The use of mass and energy balances for observation in process plant diagnosis

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THE USE OF MASS AND ENERGY BALANCES FOR OBSERVATION IN PROCESS PLANT DIAGNOSIS

Morten Lind and Hans Talmon

Abstract. A method is described that uses the invariant mass and energy conservation laws in order to extract a detailed pattern of mass and energy flows from the instrumentation of a process plant. The basic feature of the method is that it is applicable to a large range of plant operational situations, such as those initiated by unforeseen failures, failures with dynamic symptoms, multiple failures, and failures during sequential operations.

The authors' intentions with this interim progress report are to describe the basic ideas behind the method, as well as to discuss some of its implications for man-computer cooperation in process plant diagnosis.

INIS-descriptors ALGORITHMS; CONSERVATION LAWS; CONTROL SYSTEMS; DATA PROCESSING; ENERGY BALANCE; FLOW MODELS; MAN-MACHINE SYSTEM; MASS BALANCE; MONITORING; NUCLEAR POWER PLANTS; REACTOR OPERATION; SYSTEM FAILURE ANALYSIS.

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INTRODUCTION

The performance of a system for computer-aided fault diagnosis in a process plant can be judged by its ability to give adequate support to the operator during abnormal plant operations. Considering the different aspects of diagnosis this means that a diagnostic method should be evaluated according to the following requirements:

1. The method should be able to cope with unforeseen failures, failures with dynamic symptoms, multiple failures, and failures during sequential operations.

2. The method should supply information in a form that is useful in man-computer cooperative system supervision.

3. The method should be useful in linking the results of fault identification to compensatory actions.

Methods currently in use or at a stage of practical evaluation seem not to satisfy all these requirements, and problems especially occur with unforeseen failures.

The importance of the above requirements has been stressed by the Three Mile Island accident. Several reports on this accident (Kemeny, 1979; TMI-2 Lessons Learned Task Force, 1979) clarify one of the basic deficiencies: the operators did not know - and could not be expected to know - what was going on in the plant.

The operators failed to recognize:

1. A lack of flow through the auxiliary feedwater pumps.
2. The empty steam generators.
3. A leak in the primary circuit.
4. The lack of natural circulation cooling.
5. The steam voids in the core.

It has been concluded from several analyses of the TMI accident (see e.g. Cummings, 1980) that the number of measurements available at TMI for plant supervision was not sufficient to support the operator in diagnosing plant abnormalities. However, these conclusions are based on the specific sequence of events that occurred at TMI. If they are generalized the result could be an immense amount of additional instrumentation.

While on the one hand the financial consequences need no elaboration, our emphasis lies on the other hand with the use of information by the operator:

1. Very often operators do not use the redundancy in the presented information in order to check inferences (Duncan and Gray, 1975).

2. Another frequently found behavioural aspect is that they use signs for the presence of certain conditions which are based on experience gathered during normal operation (Rasmussen, 1979a).

The addition of instrumentation alone will thus leave a part of the problem unsolved.

The method that will be considered here seems promising in resolving the fore-mentioned problems. It is based on a type of plant model called flow model, developed by one of the present authors (Lind, 1980). The idea of using flow models for diagnosis has been introduced by Rasmussen (1978), and Lind (1979; 1981) has considered different aspects of the diagnosis problem in process plants in more detail within the framework of flow models.

The observation of flow variables in a process plant using this method is based on mass and energy balance calculations. The general nature of the invariant conservation laws makes the method independent of the specific operating state and of the mode of malfunctioning of the plant. Later we will show how complete observation of the plant in terms of mass and energy

flows can be achieved. But before doing so, a further discussion of the background of flow modelling and its relation to operator support is justified.

While accumulation of mass and energy is a potential source of risk, the goal of the diagnostic task may vary (Rasmussen, 1978):

1. Identification of the plant state (e.g. in terms of mass and energy flows), and - indirectly - monitoring of the critical variables.

2. Compensation of unbalances and disturbances through a search for causal paths which connect the serious effects of a failure to control actions.

3. Restoration of normal operation by means of localization and correction of the failed component.

It is important to note that these different tasks warrant system representation at varying levels of abstraction (Rasmussen, 1979b). At a low level of abstraction, the model is related to the specific physical system and can thus be modified by changes in the physical structure, due to faults and their eventual consequences. On the other hand, abstract models, such as flow models, are more tied to the actual purpose and function of the system and thus relate to the reasons for correct behaviour. The potential paths for transfer of knowledge at these levels of abstraction are in a way independent since transfer at one level follows physical properties, while at the other it follows purpose. To a certain extent these models thus form a redundancy in the problem space.

We should emphasize, however, that the present discussion of the multi-level modelling approach is very simplified. For a systematic discussion we refer to the report of Rasmussen (1979b).

If the system is represented in terms of the abstract concepts of mass and energy flows, then a framework is given for the

detection of endangered critical variables, because high pressures are related to disturbed mass balances, while both high pressures and high temperatures are the result of energy pile-up. The early warning possible with this representation may leave time for compensatory actions. Especially in extreme situations, when no standard procedures are available, this high level representation constitutes a domain for a search for control devices through which counteraction of the unbalances might be achieved, while also keeping track of the primary side-effects. When we discuss control actions in the above, the reader should not only interpret these as stabilizing or setpoint control, but sometimes as higher level sequential control - such as starting up a pump and closing a valve - i.e. a change of the functional structure of the plant. One of the present authors recently made an attempt to formalize this kind of control (Lind, 1979).

However, the lower level physical model of the system is needed to give limitations and consequences of the proposed actions and for their actual implementation. In addition to the need for shifts to the physical level in fault compensation, these shifts will be advantageous when search is needed for the exact location of the failed component, because the physical domain allows a high local resolution in the results.

Implication for Man-Computer Cooperation

If we now look at the implications of the above for man-computer cooperation in plant diagnosis, then we see that the physical variables which are measured in the plant will only enhance the physical model of the plant. To stimulate the correct use of the abstract model a reliable transformation of the plant variables to mass and energy information - such as discussed in the remainder of this paper - must be found in order to relieve man of the burden of performing this transformation himself. The resulting representation in terms of mass and energy flows seems especially well suited for human data processing, since flows in a topographic map would appear to

allow the human to take advantage of his excellent pattern recognition abilities. This state display may give the operator "at-a-glance" a coherent overall impression of the state of the plant, which will prevent instances of "cognitive tunnel vision" such as occurred at TMI.

