

PROCESS MONITORING/DIAGNOSTIC/SUPPORT APPARATUS

FIELD

Embodiments described herein relate generally to a process monitoring/diagnostic/support apparatus capable of supporting a plant operator in an unsteady state under abnormal conditions or the like when monitoring a process system for a sewage treatment process, an effluent treatment process, a sludge digestion process, a water purification process, a water supply/distribution process, a chemical process, a steel process, or the like.

BACKGROUND

In a plant of a process system for a water treatment/water management process such as a sewage treatment process, a sludge digestion process, a water purification process, or a water supply/distribution process, a petrochemical process, a steel process, a semiconductor manufacturing process, or the like, a plurality of online sensors for measuring a plurality of process states are installed. A process monitoring apparatus (SCADA: Supervisory Control And Data Acquisition) converts process data (flow rate, temperature, water quality, manipulated variable, and the like) obtained by measurement of a sensor group installed in a normal process system into time series data (trend graph). A plant manager or operator monitors the time series data so as to grasp the

process states and change or control the process operations. Upper and lower limits called control limits or the like are normally set for the time series data of each piece of process data. An alarm is raised
5 if a value exceeds the upper limit or is lower than the lower limit. Based on the alarm, the plant manager or operator confirms and revises the plant operation. Such operation management based on alarms forms the basis of the plant operation.

10 More advanced plant operation management needs to not only cope with simple process unsteadiness but also an operation that can achieve predetermined target performance of a process and also lead to energy saving and cost reduction. The predetermined target
15 corresponds to, for example, obeying effluent quality regulations in a sewage treatment. In a water purification treatment, the predetermined target is, for example, keeping the residual chlorine concentration in purified water equal to or less than a
20 predetermined upper limit or the absence of pathogenic microorganisms represented by Cryptosporidium. In a chemical process or a steel process, the predetermined target corresponds to maintaining the quality (for example, purity or strength) of a product (oil refined
25 article or steel) within a predetermined range. At this time, it is important for the operation management to monitor the process states concerning the target

performance, quickly detect a state change or abnormal state that may inhibit achievement of the predetermined target, and take countermeasures in advance, thereby preventing failures in achieving the predetermined target. Additionally, to perform an operation that can lead to energy saving and cost reduction under restrictions for achieving the predetermined target, it is necessary to always maintain excellent process states concerning energy saving and cost reduction and quickly detect a process state change that may cause deviation from the excellent states.

As a method of diagnosing such a process state change or abnormality, there is known a method called MSPC (Multi-Variate Statistical Process Control) using "multivariate statistical analysis" which has been utilized in the field of a petrochemical process or a steel plant.

As the most commonly used methods, PCA (Principal Component Analysis) and PLS (Projection to Latent Structure/Partial Least Square) are known.

The main objects of the MSPC are to (1) detect a sign of abnormality of a plant (Fault Detection) and (2) estimate a process variable (data) as an abnormality factor (Fault Isolation) using the multivariate statistical analysis such as PCA or PLS.

For (1), a sign of abnormality that is undetectable using only one variable can be detected

using the correlation information of a plurality of process variables.

For (2), after an abnormality is detected using abnormality detection data (called a Q statistic or Hotelling's T^2 statistic) synthesized from a plurality of process variables, a process variable (data) as an abnormality factor candidate is estimated using information called a contribution amount representing the degree of contribution of each piece of process data to the abnormality detection data.

As described above, using MSPC makes it possible to perform advanced monitoring and diagnosis that is more useful for the plant manager or operator than conventional monitoring based on simple control limits for individual process variables (sometimes called SPC (Statistical Process Control) in contrast with MPSC for monitoring a production line or the like).

On the other hand, users such as a plant manager and operator have not only the needs for (1) abnormality sign detection and (2) abnormality factor variable estimation described above but also strong potential needs for countermeasure support information that recommends a countermeasure the users should take in an abnormal state of a process. Especially, inexperienced plant operators strongly demand this information. Information simply indicating "there is a sign of abnormality" or diagnostic information

representing "process variables exhibiting abnormality are OO and $\Delta\Delta$ " is insufficient. Demanded is support information in a form "there is a sign of abnormality, and process variables of the factor are probably OO and $\Delta\Delta$ ". You are advised to take countermeasure $\square\square$ ".

There exists a large gap between the needs for the support information and the above-described FDI (Fault Detection and Isolation) (1) and (2). This is because although FDI can perform diagnosis mechanically to some extent (i.e., automatically without intervening engineering) regardless of the target process using "a statistical method such as multivariate statistical analysis", providing countermeasure support information generally requires knowledge of the target process and related engineering.

Abnormality cause estimation methods for providing countermeasure support information are often classified into [1] empirical methods (decision tree, pattern learning, and the like), [2] logical methods (using a physical model, a fault tree, or the like), [3] knowledge engineering methods (expert system and know-how extraction), and the like. To use these methods, however, knowledge about the target process, knowledge of the operator who is operating the target process, and the like are necessary in some form. For this reason, to track down the true cause of the unsteady state (abnormal state) of a process and do

countermeasure support, an enormous amount of engineering is necessary to build up a diagnostic system for each target process. The necessity of development according to the features of the target process is one hurdle in developing an unsteady state countermeasure support system.

It is an object of the present invention to provide a process monitoring/diagnostic/support apparatus capable of providing countermeasure support information in an abnormal state regardless of a target process.

A process monitoring/diagnostic/support apparatus according to an aspect comprises a data collection/storage means, process variable classification means, process variable correlation defining means, abnormality detection data defining means, abnormality detection data contribution amount defining means, abnormality countermeasure support information defining means, abnormality detection means, abnormality factor variable separation means, and abnormality countermeasure support information providing means.

The data collection/storage means collects time series data of n ($n \geq 2$) process variables representing measurement results from n sensors for measuring a quantity of state or a manipulated variable of a target process and stores the time series data.

The process variable classification means stores classification information representing a result of classifying the n process variables into p ($1 \leq p < n$) output variables Y that are the quantities of states and represent performance indices, L ($1 \leq L < n$) input variables U representing the manipulated variables, and m ($0 \leq m < n$) intermediate variables Z that are the quantities of states and represent control/monitor values.

10 The process variable correlation defining means defines, from the classification information and the time series data of the n process variables for a predetermined period, correlation information representing correlation between the n process variables including the classification result.

15 The abnormality detection data defining means defines an equation to generate q ($1 \leq q \ll n$) abnormality detection data less than n and a determination criterion to determine one of
20 presence/absence and a strength of an abnormality based on the abnormality detection data from the time series data of the n process variables for the predetermined period.

25 The abnormality detection data contribution amount defining means defines a contribution amount of each piece of the time series data of the n process variables to the abnormality detection data.

The abnormality countermeasure support information defining means defines a first rule to extract a predetermined number of top-ranked abnormality factor candidate variables out of abnormality factor candidate variables that are process variables as abnormality factor candidates in an abnormal state, a second rule to classify the extracted abnormality factor candidate variables into the output variables Y, the input variables U, and the intermediate variables Z based on correlation information, and a third rule to provide countermeasure support information including a message to support a countermeasure in the abnormal state based on the classification result.

The abnormality detection means generates the abnormality detection data corresponding to the time series data at a predetermined time in accordance with the stored time series data of the n process variables at the predetermined time and a definition of the abnormality detection data defining means and diagnoses the presence/absence of an abnormality in the data at the predetermined time based on the abnormality detection data.

When an abnormality exists as a result of the diagnosis, the abnormality factor variable separation means calculates the contribution amount of the time series data at the predetermined time based on a definition of the contribution amount and separates and

extracts the abnormality factor candidate variables from the time series data at the predetermined time based on the calculated contribution amount and the first rule.

5 The abnormality countermeasure support information providing means provides the countermeasure support information based on the separated and extracted abnormality factor candidate variables, the correlation information, the second rule, and the third rule.

10 According to another aspect, there is provided a computer-readable storage medium storing a program to be executed by a processor of a process monitoring/diagnostic/support apparatus including a memory, comprising: a first program code that causes
15 the processor to execute processing of collecting time series data of n ($n \geq 2$) process variables representing measurement results from n sensors for measuring a quantity of state or a manipulated variable of a target process and storing the time series data in the memory;
20 a second program code that causes the processor to execute processing of storing classification information representing a result of classifying the n process variables into p ($1 \leq p < n$) output variables Y that are the quantities of states and represent
25 performance indices, L ($1 \leq L < n$) input variables U representing the manipulated variables, and m

($0 \leq m < n$) intermediate variables Z that are the quantities of states and represent control/monitor values; a third program code that causes the processor to execute processing of defining, from the
5 classification information and the time series data of the n process variables for a predetermined period, correlation information representing correlation between the n process variables including the classification result; a fourth program code that
10 causes the processor to execute abnormality detection data defining processing of defining an equation to generate q ($1 \leq q \ll n$) abnormality detection data less than n and a determination criterion to determine one of presence/absence and a strength of an abnormality
15 based on the abnormality detection data from the time series data of the n process variables for the predetermined period; a fifth program code that causes the processor to execute processing of defining a contribution amount of each piece of the time series
20 data of the n process variables to the abnormality detection data; a sixth program code that causes the processor to execute processing of defining a first rule to extract a predetermined number of top-ranked abnormality factor candidate variables out of
25 abnormality factor candidate variables that are process variables as abnormality factor candidates in an

abnormal state, a second rule to classify the extracted
abnormality factor candidate variables into the output
variables Y, the input variables U, and the
intermediate variables Z based on correlation
5 information, and a third rule to provide countermeasure
support information including a message to support a
countermeasure in the abnormal state based on the
classification result; a seventh program code that
causes the processor to execute processing of
10 generating the abnormality detection data corresponding
to the time series data at a predetermined time in
accordance with the stored time series data of the n
process variables at the predetermined time and a
definition of the abnormality detection data defining
15 means and diagnosing the presence/absence of an
abnormality in the data at the predetermined time based
on the abnormality detection data; an eighth program
code that causes the processor to execute processing
of, when an abnormality exists as a result of the
20 diagnosis, calculating the contribution amount of the
time series data at the predetermined time based on a
definition of the contribution amount and separating
and extracting the abnormality factor candidate
variables from the time series data at the
25 predetermined time based on the calculated contribution
amount and the first rule; and a ninth program code

that causes the processor to execute processing of
providing the countermeasure support information based
on the separated and extracted abnormality factor
candidate variables, the correlation information, the
5 second rule, and the third rule.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. 1 is a schematic view showing the basic
system arrangement of a process
monitoring/diagnostic/support apparatus according to
10 the first embodiment;

FIG. 2 is a schematic view showing an example of a
process variable classification user interface unit;

FIG. 3 is a schematic view showing Example 1 of a
correlation determination rule;

15 FIG. 4 is a schematic view showing Example 2 of
the correlation determination rule;

FIG. 5 is a schematic view showing Example 3 of
the correlation determination rule;

20 FIG. 6 is a schematic view showing an example of a
process variable correlation defining interface unit;

FIG. 7 is a schematic view showing an abnormality
factor candidate classification rule;

FIG. 8 is a schematic view showing an example of

an abnormality countermeasure support message
generation rule;

FIG. 9 is a schematic view showing an example of
the abnormality countermeasure support message
5 generation rule;

FIG. 10 is a schematic view for explaining a
function of generating an abnormality countermeasure
support message in an abnormal state;

FIG. 11 is a schematic view showing an example of
10 a countermeasure support message;

FIG. 12 is a schematic view showing an example of
a system arrangement according to another embodiment;

FIG. 13 is a schematic view showing an example of
a system arrangement according to still another
15 embodiment; and

FIG. 14 is a schematic view showing an example of
a system arrangement according to yet another
embodiment.

