

(57) **Abrégé(suite)/Abstract(continued):**

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ABSTRACT OF THE DISCLOSURE

The present invention provides a system and method for monitoring the integrity of a furnace containing molten material and giving a prior warning of a potential breakout or process equipment condition using multivariate statistical tools. Multiple multivariate models are used in combination to provide status of the process and deal with long term process drift. The various model results are then used in conjunction to arrive at a conclusion, which indicates the furnace integrity. In the case of an extreme value of a monitored variable, the system allows for automatic halting of the process in order to prevent a catastrophic failure of furnace integrity.

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TITLE OF THE INVENTION

SYSTEM AND METHOD FOR FURNACE MONITORING AND CONTROL

5 FIELD OF THE INVENTION

The present invention relates to a system and method for the monitoring and control of a furnace. In particular, the present invention relates to a system and method for the monitoring and predictive control of a furnace containing molten
10 metal based on a multivariate statistical control model for predicting changes in furnace integrity.

BACKGROUND OF THE INVENTION

15 The safe and efficient operation of a furnace holding molten material must include a suitable control system to detect and act on any changes in the integrity of the furnace. These furnaces have a refractory lining that can be breached by the molten material they contain, causing a run-out of molten material which can damage equipment, injure workers and cause loss of
20 production.

Typical instrumentation for monitoring such a furnace includes measuring the temperature at various locations in the furnace walls, hearth and roof and at various depths within the lining. Additionally, temperature measurements can
25 be embedded in the refractory lining or lining cooling elements. In general, temperatures are measured using thermocouples which sense temperature as a result of a voltage generated between the joined end of two dissimilar metal wires and the open end when the temperature at the joined end, the "hot" junction, is different from the temperature at the open end, the "cold" junction.

30 The voltage is proportional to the difference in temperature. Voltage from a plurality of thermocouples can be readily sampled and provided to an online control system for further processing.

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Existing technology for integrity and condition monitoring of these furnaces entails triggering alarms based on high limits on temperature measurements within the furnace lining. The usefulness of this approach is limited by the need to set the sensitivity of the alarms high enough to detect true threats to the integrity of the furnace lining and the need to reduce the sensitivity of the alarms to avoid numerous false alarms. In an industrial application, alarm points must be set high enough to allow for normal fluctuations in furnace operating temperatures. Batch mode furnaces have lining temperatures fluctuating significantly from the start to the end of a heat which necessitates insensitive alarms of the standard type. In a continuous process mode furnace, lining temperature changes rapidly on re-start following a period of prolonged idleness or if the throughput or processing intensity of the furnace is increased which also necessitates insensitive standard type alarms. The need to set alarm points high enough to avoid triggering false alarms from normal operating fluctuations can frequently result in non-detection of true high risk conditions.

Therefore there is a need to provide a furnace temperature control system which is insensitive enough to avoid triggering false alarms while at the same sensitive enough to detect all true high risk conditions.

Current methods of fault detection and diagnosis in processes are typically grouped into one of three main classes: methods based on a mechanistic model, methods based on knowledge of the process and methods based on data analysis. Since obtaining empirical data from sensors positioned throughout the process is relatively easy there is an increasing interest in methods of the third class, i.e. those based on data analysis. However, as most modern processes are data abundant, control of the process via the flow of empirical data in its raw format is exceedingly difficult given the overwhelming size of the databases and because of the generally ill conditioned nature of the data being collected. On the other hand, all these variables are not independent of one another. In fact, in a large industrial process typically only a

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few underlying events are driving a process at any time, and all these measurements are simply different reflections of these same underlying events. Therefore, examining them one variable at a time as though they were independent, makes interpretation and diagnosis extremely difficult. Such
5 methods only look at the magnitude of the deviation in each variable independently of all others.

There is therefore a need for an online furnace monitoring and diagnosis system which examines a large number of temperature readings
10 simultaneously in order to extract information on the directionality of the process variations, that is on how all the temperature variables are behaving relative to one another. Furthermore, as important events occur in the furnace which are difficult to detect because the signal to noise ratio in each variable is very low, there is also needed a furnace control system which can detect
15 variations in the furnace in the presence of a high signal to noise ratio and/or reduce the noise levels. Finally, due to sensor failure and the like there is also often significant amounts of missing data and therefore there is a need for a furnace control system which can continue to operate in the absence of at least a portion of data related to the current status of the furnace.

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SUMMARY OF THE INVENTION

There is disclosed a method for monitoring the integrity of a furnace containing molten metal. The method comprises the steps of deriving a model of normal
25 operation of the furnace from a plurality of furnace variables, periodically measuring current values of the plurality of furnace variables, analysing the current values, the analysing step resulting in a representation of current operation, comparing the representation of current operation with the model of normal operation, and generating an alarm when the representation of current
30 operation deviates from the model of normal operation by a predetermined amount.

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There is also disclosed a system for monitoring the integrity of a furnace, the furnace comprising a refractory lining and containing molten metal. The system comprises a plurality of thermocouples for periodically measuring a current temperature of the refractory lining, a model of normal operation of the furnace, a means for analysing the current temperatures, the analysing means generating a model of current operation, and a means for comparing the model of current operation with the model of normal operation. The comparing means generates an alarm when the model of current operation deviates from the model of normal operation by a predetermined amount.

Other objects, advantages and features of the present invention will become more apparent upon reading of the following non-restrictive description of specific embodiments thereof, given by way of example only with reference to the accompanying drawings.

BRIEF DESCRIPTION OF THE DRAWINGS

In the appended drawings:

Figure 1 is a perspective view of a Mitsubishi continuous copper converting furnace according to an illustrative embodiment of the present invention;

Figure 2a is cut-away side view of a converting furnace hearth according to an illustrative embodiment of the present invention;

Figure 2b is a detailed view of the hearth in Figure 2a;

Figure 3a is a top view of a cooling block according to an illustrative embodiment of the present invention;

Figure 3b is a side view of a cooling block according to an illustrative embodiment of the present invention;

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Figure 3c is a cut-away view along 3c-3c in Figure 3b;

5 Figure 3d is a cut-away view along 3d-3d in Figure 3a of a cooling block according to an illustrative embodiment of the present invention;

Figure 4 is a top view of a converting furnace hearth according to an illustrative embodiment of the present invention;

10 Figure 5 is a schematic diagram of a cooling system for cooling a converting furnace according to an illustrative embodiment of the present invention; and

15 Figure 6 is a schematic diagram of a data acquisition and monitoring system, system for a converting furnace according to an illustrative embodiment of the present invention.

DETAILED DESCRIPTION OF THE ILLUSTRATIVE EMBODIMENTS

20 The present invention is a method for indicating an abnormal operation of a high temperature furnace containing molten material and a system for predicting changes in the integrity of a high temperature furnace containing molten material. Predicted changes can include potential breach of the furnace's refractory lining, changes in the condition of the furnace wall, build up and/or process equipment failure.

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The interpretation of the furnace measurements, including but not limited to furnace lining temperatures, using multivariate analysis greatly increases the sensitivity in detecting upset conditions without triggering alarms due to normal process variations. Additional measurements can be added to improve
30 performance such as feed rates, including gas flow rates and solid addition rates, temperatures in the freeboard and molten phases of the furnace, product withdrawal rates, including waste gases and molten products and compositions

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of all feed and product materials. Additional variables relevant to monitoring can be calculated from these measurements and added to the analysis such as heat fluxes and estimated thickness of the lining.

- 5 Multivariate monitoring uses a model to produce a small number of variables that summarise the state of the process. The state of the process is contained in a larger set of variables that are input to the model. The model is calibrated on a training set of historical data taken from a time when the process operation is deemed normal. The model is then applied to new data and
- 10 variables are produced that are monitored to indicate whether the state of the process has changed. The advantages of multivariate monitoring over monitoring all of the individual variables in the input to the model include a reduction in the number of variables monitored, increased sensitivity to faults that are indicated by changes in the relationships between variables and a
- 15 reduction in false alarms.

When the number of measured variables is large, it is often found that the variables are highly correlated with one another and with a covariance matrix which is nearly singular. Approaches to reducing the dimensionality of the

20 variable space in such cases include Principal Components Analysis (PCA) and Partial Least Squares (PLS). PCA is used throughout the present illustrative embodiment as a basis for developing the models, although it should be understood that PLS is also applicable.

- 25 PCA is concerned with explaining the variance-covariance structure of a set of variables through a few linear combinations of these variables. Its general objectives are data reduction and interpretation. Additionally, an analysis of principal components often reveals relationships that were not previously suspected and thereby allows interpretation that would not ordinarily result.

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PCA can reduce the dimensionality of large numbers of highly correlated process measurements by projecting the information of original measurement

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spaces into low dimensional spaces defined by a handful of latent variables. Given a sample of measurements with n observations on k variables y , The first principal component of y is defined as that linear combination $t_1 = p_1^T y$ that has maximum variance subject to $|p_1| = 1$. The second principal component is

5 that linear combination defined by $t_2 = p_2^T y$ which has next greatest variance subject to $|p_2| = 1$, and subject to the condition that it be uncorrelated with (orthogonal to) the first principal component (t_1). Additional principal components up to k are similarly defined. In effect, PCA decomposes the observation matrix Y as:

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$$Y = TP^T = \sum_{i=1}^k t_i p_i^T \quad (1)$$

with the property that $t_i^T t_j = 0, (i \neq j)$ and $p_i^T p_j = 0, (i \neq j)$.