If the operator and the computer reason in the same domains when working at this high level, then there will be a considerable freedom in the design of the cooperation: they can explain to each other; assist each other; check each other (viz. human errors); and learn from each other.

Whether we look at the short term goal of displaying coherent high level information to the operator, or at the long term goal of achieving a proper man-computer cooperation, it seems that the representation in terms of mass and energy flows might be an essential element of both.

There are two other aspects of flow models, seen as high level system representations, which have implications from a "man--machine systems" point of view:

1. A flow model provides an abstract - plant and device independent - level of description that can be used to guide a total system approach in design of man-computer cooperation for system supervision (Rasmussen, 1981).

2. It is conceivable that the use of flow models will reduce the proportion of context-specific versus context-free training and may thus result in a high transfer of training (i.e. less training expenses) and in high transfer of experience among different diagnostic tasks (i.e. higher adaptivity of operators). See e.g. the background of the research of Rouse and his colleagues (Rouse, 1981).

FLOW MODELS

Flow models describe the topology of the pattern of material and energy flows in a plant. In this section we will give a short description of the basic concepts of flow modelling. For more details, see (Lind, 1980).

In flow modelling, the basic assumption is that every material and energy process can be described as an interaction between two fundamental types of processes namely storage and transport processes. Storage processes include simple accumulation phenomena, i.e. pile-up of material or energy in a volume. But in addition to accumulation phenomena, storage processes may also include chemical processes, i.e. changes of material composition and changes of phase. Transport processes include the transfer of material and energy between two locations in space by convection, conduction and diffusion phenomena. A processing plant is then described as an interconnection of material and energy storage and transport processes. The interconnection between processes is called a boundary.

The underlined concepts above constitute the basic vocabulary of flow modelling. These concepts are summarized in fig. 1, and we have furthermore introduced symbols in order to represent the different processes in a model. Using these symbols, a graph called the flow structure can be constructed from e.g. a plant flow sheet.

In addition to the basic concepts defined above, we use the concepts conditioned process and aggregate. A conditioned process is a process that can be influenced (controlled). An aggregate is a collection of interrelated transport and storage processes. Aggregates are used in order to represent plant subsystems for which the internal structure is ignored. These concepts are summarized in fig. 2.

An example of a flow structure is shown in fig. 3 for a conventional power plant. This flow structure describes the

plant functional structure in an intermediate operating regime during boiler start-up. The location of a number of subsystems in the power plant is given for convenience.

An important property of a flow structure is that the general conservation laws of mass and energy are valid for any aggregate, i.e. they can be applied on all levels of detail. For a subsystem represented by an aggregate, we have the following balance equations expressing the laws of conservation (see fig. 4):

Mass conservation:

$$\sum_{n=1}^{N} m_n = \frac{dM}{dt} \qquad (1)$$

Energy conservation:

$$\sum_{n=1}^{N} a_n u_n + \sum_{k=1}^{K} e_k = \frac{dE}{dt} \qquad (2)$$

where

m: mass flow rate
u: energy density
e: energy flow rate
M: mass accumulated inside aggregate
E: energy accumulated inside aggregate

These equations are sufficient for all single component processes (i.e. processes in which only one chemical component is involved). In the multicomponent case the mass conservation laws should be applied for each component. Chemical reactions result in cross-couplings among the balance equations.In this report we will, however, limit ourselves to the single component case (which e.g. applies to the water/steam cycle of a power plant).

INFORMATION SOURCES

The information from a plant that can be used for observation of mass and energy flows is the set of measurements of flows, levels, temperatures and pressures, as well as conditions (e.g. "valve A closed") (compare (Lind, 1981)).

Mass flows are only known if they are directly measured. The energy density of a fluid can in most cases be obtained from its temperature (this holds only for single component flows). The energy density of vapours must be computed with the aid of the Mollier (h, s) diagram from temperature and pressure information. Measurement in a two-phase flow is not practically achievable with current technology. Also, information on pure energy flows cannot always be obtained directly, e.g. if they are common exchanges of heat; mechanical energy flows on the other hand can be measured.

It must be stressed that -- in order to keep the method, that will be proposed, a general one -- one has either to assume that a flow is in a certain phase and to check the implications afterwards by means of the redundancy in the information (if there is consistency then the assumption is valid), or to measure both temperature and pressure (this is also the case with fluids of significant compressibility). Another problem is that a change of plant state -- be it anticipated or not -- may thus vary the availability of information.

Our experience with power plant instrumentation shows that primary information on mass flow rates and energy densities is very limited. A cause for this is that the instrumentation on existing plants is designed mainly with the purpose of supporting a conventional control system that does not have advanced diagnostic facilities. This emphasizes the need for a method to infer unknown information, which will be the topic of the following.

It should be mentioned at this point that -- during normal operation of the plant -- we can of course obtain the pattern of mass and energy flows by means of more known methods, e.g. through reconstruction of the state of the system such as with the aid of observer filters. We are however primarily interested in malfunction situations.

COMPLETELY OBSERVABLE SUBSYSTEMS

In the next sections we will present an algorithm for inference in completely observable subsystems. First, we will define what these are and we will discuss how instrumentation must be added to obtain a partitioning of the total plant into useful aggregates. It should be emphasized that the following relates to design of the instrumentation.

A completely observable subsystem is defined to be any arbitrary aggregation of connected nodes and the arcs related to this aggregate with the restriction that all the arcs connecting the aggregate with the rest of the plant as well as the contents of the nodes with significant capacities should be fully measured (see (Lind, 1981)).

Several reasons motivate this approach:

1. The plant flow structure contains by its nature several clusters of nodes (often subsystems or functions). The choice of additional measurements on the boundaries of these clusters results in a great number of aggregates produced relative to the additional cost of instrumentation. Operator understanding is stimulated by this kind of aggregation.

2. By partitioning the plant into these subsystems we achieve an independency of the performance of the method in the different aggregates. The method may break down in one aggregate,

meanwhile giving results in the other.