DETAILED DESCRIPTION

20 In general, according to one embodiment, the
embodiments will now be described with reference to the
accompanying drawings. Note that the process
monitoring/diagnostic/support apparatus to be described
below can be implemented by either a hardware
25 arrangement or a combination of hardware resources and
software. The combined arrangement uses, as the
software, a program that is installed from a network or

a computer-readable storage medium to a computer serving as the process monitoring/diagnostic/support apparatus in advance so as to implement the functions of the process monitoring/diagnostic/support apparatus.

5 <First Embodiment>

FIG. 1 is a schematic view showing the basic arrangement of a process monitoring system to which a process monitoring/diagnostic/support apparatus according to the first embodiment is applied.

10 The process monitoring system includes a process monitoring/diagnostic/support apparatus which has, as a target process, a sewage complete treatment process 1 designed for, for example, removing nitrogen and phosphorus, and includes a process measurement data
15 collection/storage unit 2 configured to collect the time series data of n ($n \geq 2$) process variables representing measurement results from n sensors for measuring the quantity of state or manipulated variable of the target process and store the data. This
20 embodiment is not dependent on the target process because of its object but will be explained by exemplifying a sewage treatment process to obtain a distinct image of implementation. That is, implementation is not substantially limited to the
25 sewage treatment process.

The sewage complete treatment process 1 includes a primary sedimentation basin 101, an anaerobic tank 102,

an anoxic tank 103, an aerobic tank 104, and a final settling basin 105. The sewage complete treatment process 1 also includes a primary sedimentation basin excess sludge extraction pump and its extraction flow rate sensor 111, an oxygen supply blower and its supply air flow rate sensor 112 for the aerobic tank 104, a circulating pump and its circulating flow rate sensor 113, a return sludge pump and its return flow rate sensor 114, and a final settling basin excess sludge extraction pump and its extraction flow rate sensor 115 as actuators and manipulated variable sensors thereof.

The sewage complete treatment process 1 also includes, as process sensors, a rainfall sensor 121, a sewage inflow amount sensor 122 for measuring the amount of influent sewage, an influent TN sensor 123 for measuring the total amount of nitrogen contained in the influent sewage, an influent TP sensor 124 for measuring the total amount of phosphorus contained in the influent sewage, an influent UV sensor or influent COD sensor 125 for measuring the amount of organic substances contained in the influent sewage, an anaerobic tank ORP sensor 126 for measuring ORP in the anaerobic tank 102, an anaerobic tank pH sensor 127 for measuring the pH in the anaerobic tank 102, an anoxic tank ORP sensor 128 for measuring ORP in the anoxic tank 103, an anoxic tank pH sensor 129 for measuring the pH in the anoxic tank 103, a phosphoric acid sensor

1210 for measuring the phosphoric acid concentration in the aerobic tank 104, a DO sensor 1211 for measuring the dissolved oxygen concentration in the aerobic tank 104, an ammonia sensor 1212 for measuring the ammonia concentration in the aerobic tank 104, an MLSS sensor 1213 for measuring the activated sludge amount in at least one of the reaction tanks 102 to 104, a water temperature sensor 1214 for measuring the water temperature in at least one of the reaction tanks 102 to 104, an excess sludge SS sensor 1215 for measuring the solid concentration in sludge extracted from the final settling basin 105, an effluent SS sensor 1216 for measuring the SS concentration in water discharged from the final settling basin 105, a sludge interface sensor 1217 for measuring the sludge interface level in the final settling basin 105, a sewage discharge amount sensor 1218 for measuring the amount of effluent sewage, an effluent TN sensor 1219 for measuring the total amount of nitrogen contained in the effluent sewage, an effluent TP sensor 1220 for measuring the total amount of phosphorus contained in the effluent sewage, and an effluent UV or effluent COD sensor 1221 for measuring the amount of organic substances contained in the effluent sewage.

25 The above-described various kinds of actuators 111 to 115 operate at predetermined periods. The manipulated variable sensors of the various kinds of

actuators 111 to 115 and the various kinds of process sensors 121 to 1221 perform measurements at predetermined periods.

5 The process monitoring/diagnostic/support apparatus includes the process measurement data collection/storage unit 2 configured to collect the time series data (process data) of process variables obtained from the manipulated variable sensors of the various kinds of actuators 111 to 115 and the various
10 kinds of process sensors 121 to 1221 at the predetermined periods and hold them in a memory.

 The process monitoring/diagnostic/support apparatus also includes a process variable registration unit 3, a process variable classification user
15 interface unit 4, an abnormality diagnostic model construction unit 5, a process variable correlation defining interface unit 6, an abnormality monitoring/diagnostic/countermeasure support unit 7, an abnormality countermeasure record holding unit 8, and a
20 user interface unit 9.

 The process variable registration unit 3 registers the names of process variables necessary for constructing the process monitoring/diagnostic/support apparatus of this embodiment out of the process
25 variables measured by the manipulated variable sensors of the various kinds of actuators 111 to 115 and the various kinds of process sensors 121 to 1221.

The process variable classification user interface unit 4 is a user interface to be used to display a list of process variables registered by the process variable registration unit 3 and classify them into input
5 variables U, output variables Y, and intermediate variables Z. More specifically, the process variable classification user interface unit 4 displays the names of n process variables, and selects input variables, output variables, and intermediate variables in a
10 process variable classification unit 51 in accordance with a user operation during the display.

The abnormality diagnostic model construction unit 5 extracts, from the process measurement data collection/storage unit 2, past time series data of the
15 process variables registered by the process variable registration unit 3 out of the process variables measured by the manipulated variable sensors of the various kinds of actuators 111 to 115 and the various kinds of process sensors 121 to 1221, and constructs an
20 abnormality diagnostic model.

The process variable correlation defining interface unit 6 is a user interface that presents the correlation information between the process variables defined by the abnormality diagnostic model
25 construction unit 5 to the user and allows him/her to correct the information.

The abnormality

monitoring/diagnostic/countermeasure support unit 7
extracts, from the process measurement data
collection/storage unit 2, current time series data of
the process variables registered by the process
5 variable registration unit 3 out of the process
variables measured by the manipulated variable sensors
of the various kinds of actuators 111 to 115 and the
various kinds of process sensors 121 to 1221, and
detects an abnormality sign, extracts factor variable
10 candidates and provides abnormality countermeasure
support information using the functions defined by the
abnormality diagnostic model construction unit 5.

The abnormality countermeasure record holding unit
8 holds the result of a countermeasure actually taken
15 based on information from the abnormality
monitoring/diagnostic/countermeasure support unit 7.
More specifically, the abnormality countermeasure
record holding unit 8 records an operation performed by
the user after countermeasure support information
20 provided by an abnormality countermeasure support
information providing unit 74 has been presented. When
countermeasure support information is provided, the
abnormality countermeasure record holding unit 8
presents the countermeasure support information and the
25 values of the input variables U , the values of the
output variables Y , and the values of the intermediate
variables Z before the current time based on the time

series data and classification information. After the countermeasure support information has been presented, the abnormality countermeasure record holding unit 8 continuously records the operation records of the input variables U as the operation performed by the user, the values of the output variables Y, and the values of the intermediate variables Z.

The user interface unit 9 includes the process variable registration unit 3, the process variable classification user interface unit 4, and the process variable correlation defining interface unit 6, and can notify the plant manager or operator of information from the abnormality monitoring/diagnostic/countermeasure support unit 7, send a countermeasure instruction based on the countermeasure support information to the plant as a command signal, and send a recording operation instruction to the abnormality countermeasure record holding unit 8.

The abnormality diagnostic model construction unit 5 comprises the process variable classification unit 51, a past (offline) data extraction unit 52, a process variable correlation defining unit 53, an abnormality detection data defining unit 54, an abnormality detection data contribution amount defining unit 55, and an abnormality countermeasure support information defining unit 56.

As shown in FIG. 2, the process variable classification unit 51 classifies the process variables into input variables, output variables, and intermediate variables in accordance with input to the process variable classification user interface unit 4, and supplies the information at the time of abnormality countermeasure. More specifically, the process variable classification unit 51 has a function of storing classification information representing a result of classifying the n process variables into p ($1 \leq p < n$) output variables Y that are quantities of states and represent performance indices, L ($1 \leq L < n$) input variables U representing manipulated variables, and m ($0 \leq m < n$) intermediate variables Z that are quantities of states and represent control/monitor values.

The past (offline) data extraction unit 52 extracts, from the process measurement data collection/storage unit 2, the past offline data of the variables registered by the process variable registration unit 3.

The process variable correlation defining unit 53 defines the correlation information between the process variables defined by the process variable registration unit 3 using the offline data extracted by the past (offline) data extraction unit 52. More specifically, the process variable correlation defining unit 53

defines, from the classification information and the time series data of the n process variables for a predetermined period, correlation information representing the correlation between the n process variables including the classification result represented by the classification information, as shown in FIGS. 3, 4, 5, and 6. Note that the process variable correlation defining unit 53 may define the correlation information based on the correlation matrix or principal component loading matrix of the time series data of the n process variables for a predetermined period. The process variable correlation defining unit 53 may have, as correlation information, a table in n rows $\times$ n columns representing the presence/absence or strength of the correlation between the n process variables. In this case, the process variable correlation defining interface unit 6 displays the table of the correlation information and corrects the contents of the table in accordance with a user operation.

The abnormality detection data defining unit 54 defines abnormality detection data synthesis method using the offline data extracted by the past (offline) data extraction unit 52. More specifically, the abnormality detection data defining unit 54 defines an equation to generate q ($1 \leq q \ll n$) pieces of abnormality detection data less than n and a

determination criterion to determine the presence/absence or strength of an abnormality based on the abnormality detection data from the time series data of the n process variables for a predetermined period.

The abnormality detection data defining unit 54 may define the equation to generate abnormality detection data using at least one of PCA (Principal Component Analysis), PLS (Projection to Latent Structure/Partial Least Square), PCR (Principal Component Regression), CVA (Canonical Variate Analysis), Mahalanobis distance, robust PCA, kernel PCA, discriminant analysis, fuzzy C-means clustering, K-means clustering, SVM (Support Vector Machine), RVM (Relevance Vector Machine), and the subspace method.

The abnormality detection data contribution amount defining unit 55 defines the contribution amounts of the process variables (the contribution amount of each piece of the time series data of the n process variables) registered by the process variable registration unit 3 to the abnormality detection data defined by the abnormality detection data defining unit 54. Note that the abnormality detection data contribution amount defining unit 55 may define the contribution amount of a process variable k ($k = 1, 2, \dots, n$) of interest out of the n process variables by one of

[a] projecting from the abnormality detection data defined by the abnormality detection data defining unit 54 to a space spanned by the process variable k ,

5 [b] decomposing the abnormality detection data to a sum of n components so as to define the contribution amount as a k th component affected only by the process variable k , and

[c] using independent component analysis.