15 PCA is scale dependent, and so the Y matrix must be scaled in some meaningful way. In practice, it is rarely needed to compute all the k principal components, since most of the variability in the data is typically captured in the first few principle components. Stated differently, although k components are required to reproduce the total system variability, often much of this variability

20 can be accounted for by a small number m of the principal components. If so, there is almost as much information in the m components as there is in the original k variables. The m principal components can then replace the k variables, and the original data set, consisting of n measurements of k variables, is reduced to a data set consisting of n measurements on m principal

25 components. By abandoning the components which have little influence, the data matrix Y can be rewritten as the sum of an estimation value $\hat{Y}$ and residual E :

$$Y = \hat{Y} + E, \text{ where } \hat{Y} = \sum_{j=1}^m t_j p_j^T \quad (2)$$

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The number m of principal components that are required to provide an adequate description of the data can be assessed using a variety of methods. A first group of methods are very much ad hoc rules of thumb, the use of which are justified mainly on the grounds that they are intuitively plausible and that they work in practice. Others select a cumulative percentage point of the total variation that the selected principal components contribute, say 80% or 90%. The required number of principal components is then the smallest value of m for which the chosen percentage threshold is reached. Finally others, such as the Predicted Residual Sums of Squares (PRESS) statistic, are computationally intensive and use cross-validation. It is this final set of methods which are exploited in the present illustrative embodiment to determine the number of principle components necessary to adequately describe the data.

Generally, the PRESS statistic m of the number of principal components is determined for a data matrix Y by increasing the number of principal components successively until overall prediction of the y_{ij} th element is not significantly improved. The y_{ij} th element is predicted based on a submatrix of Y that does not include the y_{ij} th element.

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PCA models are created by "training" the model over a historical set of data. By establishing a PCA model based on historical data collected when only common cause variation is present, future behaviour can be referenced against this model (generally referred to as an "in control" model). Therefore, the PCA model is built based on historical databases of data collected from periods of operation when performance was good. Any periods containing variations arising from special events that are wished to be detected in the future are omitted at this stage. The choice of the reference set is critical to the successful application of the procedure. When the data are serially autocorrelated the X and Y matrices can be augmented with time-lagged values, in order to account for the dynamics of the process and the disturbances. Dead times between variables are accounted for by time shifting.

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Development of a Model

5 The development of a model of the present illustrative embodiment is primarily an exercise in data mining, i.e. the analysis of a large observational data set to determine relationships between variables and to summarise the data in ways which are meaningful to the user. The relationships and summaries derived through the data mining exercise are typically referred to in the art as models.

10 The process of seeking relationships within a data set, i.e. of seeking accurate, convenient, and useful summary representations of some aspect of the data, involves a number of steps:

- determining the nature and structure of the representation to be used;
- 15 • deciding how to quantify and compare how well different representations fit the data (i.e. choosing an evaluation function);
- choosing an algorithmic process to optimise the evaluation function; and
- deciding what principles of data management are required to implement the algorithms efficiently.

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In this manner a control system can analyse a large amount of data by simplifying the way it is used. In this manner not all variables are modelled individually but rather they are combined through the use of the model and the model's output monitored.

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Traditionally, large fundamental models have been built and then these models optimised for use in process monitoring and fault detection. However, building such models or customising existing general models to a specific plant require time and effort. Additionally, the theoretical equations only provide a structure
30 of a model and many of the parameters must be fixed using expert knowledge or estimated using past plant data. Also, both physical and chemical mechanisms may be unknown and online measurements may be unavailable

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of inaccurate.

One approach to modelling a process with the objective of predicting abnormal process behaviour is to first develop a model of the normal process behaviour.

- 5 In complex processes the model of normal behaviour is typically derived from historical data collected over time during normal process operation. The historical data is collected by means of a large number of sensors distributed throughout the process. It will be apparent to one of ordinary skill in the art that the amount of historical data collected in a complex system can be quite large
10 and therefore, the step of deriving a model of normal behaviour is invariably supported by a computerised data processing system.

Multiple Models

- 15 At least two models are implemented. One model uses input variables whose means have not been adjusted for drift over time (Long Range Model) and at least one model has some input variables whose means are adjusted to compensate for drift (Short Range Model). Compensation for drift may be accomplished by calculating an average of the input samples over a period of
20 time that is short enough that no serious drift has occurred. Different periods may be used for different models or different input variables in the same model. A high pass filter may also be used to remove changes in the data that occur over a long time scale and focus the model on short time scale variation.

25 Application of the Invention to a Mitsubishi Continuous Copper Converting Furnace

Referring now to Figure 1, the invention will be applied to a Mitsubishi continuous copper converting furnace in order to illustrate its use.

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The Mitsubishi process is a continuous copper smelting and converting technology which uses three furnaces: a circular smelting furnace 10, an

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elliptical slag cleaning furnace 12 and a circular converting furnace 14. The three furnaces are linked with covered launders as in 16, through which all the molten materials (not shown) are continuously transferred by gravity force. Typically, blister copper from the converting furnace 14 is continuously delivered by gravity force to a blister holding furnace 18 (or alternatively a pair of anode furnaces, not shown).

Copper concentrate (Cu: 30%, S: 30%, Fe: 25%, Gangue minerals 15%) is fed through lance pipes with oxygen enriched air into the smelting furnace then oxidised and melted by exothermic reaction to form molten mixture of matte (Cu: 68%) and slag. The matte is separated from slag by difference of specific gravity in the slag cleaning furnace. The matte is further oxidised to form blister copper (Cu: 98 to 99%) in the converting furnace within which the sulphur content has been controlled to about 0.8%.

The blister copper is purified in anode furnaces (not shown) by oxidation and reduction to produce anode copper (Cu: 99.4%), and a strip produced by a caster is cut into copper anodes (all not shown).

The mixture of matte and slag formed in the smelting furnace 10 flows continuously to the slag cleaning furnace 12, where the denser copper matte separates from the discard slag. The matte is then siphoned to the converting furnace 14, to be continuously converted to blister copper and slag. The latter is water granulated, dried, and recycled to the smelting furnace 10, while blister copper is siphoned continuously from the converting furnace 14 to the blister holding furnace 18 from where it is transported by crane to a pair of anode furnaces (all not shown) for casting into anodes. Anode casting can be by "wheel" or by twin-belt Hazelett caster.

Each furnace in the three-furnace system can be regarded as a "steady state" reactor. The bath line within each furnace is constant (no tapping), allowing for a simplified refractory design and brick cooling. Control of the smelting process

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maintains the matte grade at steady values and ensures optimum operating conditions right through to continuous blister delivery to the blister holding furnace.

- 5 Referring now to Figures 2a and 2b, a cross section of the lower portion of a converting furnace 14 is disclosed. The converting furnace 14 is comprised of a bowl-like dish fabricated from structural steel plate 22 and lined with a composite structure comprised of a first layer 24 of, for example, high alumina ram mix/plastic and a second layer 26 of, for example, fused cast refractory
- 10 bricks manufactured from magnesia chrome. As is known in the art, the high alumina mix can be rammed to a high density and has expansile properties at high temperature which reduces the possibility of cracking and ensures a tightening of the lining at high temperatures.
- 15 Molten copper 28 is held in the converting furnace 14 within the refractory lining 26 and, due to the continuous nature of the Mitsubishi refining process, a constant bathline 30 is maintained between the molten copper blister 32 and the layer of slag 34 which rests on top of the blister 32. Typically, a drain 36 is also provided for in the bottom of the converting furnace 14 to allow for molten
- 20 copper to be drained off when carrying out maintenance, or repairs on the refractory lining 26, etc..

Referring now to Figures 3a through 3d in addition to Figures 2a and 2b, a cooling system, comprised of a series of water cooled cooling blocks as in 38,

25 rings the refractory lining 26 at a point straddling the bath line 30 of the molten copper 28. The cooling blocks 38, which are manufactured from, for example, a block of a conductive material such as copper, are cast around formed hollow tubing such as Schedule 40 Monel 400 pipe, thus forming a series of hollow passages 40 to allow the circulation of a coolant such as water therein. The

30 cooling liquid is pumped into the cooling block 38 via an inlet 42, circulates through the passages 40 and exits the cooling block 38 via an outlet 44. The curved hotface 46 of the cooling block 38 is comprised of a series of horizontal

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and vertical grooves as in 48 and is in contact with the rearward side of the refractory lining 26 which shield the cooling blocks 38 from the molten copper 28. Additionally, thermowells as in 50 fabricated from, for example, Schedule 80 AISI 304L pipe, are cast into the cooling blocks 38 at various points into
5 which thermocouples (not shown) are inserted for measuring temperature.

Referring now to Figure 4 in addition to Figures 2a and 2b, the cooling blocks as in 38 are arranged side by side such that they form a ring around the converting furnace 14 at the bath line 30. Molten copper matte is introduced
10 into the converting furnace 14 from the slag cleaning furnace (12 on Figure 1) via a matte inlet 52. A blister siphon 54 is provided at the bath line 30 for allowing molten copper blister 32 to flow by gravity via covered launders into the blister holding furnace (18 on Figure 1). Additionally, a slag outlet 56 is provided for removing slag 34 from the surface of the molten copper blister 32.

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Referring now to Figure 5, as discussed hereinabove, cooling liquid, such as water, is circulated through the cooling blocks 38 via a series of inlets 42 and outlets 44 thereby providing cooling to the rearward side of the refractory lining 26 at the level of the bathline. In the disclosed illustrative embodiment thirty two
20 (32) circuits are provided at the bathline through each of which 200 litres per minute of water circulates. The thirty two (32) circuits are arranged in parallel such that 6400 litres per minute is used to cool the cooling blocks 38. Although not shown, cooling water is also circulated through the roof of the converting furnace 14 to provide cooling therein.

