OPEN ACCESS
Global Journal of Research in Engineering & Computer Sciences
ISSN: 2583-2727 (Online)
Volume 05| Issue 03 | May-June | 2025
Journal homepage: https://gjrpublication.com/gjrecs/
Research Article

How an artificial intelligence diagnostic system constructs

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DOI: 10.5281/zenodo.15603067 **Submission Date:** 28 April 2025 | **Published Date:** 05 June 2025

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Abstract
In this paper artificial intelligence for diagnostic system was studied. The diagnosis phenomena intelligent analysis have defined. Diagnostic information modelling method was developed. The diagnosis algorithm was derived. How artificial intelligence for diagnosis constructs and operates has examined. Artificial intelligence programs are programs that exhibit behavior normally identified with human intelligence. Hypothesis, testing, frequency analysis and troubleshooting system were developed. A human like reasoning mechanism uses this knowledge to solve problems in diagnosis domains. Artificial intelligence architecture for fault quantifying in knowledge base and data base environment has developed.

Keywords: *diagnosis phenomena, algorithm, knowledge coded, artificial intelligence, troubleshooting.*

1. Introduction
Various methods of automated fault diagnosis have been proposed. Diagnosis by cause- and -effect analysis using patterns of process alarms were studied by many authors. These methods are not quantitative and therefore are not highly sensitive detectors of violations of process mass and heat balances.

Quantitative diagnostic methods based on filtering and estimation techniques have been discussed by authors [1]-[3]. Particularly when dynamic models are used, these techniques require extensive modelling and computation and are not well suited for monitoring and diagnosis at the fault plant level.

Improved statistical methods for detecting gross errors in process measurements have been suggested. Another approach to fault diagnosis involves expert systems. Expert systems have been applied to diagnosis problems in several domains, for example, in medical diagnosis, in electronic and mechanical systems diagnosis, general safety systems, and in process plant domain. Expert systems allow the accumulated experience, judgment, and heuristics of process engineers and operators to be incorporated into automated reasoning systems. Application of this expert knowledge in real time by direct access to plant measurements in theory allows for improved and more consistent plant operation in spite of personnel turnover.

Expert systems based solely on experience are not ideal in chemical plant fault diagnosis. Experts may not be as readily available or as highly trained. Many faults needing to be diagnosed may never have been experienced, and for new or recently retrofitted plants, there may be no applicable experiential knowledge. The experiential approach requires that most if not all of the knowledge be developed from scratch for each new application. This is a critical problem because the number of rules required for large plants may be as high as 10,000 to 100,000. Experiential approach is most appropriately applied to unstructured, where the theoretical and conceptual basis for reasoning is not well understood. In the chemical engineering environment, a large fraction of the knowledge is structured, and physical models based on heat, mass and momentum transfer, kinetics, and process chemistry can be incorporated into the diagnosis and safety.

In recognition of these difficulties, this chapter focuses on model based approaches to fault diagnosis. Nonetheless, it is recognized that experiential knowledge will play a key role in actual applications of expert system to fault diagnosis and other areas of process operations. Therefore, the current work emphasizes the translation of model based diagnostic techniques into sets of rules which can be incorporated into a large expert system that includes experimental rules.

Diagnostic technique, which has presented here, is intended only as one element in a three- part approach to diagnosis which includes causal. In this paper artificial intelligence-AI methods have applied to diagnostic system building.

2. How phenomena in diagnostic process defined

Definition signals some phenomena is achieving seek out because it appears. Modelling method started with system, subsystem, elements, and their interrelations definition according to goal state. It follows methods and procedures formulation for model development. Model establishing, solving, testing and applications is final phase of the information diagnostic phenomena building [4]-[6] (Fig. 1).

$$M_i = \sum_{i}^{n+m} f\,(entity,\ relation,\ source) \qquad (1)$$

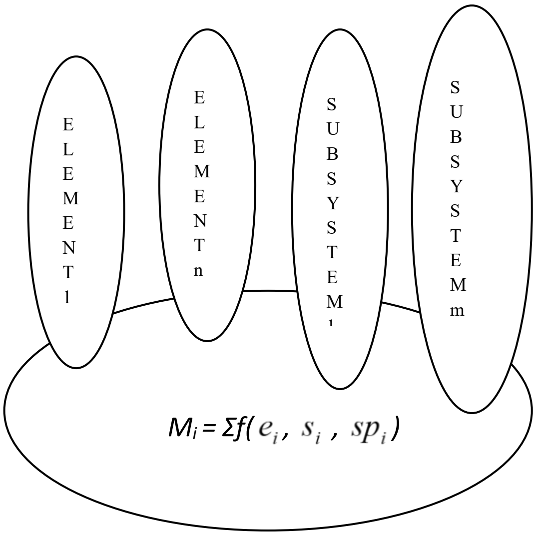


Fig. 1: Information building

where e - entity, r - relation, s - source, n - number of basic elements, and m is number of subsystems.

