample through multiple linear correlation regression, and calculate correlation coefficient R^2.

[00132] In Example 34, the computer program product according to Example 29 is disclosed, wherein the step of rejecting window size further comprises rejecting window size which constructs samples with small mean value of R^2.

[00133] In Example 35, the computer program product according to Example 29 is disclosed, wherein the step of calculating confience interval further comprises calculating 95% confidence interval on anomaly samples' R^2, according to window size, anomaly size, and so on.

[00134] In Example 36, the computer program product according to Example 29 is disclosed, wherein the step of determining further comprises determining an optimal window size based on 95% confidence interval of R^2. The window size with the narrowest width of confidence interval is selected as optimum.

[00135] In Example 37, a computer program product, embodied in one or more non-transitory computer-readable storage mediums, is disclosed, comprising instructions executable by at least one processor to show the window size (e.g., via a GUI displayed on an operator device) that is calculated and used for the RCA diagnosis.

[00136] In Example 38, a computer program product related to the double-layer RCA model, embodied in one or more non-transitory computer-readable storage mediums, is disclosed, comprising instructions executable by at least one processor to show both the window sizes determined for the upper model and the lower model (e.g., via a GUI displayed on an operator device).

[00137] Accordingly, various embodiments of the present invention may be applied on various chillers' anomaly diagnosis in a cooling plant, including steam absorption chiller, centrifugal chiller, screw chiller, and so on. For example, the chiller operator (e.g. maintainence personnel) may use the system based on various embodiments of the present invention to more quickly and accurately find out the root cause of the anomaly, thus saving maintenance time and cost.

[00138] Various embodiment of the present invention may also be applied in chiller's operation optimization. For example, a plant operator may apply various embodiments of the present invention to identify chiller's performance bottleneck and optimize operation decision to solve the bottleneck. In this regard, chiller's performance improvement will effectively reduce energy consumption in chiller operation.

[00139] For example, various embodiments of the present invention may be applied to the whole cooling plant diagnosis with multiple and hybrid cooling equipments, such as chiller, cooling tower, thermal energy storage (TES) and heat exchanger (HEX), while in larger cogeneration plant, various embodiments of the present invention may extend diagnosis from cooling equipment to power generation equipment, such as steam turbine generator, gas turbine generator, and so on.

[00140] While embodiments of the invention have been particularly shown and described with reference to specific embodiments, it should be understood by those skilled in the art that various changes in form and detail may be made therein without departing from the spirit and scope of the invention as defined by the appended claims. The scope of the invention is thus indicated by the appended claims and all changes which come within the meaning and range of equivalency of the claims are therefore intended to be embraced.

CLAIMS

What is claimed is:

1. A computer-implemented method for chiller performance anomaly diagnosis, the method comprising:

setting a first correlation model between a performance parameter of a chiller and a first plurality of operational parameters;

determining a window size for performing a root cause analysis diagnosis based on the first correlation model with respect to an anomaly identified in the performance parameter; and

performing the root cause analysis diagnosis based on the first correlation model and the determined window size with respect to the anomaly for determining a root cause of the anomaly identified in the performance parameter of the chiller, the root cause analysis diagnosis being performed on a dataset comprising measurement data relating to the performance parameter and the first plurality of operational parameters collected over a period of time, including anomaly measurement data having an anomaly period associated with the anomaly.

2. The method according to claim 1, wherein said determining a window size comprises:

obtaining a plurality of candidate window sizes; and

assessing each of the plurality of candidate window sizes with respect to the first correlation model for determining the window size amongst the plurality of candidate window sizes for performing the root cause analysis diagnosis based on the first correlation model with respect to the anomaly.

3. The method according to claim 2, wherein said assessing each of the plurality of candidate window sizes comprises, for each candidate window size:

generating a set of anomaly data samples from the dataset, each anomaly data sample generated based on the candidate window size and includes at least an anomaly data point belonging to the anomaly measurement data;

performing a multiple linear regression analysis on the set of anomaly data samples based on the first correlation model; and

determining an overall quality measure of fit of the first correlation model to the set of anomaly data samples generated.

4. The method according to claim 3, wherein the set of anomaly data samples is generated based on a sliding window technique performed across the anomaly period.

5. The method according to claim 4, wherein the sliding window technique comprises generating a first anomaly data sample comprising a starting data point of the anomaly measurement data and generating a subsequent anomaly data sample for each subsequent time interval until a last anomaly data sample comprising a last data point of the anomaly measurement data to generate the set of anomaly data samples.

6. The method according to claim 5, wherein the first anomaly data sample has an anomaly sample period ending at the starting data point of the anomaly measurement data, and the last anomaly data sample has an anomaly sample period starting at the last data point of the anomaly measurement data.

7. The method according to any one of claims 4 to 6, wherein each anomaly data sample of the set of anomaly data samples has an anomaly sample period length determined based on the candidate window size.

8. The method according to any one of claims 3 to 7, wherein said performing a multiple linear regression analysis comprises:

performing, for each anomaly data sample of the set of anomaly data samples, a multiple linear regression analysis on the anomaly data sample based on the first correlation model; and

determining, for each anomaly data sample of the set of anomaly data samples, a first quality measure of fit of the first correlation model to the anomaly data sample to generate a set of first quality measures for the set of anomaly data samples,

wherein the overall quality measure of fit of the first correlation model to the set of anomaly data samples is determined based on the set of first quality measures.

9. The method according to claim 8, wherein the first quality measure comprises a square of multiple correlation coefficients of the first correlation model to the anomaly data sample, and the overall quality measure comprises a confidence interval of the set of first quality measures determined.

10. The method according to any one of claims 3 to 9, wherein said assessing each of the plurality of candidate window sizes further comprises determining one of the plurality of candidate window sizes as the window size based on the respective overall quality measures determined for the plurality of candidate window sizes.

11. The method according to any one of claims 1 to 10, further comprising:

determining whether the root cause determined from the root cause analysis diagnosis with respect to the anomaly based on the first correlation model and the determined window size is a synthesized operational parameter synthesized from a second plurality of operational parameters.

12. The method according to claim 11, further comprising:

determining the root cause to be a synthesized operational parameter;

setting a second correlation model between the performance parameter and the second plurality of operational parameters associated with the synthesized operational parameter;

determining a second window size for performing a second root cause analysis diagnosis with respect to the anomaly based on the second correlation model; and

performing the second root cause analysis diagnosis based on the second correlation model and the determined second window size with respect to the anomaly for determining a second root cause of the anomaly identified in the performance parameter of the chiller, the second root cause analysis diagnosis being performed on a second dataset comprising measurement data relating to the performance parameter and the second plurality of operational parameters collected over said period of time, including the anomaly measurement data.

13. The method according to claim 11 or 12, wherein:

the performance parameter is selected from a group consisting of chilled water supply, coefficient of performance, and chilled water supply temperature;

the operational parameters are selected from a group consisting of chilled water return temperature, chilled water flow rate, cooling water supply temperature, cooling water flow rate, steam flow rate, steam pressure, cooling water return temperature, electricity consumption, and ambient air temperature; and

the synthesized operational parameter is selected from a group consisting of chilled water return quality, cooling water supply quality, and steam supply quality.

14. A system for chiller performance anomaly diagnosis, the system comprising:

a memory; and

at least one processor communicatively coupled to the memory and configured to perform the method for chiller performance anomaly diagnosis according to any one of claims 1 to 13.

15. A computer program product, embodied in one or more non-transitory computer-readable storage mediums, comprising instructions executable by at least one processor to perform a method for chiller performance anomaly diagnosis according to any one of claims 1 to 13.