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Still referring to Figure 5, cooling water is circulated by means of a series of controllable pumps 58, such as 150 HP BJ VT pumps running at 1800 RPM, which draw the cooling water from a hot well 60 and pump the water through a network of pipes as in 62. The flow of water through the network of pipes 62 is
30 controlled by the speed of the pumps and a series of controllable valves as in 64 which interconnect various sections of the network of pipes 62. One way valves as in 66 may also be provided for to prevent super heated water or

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steam from entering the network of pipes 62. A straining system 68 may also be provided for in order to remove particulate matter from the cooling water. In order to provide for failure of one or more of the pumps 58, supplementary cooling liquid may be provided from an auxiliary water tower 70. Illustratively, the water tower 70 is connected to the network of pipes 62 via a one way valve 72 and a controllable valve 74 which is actuated by a pressure sensor 76.

Heated water is returned from the cooling blocks 38 to the hot well 60 by a return pipe 78. Water in the hot well 60 is cooled by transferring it by means of a pump 80 and piping 82 to a cooling tower 84. Cooled water is then returned from the cooling tower 84 to a cooling tower basin 86. Water held in the cooling tower basin 86 is pumped to other parts of the system (indicated generally by the numeral 88), for example to the slag cleaning furnace (12 on Figure 1) by pumps as in 90. These pumps are, for example, 300HP pumps operating at 1800 RPM. This cooling water is then returned to the hot well 60 from the other parts of the system 88 via a second return pipe 92. Provision is also made in the cooling system to make up for water lost due to evaporation, etc..

Referring back to Figures 3a through 3d, provision of multiple thermowells 50 is made in each of the cooling blocks 38 for insertion of a thermocouple (not shown), thereby allowing remote measurement and recording of the temperature of the cooling blocks 38 at a given point in time. Referring now to Figure 4, in the present illustrative embodiment eighty-four (84) K-type thermocouples as in 94, three (3) to each of the twenty-eight (28) cooling blocks 38, were distributed around the bathline of the converting furnace 14. As is well known to persons of ordinary skill in the art, K-Type thermocouples have an operating range of between 0°F and 2500°F, nominally between 750°F and 2000°F. Two (2) thermocouples as in 94 were placed within two of the thermowells 50 cast in the cooling blocks 38 while the third thermocouple was attached using a water thermowell (not shown) to the outlets 44 of each of the cooling blocks 38. Note that in the present illustrative embodiment no thermocouples were used to take measurements in those cooling blocks

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immediately adjacent to the blister siphon 54 or the slag outlet 56, although in a given embodiment such thermocouples and their related temperature readings could be provided for.

- 5 Referring now to Figure 6, temperature readings from the thermocouples 94 were sampled by a control module as in 96 and the value relayed via a communications system 98, for example a local area network (LAN), to the furnace temperature control monitoring subsystem 100. Additionally, the flow of oxygen 102 into the converting furnace was continually sampled by read
10 monitored by a control module as in 96 and relayed to the monitoring subsystem 100, oxygen flowing into the furnace providing an indication that the furnace was indeed in operation. Values sampled from the eighty-four (84) thermocouples 94 provided a correlated set of data measurements. The thermocouples 94 are correlated in that the measurements tend to move
15 together with the temperature of the furnace. A pending breach of the refractory lining, changes in the condition of the furnace wall or build up and /or process equipment failure is typically indicated by one or more proximate thermocouples deviating from an overall pattern of normal operation.
- 20 During furnace operation, sampled data was stored in a data store 104 for later retrieval and processing by the analysis subsystem 106.

The primary task of the analysis subsystem 106 comprises at a first step of generating the models of normal system operation 108 and at a second step
25 processing data received to determine a representation of current system operation 110 for comparison to the model of normal system operation 108. Both the models of normal system operation 108 and the representation of current system operation 110 are made available to the monitoring subsystem 100 which compares the representation of current system operation 110 with
30 the models of normal system operation 108 in order to determine if the furnace is operating abnormally.

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In the present illustrative embodiment abnormal furnace operation is an indication that the refractory lining of the furnace is in danger of being pierced by the molten copper held within the furnace. The monitoring subsystem 100 also displays, via a visual display 112, such as a CRT, both raw and analysed data in ways which are meaningful to the operator. In particular, the data processing subsystem generates alarm messages 114, for display, for example, on the visual display 112 or, provided the requisite data transfer network is present, for transfer to the operator via e-mail, etc.. On detection of abnormal operation the monitoring subsystem 100 may also take appropriate actions to restore normal system operation and protect furnace integrity, for example by shutting down the furnace. These steps include, for example, shutting off the air oxygen flow into the converting furnace, conducting field checks and shutting down the smelting furnace.

As stated above, in order to generate the models of normal system operation, the analysis subsystem 106 analysed data related to temperature of the refractory lining and water used to cool the lining collected over an extended period of operation and stored in the data store 104. In this regard, once the converting furnace 14 was filled with molten copper and in operation, each of the eighty-four (84) thermocouples 94 was sampled regularly with a sampling rate of a couple of seconds although it will be understood to a person of ordinary skill in the art that a different sampling rate could also be used. Indeed, as will be understood by a person of ordinary skill in the art, the selection of sampling rate is a trade-off between the data generated and the level of accuracy required.

Although as stated above the input variables for the models were temperatures measured via the eighty-four (84) bath line thermocouples 94 only (as it was found that the majority of problems *vis-à-vis* the integrity of the refractory lining occurred at the bath line, which suggested that the bath line thermocouples would provide the strongest indications of a change in the bath line), other temperature measurements, as well as other process parameters such as the

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oxygen lance flows and feed rates were available but not used. However, in a given embodiment data with regard to these parameters could also serve as input to the model and used subsequently for controlling the copper conversion process.

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In order to train the PCA model, a training data set comprising data collected over the previous three months of operation was used. Certain periods of time (such as shutdowns) were masked from the data set, so that the data set represented normal operation is represented as closely as possible.

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Although data was collected over an extended period of time, the duration of time over which the data is collected must only be sufficient to provide a good representation of furnace operation. In this regard, data from several successive periods of operation may be combined to provide the basis for the model. The collected data was analysed offline using the analysis software package monitorMV™ by Perceptive Engineering Ltd. (although many commercial analysis software packages would suffice, for example SIMCA-P™ from UMETRICS or UNSCRAMBLER™ from CAMO).

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The first step in the analysis was the generation of a Long Range Model (LRM) data matrix and a Short Range Model (SRM) data matrix. In this regard, the data in the SRM data matrix was pre-processed using a sliding window which subtracted the previous four (4) day average from the raw data prior to placing it in the data matrix in order to take into account any long term drift in the temperature values sampled in the furnace. Pre-processing the data in this manner provides a method by which measurement drift can be compensated for. The difference in the response of the resultant LRM and the SRM provides an indication of the rate of drift of the furnace. Drift compensation is generally necessary given subtle changes in the furnace and other factors, such as an increase or decrease in the ambient seasonal temperatures. However, changes which the drift compensated SRM might miss were shown by the uncompensated LTM.

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The LRM data matrix and the SRM data matrix are then decomposed to provide the coefficients used in the PCA model. A number of different algorithms may be used to calculate the Principal Components of a set of data, for example the NIPALS Algorithm or Decomposition of Covariance. The NIPALS Algorithm gives more numerically accurate results when compared with the Decomposition of Covariance method, but is slower to calculate. It is believed that these algorithms are known to a person of ordinary skill in the art and will not be dealt with in more detail here.

- 10 The result of the decomposition of the LRM data matrix and the SRM data matrix are the Principal Components. The n^{th} Principal Component of p random variables is represented by the coefficients of a linear function of the form:

$$\alpha'_n x = \alpha_{n1}x_1 + \alpha_{n2}x_2 + \dots + \alpha_{np}x_p = \sum_{j=1}^p \alpha_{nj}x_j \quad (3)$$

- 15 Once the n^{th} Principal Component has been determined, the linear function $\alpha'_{n+1}x$ is sought which is uncorrelated to $\alpha'_n x$ and has maximum variance. As a result, although up to p Principal Components can be found, the bulk of the variation in x will be accounted for by m Principal Components, where $m \ll p$.

- 20 As stated above, in order to select the requisite number of Principal Components (m) in the developed models, the PRESS statistic was used. Using the method as proposed in "Cross-Validatory Estimation of the Number of Components in Factor and Principal Components Models", S. Wold, 1978, Technometrics, vol. 20, pages 397-405, the PRESS statistic of m Principal Component can be determined using the following equation:

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$$PRESS(m) = \sum_{i=1}^n \sum_{j=1}^p (\hat{x}_{ij} - x_{ij})^2 \quad (4)$$

To decide whether or not to include the m^{th} Principal Component, the following ratio R is examined:

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$$R = \frac{PRESS(m)}{\sum_{i=1}^n \sum_{j=1}^p (\hat{x}_{ij} - x_{ij})^2} \quad (5)$$

If $R < 1$ then the implication is that a better prediction is achieved using m rather than $m-1$ Principal Components, so that the m^{th} Principal Component should be included. Note that the above describes only one method for determining the number of Principal Components to be included, and others, for example those developed in "Cross-Validatory Choice of the Number of Components From a Principal Component Analysis", H. Eastment and W. Krzanowski, 1982, Technometrics, vol. 24, pages 73-77, might also be applied without removing from the spirit of the present invention.

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Applying the above methodology to the training data set, it was first found that two Principal Components would give good results. However, during operation it was found that two Principal Components led to too many false alarms and therefore a single Principal Component was used. Using a single Principal Component it was found that for the LRM 96.4% of the original training data variance was recovered and for the SRM 94.1% of the original training data variance was recovered.

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As will now be apparent to a person of ordinary skill in the art, the PCA models reduce the large number of input data variables down to a few Principle Components which can be used to create an estimate of the raw value of each variable. When this is done, not all of the original signal is recovered, even over the training data set used to create the model. This is in fact a benefit as during normal operation the part of the raw signal that the model projection misses may be regarded as random signal noise. Under abnormal operation, the difference between the raw signal and the model projection is used to determine which thermocouple (or thermocouples) are responsible for the deviation from normal operation.