The system topology or component interconnections are defined by the process connections of the working process model. The level of aggregation is defined by the modular component interconnections which define propagation paths of attributes within the system.

Initial research starting by phase of the development of a conceptual framework which facilitate the modular specification of models, and second phase the development of a logic framework which will permit object using attributes and simulation techniques to be linked into executable models.

Various rules can be applied to this system based on the transitivity relationships of the qualitative variable. To organize the logic of the rules, states variables must be defined within the system. Three types of state variables can be defined within a given component. The first are those variables whose values can be controlled by the system operator. These are controllable variables. The second set of state variables are those variables whose values are observable to the system operator over the acquisition data system. Last are those variables whose values are not immediately discernible by the system operator such as attributes of inner state, and so on.

Scenarios are used to set initial states of the system state variables and attributes to predefined values prior to a model.

3. Diagnosis

Diagnosis means gathering information, hypothesis formulation and hypothesis testing with available data. Sometimes it is not enough iterating several times, if hypothesis return negative output.

Framework definition includes all component, input and output attributes, variables state, rules behavior and initial data. Analysis this information by appropriate technique, synthesis, and decision making seek out the new useful framework.

An algorithm for diagnosis is shown in Fig. 2.

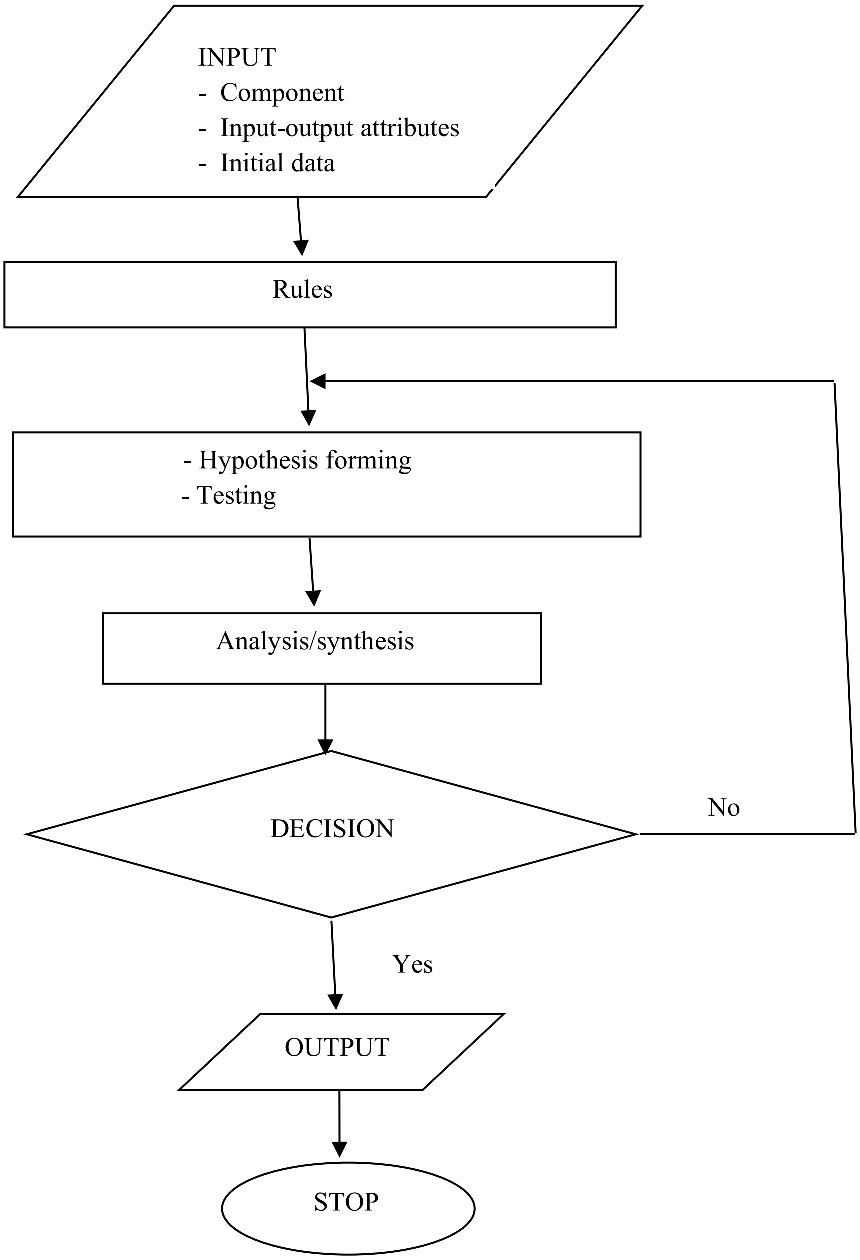


Fig. 2: Hypothesis producing

4. Artificial intelligence diagnostic system construction

Diagnosis requires knowledge of the system and how it operates normally. Faulty equipment that monitors, for example, information, chemical or hospital patients may cause death. Because of that diagnostic system forming is widely significant.

Diagnosing and troubleshooting processes are developed follows functional relation fault and symptoms. This paper contributes in user's diagnostic level system establishing.

Diagnosing and troubleshooting skills have been noted in many industries, and this in time when equipment and machinery are becoming increasingly complex and require more skill, and often time, to troubleshoot. For example, airline reservation systems report a loss lot of money for every minute a failed computer reservation system is out of order, and utilities report millions of dollars in lost revenues every time a failed machine causes loss of power generation.

What makes diagnosis difficult is the large amount of knowledge and experience it requires [7],[8]. First, it requires knowledge of the interface and how it operates normally. Second, it requires gathering some information about the failed interface and its fault symptoms. Third, it requires knowledge of what type of equipment information it is necessary to gather that is relevant to the fault. Fourth, it requires the ability to use the knowledge about the equipment and the information gathered to explain how the fault could have occurred. Fifth, it requires the ability to form a hypothesis and perform some tests to get back more information that either confirms or denies the hypothesis.

4.1 Hypothesis

The process of gathering information and formulating and testing hypothesis may need to be done several times if the hypothesis formulated turn out negative (Fig. 3). Only at the end of this process can the diagnostician repair the fault or replace the malfunctioning part.