3. There are benefits from a more efficient use of computer time. The completely observable subsystems allow the possibility to compute their overall unbalances as well as to observe the disturbances of the boundary flows. The more disturbed and unbalanced they are, the more often a detailed flow pattern should be generated/updated. Of course, the importance of the specific subsystem and operator demands play significant roles too.

4. As each boundary measurement connects two aggregates, the method enables us to detect instrument error and even to infer the missing value.

The problem we have sketched above is basically that of partitioning the nodes of a graph -- with costs (of additional measurements) on its arcs -- into aggregates of limited sizes, so as to minimize the sum of the costs on all arcs cut. This problem has been discussed by others (e.g. Kernighan and Lin, 1970). An optimal solution seems to give computational problems. However, a set of "good" solutions is of much more value than an optimal one, because the optimization obviously does not take into account operator understanding.

The heuristic procedure that is given in the referenced paper seems to be easily extendable and may then be used as a design aid.

INFERENCE OF UNKNOWN INFORMATION

In the following we will describe a method that allows the observation of non-measured flows. It is based on the conservation laws for mass (1) and energy (2). Applying these balance

equations for any aggregation of connected nodes, we can infer two unknown boundary variables, of which at most one can represent energy information (for details see (Lind, 1981)). However, three limitations must be mentioned:

1. We assume knowledge of all other boundary variables and of the contents of the nodes (changes in contents may be regarded as boundary variables related to flows to a sink-/from a source).

2. If the observed aggregate has a significant leak, i.e. a mass and/or energy flow that is not represented in the flow structure, then the inferred information is wrong.

3. When the two unknown variables are mass flows with (near) equal energy densities, then the equation set becomes singular so that no solution can be obtained.

The above gives only the possibility for inferences under the assumption that the two equations are valid, i.e., that there are no leakages within the aggregate. Fortunately, inferred information can be checked for consistency as soon as aggregates are found with at most one unknown boundary variable.

The problem we are faced with during implementation of the inference method, is a combinatorial one: during each iteration of the method, it has to search for aggregations of nodes with either one or two unknown boundary variables. If we have a completely observable subsystem with n nodes then the number of possible combinations is:

$$\sum_{i=1}^{n} \binom{n}{i} = 2^n - 1$$

These have to be evaluated for connectivity and for the number and kind of unknown boundary variables. As has been discussed earlier, the quantity of information initially available is only very limited so that the efficiency of a method such as sketched

above will approach zero for large n. The main reason for the inefficiency of a pure combinatorial approach to aggregation is that the topology of the system under consideration and its instrumentation structure are largely ignored. Below we will consider another more efficient approach.

In system partitioning there are three factors which support the preference for aggregates which consist of a single node at some level of detail:

1. As measurements in general are scarce, it should be avoided that aggregates have too many boundary arcs, in order to increase the probability that they can be used for inference. The expected number of boundary arcs rapidly increases with the number of internal nodes, so that we should spend search time on small aggregates (note that this is especially true for systems with many node interconnections).

2. A limitation of aggregate size to one node will result in avoiding the combinatorial problem.

3. Intricate aggregations of seemingly unrelated nodes have a negative influence on operator understanding. On the other hand, partitioning into meaningful aggregates, such as single nodes, will allow judgments based on the original components or functions (the validity of this argument depends on the level of detail of the plant model).

Partitioning of completely observable subsystems

Our problem of finding suitable aggregates which could be used for inference was formulated above as a problem of partitioning the flow structure of the completely observable subsystem under consideration. We will now reformulate this problem by creating a new kind of graph that represents both the system topology (i.e. flow structure) and the structure of the instrumentation system. Using this graph our problem can be solved by using standard partitioning procedures from graph theory (see e.g. (Deo, 1974)).

The new graph to be analyzed will be called the plant variable graph in the following. It is obtained from the flow structure by substituting two parallel arcs for each material arc. One represents the energy density variable related to the material flow and the other represents the mass flow rate variable. Furthermore, all processes and aggregates in the flow structure are replaced by simple nodes. An example is shown in fig. 5. By this transformation we have made explicit the fact that the flow structure represents two superimposed graphs (material and energy flow structures). The interaction of the mass and energy balances prevents a separation of the two flow structures into independent graphs; our partitioning thus has to take this into account.

If all arcs representing known (measured) variables are removed from the plant variable graph, our partitioning problem can be formulated as the problem of finding cut-sets of order one or two in this modified graph. To each cut-set (i.e. set of arcs which will divide the graph into two if they are removed) corresponds a partitioning of the subsystem under consideration into two aggregates which may be used for inference. However, cut-sets consisting of two pure energy arcs must be discarded as they correspond to aggregates which cannot be used for inference. In addition, cut-sets consisting of two mass arcs must be rejected if the actual values of the related energy densities lead to a singular problem (compare the mass and energy conservation laws (1) and (2)).

This procedure will in general generate many alternative ways of partitioning a given subsystem into two aggregates. The number of alternatives depends on the amount of instrumentation available for the subsystem (if many plant variables are known by measurement, then the modified plant variable graph will have low connectivity and accordingly there will be a high probability of finding cut-sets of low order). Furthermore, as the partitioning procedure should be applied iteratively, we may in principle generate a whole hierarchy of aggregations. This creates computational problems and it is clear that it is necessary to set up criteria for choosing a suitable partition-

ing in a given situation. This is a topic of further investigation. In the next section we will present an algorithm which applies to a particularly simple partitioning procedure.

A SELECTED INFERENCE PROCEDURE

As a consequence of the arguments in the previous section, we will now consider the use of single node aggregates, i.e. a partitioning where one of the two aggregates has only one internal node. In this case it is not reasonable to use the general cut-set algorithms, as single nodes with only one or two connecting arcs can be found by means of simple search through the set of nodes of the modified plant variable graph.

We thus search for nodes which allow balance computations and we derive information from the assumption that the conservation laws over these nodes apply. Iteratively, information is inferred until nodes are found which allow checks of derived information. If these checks point at consistency, then the foregoing assumptions are confirmed and the inferred information is true. If, however, in particular classes of fault conditions, the check is contradictory, then at least one of the intermediate assumptions might have been wrong. Other branches of assumptions or other checks have to be found in order to obtain consistent information. In this way, suspected nodes (e.g. leakages) or suspected measurements are avoided by making use of the (small) redundancy in the instrumentation.