10 The abnormality countermeasure support information defining unit 56 defines rules to provide support information to be used to advise a countermeasure in an abnormal state, based on the classification information of the input variables, the output variables, and the intermediate variables from the process variable
15 classification unit 51, the correlation information between the process variables defined by the process variable correlation defining unit 53, and the information about the contribution amounts defined by the abnormality detection data contribution amount
20 defining unit 55.

More specifically, the abnormality countermeasure support information defining unit 56 defines a first rule to extract a predetermined number of top-ranked abnormality factor candidate variables out of the
25 abnormality factor candidate variables that are process variables as the abnormality factor candidates in an abnormal state, a second rule to classify the extracted

abnormality factor candidate variables into the output variables Y, the input variables U, and the intermediate variables Z based on correlation information, as shown in FIG. 7, and a third rule to
5 provide countermeasure support information including a message to support a countermeasure in an abnormal state based on the classification result, as shown in FIGS. 8 and 9.

The second rule may include a rule to classify the
10 extracted abnormality factor candidate variables into input factor variables FU belonging to the input variables U, output factor variables FY belonging to the output variables Y, and intermediate factor variables FZ belonging to the intermediate variables Z
15 based on classification information.

The third rule may include a fourth rule A, a fifth rule B, and a sixth rule C.

The fourth rule A stipulates to, when the abnormality factor candidate variables include the
20 output factor variable FY, notify that the output factor variable FY has deteriorated and provide countermeasure support information including a message for prompting to confirm and revise the value of the input variable U defined by the correlation information
25 to be correlated with the output factor variable FY.

The fourth rule A preferably stipulates to, when the input variables U include the input factor variable

FU, provide countermeasure support information including a message for prompting to particularly revise the input factor variable FU.

5 The fourth rule A more preferably stipulates to, when the intermediate variable Z (a plurality of intermediate variables in general) defined by the correlation information to be correlated with the output factor variable FY is managed, and the intermediate variable Z includes the intermediate
10 factor variable FZ, provide countermeasure support information including a message for prompting to return the control value of the intermediate factor variable FZ to a normal value.

15 The fifth rule B stipulates to, when the abnormality factor candidate variables include not the output factor variable FY but the input factor variable FU, notify that the input factor variable FU deviates from the normal state to an abnormal state and provide countermeasure support information including a message
20 for prompting to revise the manipulated variable represented by the input factor variable FU and notifying that the output variable Y defined by the correlation information to be correlated with the input factor variable FU may deteriorate in the future.

25 In addition to this stipulation, the fifth rule B more preferably stipulates to provide countermeasure support information including a message for notifying

that the intermediate variable Z defined by the correlation information to be correlated with the input factor variable FU may deteriorate in the future as well, and when the intermediate variables Z include the intermediate factor variable FZ, the deterioration may have occurred due to the input factor variable FU.

The sixth rule C stipulates to, when the abnormality factor candidate variables include only the intermediate factor variables FZ, provide countermeasure support information including a message for notifying that the intermediate factor variables FZ have deteriorated, and the output variables Y defined by the correlation information to be correlated with the intermediate factor variables FZ may deteriorate in the future.

In addition to this stipulation, the sixth rule C more preferably stipulates to include a message for prompting to confirm the values of the input variables U defined by the correlation information to be correlated with the intermediate factor variables FZ and examine the necessity of operation changes.

The abnormality monitoring/diagnostic/countermeasure support unit 7 comprises a current (online) data extraction unit 71, an abnormality detection unit 72, an abnormality factor variable separation unit 73, and the abnormality countermeasure support information providing unit 74.

The current (online) data extraction unit 71 extracts the current online data of the variables registered by the process variable registration unit 3 from various kinds of time series data stored in the process measurement data collection/storage unit 2.

The abnormality detection unit 72 checks the current degree of abnormality by inputting the online data extracted by the current (online) data extraction unit 71 to the equation of abnormality detection data defined by the abnormality detection data defining unit 54 and thus generating abnormality detection data, and detects the presence/absence of an abnormality in accordance with a preset abnormality/normality determination criterion. More specifically, the abnormality detection unit 72 generates abnormality detection data corresponding to time series data at a predetermined time in accordance with the stored time series data of the n process variables at the predetermined time and the definition of the abnormality detection data defining means, and detects (diagnoses) the presence/absence of an abnormality in the data at the predetermined time based on the abnormality detection data.

When the abnormality detection unit 72 has detected an abnormality, the abnormality factor variable separation unit 73 calculates the degrees of contribution of the process variables to the

abnormality, which are defined by the abnormality
detection data contribution amount defining unit 55.
More specifically, if an abnormality exists as the
result of detection (diagnosis) by the abnormality
5 detection unit 72, the abnormality factor variable
separation unit 73 calculates the contribution amount
of the time series data at the predetermined time based
on the definition of the contribution amount, and
separates and extracts abnormality factor candidate
10 variables from the time series data at the
predetermined time based on the calculated contribution
amount and the first rule of the abnormality
countermeasure support information defining unit 56.

The abnormality countermeasure support information
15 providing unit 74 provides countermeasure support
information in an abnormal state to the operator via
the user interface unit 9 in accordance with the
information of the process variables as the
predetermined number of top-ranked abnormality factor
20 candidates extracted by the abnormality factor variable
separation unit 73, the correlation information, and
the second and third rules defined by the abnormality
countermeasure support information defining unit 56, as
shown in FIGS. 10 and 11.

25 The function of the process monitoring system
having the above-described arrangement will be
explained next.

In the sewage complete treatment process 1, the manipulated variable sensors of the various kinds of actuators 111 to 115 and the various kinds of process sensors 121 to 1221 measure process information at
5 predetermined periods. These pieces of measurement information are stored in the process measurement data collection/storage unit 2 as time series data in accordance with a predetermined format.

When constructing the process
10 monitoring/diagnostic/support apparatus, the process variable registration unit 3 first defines variables to be used to construct the process monitoring/diagnostic/support apparatus out of the items measured by the manipulated variable sensors of
15 the various kinds of actuators 111 to 115 and the various kinds of process sensors 121 to 1221 and stored in the process measurement data collection/storage unit 2.

For example, the process variable registration
20 unit 3 registers, as variables to be used, "[1] air supply amount" corresponding to the oxygen supply blower and its supply air flow rate sensor 112 for the aerobic tank 104, "[2] circulating flow rate" corresponding to the circulating pump and its
25 circulating flow rate sensor 113, "[3] return flow rate" corresponding to the return sludge pump and its return flow rate sensor 114, "[4] excess flow rate"

corresponding to the final settling basin excess sludge
extraction pump and its extraction flow rate sensor
115, "[5] rainfall" corresponding to the rainfall
sensor 121, "[6] sewage inflow amount" corresponding to
5 the sewage inflow amount sensor 122 for measuring the
amount of influent sewage, "[7] influent TN"
corresponding to the influent TN sensor 123 for
measuring the total amount of nitrogen contained in the
influent sewage, "[8] influent TP" corresponding to the
10 influent TP sensor 124 for measuring the total amount
of phosphorus contained in the influent sewage, "[9]
influent UV" corresponding to the influent UV sensor or
influent COD sensor 125 for measuring the amount of
organic substances contained in the influent sewage,
15 "[10] anaerobic tank ORP" corresponding to the
anaerobic tank ORP sensor 126 for measuring ORP in the
anaerobic tank 102, "[11] anaerobic tank pH"
corresponding to the anaerobic tank pH sensor 127 for
measuring the pH in the anaerobic tank 102, "[12]
20 anoxic tank ORP" corresponding to the anoxic tank ORP
sensor 128 for measuring ORP in the anoxic tank 103,
"[13] anoxic tank pH" corresponding to the anoxic tank
pH sensor 129 for measuring the pH in the anoxic tank
103, "[14] aerobic PO4-P" corresponding to the
25 phosphoric acid sensor 1210 for measuring the
phosphoric acid concentration in the aerobic tank 104,
"[15] aerobic tank DO" corresponding to the DO sensor

1211 for measuring the dissolved oxygen concentration in the aerobic tank 104, "[16] aerobic tank NH₄-N" corresponding to the ammonia sensor 1212 for measuring the ammonia concentration in the aerobic tank 104,
5 "[17] aerobic tank MLSS" corresponding to the MLSS sensor 1213 for measuring the activated sludge amount in at least one of the reaction tanks 102 to 104, "[18] reaction tank water temperature" corresponding to the water temperature sensor 1214 for measuring the water
10 temperature in at least one of the reaction tanks 102 to 104, "[19] effluent TN" corresponding to the effluent TN sensor 1219 for measuring the total amount of nitrogen contained in the effluent sewage, and "[20] effluent TP" corresponding to the effluent TP sensor
15 1220 for measuring the total amount of phosphorus contained in the effluent sewage. A registration screen is preferably constructed as a GUI on the monitor screen so that the user can easily execute the registration.

20 The function of registering process variables is the function of the process variable registration unit 3.

Next, the process variable classification user interface unit 4 displays a list of the registered
25 process variables as shown in FIG. 2 as a GUI on the monitor screen, and allows to select the input variables, the output variables, and the intermediate

variables. In FIG. 2, the columns of the input variables, the output variables, and the intermediate variables are marked with O. When constructing the actual monitor screen (GUI), the user marks checkboxes.

5 When all variables are set to intermediate variables in the default state, and the user is caused to select only the input variables and output variables from them, labor for marking the checkboxes can be saved, and the efficiency can be increased. The GUI is an

10 example of a process variable classification user interface corresponding to claim 2 and an example of the function of the process variable classification user interface unit 4.

The process variable classification unit 51

15 classifies the process variables registered by the process variable registration unit 3 into three types, that is, an input variable representing the manipulated variable of a process, an output variable representing the performance index of a process, and an intermediate

20 variable corresponding to the control value of a process or the like in accordance with the criteria checked by the process variable classification user interface unit 4.

For the above-described example, the

25 classification is done, for example, in the following way.

Input variables: [1] air supply amount, [2]

circulating flow rate, [3] return flow rate, and [4] excess flow rate

Output variables: [19] effluent TN and [20] effluent TP

5 Intermediate variables: [5] rainfall, [6] sewage inflow amount, [7] influent TN, [8] influent TP, [9] influent UV, [10] anaerobic tank ORP, [11] anaerobic tank pH, [12] anoxic tank ORP, [13] anoxic tank pH, [14] aerobic PO₄-P, [15] aerobic tank DO, [16] aerobic tank NH₄-N, [17] aerobic tank MLSS, and [18] reaction tank water temperature

 The input variables can directly be changed by operating a blower (fan) or a pump. In addition to these variables, an injection amount of a chemical or
15 the like, a pump discharge (storage pump) for pumping water to the sewage treatment process, and the like can also be input variables.

 Discharge water qualities as described above are the output variables because the direct object of the
20 sewage treatment is to maintain each discharged water quality within the regulation value range. If another discharge water quality to be monitored exists, it can also be an output variable. A discharge water quality loading amount obtained by multiplying a discharge
25 water quality by a discharge water amount, and the like can also be output variables. If electric energy or the like is monitored, power consumption, an energy

consumption rate obtained by dividing the power consumption by a throughput, and the like can also be output variables.

5 The intermediate variables represent process states or disturbance factors input to the processes, as described above. Not only the above-described direct control/monitor values but also control values converted using them may be defined as intermediate variables. Typical examples are control values such as
10 HRT (Hydraulic Retention Time), SRT (Sludge Retention Time), A-SRT (Aerobic Sludge Retention Time), and a BOS-SS load unique to the sewage treatment process. These values may be included as intermediate variables by incorporating equations to calculate them in
15 advance.