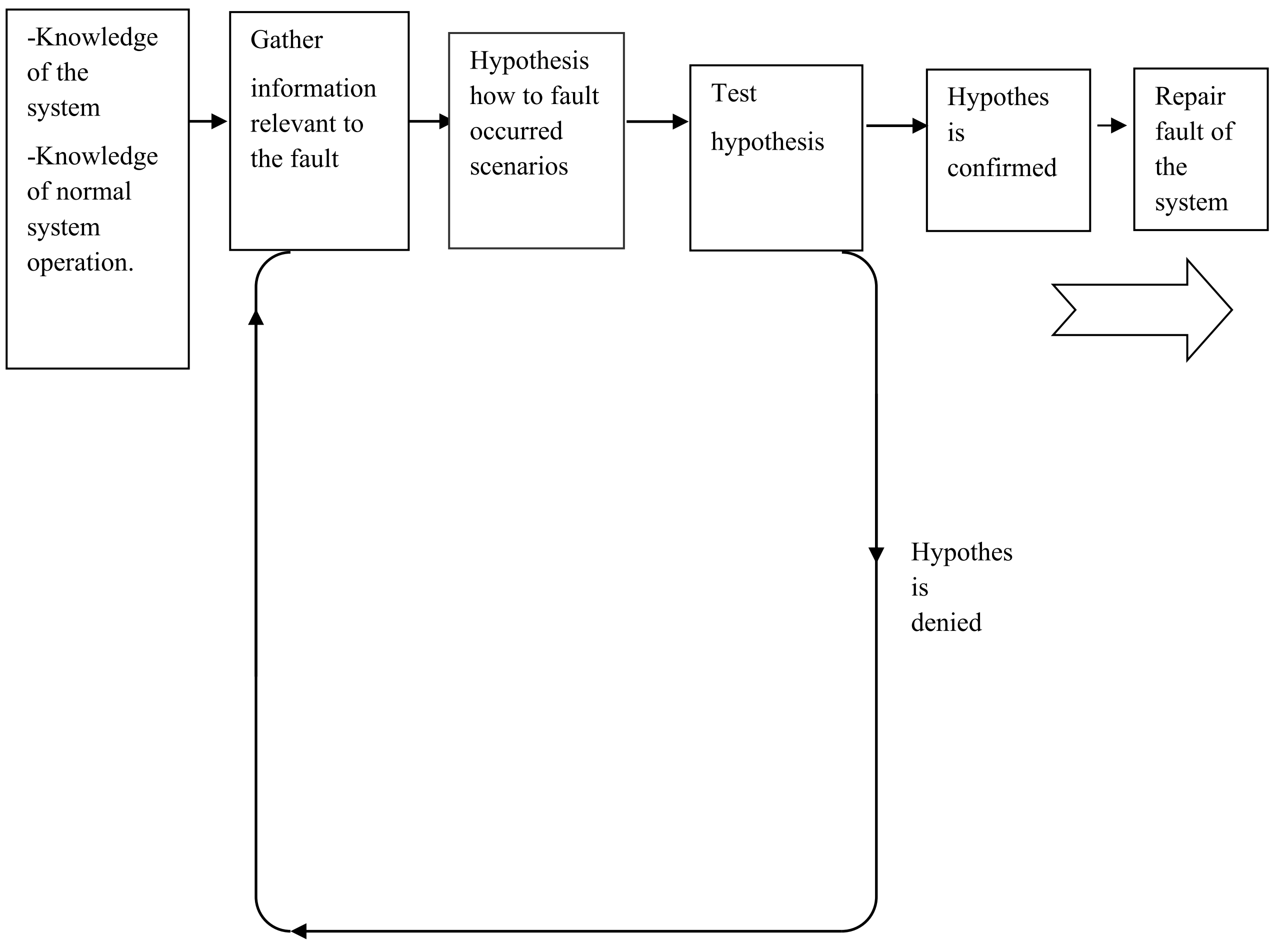


Fig. 3: The diagnosing and troubleshooting system

Unfortunately, few people appear to have this body of knowledge necessary to make them good troubleshooters. Those that do tend to be promoted so that they do not use their troubleshooting expertise anymore. The remaining troubleshooters may be competent, but they lack the spark and instincts that made the expert unique.

Knowledge systems offer a way to preserve and protect a troubleshooter's expertise and to make that expert troubleshooter a consultant to many people.

The idea is to encode as much as possible of the expert's wisdom, judgments, and decision making techniques in a representation that can be understood and manipulated by a computer that is accessible to other troubleshooters. In this manner, the knowledge and skills of the expert can be used to advise and amplify the knowledge of less experienced personnel.

A decision to develop knowledge systems for diagnosis requires the consideration of certain factors that are relevant to the system's cost effectiveness. For example, several equipment diagnosis systems are likely to be needed at many locations rather than one or a few needed at a centralized site. This multifunctional requirement limits the amount of money that is likely to be allocated for dedicated to process safety the completed systems.

In addition, the diagnosis process often requires a good deal of ancillary information about many equipment components and related previous troubles.

Since such information is usually present in company database, companies with knowledge based diagnostic systems would like them to be able to access the relevant databases automatically, instead of repeatedly needed information into a knowledge base.

A flurry of equipment diagnostic activity has produced several knowledge systems than can diagnose plant, steam generators, networks, locomotives, automobiles, computers, disk drivers, circuit boards, and communication cable troubles. Many companies experience with a knowledge system designed and can be gained by applying expert system techniques to diagnosis problems.

For example, if the production is easy to maintain and service, it reduces the buyer's operational costs and increases the seller's advantages. Therefore, company took a hard look at how to increase productivity of the maintenance plant.

The first level of maintenance that the production sees is in" running repair", for diagnosis and repairs, for example, checking dirty fuel strainers and clogged fuel lines, and adjusting governors.

Otherwise, the equipment is sent to a major repair plant, where it remains for some time while it is scheduled for overhand.

Troubleshooting manuals proved unsuccessful in increasing productivity. So, company decided to have a try at expert and make it available at remote locations.

Company can put together prototypes of equipment operation trainings center for testing, in the field at various equipment around. Those prototypes contained numerous rules. Of these, roughly many rules were devoted to fault diagnosis and repair procedures. The other rules formed a help system which, on demand provided additional information for the user.