This inference method leads in general to long chains of inferences and may with advantage be combined with the following clustering method that is aimed at decomposing the problem into smaller, more manageable parts. It is based on search for cut-sets of order one (order two cut-sets may present computational problems).

We try to find a subpartitioning of the graph, through cutting one unknown arc that divides it into two unspecified clusters of nodes, and we order the different subsystem partitionings such that aggregate pairs which have the smallest difference in the number of internal nodes are selected first. Basically, this heuristic results in a very fast clustering of the problem, while the connecting arc can be computed from two sides (there are four equations and one unknown variable). For the inference, use can be made of the cluster that most agrees with the information that is already available. If the conservation laws for both clusters agree, then the means of the independent inferences may yield good results.

In appendix A we propose an algorithm that makes combined use of the two methods as discussed in this paragraph. The algorithm can easily be implemented on a minicomputer in a list processing language, such as LISP. For tutorial reasons it is given in its original form. In appendix B an example is given of its behaviour on an actual subsystem, namely the preheater part of a conventional power plant.

THE INFLUENCE OF UNCERTAINTY

Until now we have disregarded the fuzzy distinction between aggregates which have consistent information and those which have not. A tolerance is needed that should be crossed before deciding upon not using the inference potential of a particular aggregate. If this tolerance is too low then different sources of uncertainty (measurement noise or dynamic effects caused by the distributed character of the process) may result in a breakdown of the inference method. However, when the tolerance is too high, then failed measurements and significant leakages may cause incorrect inferences, while the redundancy in the information has not fully been utilized. The allowable errors in

the conservation laws are thus a result of a weighting of the probability of breakdown versus that of wrong information. The tolerance for each completely observable subsystem can be stated beforehand, based on the degree of redundancy in the available information, but on-line adaptations are of course needed, e.g. to cope with sudden extremely dynamic behaviour.

We should stress, however, that the foregoing can also be used during the design of the instrumentation, as additional measurements should be located internally to the completely observable subsystems in places where the resolution of information appears to be too low in practice to allow coping with the required maximal local multiplicity of failures.

It must be emphasized that only disabling failures, such as leakages and faulty measurements, are important in this context. The method's functioning does not suffer, for instance, from a pump trip.

CONCLUSIONS AND COMMENTS

In this report we have considered the use of flow models (Lind, 1980) for observation of mass and energy flows in process plants. The main motivation for this work has been to develop methods to support the human operator in a high level state identification task. A more detailed discussion of the background of this work is given in the introduction to this report. An algorithm has been developed that may be used for inference of non-measured flow variables and for the identification of leaks and disturbances. The method is based on the general laws of mass and energy conservation. This provides the method with some basic advantages. It is applicable to any material and energy processing system on any level of detail and it is able to handle unforeseen malfunctions.

However, it should be stressed that the presented algorithm is not in a final form and should be considered as preliminary. The algorithm suffers from several shortcomings. It does not take into account or do not make efficient use of important plant information that is normally available, such as sequential (time) information and much information in the physical domain (e.g. valve characteristics). Further work on the development of strategies for the selection among alternative aggregates for inference will consider such problems.Furthermore, the influence of noise and other sources of uncertainty on the quality of the inferences which are made should be investigated. Uncertainty characteristics of a plant situation may provide an important basis for the strategic choice of aggregates for inference. Finally, the inference principle should be evaluated experimentally. The preliminary method is published now as a record of the current status and as a basis for future development. It might eventually provide a tool for an advanced diagnostic system.

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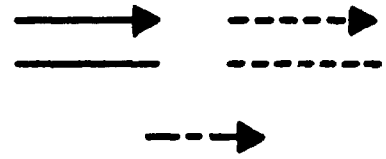
PROCESS	PROPERTIES	VARIABLES	SYMBOLS USED IN FLOW STRUCTURES MATERIAL	PURE ENERGY
STORAGE	CONTENT	INTENSIVE EXTENSIVE		
TRANSPORT	FLOW	ACROSS THROUGH		
BOUNDARY	INTERFACE	POTENTIAL FLUX CONDITION		

Fig. 1. Flow Modelling Concepts

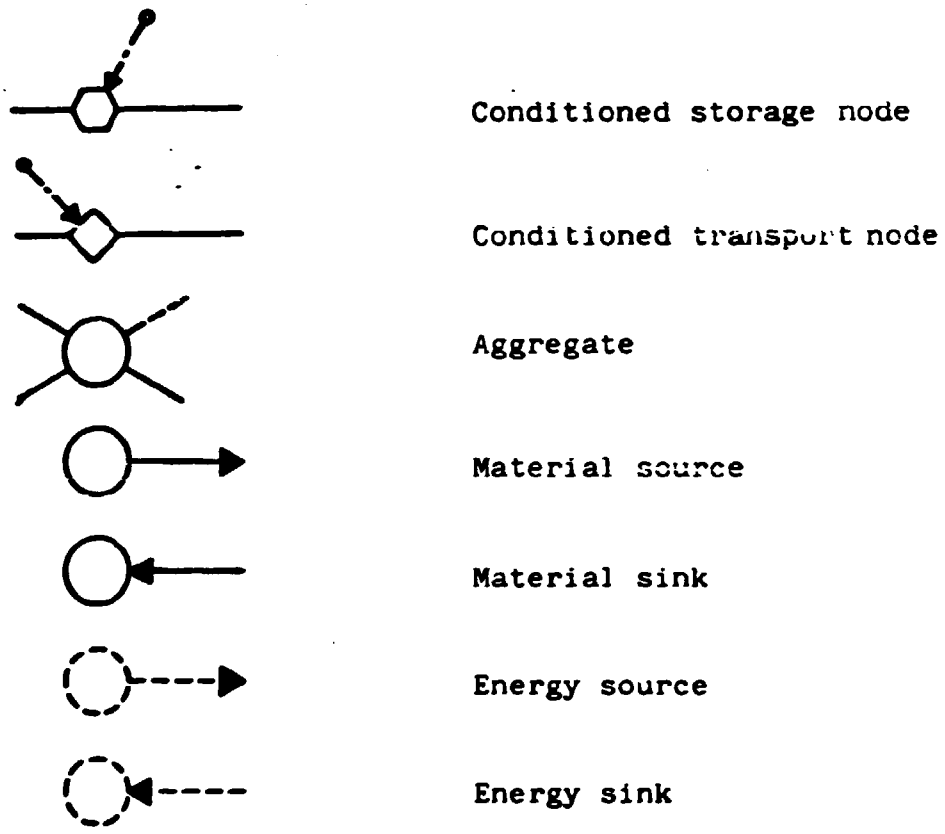


Fig. 2. Additional concepts.