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In application, the PCA Model is used to generate Principal Component scores t_j from which a Hotelling T^2 chart is generated, as well as a SPE_x (Squared

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Prediction Error) chart. Hotelling T^2 and SPE_x charts are used to recognise trends in the measured values of the variables (in the case at hand, the temperature of the refractory lining as measured by the thermocouples). Typically, both the Hotelling T^2 and SPE_x charts are periodically regenerated and graphed versus time with earlier values for display on the display device.

Illustratively, the Hotelling T^2 and SPE_x charts are determined as follows: the scores t_j can be determined as follows:

$$t_j = a'_1 x_j, j = 1, 2, \dots, m \quad (6)$$

where m is the number of principal components in the model. The Hotelling T^2 chart can be derived from the PCA Model scores according to the following formula:

$$T_m^2 = \sum_{j=1}^m \frac{t_j^2}{\lambda_j} = \sum_{j=1}^m \frac{t_j^2}{s_{t_j}^2} \quad (7)$$

where s_{t_j} is the estimated variance of the corresponding latent variable t_j . The estimated variance of the latent variable is determined from the scores from the modelling data set according to the following equation:

$$s_{t_j}^2 = \frac{\sum_{i=1}^N t_{j,i}^2}{N-1} \quad (8)$$

where N is the number of observations.

The Hotelling T^2 chart can be used to check whether a new observation of measurements on k process variables projects on the hyperplane within the limits determined by the training data set. The Hotelling T^2 chart gives an indication of how far in the hyperplane the new observation lies from the centre

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point of the data used to train the models. As such, it provides an indication of how far the new observations, i.e. the current state of the process, have strayed from the model of normal behaviour.

- 5 The SPE_x chart can be calculated according to the following formula:

$$SPE_x = \sum_{j=1}^k (x_{new,j} - \hat{x}_{new,j})^2 \quad (9)$$

where $\hat{x}_{new}$ is computed from the PCA model. The SPE_x is the sum of the
 10 squares of the normalised residuals. The SPE_x detects the occurrence of any new events that cause process to move away from the hyperplane defined by the training data set. As such, the SPE_x provides a measure of how much the measured values are in agreement with the PCA model. In the case at hand, a low SPE value indicates that the furnace is behaving similarly to the furnace
 15 which was used to train the PCA model (normal operation). A high SPE value is an indication to the contrary (abnormal operation).

Another feature of a PCA Model is that it does not predict sampled values ahead in time. Instead, all of the values associated with a PCA Model are
 20 typically from the same sampling instant (although samples from different times can be used, although this was not done in the development of the present illustrative embodiment). It is more accurate, therefore, to refer to model 'Projections' rather than model 'Predictions', although the term Prediction is retained in the interests of continuity.

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The training data set was passed through the PCA Models a number of times which allowed the identification and removal from the training data set of portions of the data which did not appear to represent normal operation. After removal of data from the training data set the model was regenerated. The final
 30 result of this iterative process was a stable model representative of normal furnace operation.

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The above developed Short Range and Long Range PCA Models were implemented within the furnace temperature control monitoring system. The initial response of the control system was to raise an alarm when the monitored system was found to be operating outside the modelled normal operating ranges. Typically, during operation the following series of steps would be repeated until an alarm condition is determined. Note that although data was sampled from each thermocouple typically every couple of seconds, data was fed into the monitorMV program for analysis once a minute.

- *Retrieve current operation:* measurements are read or sampled from the thermocouples;
- *Pre-process measurements for short range model:* a four (4) day moving average was subtracted from each of the 84 measurements for the short range model;
- *Analyse current operation:* generate scores, Hotelling T^2 and SPE;
- *Raise alarm:* (1) check SPE against limit, raise alarm and continue of over (2) check individual residuals against limit, raise alarm and continue of over (checks can include multiple residuals in one area being over the limit), (3) shut off air and oxygen, and (4) investigate source of alarm; and
- *Resolve alarm:* identify the five (5) thermocouples having the largest contributions.

Various levels of alarms are raised depending on how far the data was determined to be from the hyperplane. In general the setting of the alert and alarm limits is done in two steps. The alarm levels are initially determined offline using past process data. An iterative process is then used to derive suitable levels for the detection limits, i.e. in order to determine limits that only very rarely result in alarms during normal operation but always result in alarms in cases of abnormal operation. Once the monitoring system is in operation, the levels of the monitored variables and any instances of false or missed alarms are used to adjust the alarm limits. The alarms levels on the SPE are 200 for an

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advisory alert, 300 for a critical alert and 600 for a super-critical alert that would trigger the logic for shutting down the furnace automatically.

A similar iterative approach would also be used if introducing additional thermocouples once the monitoring system was in actual operation. The limits are adjusted based on the frequency of alarms and any instances of false or missed alarms during actual operation of the furnace.

In addition to raising alarms, E-mail notifications are sent by a mechanism in the monitoring system when the SPE goes above a certain level, illustratively when the SPE is greater than 300. Additionally, the five (5) thermocouples with the largest contributions are identified and provided to the operator to help diagnose the cause of any alarms.

Measurements from particular thermocouples can be temporarily removed from the monitoring system by 'masking' them out (in which case missing data methods are used, for example based on the NIPALS algorithm as known in the art) or may be permanently removed if they are the source of many false alarms. Differential temperatures across the coolers were initially included but found to be unsuitable for monitoring. They were therefore removed from the monitoring system.

The models also need to be periodically re-built with new data when the furnace has changed significantly or thermocouples have been added. This was done after the furnace was re-built when enough data had been gathered to have a representative sample from the new furnace.

WHAT IS CLAIMED IS:

1. A method for monitoring the integrity of a furnace containing molten metal, the method comprising the steps of:

deriving a model of normal operation of the furnace from a plurality of furnace variables;

periodically measuring current values of said plurality of furnace variables;

analysing said current values, said analysing step resulting in a representation of current operation;

comparing said representation of current operation with said model of normal operation; and

generating an alarm when said representation of current operation deviates from said model of normal operation by a predetermined amount.

2. The method of Claim 1, wherein said deriving step includes periodically measuring normal values of said plurality of furnace variables during a period of normal operation and analysing said normal values, said analysis resulting in said model of normal operation.

3. The method of Claim 1, wherein the furnace comprises a refractory lining and said furnace variables comprise a plurality of temperatures of said refractory lining.

4. The method of Claim 3, wherein said refractory lining is cooled by a plurality of cooling blocks.

5. The method of Claim 4, wherein said cooling blocks are fabricated from a conductive material.

6. The method of Claim 5, wherein said conductive material is copper.

7. The method of Claim 4, wherein said cooling blocks each comprise at least one passage through which a coolant can flow, said passages having an outlet.

8. The method of Claim 7, wherein said coolant is water.

9. The method of Claim 7, wherein said passages are formed by casting said cooling block around a hollow tubing.

10. The method of Claim 9, wherein said hollow tubing is fabricated from a conductive material.

11. The method of Claim 10, wherein said conductive material is copper.

12. The method of Claim 4, wherein said refractory lining temperatures are measured as a temperature of a plurality of said cooling blocks.

13. The method of Claim 7, wherein said refractory lining temperatures are measured as a temperature of said coolant at a plurality of said outlets.

14. The method of Claim 2, wherein analysing said normal values comprises the steps of:

generating a data matrix by ordering said values;
deriving principal components from said data matrix;
selecting a subset of said principal components; and
establishing said model of normal operation using said subset of principal components.

15. The method of Claim 14, wherein said values are first pre-processed.

16. The method of Claim 15, wherein said pre-processing includes subtracting moving averages of said values from said values.

17. The method of Claim 16, wherein said moving averages are the average of said values over the previous four days.

18. The method of Claim 14, wherein said principal components are derived using the NIPALS algorithm.

19. The method of Claim 14, wherein said principal components are derived according to decomposition of covariance.

20. The method of Claim 14, wherein said subset of principal components are selected using the PRESS statistic.

21. The method of Claim 14, wherein said subset of principal components consists of one principal component.

22. The method of Claim 14, wherein said model of normal operation comprises threshold values.

23. The method of Claim 22, wherein analysing said current values comprises generating scores.

24. The method of Claim 23, wherein analysing said current values further comprises deriving a Hotelling T^2 value from said scores.

25. The method of Claim 24, wherein analysing said current values further comprises deriving a SPE value from said scores.

26. The method of Claim 25, wherein said comparing step comprises comparing said SPE with its corresponding threshold value and wherein said

alarm is generated when said SPE exceeds its corresponding threshold value.

27. A system for monitoring the integrity of a furnace, the furnace comprising a refractory lining and containing molten metal, the system comprising:

- a plurality of thermocouples for periodically measuring a current temperature of the refractory lining;
- a model of normal operation of the furnace;
- a means for analysing said current temperatures, said analysing means generating a model of current operation; and
- a means for comparing said model of current operation with said model of normal operation, said comparing means generating an alarm when said model of current operation deviates from said model of normal operation by a predetermined amount.

28. The system of Claim 27, wherein said current temperature of the refractory lining is measured at a plurality of locations distributed around a bath line of the furnace.

29. The system of Claim 27, wherein said refractory lining is cooled by a plurality of cooling blocks.

30. The system of Claim 29, wherein said cooling blocks are fabricated from a conductive material.

31. The system of Claim 30, wherein said conductive material is copper.

32. The system of Claim 29, wherein said cooling blocks each comprise a passage through which a coolant can flow, said passage having an outlet.