 Note that there is no objective criterion to classify the intermediate variables and the output variables, and they can be defined appropriately, though slightly subjectively, at the discretion of the
20 person concerned who constructs the process monitoring/diagnostic/support apparatus.

 This is the function of the process variable classification unit 51.

 The past (offline) data extraction unit 52
25 extracts the past data of the variables registered by the process variable registration unit 3 for a predetermined period from the past process data stored

in the process measurement data collection/storage unit

2. At this time, the "predetermined period" is preferably implemented as a GUI on the monitor screen or the like together with the process variable

5 registration unit 3 so that the user can easily select it as needed. The past time series data extracted here will be referred to as X. X is a matrix having variables (variables [1] to [20] in the above-described case) in the row direction and time series samples

10 (time series data) for the "predetermined period" defined above in the column direction. In the following description, let n be the number of variables, and m be the number of time series data.

Hence, X includes $m \times n$ time series data. This is the
15 function of the past (offline) data extraction unit 52.

The process variable correlation defining unit 53, for example, appropriately removes missing data and outliers from X extracted by the past (offline) data extraction unit 52 or normalizes (= subtracts the
20 average value and divides the result by a variance) a plurality of monitoring items of different dimensions (monitoring model construction variables), and then obtains the correlation matrix of X. At this time, decimation (thinning out the time series samples at a
25 predetermined period) and the like may be performed as needed. In this case, the number m of time series data changes. At any rate, the appropriately processed data

will be referred to as X anew hereinafter. When the variables are normalized, the correlation matrix of X matches the variance-covariance matrix and can simply be calculated by

5 correlation matrix $S = X^T X$... (1)

Equation (1) represents an $n \times n$ matrix (n is the number of process variables) in which each element is a real number representing a correlation coefficient from -1 to 1. According to the definition of
10 correlation coefficients, this matrix is a symmetric matrix (correlation between $\underline{a}$ and b equals correlation between b and $\underline{a}$) in which all diagonal elements are 1 (the correlation coefficient for a variable itself is 1). Appropriate criteria are set for the correlation
15 coefficients of equation (1) to define the presence/absence and strength of correlation. Simplest definition uses the presence/absence of correlation as a criterion. For example, a correlation determination rule (Example 1) can be defined as shown in FIG. 3.

20 This is a criterion to determine the presence/absence of correlation. For example, $Th = 0.5$, $Th = 0.7$ ($Th2 \approx 0.5$), or the like is used. In addition, an appropriate expression form such as correlation is present = 1 and correlation is absent =
25 0, or correlation is present = $\bigcirc$ and correlation is absent = $\times$ is used. SS is a matrix representing the presence/absence of correlation, which is an example of

the matrix defined by the process variable correlation defining unit 53.

As another example, the correlation strength is determined at several levels. For example, to separate
5 the strengths into three levels, a correlation determination rule (Example 2) may be set as shown in FIG. 4.

Th1 and Th2 are thresholds that satisfy $0 < Th2 < Th1 < 1$. For example, $Th1 = 0.7$ and $Th2 = 0.5$ are
10 used. In addition, an appropriate expression form such as strong correlation = 2, weak correlation = 1, and no correlation = 0, or strong correlation = $\odot$, weak correlation = $\circ$, and no correlation = $\times$ can be used.

As well as from the simple viewpoint of
15 correlation between the variables, the presence/absence (or strength) of the relationship between the variables may be defined using a loading matrix of principal component analysis to be described later. A principal component loading having a size of $n \times n$ considering
20 all variables is represented by P_a , and the k th row and j th column of the matrix is represented by $P_a(k, j)$.

Since the loading matrix P_a is a normal orthogonal matrix because of its characteristic, each element of $P_a(k, j)$ takes a value from -1 to 1. The square-sum
25 $\sum_{j=1}^{15} P_a(k, j)^2$ of the i th principal component defined by the k th row of P_a (to be referred to as $P_a(k, :)$ hereinafter) is 1. This means that the

average value of $P_a(k, j)^2$ is $1/n$. Using this characteristic, the presence/absence of the relationship between the variables can be determined by a correlation determination rule (Example 3) as shown in FIG. 5.

In the above-described case, the relationship is defined based on the criterion that variables larger than the average value of the k th principal component of the k th row of the principal component loading matrix are associated with each other. The threshold may be changed by appropriately correcting the average value $1/n$, or the strength of the relationship may be defined by a plurality of thresholds as in Example 2 of the correlation determination rule, as a matter of course.

FIG. 6 shows an example in which the strength of the relationship (or correlation) between the process variables is defined in the above-described way. The process variable correlation defining unit 53 consequently defines the correlation between the process variables as shown in FIG. 6 by some mechanical means. At this time, note that the input variables, the output variables, and the intermediate variables classified by the process variable classification unit 51 are classified and held as shown in FIG. 6. This is the point in performing abnormality countermeasure support to be described later.

The above-described embodiment is an example of a process variable defining means corresponding to claim 5. This is the function of the process variable correlation defining unit 53.

5 At this time, a table representing the correlation between the process variables as shown in FIG. 6 is preferably presented to the user via a GUI on the monitor screen. In this case, the process variable correlation defining interface unit 6 allows the user
10 to rewrite the presence/absence or strength of correlation in the table as needed. This makes it possible to easily reflect a user's requirement on the system when he/she has doubts about the correlation relationship mechanically determined in the
15 above-described manner and wants to correct it appropriately. An important point of this embodiment is that instead of requiring the user to define the presence/absence of correlation in advance, only when the user wants to customize the mechanically defined
20 correlation, he/she is allowed to customize it.

This function is an example of a user interface corresponding to claim 6 and an example of the function of the process variable correlation defining interface unit 6.

25 The abnormality detection data defining unit 54 generates a small number of abnormality detection data by applying various methods of multivariate statistical

analysis or machine learning to X extracted by the past
(offline) data extraction unit 52. It is important
that the abnormality detection data includes the
information of the n process variables because it is
5 generated from X, and the number of abnormality
detection data is much smaller than n and as large as 1
or 2.

A method commonly used as a process diagnostic
technique is called MSPC (Multi-Variate Statistical
10 Process Control). In this method, normally,
abnormality detection data called a Q statistic or a T^2
statistic is synthesized using PCA (Principal Component
Analysis) or PLS (Projection to Latent
Structure/Partial Least Squares). PCA handles all the
15 n variables as equal variables, whereas PLS handles the
n variables separately as input variables and output
variables.

In this embodiment, the process variables are
classified into input variables, output variables, and
20 intermediate variables. The process variables are
classified so as to be used for abnormality
countermeasure support after diagnosis. Hence, in this
embodiment, either of PCA and PLS can be used
independently of the classification. When PCA is
25 applied, the already defined input variables, output
variables, and intermediate variables are applied
without distinction. When PLS is used, the classified

intermediate variables are further classified into input variables and output variables and then applied. In place of PLS, PCR that combines PCA and multiple regression analysis may be used. When, for example, a plurality of process variables are repetitively measured in different places, CVA (Canonical Variate Analysis) can be used. This corresponds to a case in which, for example, five variables such as water temperature, pH, electric conductivity, nitric acid, and turbidity are repetitively measured in a plurality of places of a water treatment process.

If data is assumed to include many outliers, various robust PCA algorithms considering robustness against outliers, such as literature 1 "Mia Hubert, Peter J. Rousseeuw, and Karlien V, ROBPCA: a New Approach to Robust Principal Component Analysis (2005), Technometrics" and literature 2 "C Croux and A Ruiz-Gazen, High breakdown estimators for principal components: the projection-pursuit approach revisited, Journal of Multivariate Analysis", may be used. Alternatively, robust PCA may be expanded and used as robust PLS.

If strong nonlinear correlation is assumed to exist between data, kernel PCA considering nonlinearity described in literature 3 "K.-R. Muller, S. Mika, G. Ratsch, K. Tsuda, and B. Scholkopf, An introduction to kernel-based learning algorithms. IEEE Trans. Pattern

Anal. Machine Intell., 12(2):181.201, March 2001" or
literature 4 "B. Scholkopf, A.J. Smola, and K.-R.
Muller, Nonlinear component analysis as a kernel
eigenvalue problem. Neural Computation,
5 10(5):1299.1319, 1998", or kernel PLS as an expansion
thereof may be used. If both the problem of
nonlinearity and that of outliers exist, a method that
combines robust PCA and kernel PCA is usable.

Detection data can also be generated by a
10 technique similar to MSPC using the Mahalanobis
distance, for example, a Taguchi method used in the
field of quality engineering. Note that the detection
data using the Mahalanobis distance is substantially
the same as the Hotelling's T^2 statistic using PCA to
15 be described later. The method using PCA is different
in that the dimensionality is lowered by PCA. However,
even the method using the Mahalanobis distance
sometimes lowers the dimensionality to stabilize the
numerical values. Hence, the detection data using the
20 Mahalanobis distance is substantially the same as the
Hotelling's T^2 statistic.

Regarding abnormality detection as a 2-class
clustering problem for identifying certain data as
normal class or abnormal class allows to use various
25 kinds of clustering techniques used in the field of
machine learning. As such a technique, clustering such
as discriminant analysis, K-means clustering, or fuzzy

C-means clustering may be used. Alternatively, SVM (Support Vector Machine) or RVM (Relevance Vector Machine) using Bayesian inference may be applied as 2-class clustering. To use these clustering techniques, it is necessary to appropriately define the abnormality detection data. As the simplest method, the distance from the center of the normal class separated by clustering is defined as abnormality detection data.

As another technique in the field of machine learning, the technique of the subspace method widely used in the field of image recognition is applicable. At this time, the concept of "similarity" defined by the subspace method is usable as abnormality detection data. That is, data having low similarity to normal data can be defined as abnormal data and used. However, the concept of similarity is very close to the concept of "Q statistic" of PCA to be described later. The Q statistic represents the "degree of abnormality" representing the distance from certain diagnosis target data to a low-dimensional space. On the other hand, similarity is a quantity of projection of certain diagnosis target data to a low-dimensional space and represents the "degree of normality" corresponding to the degree of closeness between the certain data and the low-dimensional space. The degree of abnormality and the degree of normality are orthogonal complements.

These concepts are almost the same in principle because they can be converted into each other.

Abnormality detection data can also be synthesized by combining the above-described methods in various forms. For example, out of PCR that combines PCA and multiple regression analysis, the portion of multiple regression analysis may be replaced with SVR (Support Vector Regression) that is regression analysis expanded from support vector machine or RVM applied to the regression problem.

At any rate, it is important for the abnormality detection data defining unit 54 to generate a small number of abnormality detection data from X, and any generation method is usable.

Detailed equations of abnormality detection data generation using normal PCA will be described below for a subsequent explanation of functions. X can be decomposed as follows.

$$\begin{aligned} X &= \sum_{i=1}^n t_i * p_i^T \\ &= T_a P_a^T \\ &= \sum_{i=1}^p t_i * p_i^T + \sum_{i=p+1}^n t_i * p_i^T \\ &= TP^T + E \end{aligned} \tag{2}$$

$T_a \in R^{m \times n}$ is a matrix called a score matrix having m samples (or time series data) and n principal components. $P_a \in R^{n \times n}$ is a matrix called a loading

matrix representing the relationship between n constituent variables and n principal components. $T \in R^{m \times p}$ is a submatrix of T_a terminated in $p \ll n$ principal components and normally called a score matrix. Similarly, $P \in R^{n \times p}$ is a submatrix of P_a representing the relationship to principal components terminated in $p \ll n$ for the n variables, and P is normally called a loading matrix. $E \in R^{m \times n}$ is an error matrix including having m samples (or time series data) and n variables and represents an error when the principal components are terminated in $p \ll n$.