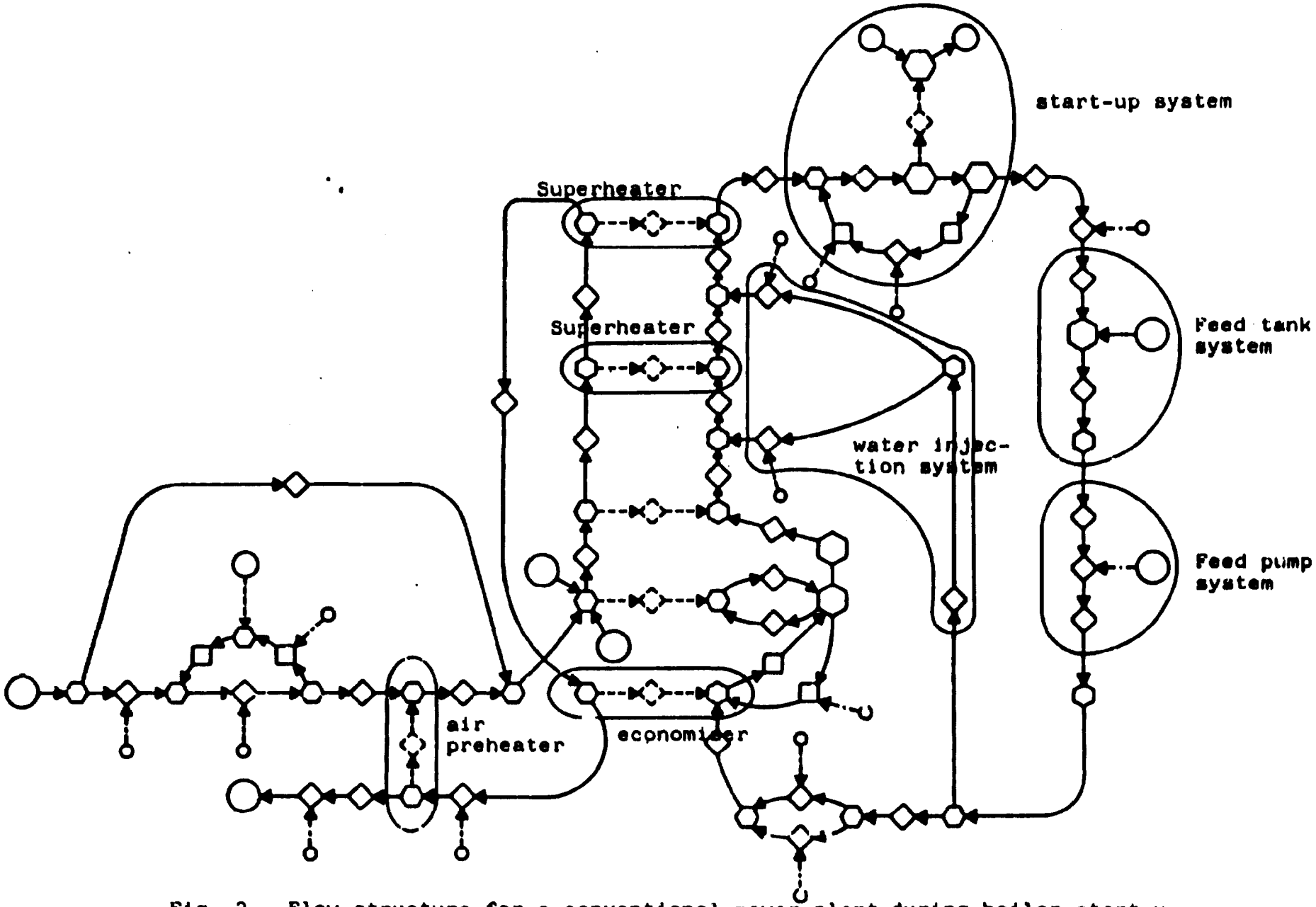


Fig. 3. Flow structure for a conventional power plant during boiler start-up.