33. The system of Claim 32, wherein said coolant is water.

34. The system of Claim 33, wherein said passage is formed by casting said cooling block around a hollow tubing.

35. The system of Claim 34, wherein said hollow tubing is fabricated from a conductive material.

36. The system of Claim 35, wherein said conductive material is copper.

37. The system of Claim 29, wherein said refractory lining temperatures are measured as a temperature of a plurality of said cooling blocks.

38. The system of Claim 32, wherein said refractory lining temperatures are measured as a temperature of said coolant at a plurality of said outlets.

39. The system of Claim 27, wherein said model of normal operation is established during a period of normal operation, establishment of said model of normal operation comprising the steps of:

periodically measuring normal values of said thermocouples during the period of normal operation;

generating a data matrix by ordering said values;

deriving principal components from said data matrix;

selecting a subset of said principal components; and

establishing said model of normal operation using said subset of principal components.

40. The system of Claim 39, wherein said values are first pre-processed.

41. The system of Claim 40, wherein said pre-processing includes subtracting moving averages of said values from said values.

42. The system of Claim 41, wherein said moving averages are the average of said values over the previous four days.

43. The system of Claim 39, wherein said principal components are derived using the NIPALS algorithm.

44. The system of Claim 39, wherein said principal components are derived according to decomposition of covariance.

45. The system of Claim 39, wherein said subset of principal components are selected using the PRESS statistic.

46. The system of Claim 39, wherein said subset of principal components consists of one principal component.

47. The system of Claim 39, wherein said model of normal operation comprises threshold values.

48. The system of Claim 39, wherein said analysing means generates scores from said current temperatures.

49. The system of Claim 48, wherein said analysing means derives a Hotelling T^2 value from said scores.

50. The system of Claim 48, wherein said analysing means derives a SPE value from said scores.

51. The system of Claim 50, wherein said comparing means compares said SPE with its corresponding threshold value, said comparing means generating said alarm when said SPE exceeds its corresponding threshold value.

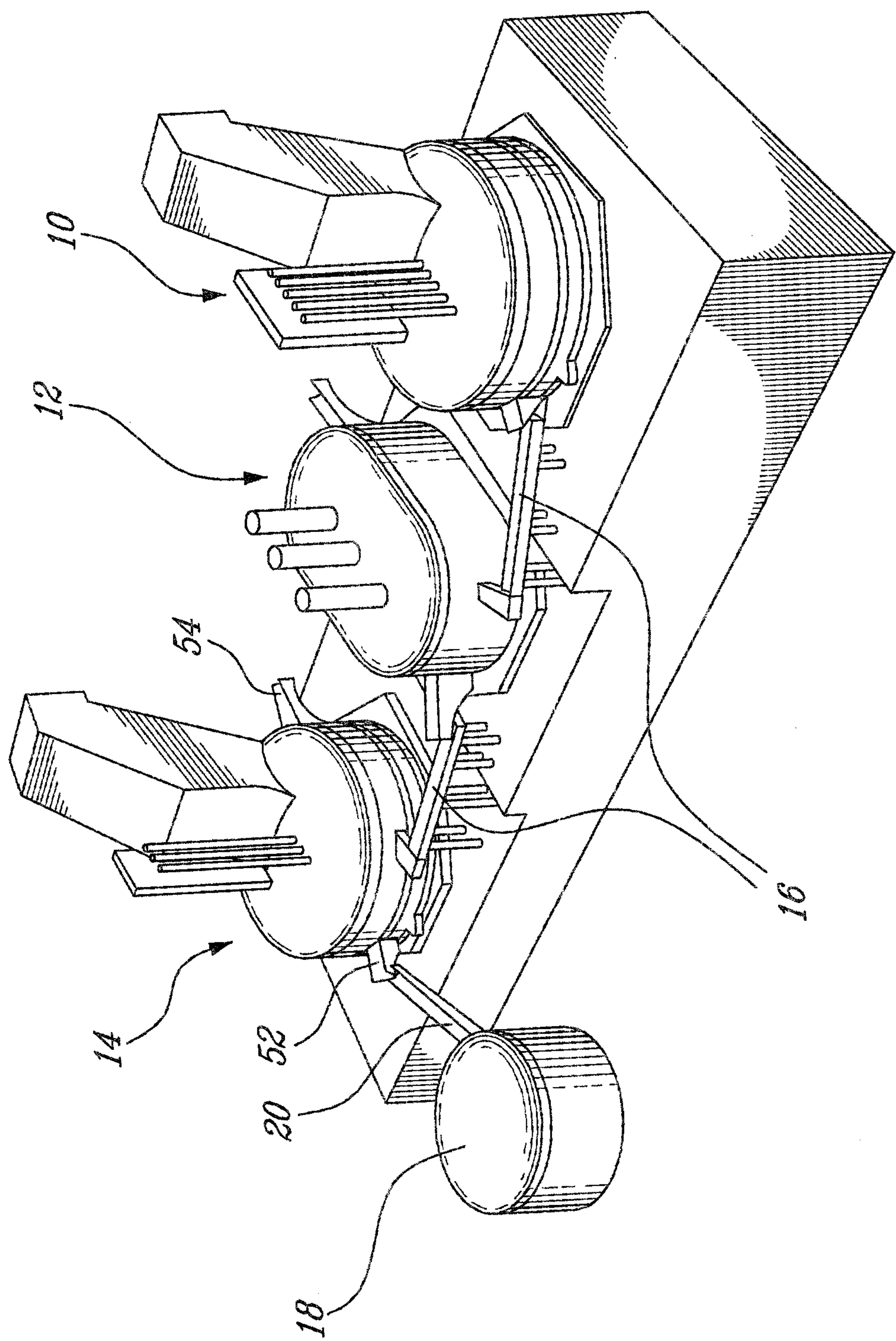


Fig. 1

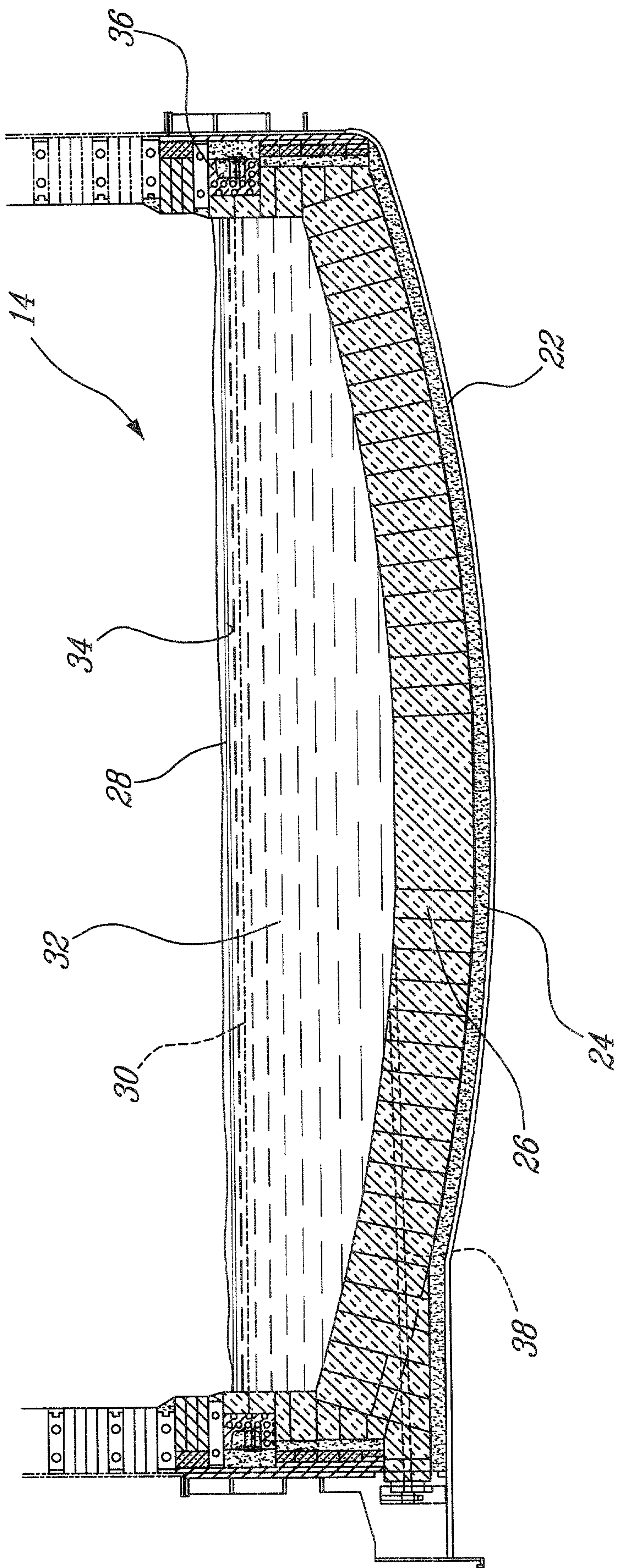
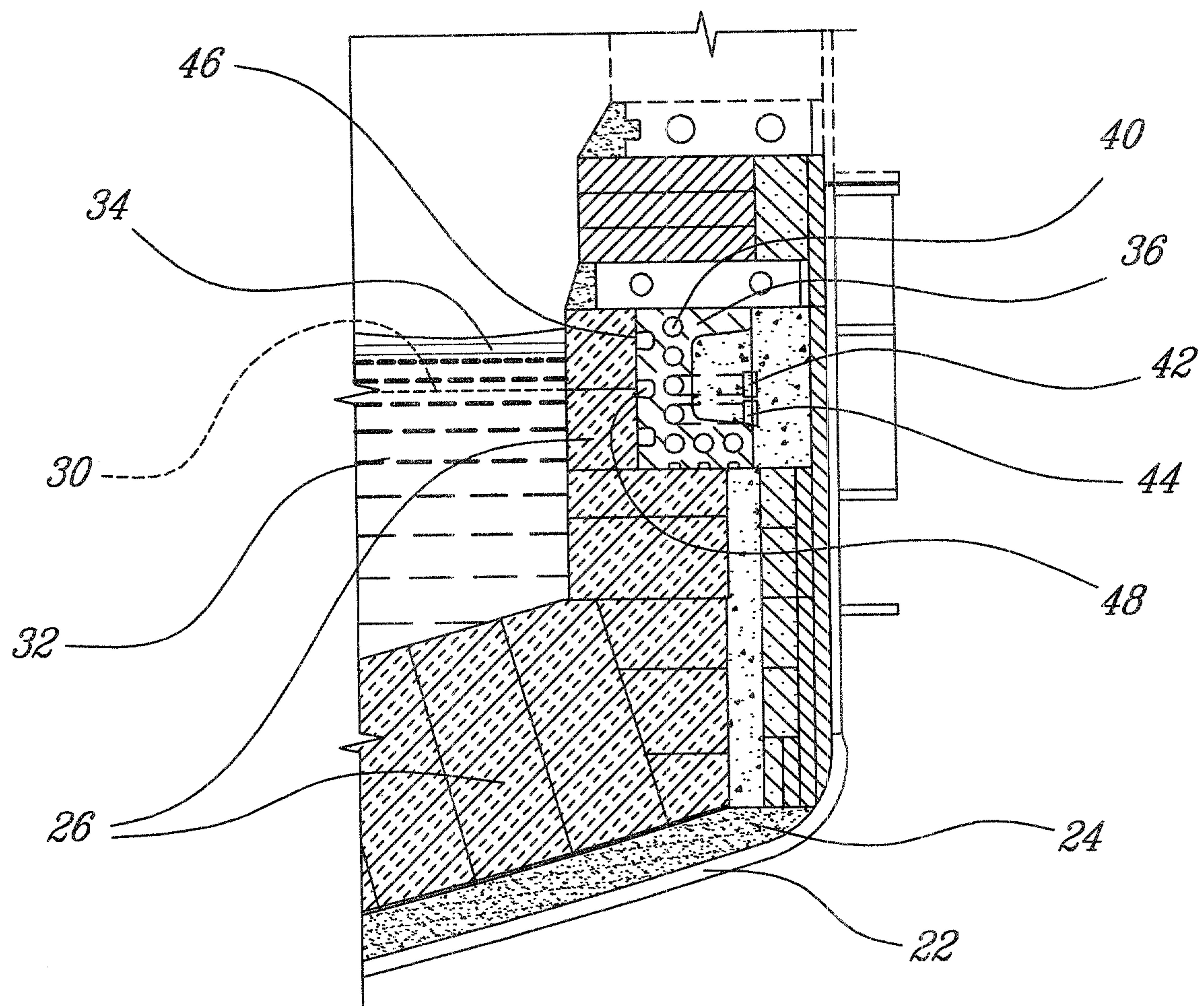