T_a and T , or P_a and P are clearly discriminated. T_a and P_a will be referred to as a score matrix and a loading matrix, respectively, and T and P will be referred to as a main score matrix and a main loading matrix, respectively. Using these matrices, a Q statistic and a Hotelling's T^2 statistic are defined as abnormality detection data.

Q statistic:

$$Q(x(t)) = X^T(t)(I - PP^T)x(t) \quad \dots (3)$$

Hotelling's T^2 statistic:

$$T^2(x(t)) = X^T(t)P^T\Lambda^{-1}Px(t) \quad \dots (4)$$

where Λ is a matrix having the variances of the principal components as diagonal elements and means that the variances are normalized, I is a unit matrix having an appropriate size, and $x(t)$ is the t th element of the matrix X . In abnormality monitoring/diagnosis

to be described later, $x(t)$ is calculated to replace process data measured online. Equations (3) and (4) are examples of abnormality detection data defined by the abnormality detection data defining unit 54. Two abnormality detection data are used here.

In addition, thresholds serving as determination criteria to identify abnormality and normality are set for the statistics. The setting method is important because the set thresholds greatly concern detection of a state change or abnormality sign. However, the threshold setting method is not relevant to the idea of this embodiment, and only a typical setting method will be described.

If no preliminary information exists for past offline data, the statistical confidence limit of the Q statistic and the statistical confidence limit of the Hotelling's T^2 statistic can be used as the default threshold setting method (literature 5: C. Rosen "Monitoring Wastewater Treatment Systems", Lic. Thesis, Dept. of Industrial Electrical Engineering and Automation, Lund University, Lund, Sweden (1998)).

This can be written in the following way.

Theoretical equation of Q_{limit} :

$$Q_{limit} = \theta_1 \left[\frac{c_\alpha (2 \theta_2 h_0^2)^{1/2}}{\theta_1} + 1 + \frac{\theta_2 h_0 (h_0 - 1)}{\theta_1^2} \right]^{1/h_0} \quad (5)$$

$$h_0 = 1 - \frac{2 \theta_1 \theta_3}{3 \theta_2^2}$$

$$\theta_i = \lambda_{p+1}^i + \lambda_{p+2}^i + \dots + \lambda_n^i$$

where p is the number of variables remaining in the model, c_α is the shift of standard deviation of the standard normal distribution when the limit of the confidence interval is $1 - \alpha$ (for example: 2.53 when
 5 $\alpha = 0.01$, and 1.96 when $\alpha = 0.05$), and λ_i is the diagonal element of Λ (that is, Θ_i is the sum of i th power of the components included in an error term).

Theoretical equation of T^2_{limit} :

$$10 \quad T^2_{limit} = \frac{p(m-1)}{m-p} F(p, m-p, \alpha) \quad (6)$$

where p is the number of variables selected (= remaining in the model), m is the total number of variables, $F(p, m-p, \alpha)$ is the F distribution when the degree of freedom is $(p, m-p)$, and the confidence
 15 limit is α (often set to 0.01 or 0.05).

Described above is an example of the function of the abnormality detection data defining unit 54 corresponding to claim 3.

The abnormality detection data contribution amount
 20 defining unit 55 sets equations to define the contribution amounts of input variables of each diagnostic model for the statistics (abnormality detection data) defined by equations (3) and (4).

A plurality of contribution amount defining
 25 methods are available. For example, the definition can be done as follows.

Contribution amount of Q statistic:

$$Q_{cont}(n, t) = X^T(t, n) F(:, n)^T F(:, n) x(t, n) \dots (7)$$

$$F = (I - PP^T)$$

Contribution amount of Hotelling's T^2 statistic:

$$T^2_{\text{cont}}(n, t) = X^T(t) P^T A^{-1} P(:, n) x(t, n) \quad \dots (8)$$

where n is the n th variable, and t is a variable

5 representing a time. Using equations (7) and (8) enables to calculate the degree of contribution of each process variable to the value of abnormality detection data. Equation (7) represents the projection of the n th process variable of the Q statistic to the axis.
10 Equation (8) does not represent a simple projection but decomposes the T^2 statistic well to the sum of the n variable components.

If abnormality detection data other than the Q statistic or Hotelling's T^2 statistic is used, the
15 contribution amount needs to be appropriately defined based on an idea similar to equation (7) or (8).

When the Mahalanobis distance used in quality engineering is used, the contribution amount can be defined using sensitivity analysis used in the Taguchi
20 method.

When applying a clustering method, abnormality detection data is defined as the distance from the center of the normal class, as described above. This allows to define the contribution component of each
25 process variable to the distance as a contribution amount. For example, abnormality detection data is defined as an Euclidean distance. Letting D be the

distance from the center of the normal class to the
diagnostic data, decomposition can be done by
 $D^2 = D_1^2 + D_2^2 + D_3^2 + \dots + D_n^2$, D_i^2 where $i = 1,$
2, ..., n is the distance of each component of the
5 diagnostic data, thereby defining D_i^2 as the
contribution amount.

Alternatively, after abnormality detection, ICA
(Independent Component Analysis) may be used to analyze
which data causes abnormality at high possibility so as
10 to enable to consequently extract some process
variables as abnormality factor candidates without
positively defining the contribution amount.

Independently of the method to be used, the
abnormality detection data contribution amount defining
15 unit 55 needs to have a mechanism capable of ranking
the process variables in descending order of
possibility to cause abnormality and outputting them
when abnormality detection data calculated in
accordance with the method defined by the abnormality
20 detection data defining unit 54 is input for certain
diagnostic data. Any method is usable as long as the
mechanism can be implemented.

The above-described function corresponds to
claim 4, which is an example of the function of the
25 abnormality detection data contribution amount defining
unit 55.

The abnormality countermeasure support information

defining unit 56 constructs rules to provide
information for abnormality countermeasure support
based on the information of process variables ranked in
descending order of possibility to cause abnormality,
5 which is supplied as the output of the abnormality
detection data contribution amount defining unit 55,
and information from the process variable correlation
defining unit 53.

First, top-ranked factor candidates are extracted
10 from the ranked abnormality factor candidate variables
in accordance with a predetermined rule. As the
simplest rule, several (for example, three) abnormality
factor candidates from the top are extracted as the
top-ranked abnormality factor candidates. However,
15 this simplest rule uses only the order information of
the abnormality factor candidates and does not consider
the degree of abnormality. For this reason, a rule to
extract candidate variables having high degrees of
abnormality is more preferable. For example, an
20 average value μ and standard deviation σ of the
contribution amounts are calculated. The rule is set
such that a variable whose distance from the average μ
exceeds $k\sigma$ (for example, $k = 3$) is extracted as an
abnormality factor candidate. At this time, μ and σ
25 can be either calculated for diagnostic target data at
the time of abnormality detection or calculated in
advance from contribution amount data for a

predetermined period. In the former case, some form of robust processing, such as trimmed averaging or trimmed variance, for performing calculation after discarding some data is preferably performed because abnormality
5 detection always involves abnormal data. The rules may be combined so as to select three variables at maximum as factor candidates from variables having high degrees of abnormality. At any rate, extracting several top-ranked abnormality factor candidates is the first
10 rule defined by the abnormality countermeasure support information defining unit 56.

Next, a rule is set to classify the extracted abnormality factor candidate variables into input variables, output variables, and intermediate variables
15 shown in FIG. 6. For example, when the definition that top-three variables are extracted by the first rule is employed, the three variables are classified into input variables, output variables, and intermediate variables by making them correspond to the table of FIG. 6. This
20 can easily be implemented by simply applying an abnormality factor candidate classification rule as shown in FIG. 7, letting FX be abnormality factor candidate variables (vectors), FU be an input variable (vector) out of them, FZ be an intermediate variable
25 (vector), and FY be an output variable (vector).

In this case, [] represents an empty vector, and [A B] represents a vector that connects a vector A and

a vector B.

As described above, the second rule classifies the abnormality factor candidate variables FX into the input variables FU, the output variables FY, and the intermediate variables FZ.

Next, a template to provide information for countermeasure support is created using the input variables FU, the output variables FY, and the intermediate variables FZ. This is the third rule.

The point is to have a mechanism for making the input variables FU, the output variables FY, and the intermediate variables FZ correspond to the correlation matrix in FIG. 6 to output a support message and, more particularly, to incorporate a support message to advise the operator of a countermeasure to take. For the operator, information representing an operation he/she should perform in an abnormal state and information representing the state the performance index of interest to the operator is in and in what manner the index may change are important. Hence, for example, an abnormality countermeasure support message generation rule template as shown in FIGS. 8 and 9 is created.

Points of the message template are simple classification of the process variables into the input variables, output variables, and intermediate variables without needing special knowledge about the target

plant and creation of the template solely by using the
table representing the presence/absence of the
relationship between the process variables. In
addition, the table representing the presence/absence
5 of the relationship between the process variables can
also automatically be generated from a correlation
matrix or a principal component loading matrix, as
described above. Hence, creating such a message
template allows to automatically provide countermeasure
10 support information in an abnormal state in accordance
with the template.

The above-described embodiment corresponds to
claim 7, which is an example of the function of the
abnormality countermeasure support information defining
15 unit 56.

Construction of the abnormality
monitoring/diagnostic/countermeasure support model by
the abnormality diagnostic model construction unit 5 is
thus completed in accordance with the above-described
20 procedure. Next, the abnormality
monitoring/diagnostic/countermeasure support unit 7
receives the abnormality
monitoring/diagnostic/countermeasure support model
constructed by the abnormality diagnostic model
25 construction unit 5, and performs abnormality
detection/factor variable estimation and provides
countermeasure support information.

First, the current (online) data extraction unit 71 extracts online data collected by the process measurement data collection/storage unit 2 for the diagnosis target time (to be referred to as a current time or current hereinafter). The abnormality monitoring/diagnostic/countermeasure support unit 7 monitors the process state using the current data extracted by the current (online) data extraction unit 71, and if the state has changed, or an abnormality sign has been recognized, detects it.

The abnormality detection unit 72 extracts data at the current time corresponding to the variables registered by the process variable registration unit 3, and appropriately normalizes the data using the average or variance of the variables. The abnormality detection unit 72 also removes outliers as needed. The data are substituted into $X(t)$ of the Q statistic and Hotelling's T^2 statistic defined by equations (3) and (4), thereby monitoring the Q statistic or Hotelling's T^2 statistic at the current time. The statistics change moment by moment as the time elapses and may therefore be monitored in a form like a time series graph (trend graph). If the Q statistic or Hotelling's T^2 statistic at the current time has exceeded the threshold defined by equation (5) or (6), it is determined that the process state has changed. This is an example of the function of the abnormality detection

unit 72.

When the abnormality detection unit 72 has detected an abnormality in the process, the abnormality factor variable separation unit 73 inputs the
5 abnormality detection data at that time, that is, the Q statistic and Hotelling's T^2 statistic of equations (3) and (4) at that time, thereby calculating the contribution amounts of equations (7) and (8). The process variables are ranked in descending order of the
10 contribution amount. This is an example of the function of the abnormality factor variable separation unit 73.