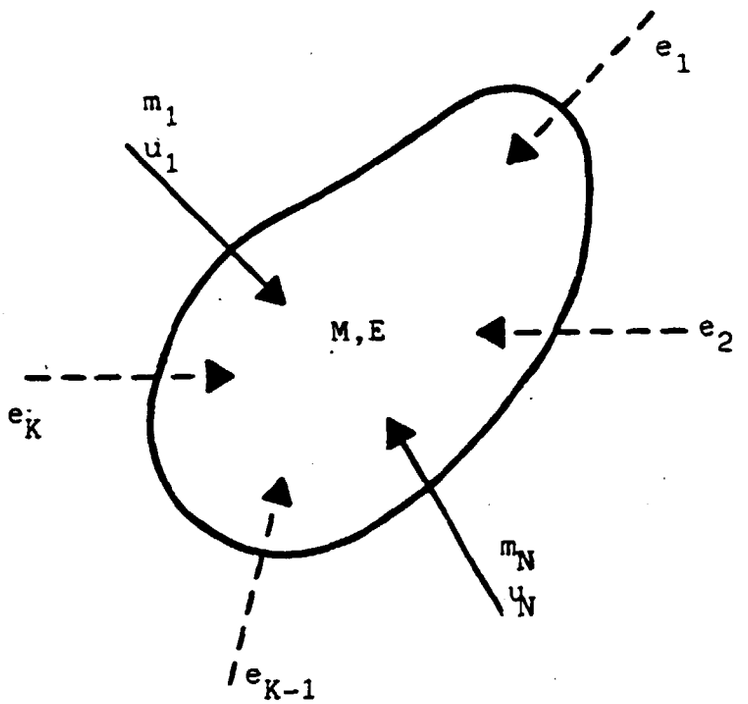


Fig. 4. Aggregate with boundary flows

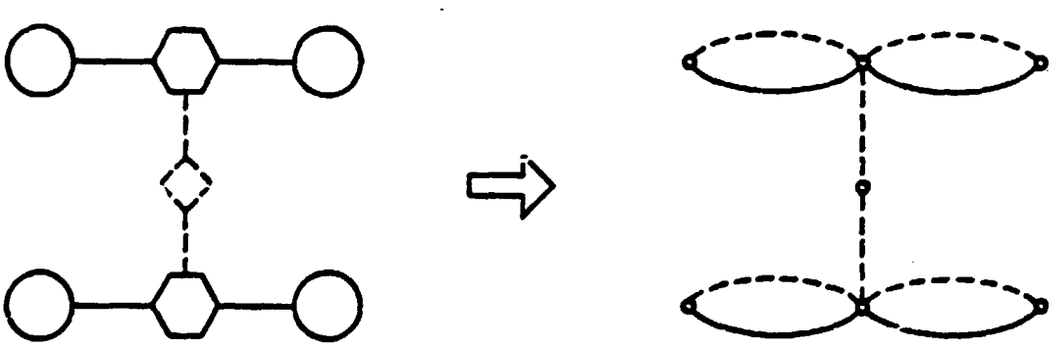
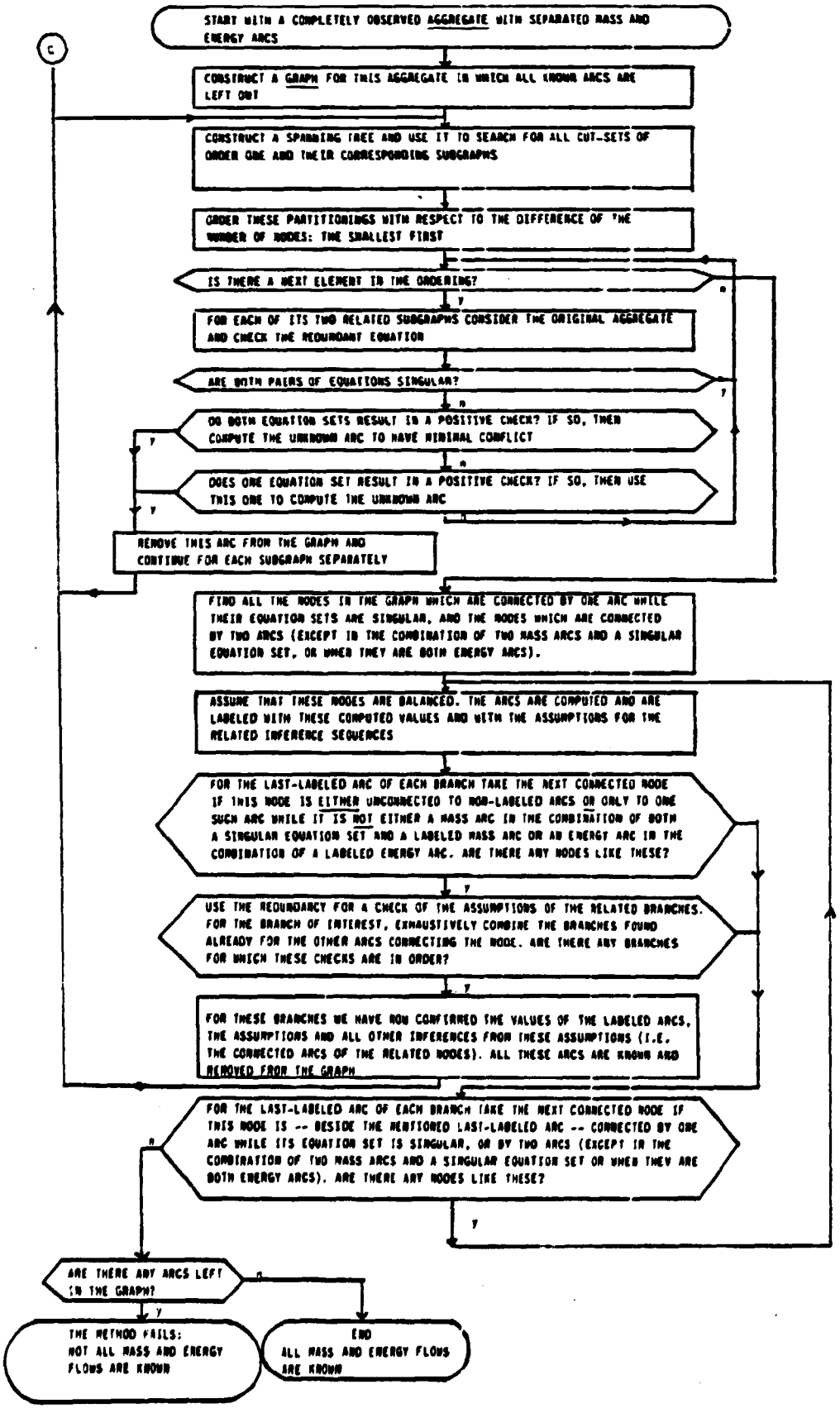


Fig. 5. Flow structure of a heat exchanger and the associated plant variable graph.

APPENDIX A: OBSERVATION ALGORITHM



APPENDIX B

EXAMPLE OF BEHAVIOUR OF OBSERVATION ALGORITHM

In figure B1 the flow sheet of the preheater subsystem of a conventional power plant has been given. Its graph representation is shown in fig. B2. For editorial reasons the normally inactive structure has been left out. Combining the information on physical variables as supplied by the instrumentation, and the knowledge (assumptions) on the phase of the different flows, the computer can directly infer the values of several mass flows and enthalpies. In the particular aggregate we have extended the instrumentation with three flow measurements in order to separate it from the rest of the plant as well as to give the algorithm a starting point. In fig. B3 the mass and energy-/enthalpy arcs have been separated whereafter the known arcs have been left out.