Fig. 2A

**Fig. 2B**

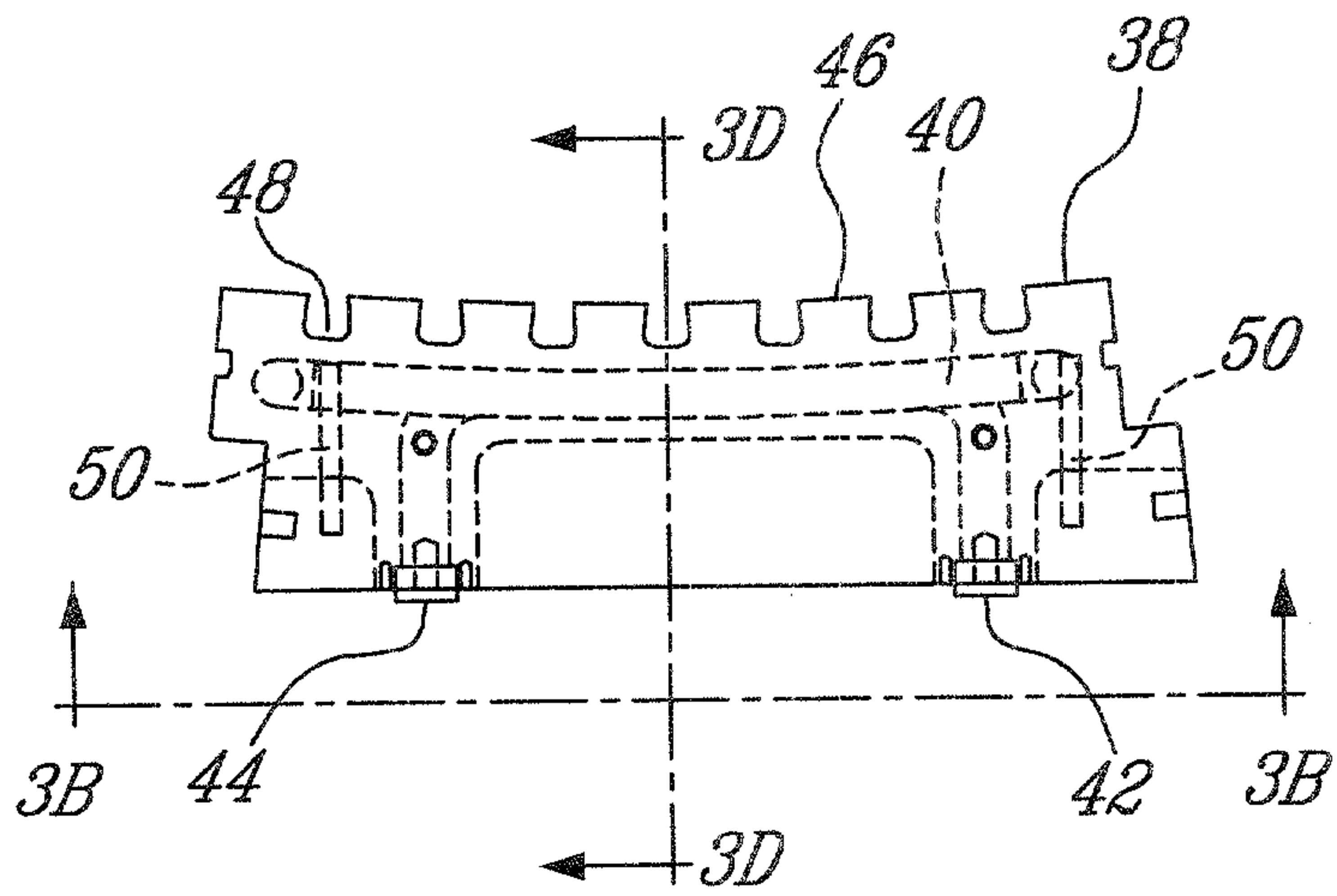


FIG. 3A

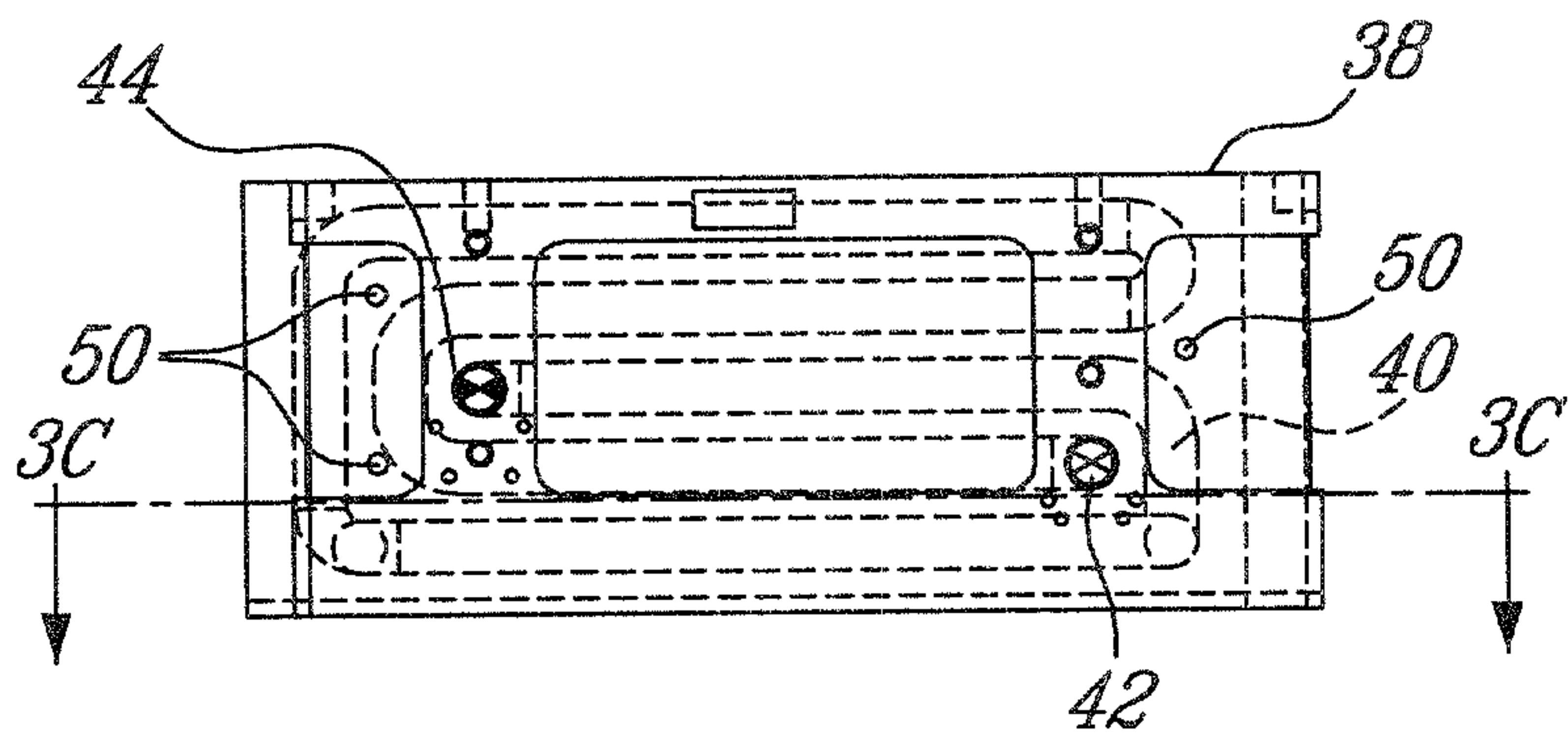


FIG. 3B