The function of the abnormality detection unit 72 and that of the abnormality factor variable separation unit 73 correspond to the function of MSPC using normal
15 PCA itself.

Next, the abnormality countermeasure support information providing unit 74 provides countermeasure support information in an abnormal state using the data
20 of the process variables ranked by the abnormality factor variable separation unit 73 and the countermeasure support message template in an abnormal state defined by the abnormality countermeasure support information defining unit 56.

25 To obtain a distinct image of implementation, a function of generating a message will be described with reference to FIG. 10 using a simple example. Referring

to FIG. 10, the process variable correlation diagram of FIG. 6 is simplified and used for ease of understanding.

5 Assume that an effluent TP, an air quantity, and a dissolved oxygen concentration DO are extracted as the top-ranked abnormality factor candidates FX. The effluent TP is classified as the output variable FY. The air quantity is classified as the input variable FU. The dissolved oxygen concentration DO is
10 classified as the intermediate variable FZ. In this case, a countermeasure support message as shown in FIG. 11 is generated using the countermeasure support message template in an abnormal state defined by the abnormality countermeasure support information defining
15 unit 56.

In this embodiment, the simplest case has been described in which the abnormality factor candidate variables FX are classified as one output variable FY, one intermediate variable FZ, and one input variable
20 FU, and all of them are associated with each other. In any other case as well, a support message is automatically provided to the user such as an operator via the user interface unit 9 in accordance with the countermeasure support message template in an abnormal
25 state defined by the abnormality countermeasure support information defining unit 56. The function of providing a message is the function of an embodiment of

the abnormality countermeasure support information providing unit 74. The function of the abnormality monitoring/diagnostic/countermeasure support unit 7 is thus completed.

5 The user to whom the abnormality countermeasure support information has been provided performs a certain operation based on the support information. In this case, it is preferable to store a countermeasure record such as a user operation record. This is the
10 function of the abnormality countermeasure record holding unit 8. For example, when the user adjusts the air quantity in accordance with the message, a record that the air quantity has been adjusted is automatically stored. In addition, fields that enable
15 the operator to input are provided on the user interface unit 9 so as to record the manner in which the air quantity has been adjusted, the level of improvement recognized for the effluent TP, and problems (side effects) caused by the air quantity
20 adjustment. The abnormality countermeasure record holding unit 8 more preferably has a function of recording the adjusted manipulated variable, the performance index for which the countermeasure has been taken, and the management item for which the
25 countermeasure has been taken and performing a search by the manipulated variable, the performance index, or the management item. More preferably, the abnormality

countermeasure record holding unit 8 has a function of searching for an operator record by a keyword. This is an example of the function of an embodiment of the abnormality countermeasure record holding unit 8.

5 When this function is imparted, the abnormality countermeasure support information providing unit 74 is preferably capable of performing an automatic search for this function and displaying a list of past records of a certain manipulated variable, performance index,
10 or management index. More preferably, the abnormality countermeasure support information providing unit 74 can present, for example, a list of past abnormality countermeasures for the effluent phosphorus concentration, a list of past abnormality
15 countermeasures in an abnormal state of air quantity, and a list of past abnormality countermeasures in an abnormal state of the dissolved oxygen concentration DO. This is an example of the function corresponding to claim 8. The function of the abnormality
20 monitoring/diagnostic/countermeasure support is thus completed.

 As described above, according to this embodiment, the process monitoring/diagnostic/support apparatus comprises the abnormality diagnostic model construction
25 unit 5 and the abnormality monitoring/diagnostic/countermeasure support unit 7. This allows to provide countermeasure support

information in an abnormal state regardless of the target process.

More specifically, in the conventional monitoring/diagnostic method, only abnormality sign
5 detection and factor variable separation can be performed. In addition, when providing countermeasure support information, an enormous amount of engineering is necessary. However, using the method of this embodiment makes it possible to not only perform
10 abnormality detection and factor variable separation but also provide countermeasure support information in an abnormal state almost mechanically without causing engineering.

That is, according to this embodiment, processing
15 of only defining process variables to be input to the diagnostic system and mechanically (i.e., automatically without intervening engineering) performing data processing from only plant monitor data collected by SCADA or the like without intervening engineering
20 except for classifying the process variables into input variables, output variables, and intermediate variables is performed. This allows to provide countermeasure support information to a user such as a plant operator or plant manager in an abnormal/unsteady state of a
25 process regardless of the target process.

In addition, providing the process variable classification user interface unit 4 that displays the

names of n process variables and selects input variables, output variables, and intermediate variables in the process variable classification unit 51 in accordance with a user operation during the display
5 allows the user to easily execute process variable classification on the GUI.

In addition, when an equation to generate abnormality detection data is defined using at least one of PCA (Principal Component Analysis), PLS
10 (Projection to Latent Structure/Partial Least Square), PCR (Principal Component Regression), CVA (Canonical Variate Analysis), Mahalanobis distance, robust PCA, kernel PCA, discriminant analysis, fuzzy C-means clustering, K-means clustering, SVM (Support Vector
15 Machine), RVM (Relevance Vector Machine), and the subspace method, the abnormality diagnostic model construction unit 54 can systematically provide the above-described effect of providing countermeasure support information in an unsteady state regardless of
20 the target process using the existing multivariate statistical analysis or machine learning technique. It is also possible to provide, to the operator or manager, detailed countermeasure support information representing a countermeasure to be taken in an
25 unsteady/abnormal state of a process based on MSPC, which is a statistical FDI method requiring no knowledge concerning the target process.

In addition, when [a] the contribution amount of the process variable k ($k = 1, 2, \dots, n$) of interest out of the n process variables is defined by projecting from abnormality detection data defined by the abnormality detection data defining unit 54 to a space spanned by the process variable k , [b] abnormality detection data is decomposed to the sum of n components, and the contribution amount is defined as the k th component affected only by the process variable k , or [c] the contribution amount is defined using independent component analysis, the abnormality detection data contribution amount defining unit 55 can further systematically provide the above-described effect of providing countermeasure support information in an unsteady state regardless of the target process.

When defining correlation information based on the correlation matrix or principal component loading matrix of the time series data of the n process variables for a predetermined period, the process variable correlation defining unit 53 can easily define the presence/absence or strength of the relationship between the process variables mechanically and systematically from data. Many of the methods such as multivariate statistical analysis of the abnormality detection data defining unit 54 perform an operation of creating a variance-covariance matrix or principal component loading matrix when creating abnormality

detection data. It is therefore possible to mechanically define the relationship between the process variables solely by slight correction at the time of diagnostic model construction.

5 The process variable correlation defining unit 53 has, as correlation information, a table in n rows $\times$ n columns representing the presence/absence or strength of the correlation between the n process variables. The process variable correlation defining interface
10 unit 6 can display the table of the correlation information and easily correct the contents of the table in accordance with a user operation. Examples of a case in which the contents of the table are to be corrected are a case in which the above-described
15 effect of the process monitoring/diagnostic/support apparatus constructed by data driven is not satisfactory for the user such as a plant manager or operator and a case in which the user wants to perform correction.

20 When the second to sixth rules are defined in the abnormality countermeasure support information defining unit 56, support information representing the manipulated variable to be confirmed and adjusted by the user in an abnormal state can be given as a more
25 detailed form of the above-described effect. In addition, information representing process monitor data readily affected by the manipulated variable (for

example, how a performance index such as a discharged water quality will change in the future) can be provided to the user.

When the abnormality countermeasure record holding unit 8 is provided, the plant operator/manager can refer to the countermeasures taken in past similar events upon being provided with support information and easily take a detailed countermeasure.

<Arrangement of Other Embodiments>

Each of FIGS. 12, 13, and 14 shows an example of a system arrangement that implements a monitoring system for a sewage complete treatment process 1 shown in FIG. 1 described in the first embodiment via a communication path, for example, a public line such as the Internet or a telephone network or a dedicated line. The communication path is wired or wireless, and is assumed to be mainly implemented by a wireless network in this example. The constituent elements of the arrangements according to the embodiments shown in FIGS. 12, 13, and 14 are almost the same as those of the arrangement shown in FIG. 1 except that the functions are divided via the communication path. Accordingly, each of the arrangements shown in FIGS. 13 and 14 further includes a remote-monitoring operation terminal 10.

In the arrangement shown in FIG. 12, collection of data measured by the sewage complete treatment process

1 and the operations of the manipulated variables by various kinds of actuators 111 to 115 of the sewage complete treatment process 1 are executed in the treatment plant. Other functions are executed via the communication path by a center apparatus 11 that exists in a place physically spaced apart.

That is, the arrangement shown in FIG. 12 further comprises the center apparatus 11 connected to a process measurement data collection/storage unit 2 via a wired or wireless communication path. Units 3, 4, 5, 6, 7, and 9 are implemented in the center apparatus 11. The center apparatus 11 collects, via the communication path, the time series data of n process variables stored in the process measurement data collection/storage unit 2, and presents the time series data to the user. When operating an input variable U in accordance with a user operation, the operation signal of the input variable U is transmitted to the sewage complete treatment process 1 via the communication path.

The arrangement shown in FIG. 13 includes a remote-monitoring operation terminal 10 that receives countermeasure support information in an abnormal state via a communication path and transmits a result of determination based on the information to a sewage complete treatment process 1 via the communication path again, unlike FIG. 12. A plurality of

remote-monitoring operation terminals 10 can exist. A plurality of plant managers or operators who operate and manage the sewage complete treatment process 1 can have the terminals.

5 That is, the arrangement shown in FIG. 13 further comprises the remote-monitoring operation terminal 10 connected to an abnormality countermeasure support information providing unit 74 and the sewage complete treatment process 1 via a wired or wireless
10 communication path. The monitoring operation terminal 10 presents, to the user, countermeasure support information provided from the abnormality countermeasure support information providing unit 74 via the communication path. When operating an input
15 variable U in accordance with a user operation, the operation signal of the input variable U is transmitted to the sewage complete treatment process 1 via the communication path.

 The arrangement shown in FIG. 14 is a
20 sophisticated combination of the arrangements shown in FIGS. 12 and 13. In a sewage complete treatment process 1, data collection and manipulated variable operations are done. A center apparatus 11 performs diagnosis via the communication path. The center
25 apparatus 11 performs diagnosis for a plurality of treatment processes. The arrangement shown in FIG. 14 further comprises a remote-monitoring operation

terminal 10 so that countermeasure support information diagnosed by the center apparatus 11 can be transmitted to the remote-monitoring operation terminal 10 via the communication path, and an operation command for a treatment process can be sent from the remote-monitoring operation terminal 10 via the communication path again.