The example we will give is for the case that there exists an internal leakage in one of the heat exchangers (from node 22 to node 9). The measurements are in order. It must be emphasized that the malfunctioning of the rest of the plant has no influence on the following.

1. There are three cut-sets of order one (of one arc): 6-7, 15-27, 22-30. The arcs are computed and removed from the graph.
2. We grow branches of assumptions until checks are possible: (10-25-26-20), (10-25-24-23), (10-11-6-5), (9), (9-8-1-2), (12). The check appears over node 22 with the branches (10-25-24-23) and (9). It will be negative.
3. The growth of branches continues: (10-25-26-20-19), (10-25-24-23-22), (10-11-6-5-4), (9), (9-8-1-2-3), (12). There is a check of branch (10-25-24-23-22) over node 9. It fails however. Next, a check of branches (10-25-26-20- 19) and (10-11-6-5-4) over node 18. This one succeeds. The assumptions are thus verified, the related arcs are known and removed from the graph (see fig. B4).

4. There are no partitionings possible at this moment.
5. The branches become: (24-23), (9), (9-8), (12), (17-16), (3), (3-2). Checks are done at nodes 22, 1, and 15. Only the latter one succeeds. The progress of the method can be seen in fig. B4.
6. The one arc cut-sets are: 9-22, 9-8, 22-21. Cutting 9-22 is not possible as the resulting equation sets are contradictory. Arcs 22-21 and 9-8 are inferred and removed. Of the three resulting subgraphs only (24, 23, 22, 9) needs further discussion. The balances over the total subgraph appear to be in order while node 9 has a mass surplus. The algorithm breaks down at this point, but an almost complete flow pattern has become available.
7. Future work will include a search for elementary rules which can be used in further diagnosis. For the present situation e.g.:

   IF AN AGGREGATION OF NODES IS BALANCED WHILE A PART OF IT IS UNBALANCED, THEN THERE MAY BE AN INTERNAL LEAKAGE

   and

   AN INTERNAL LEAKAGE IS MOST LIKELY TO OCCUR BETWEEN NODES WHICH HAVE A BOUNDARY IN THE PHYSICAL STRUCTURE.

   The second rule states that the pipework in our heat exchanger is the location where an internal leakage may occur (clearly, there cannot be a leak from e.g. valve 23 into the feedwater flow (see fig. B1)).

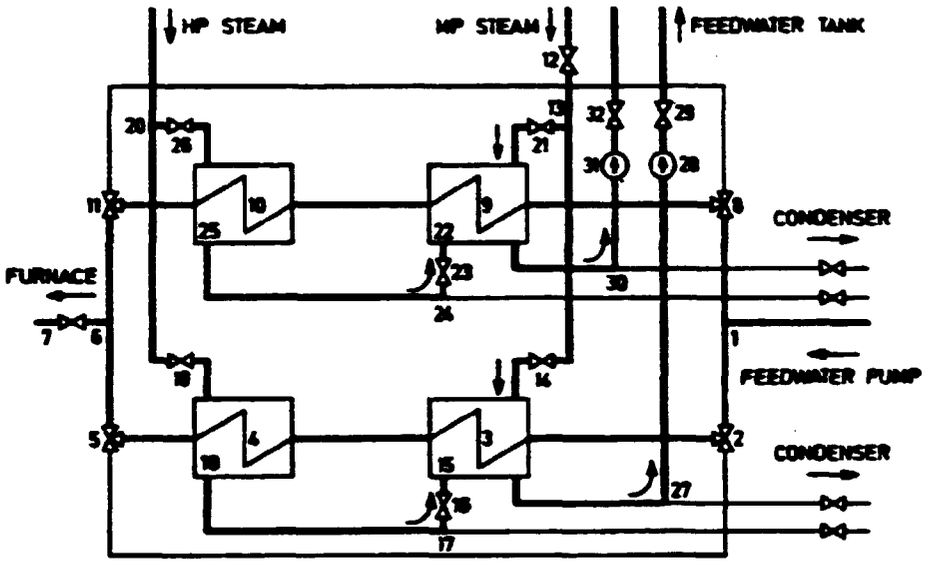


Fig. B1: Preheater subsystem of a conventional power plant.

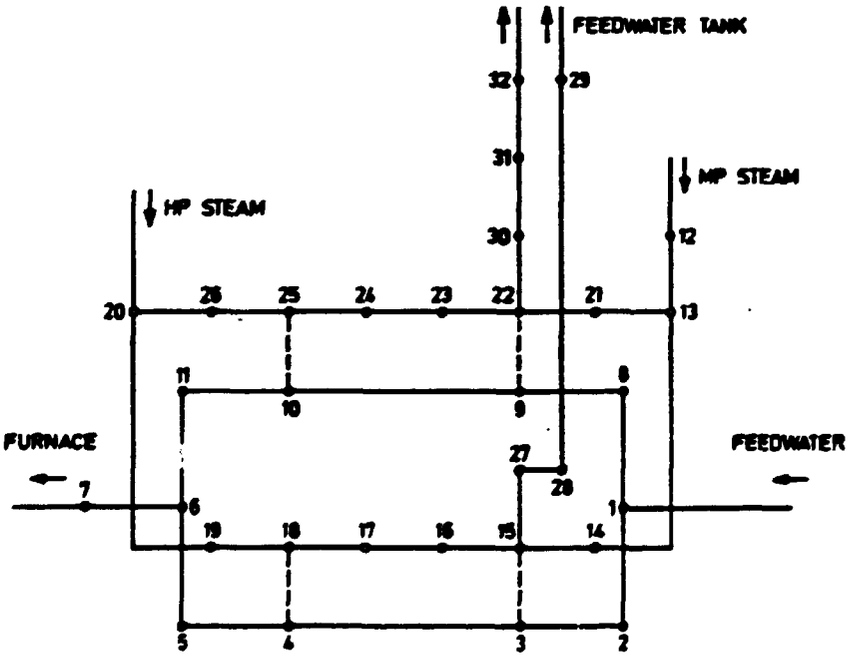


Fig. B2: Simplified flow structure of preheater subsystem.