4.2 Frequency analysis

Frequency and probability analysis involves frequency values of hazards, magnitude identification of each hazard and develop of sound criteria for quantification of logic tree.

A useful notation in process system safety is the hazard potential, a measure of the greatest harm that can occur in the worst possible event in a process plant or process plant subdivision.

It is reasonable to use this concept in assessing safety measures in a plant, the grater the hazard potential, the more and better safety measures are needed to lower the probability of occurrence of the undesired event to the point that the level of risk is at or below the acceptable risk level.

Safety measures may include intrinsic measures and conditions, which insure a priori that a hazard potential can become real only in the event of a relatively improbable combination of multiple independent failures.

Where product quality consideration makes it necessary to design the process and process control system so as to prevent for example, an exothermic reaction getting out of control, safety or protective measures can be built up on the basis of this intrinsic safety in order to lower the risk to the acceptable level.

All hazards, major and minor need to involve. The relationship between hazard and risk must be defined. Consequences modelling develops troubleshooting system, formalizing as learning tool and creates recommendation to tolerant system building.

Both traditional databases and knowledge bases are designed to store information [6]. They differ significantly from each other in the types of information they can store, the types of interrelationships between data they handle, that indicate either application specific or common sense knowledge, and in what kind of training is needed for persons who updates the stored information.

To illustrate one difference, databases store only facts. Moreover, database facts are straight forward and define. Cause-and effect knowledge, rules, and imprecise and probabilistic information store in knowledge base (Fig. 4). Typical knowledge found as knowledge bases includes information such as" Pump fails if supply absent". Or else, knowledge bases handle observed or proven rules, such as "If supply absent whole plant failure" [6]-[8].

The update requirements for data bases contrast sharply with those for knowledge base update because of the differences in the type of information and in the cause-a such as equipment name, plant subdivision, event name, event code and middle frequency traverse many applications (Fig. 4).

For example, database may be updated in data processing. The data processing workers do not, however, need to know about the mechanics of running a department or about the devices that will use parts in a database.

In contrast to database information, the knowledge and rules found in knowledge bases include both data heuristics of a professional and engineering nature, specialized for a particular application area.

It is not only the ability to store general knowledge, rules, and uncertain information that differentiates knowledge bases from databases. Knowledge is represented by models.

The ability to store these interrelationships makes it possible to build and infer a great deal of causal and common sense knowledge about the plant and environment, as well as knowledge about what is possible in a given application area. These types of knowledge base structures do not exist in databases.

Most often, a database is a fairly rigidly structured set of records and items within records, comparable to what is found in a file cabinet. Interrelationships in the basic faults are fairly simple. It easy to represent, for example, a relationship showing that both these middle frequencies and malfunction belong to end of data base.

4.3 Testing

The first problem chosen to be a test diagnosis case illustrates the difficulties that confront troubleshooters and how a knowledge based troubleshooter can be constructed to handle these difficulties. To choose the test problem, system ask its troubleshooters to identify the most recurrent problem that their running repair system have to face.

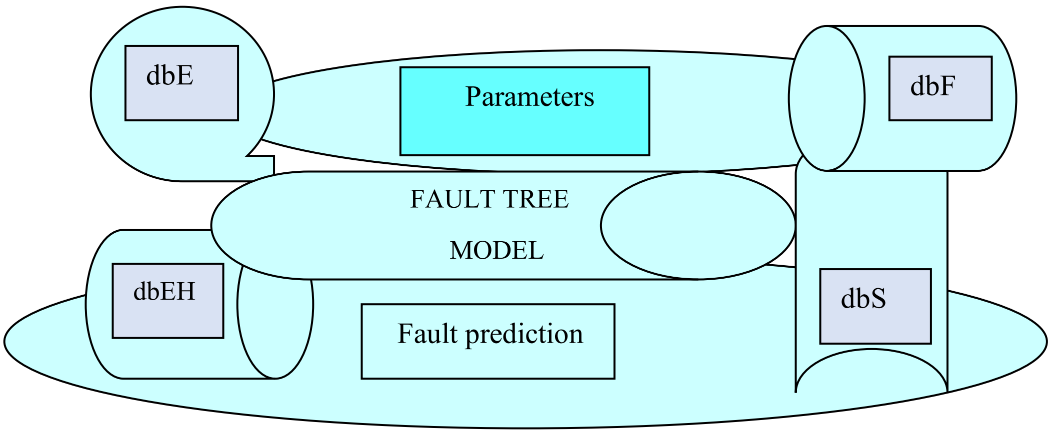
According to the process inventors, questioning of the repair shops troubleshooters revealed that something call "not loading properly", accounted for about thirty percent of reported symptoms. The problem with symptom is its vagueness. Not loading properly means there is something wrong with the process. Clearly, this symptom could result from several causes, including chemical reaction faults, mechanical faults, electrical problems, transmission information difficulties, or human causes.