That is, in the arrangement shown in FIG. 14, when there are w ($w = 1, 2, \dots, w$) sewage complete treatment processes 1, w process measurement data collection/storage units 2 are provided. The w process measurement data collection/storage units 2 are individually arranged in the w sewage complete treatment processes 1. The arrangement further comprises the center apparatus 11 connected to each process measurement data collection/storage unit 2 via a wired or wireless communication path, and w or more remote-monitoring operation terminals 10 individually connected to an abnormality countermeasure support information providing unit 74 and each sewage complete treatment process 1 via a wired or wireless communication path. The center apparatus 11 collects, via the communication path, the time series data of n process variables stored in each process measurement data collection/storage unit 2 and presents the time series data to a first user (the user of the center apparatus 11). When operating an input variable U in

accordance with the operation of the first user, the center apparatus 11 transmits the operation signal of an input variable U to the sewage complete treatment process 1 via the communication path. Each
5 remote-monitoring operation terminal 10 presents, to a second user (the user of the remote-monitoring operation terminal 10), countermeasure support information provided from the abnormality countermeasure support information providing unit
10 74 via the communication path. When operating the input variable U in accordance with the operation of the second user, each remote-monitoring operation terminal 10 transmits the operation signal of the input variable U to the sewage complete treatment process
15 1 via the communication path.

The functions of the other embodiments having the above-described arrangements will be described next.

Note that the basic functions of the other embodiments are the same as those of the first
20 embodiment, and different portions will mainly be explained.

The function of the embodiment having the arrangement shown in FIG. 12 will be described first. In the center apparatus 11, the process variable
25 registration unit 3 registers process variables necessary for constructing an abnormality diagnostic model, and the registration information is sent to the

treatment plant. In the treatment plant, the information of the registered process variables is held so as to be referred to as needed. A past (offline) data extraction unit 52 of the abnormality diagnostic model construction unit 5 and a current (online) data extraction unit 71 of the abnormality monitoring/diagnostic/countermeasure support unit 7 are provided while accompanying the process measurement data collection/storage unit 2 on the side of the sewage complete treatment process 1.

An abnormality diagnostic model is constructed next. The time series data of registered variables for a predetermined period extracted by the past (offline) data extraction unit 52 is transmitted to the center apparatus 11 via the communication path. The center apparatus 11 constructs the abnormality diagnostic model in accordance with the procedure indicated by the function of the first embodiment.

The abnormality monitoring/diagnostic/countermeasure support unit 7 performs diagnosis at a diagnostic time (to be referred to as "current" hereinafter). First, the current (online) data extraction unit 71 in the treatment plant extracts the current data of the registered variables. The data are sent to the center apparatus 11 via the communication path. The center apparatus 11 performs abnormality detection, factor separation, and support

information generation in accordance with the procedure indicated by the function of the first embodiment. The generated information is presented to the user such as the operator via the user interface unit 9.

5 The operator confirms the performance index or control value of the target process based on the countermeasure support information. If a manipulated variable needs to be changed, the operator determines the manipulated variable change command and sends the
10 information to the sewage complete treatment process via the communication path.

 In the sewage complete treatment process 1, the manipulated variables are changed automatically or manually based on the received command information. If
15 the treatment plant is unattended, the manipulated variables are changed automatically. For a manned treatment plant, after the operator in the treatment plant confirms the command information, the manipulated variables are changed manually or automatically.

20 Note that the center apparatus 11 is assumed to be a computer arranged in a monitoring room installed in a place physically spaced apart from the treatment plant. However, the center apparatus 11 may be a mobile terminal such as a cellular phone or a portable PC as
25 long as it has the functions of the units 3 to 7 and 9.

 This is the function of the embodiment having the arrangement shown in FIG. 12.

The function of the embodiment having the arrangement shown in FIG. 13 will be described next.

First, in the treatment plant with the sewage complete treatment process 1, an abnormality diagnostic
5 model is constructed in accordance with the procedure indicated by the function of the first embodiment. Next, abnormality detection, factor separation, and support information generation are performed similarly in the treatment plant with the sewage complete
10 treatment process in accordance with the procedure indicated by the function of the first embodiment. Up to this point, the function is the same as that of the first embodiment.

Then, only the generated countermeasure support
15 information is transmitted to the remote-monitoring operation terminal 10 held by the plant operator or manager via the communication path. At this time, each of a plurality of operators or managers may have the remote-monitoring operation terminal 10. In this case,
20 the countermeasure support information is provided to the remote-monitoring operation terminals 10 by broadcast.

The remote-monitoring operation terminal 10 presents the received countermeasure support
25 information to the operator or plant manager. The operator or plant manager determines the presence/absence of necessity of a manipulated variable

change based on the countermeasure support information.
If a change is necessary, the operator or plant manager
determines the manipulated variable change command and
operates the remote-monitoring operation terminal 10.

5 The remote-monitoring operation terminal 10 transmits
the change command information to the sewage complete
treatment process 1 via the communication path in
accordance with the operation of the operator or plant
manager. If a plurality of persons hold the
10 remote-monitoring operation terminals 10, priority
orders for the manipulated variable command are
preferably set to define a terminal whose command is
preferentially executed. In this method, since only
the countermeasure support information is received, the
15 performance index or control value of the target
process cannot be confirmed. For this reason, the
method preferably has a function of causing the
operator to request the treatment plant to transmit a
performance index or control value to be confirmed via
20 the remote-monitoring operation terminal 10 only upon
receiving countermeasure support information.

Finally, in the sewage complete treatment process
1, the manipulated variables are changed automatically
or manually based on the received command information.
25 If the treatment plant is unattended, the manipulated
variables are changed automatically. For a manned
treatment plant, after the operator in the treatment

plant confirms the command information, the manipulated variables are changed manually or automatically.

Note that in this embodiment, the remote-monitoring operation terminal 10 is mainly assumed to be a mobile terminal such as a cellular phone or a portable PC. However, the remote-monitoring operation terminal 10 may be a fixed terminal existing in a center such as a monitoring room that has the above-described mechanism and exists in a place physically spaced apart. The substantial difference between the embodiment shown in FIG. 13 and that shown in FIG. 12 is in the manner the functions are allocated.

This is the function of the embodiment having the arrangement shown in FIG. 13.

The function of the embodiment having the arrangement shown in FIG. 14 will be described next.

In the center apparatus 11, a process variable registration unit 3 registers process variables necessary for constructing an abnormality diagnostic model, and the registration information is sent to the treatment plant. There exist a plurality of treatment plants, unlike the embodiment shown in FIG. 12. The center apparatus 11 monitors the plurality of treatment plants from the remote site in a collective manner. Hence, the process variables are registered as many times as the number of treatment plants. At this time,

the process variables may be defined for each treatment plant, and common process variables may be registered. In each treatment plant, the information of the registered process variables is held so as to be referred to as needed. A past (offline) data extraction unit 52 of an abnormality diagnostic model construction unit 5 and a current (online) data extraction unit 71 of an abnormality monitoring/diagnostic/countermeasure support unit 7 are provided while accompanying a process measurement data collection/storage unit 2 on the side of the sewage complete treatment process 1.

An abnormality diagnostic model is constructed next. The time series data of registered variables for a predetermined period extracted by the past (offline) data extraction unit 52 is transmitted from each treatment plant to the center apparatus 11 via the communication path. The center apparatus 11 constructs the abnormality diagnostic model for each treatment plant in accordance with the procedure indicated by the function of the first embodiment.

The abnormality monitoring/diagnostic/countermeasure support unit 7 performs diagnosis at a diagnostic time (to be referred to as "current" hereinafter). First, the current (online) data extraction unit 71 in each treatment plant extracts the current data of the registered

variables. The data are sent to the center apparatus
11 via the communication path. The center apparatus 11
performs abnormality detection, factor separation, and
support information generation in accordance with the
5 procedure indicated by the function of the first
embodiment. At this time, the abnormality diagnostic
model to be referred to needs to be switched between
the treatment plants. The detection, diagnostic, and
countermeasure support operations can be implemented as
10 one algorithm, except for diagnostic model switching.

When countermeasure support information is
generated, the generated information is presented to
the user such as the operator via a user interface unit
9. At this time, an operator or manager who is in a
15 place other than the monitoring room where the center
apparatus 11 is arranged may have the remote-monitoring
operation terminal 10. In this case, the
countermeasure support information is also transmitted
to the plant operator or manager having the
20 remote-monitoring operation terminal 10 via the
communication path. Each of a plurality of operators
or managers may have the remote-monitoring operation
terminal 10. In this case, the countermeasure support
information is provided to the remote-monitoring
25 operation terminals 10 by broadcast.

The operator confirms the performance index or
control value of the target process based on the

countermeasure support information presented by the remote-monitoring operation terminal 10. At the same time, if the manipulated variables need to be changed, the operator determines the manipulated variable change command and operates the remote-monitoring operation terminal 10. The remote-monitoring operation terminal 10 transmits the change command information to the sewage complete treatment process 1 via the communication path in accordance with the operation of the operator. If there is an operator or manager who holds the remote-monitoring operation terminal 10, priority orders for the manipulated variable command are preferably set to define one of the center apparatus 11 and the remote-monitoring operation terminal 10, whose command is preferentially executed. If a plurality of persons hold the remote-monitoring operation terminals 10, priority orders for the manipulated variable command are preferably set to define a terminal whose command is preferentially executed.

Finally, in the sewage complete treatment process 1, the manipulated variables are changed automatically or manually based on the received command information. If the treatment plant is unattended, the manipulated variables are changed automatically. For a manned treatment plant, after the operator in the treatment plant confirms the command information, the manipulated

variables are changed manually or automatically.

This is the function of the embodiment having the arrangement shown in FIG. 14.

5 The effects of the embodiments having the arrangement shown in FIGS. 12, 13, and 14 are as follows.

10 According to the arrangement shown in FIG. 12, the same effects as in the first embodiments can be obtained even when the sewage treatment plant and the plant operator or plant manager who operates and manages the sewage treatment plant exist in places physically spaced apart from each other.

15 According to the arrangement shown in FIG. 13, since it is oriented to reduce the calculation load on the center side in the mechanism of FIG. 12, even a simple portable terminal which cannot handle a heavy calculation load can communicate information in an abnormal state, which is critical in process monitoring, and execute a countermeasure against it from a remote site, in addition to the effects of the first embodiment. Since the communication path is used only in an abnormal state, the load on the communication path can also be reduced simultaneously. This contributes to avoiding traffic congestion on the communication path. Additionally, even in the case of 25 traffic congestion, communication of important information (information in an abnormal state) can

easily be ensured.

More specifically, according to the arrangement shown in FIG. 13, even when the plant operator or plant manager is physically spaced apart from the target plant, and traffic congestion on the communication path is expected, an important abnormality that has occurred in the target process can be detected, and a countermeasure against it can be taken (however, monitoring the time series data of all process variables under measurement is abandoned as a result).

According to the arrangement shown in FIG. 14, since it is oriented to further divide the functions of the arrangements in FIGS. 12 and 13 and monitor a plurality of treatment plants in a collective manner, the functions and effects of the first embodiment can be provided as a remote service (cloud service).

That is, according to the arrangement shown in FIG. 14, the center apparatus 11 arranged in one or a few monitoring rooms can execute monitoring/diagnosis/support of plants in a plurality of places, and the effects of the first embodiment can be implemented as a cloud service. Even when the plant operator or plant manager is physically spaced apart from the target plant, and monitoring/diagnosis/support of the plants can be performed.

According to at least one of the above-described embodiments, the process monitoring/diagnostic/support

apparatus comprises the abnormality diagnostic model
construction unit 5 and the abnormality
monitoring/diagnostic/countermeasure support unit 7.
This allows to provide countermeasure support
5 information in an abnormal state regardless of a target
process.