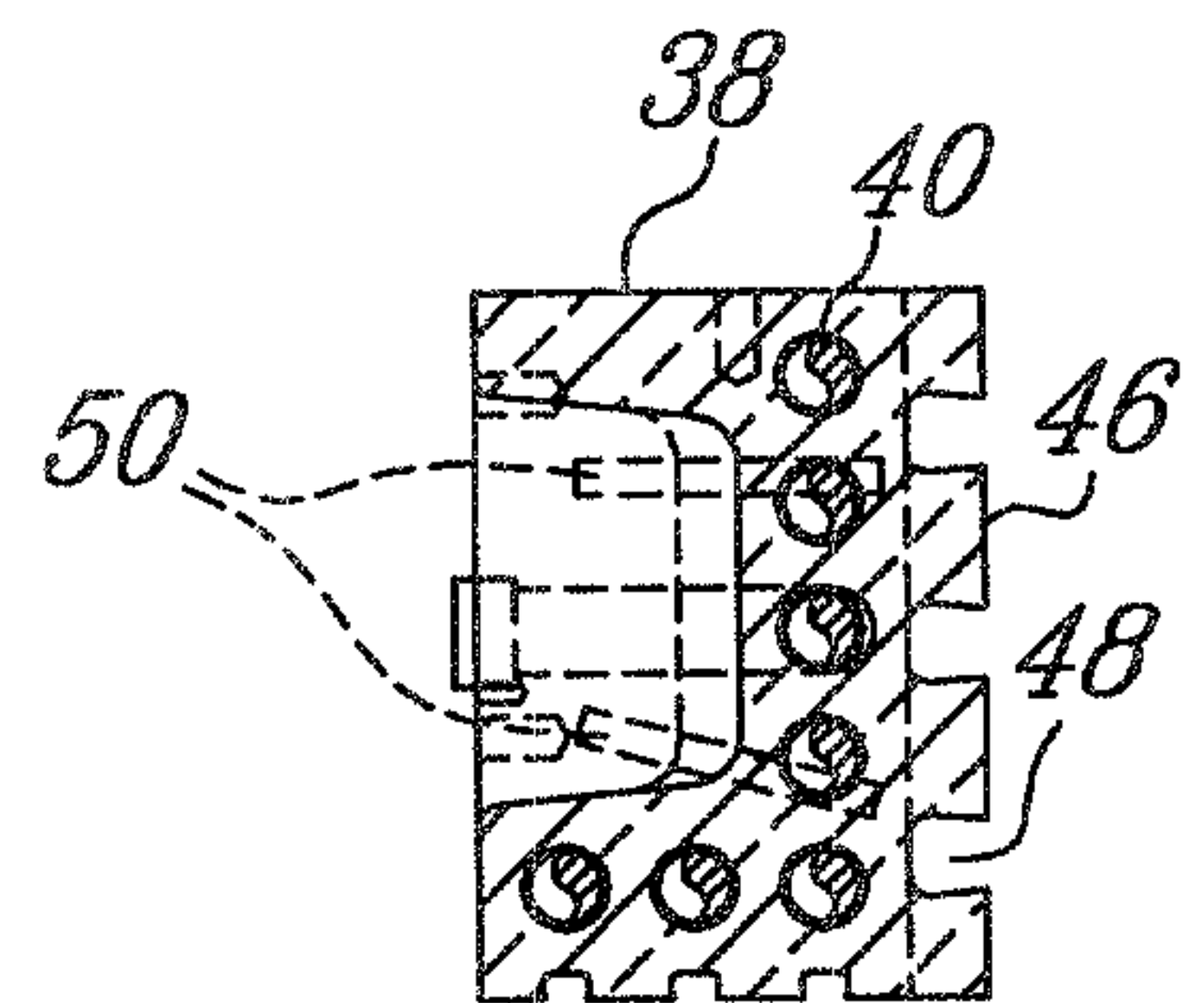


FIG. 3D

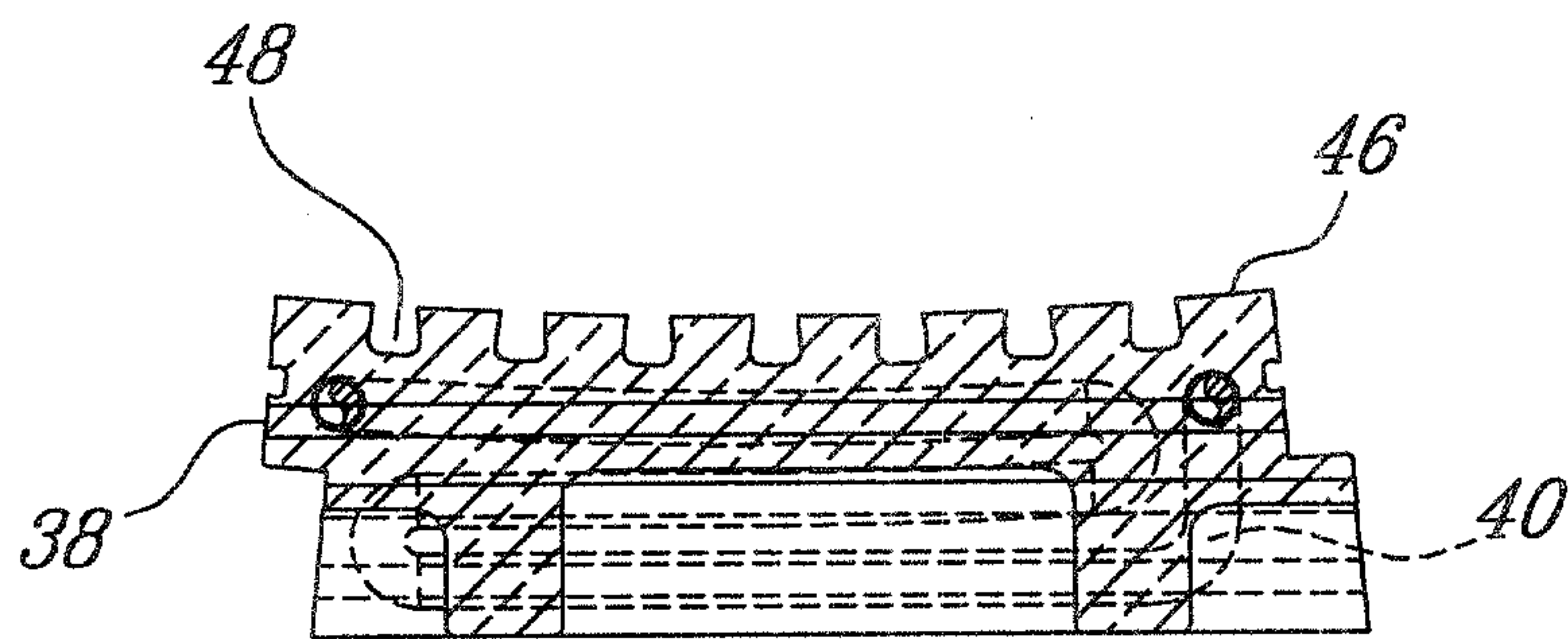


FIG. 3E

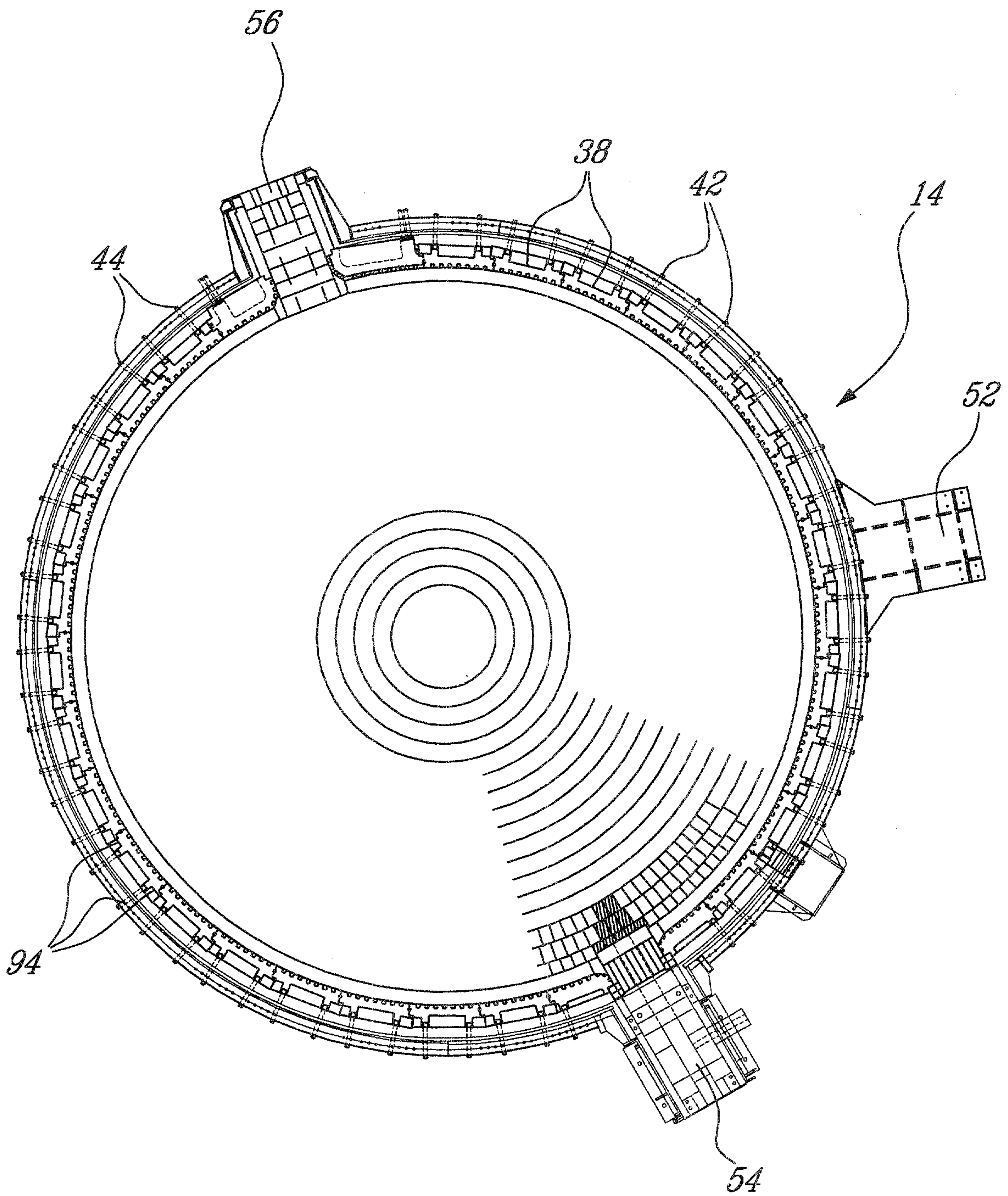