The narrow the field of possible causes for the process system problem, the process fault knowledge base is taxonomically divided into a series of different knowledge and process systems areas [9]-[11] (Fig. 4). For example, knowledge in the form of rules, is first divided according to faults, such as chemical, electrical, mechanical, transmission, or operator problems. These faults could apply to different types of process plant systems. The systems areas are further partitioned into subsystems. Each of these subsystem has components. Finally, within each subsystem division rules are subdivided according to hypothesis about faults such as operator error and engine unable to make power.

4.4 AI troubleshooting system

During a troubleshooting session, process plant fault system starts by collecting background information and problem symptoms. Upon startup, the system asks a number of questions about the process model number, model year and reported symptoms. Process plant faults system tables provide additional information, such as the process standard features, history of failures, and that model's propensity of failures (Fig.4).

The loading of the reported symptoms and background information into the knowledge system triggers its diagnostic procedures, which culminate not only in a diagnosis but also in recommended corrective actions. The diagnostic procedures involve both backward and forward chaining techniques for reasoning. To perform its deductions and diagnosis, system uses information input by users or sensors, in addition to its own knowledge in the form of IF-rules, IFF(if-end-if) rules, WHEN rules, which activate new procedures associated with newly inferred facts, and meta-rules, which control, reorganize, and reorder the reasoning processes.



dbE- accidents base, dbF-Frequencies base, dbEH-Engineering heuristic base, dbS-Symptoms base

Fig. 4: Fault quantifying in knowledge base and data base environment

The diagnosing process begins with backward chaining. Based on the initial symptoms input by the user and the possible causes that the expert has suggested, the backward chainer proposes a likely hypothesis for the particular problem area in question. A typical system question to the user, to determine the symptoms and used hypothesis that start the backward-chaining process, might be: Is the governor steady? If the answer is no, the system knows five possible causes. The order in which these causes are proposed as hypothesis for evaluation are in order of increasing cost of the test to prove of disprove the hypothesis. In the case of factors that could make an unsteady governor, the simplest thing to check first is whether there is enough supply, second is a test to determine whether or not the supply is good quality. If neither of these solves the problem, the system tries out the next, more complex, least expensive hypothesis.

Purposes equipment life is judged by rather arbitrary standards, under current laws. If the allowable depreciation life is different from the project life, cash flows to the project will be affected. Different parts of the investment may be allowed different depreciation lives; the estimate of profitability should take any significant differences into account.

5. Discussion

Diagnosis phenomena, modelling method and algorithm were defined.

Artificial intelligence for diagnostic system construction and operation was developed.

The knowledge and rules found in knowledge bases include both data heuristics of a professional and engineering nature, specialized for a particular application area.

To determine the symptoms user used hypothesis that start the backward-chaining process, might be. The symptom can result from several causes, need to seek out which one.

Troubleshooting system for fault killing was discussed.

6. Conclusions

Diagnostic system intelligent simulation can seek out fault of multiple symptoms. Knowledge base of causes-consequences can use to advice producing.

Two things make it possible to represent causal and commonsense information in a knowledge based system. One is the representation of knowledge symbolically. The other is the various types of knowledge base structure that have been developed to represent the knowledge and the relationships between the knowledge items.

Knowledge bases information store and handle far more complex and sophisticated relationships between facts, than database can. The relationship showing that both these middle frequencies and malfunction belong to end of data base.

The AI troubleshooting system stars process plant fault system by collecting background information and resolve problem symptoms.

Notation

e - entity

r - relation

s - source

n - number of basic elements

m - number of subsystems

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CITATION
J. Savkovic Stevanovic. (2025). How an artificial intelligence diagnostic system constructs. In Global Journal of Research in Engineering & Computer Sciences (Vol. 5, Number 3, pp. 88–95). https://doi.org/10.5281/zenodo.15603067