While certain embodiments have been described,
these embodiments have been presented by way of example
only, and are not intended to limit the scope of the
10 inventions. Indeed, the novel embodiments described
herein may be embodied in a variety of other forms;
furthermore, various omissions, substitutions and
changes in the form of the embodiments described herein
may be made without departing from the spirit of the
15 inventions. The accompanying claims and their
equivalents are intended to cover such forms or
modifications as would fall within the scope and spirit
of the inventions.

WHAT IS CLAIMED IS:

1. A process monitoring/diagnostic/support apparatus comprising:

5 data collection/storage means for collecting time series data of n ($n \geq 2$) process variables representing measurement results from n sensors for measuring a quantity of state or a manipulated variable of a target process and storing the time series data;

10 process variable classification means for storing classification information representing a result of classifying the n process variables into p ($1 \leq p < n$) output variables Y that are the quantities of states and represent performance indices, L ($1 \leq L < n$) input variables U representing the manipulated variables, and
15 m ($0 \leq m < n$) intermediate variables Z that are the quantities of states and represent control/monitor values;

process variable correlation defining means for defining, from the classification information and the
20 time series data of the n process variables for a predetermined period, correlation information representing correlation between the n process variables including the classification result;

25 abnormality detection data defining means for defining an equation to generate q ($1 \leq q < n$) abnormality detection data less than n and a determination criterion to determine one of

presence/absence and a strength of an abnormality based on the abnormality detection data from the time series data of the n process variables for the predetermined period;

5 abnormality detection data contribution amount
defining means for defining a contribution amount of each piece of the time series data of the n process variables to the abnormality detection data;

 abnormality countermeasure support information
10 defining means for defining a first rule to extract a predetermined number of top-ranked abnormality factor candidate variables out of abnormality factor candidate variables that are process variables as abnormality factor candidates in an abnormal state, a second rule
15 to classify the extracted abnormality factor candidate variables into the output variables Y, the input variables U, and the intermediate variables Z based on correlation information, and a third rule to provide countermeasure support information including a message
20 to support a countermeasure in the abnormal state based on the classification result;

 abnormality detection means for generating the abnormality detection data corresponding to the time series data at a predetermined time in accordance with
25 the stored time series data of the n process variables at the predetermined time and a definition of the abnormality detection data defining means and

diagnosing the presence/absence of an abnormality in the data at the predetermined time based on the abnormality detection data;

5 abnormality factor variable separation means for, when an abnormality exists as a result of the diagnosis, calculating the contribution amount of the time series data at the predetermined time based on a definition of the contribution amount and separating and extracting the abnormality factor candidate
10 variables from the time series data at the predetermined time based on the calculated contribution amount and the first rule; and

abnormality countermeasure support information providing means for providing the countermeasure
15 support information based on the separated and extracted abnormality factor candidate variables, the correlation information, the second rule, and the third rule.

2. The apparatus according to claim 1, further
20 comprising process variable classification user interface means for displaying names of the n process variables and selecting the input variables, the output variables, and the intermediate variables in the process variable classification means in accordance
25 with a user operation during display.

3. The apparatus according to claim 1, wherein the abnormality detection data defining means defines

the equation to generate the abnormality detection data using at least one of a principal component analysis (PCA), a projection to latent structure/partial least Square (PLS), a principal component regression (PCR), a canonical variate analysis (CVA), a mahalanobis distance, a robust PCA, a kernel PCA, a discriminant analysis, a fuzzy C-means clustering, a K-means clustering, a support vector machine (SVM), a relevance vector machine (RVM), and a subspace method.

5 4. The apparatus according to claim 3, wherein the abnormality detection data contribution amount defining means defines the contribution amount of a process variable k ($k = 1, 2, \dots, n$) of interest out of the n process variables by one of [a] projecting from
10 the abnormality detection data defined by the abnormality detection data defining means to a space spanned by the process variable k , [b] decomposing the abnormality detection data to a sum of n components so as to define the contribution amount as a k th component
15 affected only by the process variable k , and [c] using independent component analysis.
20

 5. The apparatus according to claim 1, wherein the process variable correlation defining means defines the correlation information based on one of a
25 correlation matrix and a principal component loading matrix of the time series data of the n process variables for the predetermined period.

6. The apparatus according to claim 1, wherein
the process variable correlation defining means has, as
the correlation information, a table in n rows $\times$ n
columns representing one of the presence/absence and
5 the strength of correlation between the n process
variables, and

the apparatus further comprises a process variable
correlation defining interface means for displaying the
table and correcting contents of the table in
10 accordance with the user operation.

7. The apparatus according to claim 1, wherein
the second rule includes a rule to classify the
extracted abnormality factor candidate variables into
input factor variables FU belonging to the input
15 variables U, output factor variables FY belonging to
the output variables Y, and intermediate factor
variables FZ belonging to the intermediate variables Z
based on the classification information, and

the third rule includes
20 a fourth rule A to, when the abnormality factor
candidate variables include the output factor variable
FY, notify that the output factor variable FY has
deteriorated and provide the countermeasure support
information including a message for prompting to
25 confirm and revise a value of the input variable U
defined by the correlation information to be correlated
with the output factor variable FY,

a fifth rule B to, when the abnormality factor candidate variables include not the output factor variable FY but the input factor variable FU, notify that the input factor variable FU deviates from a normal state to the abnormal state and provide the countermeasure support information including a message for prompting to revise a manipulated variable represented by the input factor variable FU and notifying that the output variable Y defined by the correlation information to be correlated with the input factor variable FU has a possibility of deterioration in the future, and

a sixth rule C to, when the abnormality factor candidate variables include only the intermediate factor variables FZ, provide the countermeasure support information including a message for notifying that the intermediate factor variables FZ have deteriorated, and the output variables Y defined by the correlation information to be correlated with the intermediate factor variables FZ have a possibility of deterioration in the future.

8. The apparatus according to claim 1, further comprising abnormality countermeasure record holding means for recording an operation performed by the user after the countermeasure support information provided by the abnormality countermeasure support information providing means has been presented,

when the countermeasure support information is provided, the abnormality countermeasure record holding means presenting the countermeasure support information and values of the input variables U, values of the
5 output variables Y, and values of the intermediate variables Z before a current time based on the time series data and the classification information, and

after the countermeasure support information has been presented, the abnormality countermeasure record
10 holding means continuously recording operation records of the input variables U as the operation performed by the user, the values of the output variables Y, and the values of the intermediate variables Z.

9. The apparatus according to claim 1, further
15 comprising a center apparatus connected to the data collection/storage means via a wired or wireless communication path,

wherein the process variable classification means, the process variable correlation defining means, the
20 abnormality detection data defining means, the abnormality detection data contribution amount defining means, the abnormality detection data contribution amount defining means, the abnormality detection means, the abnormality factor variable separation means, and
25 the abnormality countermeasure support information providing means are implemented in the center apparatus, and

the center apparatus collects, via the communication path, the time series data of the n process variables stored in the data collection/storage means and presents the time series data to the user,
5 and when operating the input variable U in accordance with the user operation, transmits an operation signal of the input variable U to the target process via the communication path.

10. The apparatus according to claim 1, further comprising a monitoring operation terminal connected to the abnormality countermeasure support information providing means and the target process via a wired or wireless communication path,

the monitoring operation terminal presenting, to
15 the user, the countermeasure support information provided from the abnormality countermeasure support information providing means via the communication path and, when operating the input variable U in accordance with the user operation, transmitting an operation
20 signal of the input variable U to the target process via the communication path.

11. The apparatus according to claim 1, wherein when there are w ($w = 1, 2, \dots, w$) target processes, w data collection/storage means are provided
25 and individually arranged in the w target processes, the apparatus further comprises:
a center apparatus connected to the data

collection/storage means via a wired or wireless communication path; and

not less than w monitoring operation terminals individually connected to the abnormality countermeasure support information providing means and the target processes via a wired or wireless communication path,

the center apparatus collects, via the communication path, the time series data of the n process variables stored in each data collection/storage means and presents the time series data to a first user, and when operating the input variable U in accordance with an operation of the first user, transmits an operation signal of the input variable U to the target processes via the communication path, and

each of the monitoring operation terminals presents, to a second user, the countermeasure support information provided from the abnormality countermeasure support information providing means via the communication path and, when operating the input variable U in accordance with an operation of the second user, transmits the operation signal of the input variable U to the target processes via the communication path.

12. A computer-readable storage medium storing a program to be executed by a processor of a process

monitoring/diagnostic/support apparatus including a memory, comprising:

5 a first program code that causes the processor to execute processing of collecting time series data of n ($n \geq 2$) process variables representing measurement results from n sensors for measuring a quantity of state or a manipulated variable of a target process and storing the time series data in the memory;

10 a second program code that causes the processor to execute processing of storing classification information representing a result of classifying the n process variables into p ($1 \leq p < n$) output variables Y that are the quantities of states and represent performance indices, L ($1 \leq L < n$) input variables U representing the manipulated variables, and m ($0 \leq m < n$) intermediate variables Z that are the quantities of states and represent control/monitor values;

20 a third program code that causes the processor to execute processing of defining, from the classification information and the time series data of the n process variables for a predetermined period, correlation information representing correlation between the n process variables including the classification result;

25 a fourth program code that causes the processor to execute abnormality detection data defining processing of defining an equation to generate q ($1 \leq q \ll n$)

abnormality detection data less than n and a determination criterion to determine one of presence/absence and a strength of an abnormality based on the abnormality detection data from the time series data of the n process variables for the predetermined period;

5 a fifth program code that causes the processor to execute processing of defining a contribution amount of each piece of the time series data of the n process variables to the abnormality detection data;

10 a sixth program code that causes the processor to execute processing of defining a first rule to extract a predetermined number of top-ranked abnormality factor candidate variables out of abnormality factor candidate variables that are process variables as abnormality factor candidates in an abnormal state, a second rule to classify the extracted abnormality factor candidate variables into the output variables Y, the input variables U, and the intermediate variables Z based on correlation information, and a third rule to provide countermeasure support information including a message to support a countermeasure in the abnormal state based on the classification result;

20 a seventh program code that causes the processor to execute processing of generating the abnormality detection data corresponding to the time series data at a predetermined time in accordance with the stored time

series data of the n process variables at the
predetermined time and a definition of the abnormality
detection data defining means and diagnosing the
presence/absence of an abnormality in the data at the
5 predetermined time based on the abnormality detection
data;

an eighth program code that causes the processor
to execute processing of, when an abnormality exists as
a result of the diagnosis, calculating the contribution
10 amount of the time series data at the predetermined
time based on a definition of the contribution amount
and separating and extracting the abnormality factor
candidate variables from the time series data at the
predetermined time based on the calculated contribution
15 amount and the first rule; and

a ninth program code that causes the processor to
execute processing of providing the countermeasure
support information based on the separated and
extracted abnormality factor candidate variables, the
20 correlation information, the second rule, and the third
rule.

ABSTRACT (FIG. 1)

"PROCESS MONITORING/DIAGNOSTIC/SUPPORT APPARATUS"

According to one embodiment, the abnormality
detection means generates the abnormality detection
5 data corresponding to the time series data at a
predetermined time and diagnose the presence/absence of
an abnormality in the data at the predetermined time.
The abnormality factor variable separation means
separates and extracts the abnormality factor candidate
10 variables from the time series data at the
predetermined time. The abnormality countermeasure
support information providing means provides the
countermeasure support information based on the
separated and extracted abnormality factor candidate
15 variables, the correlation information, the second
rule, and the third rule.