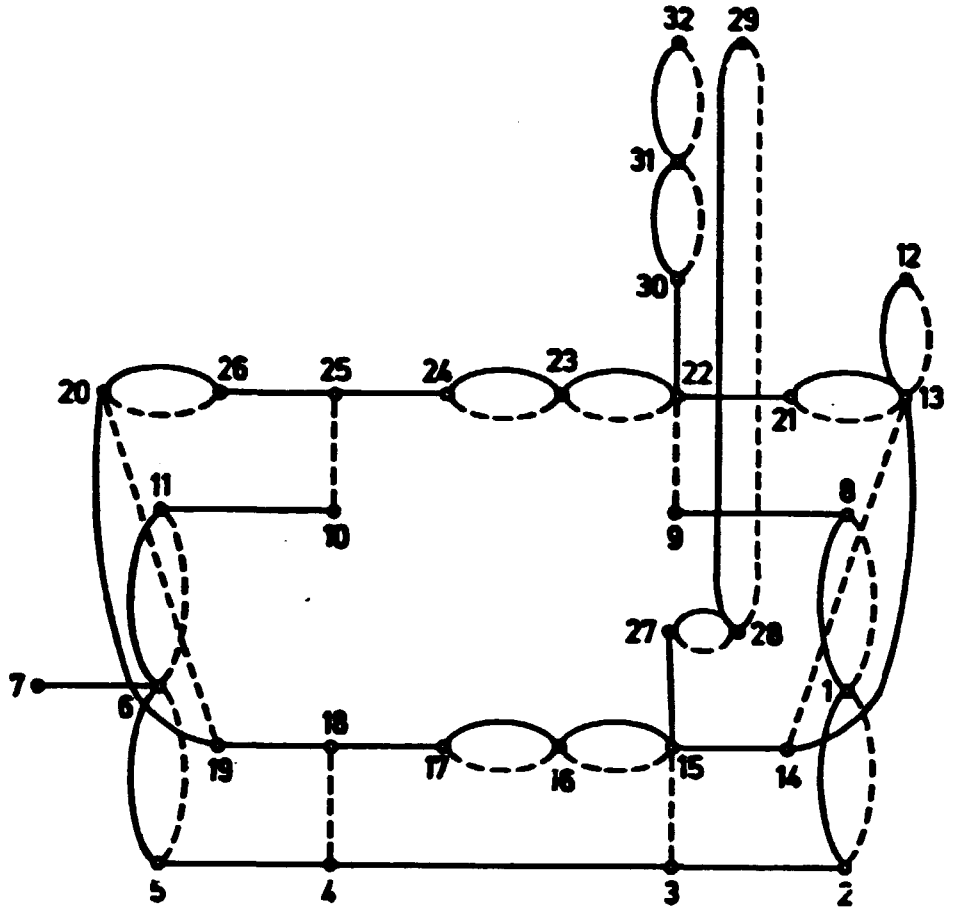


Fig. B3. Modified plant variable graph (arcs with measurements are removed).

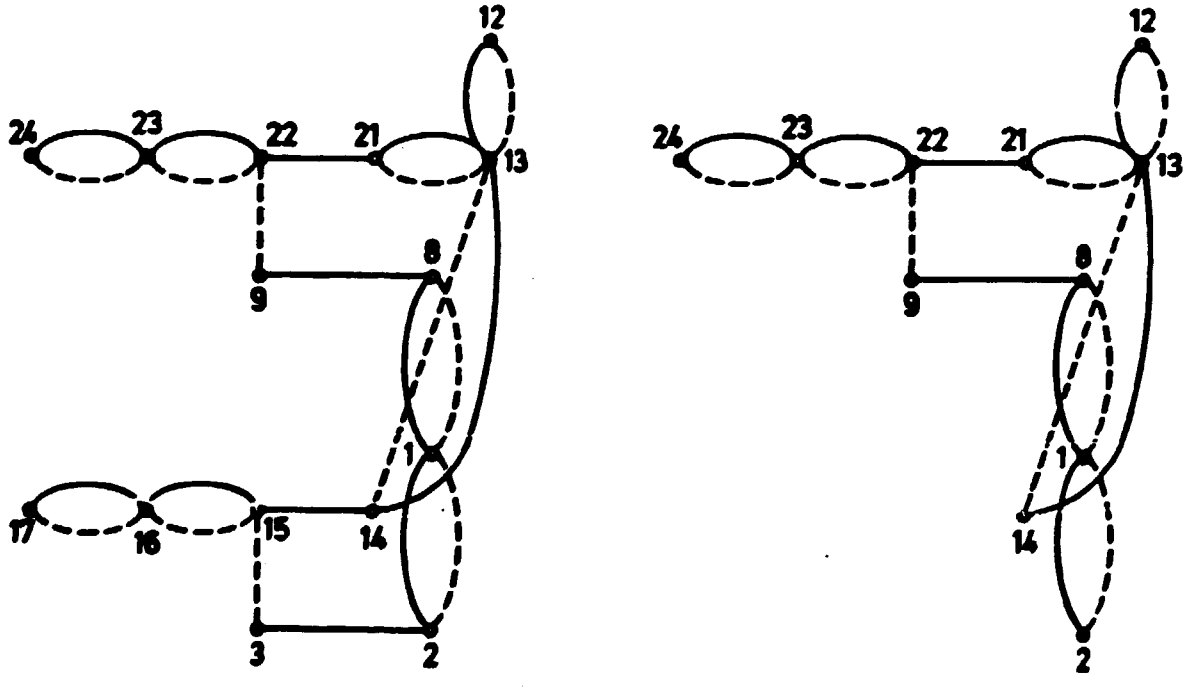


Fig. B4. Intermediate stages of the graph in fig. B3. produced by the algorithm.

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The Use of Mass and Energy Balances for Observation in Process Plant Diagnosis

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Date December 1980

Department or group
Electronics

Group's own registration number(s)
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pages + tables + illustrations

Abstract

A method is described that uses the invariant mass and energy conservation laws in order to extract a detailed pattern of mass and energy flows from the instrumentation of a process plant. The basic feature of the method is that it is applicable to a large range of plant operational situations, such as those initiated by unforeseen failures, failures with dynamic symptoms, multiple failures, and failures during sequential operations.

The authors' intentions with this interim progress report are to describe the basic ideas behind the method, as well as to discuss some of its implications for man-computer cooperation in process plant diagnosis.

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