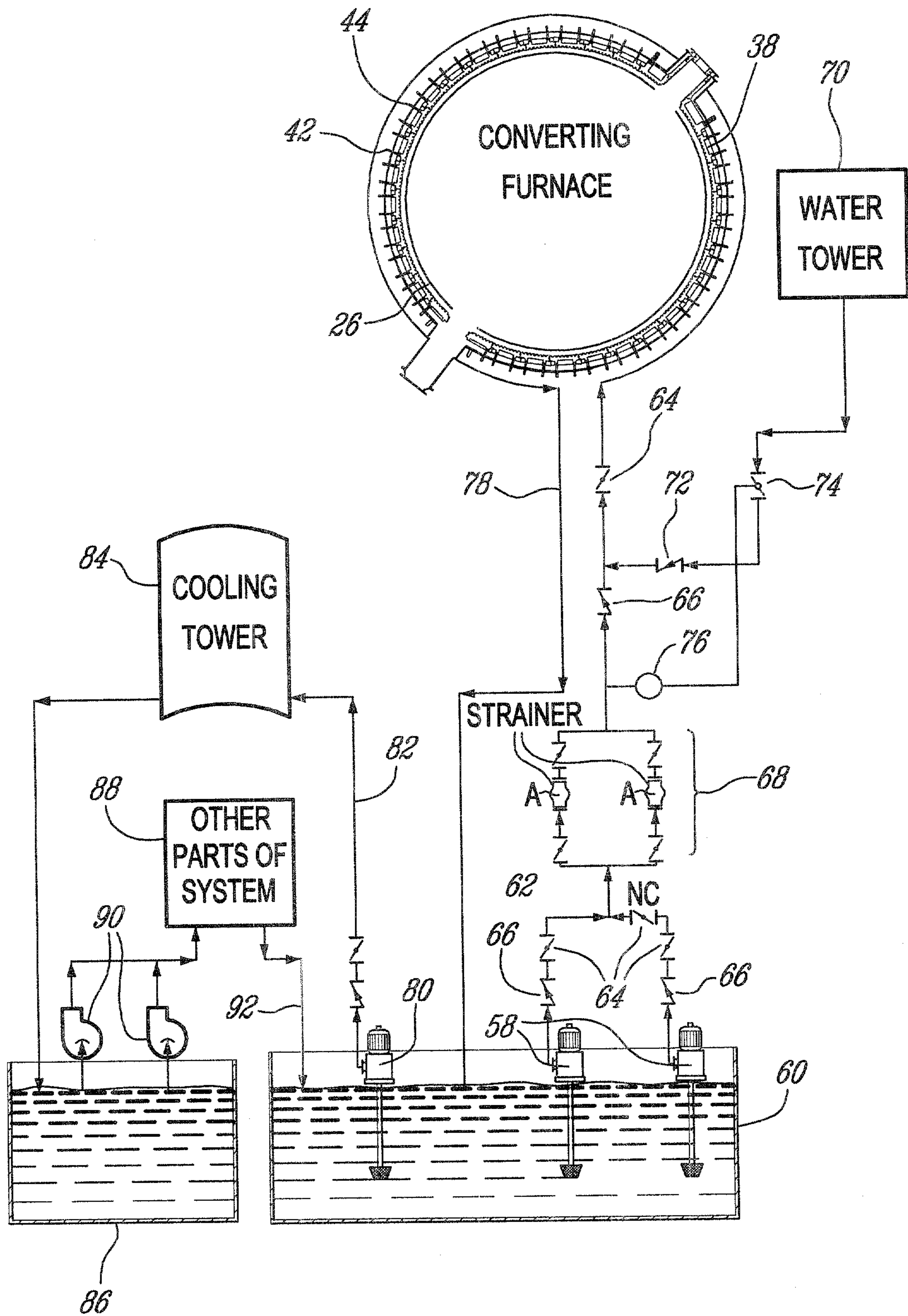


FIG-4

**Fig. 5**

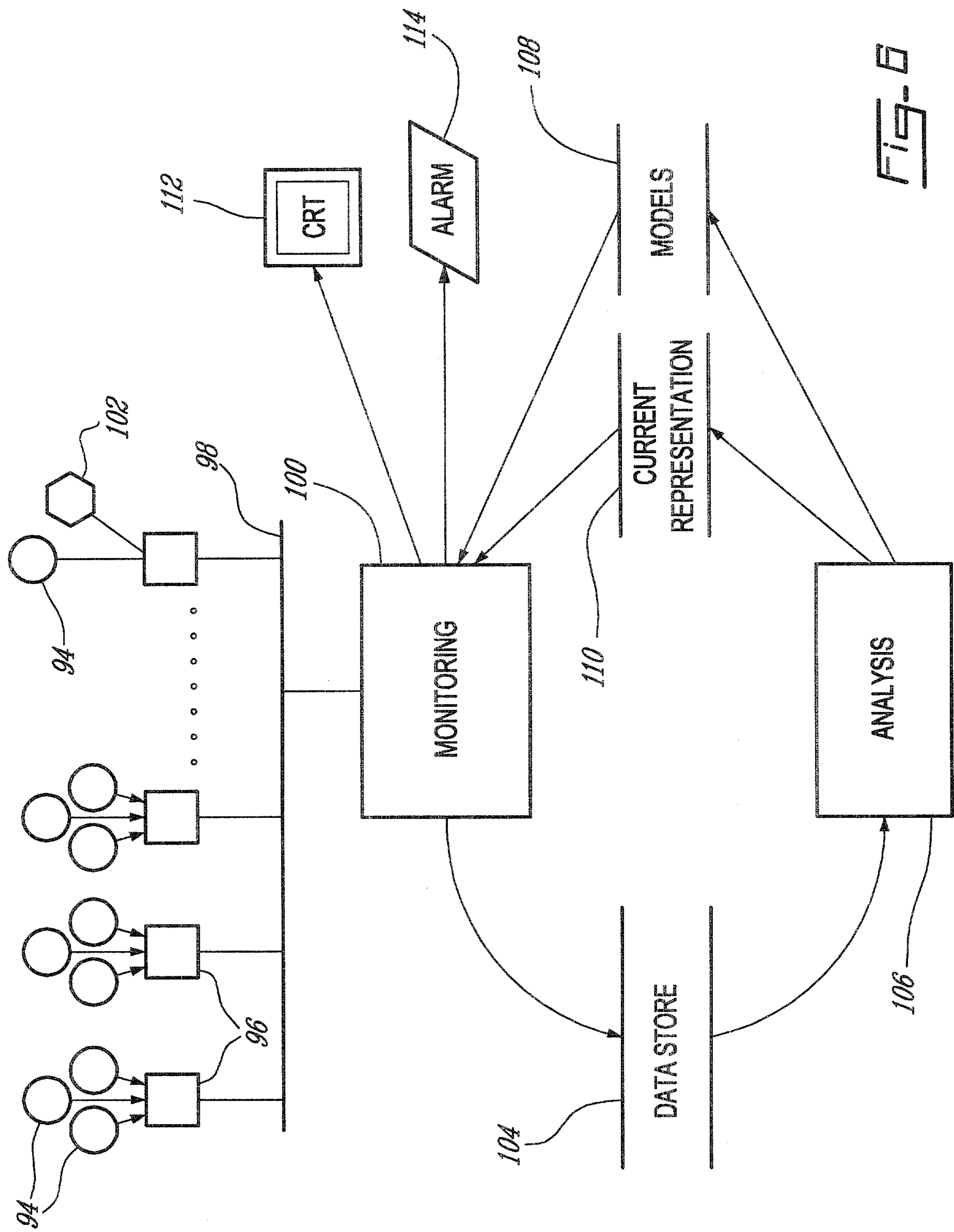


Fig. 6

