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# 43 Design of an Expert System for Signature Analysis

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## ABSTRACT

Detection of vibration faults in rotating machinery continues to be a major problem in related industries. The lack of clear physical understanding of the vibration behaviour of such machines, especially in "multiple-fault" situations, has given rise to various statistical techniques for analysing them. Vibration signature analysis appears to be promising and contains a vast amount of statistical data containing vibration faults and their corresponding vibration signatures. Development of an expert system for analysing such databases requires a mechanism for inverse (statistical) mapping of the symptom signatures on to the probable faults. Practical limitations in using Baye's theorem and the inherent shortcomings associated with rule-based approach restrict their use in statistical inference systems. The present system overcomes the problem by adopting a tabular database and manipulating it through a "simulation and simple matching" technique.

## INTRODUCTION

### Problem

Within the area of machine monitoring and diagnosis, the determination of faults is a well established technical problem. While much research has been done in this area, it still remains a difficult task. Regardless of the complexity of the problem, some companies have developed many areas and techniques for fault diagnosis. Some companies have developed and maintained expert systems. Programs are needed to diagnose their machines. A program should be developed through the use of this goal.

The programs developed should be flexible enough to handle a wide range of faults.

With the belief that a broad-based approach to everyone working in the diagnostic expert system area is needed, the following objectives should be achieved:

1. should be able to handle multiple fault situations
2. should be able to handle multiple fault situations
3. should have a diagnostic expert system
4. should be able to handle multiple fault situations
5. should be able to handle multiple fault situations
6. should have a diagnostic expert system

The next two sections describe the techniques and examples used in the system.

### Literature on Vibration Signature Analysis

Many systems have been developed for the diagnosis of faults in rotating machinery.



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## INTRODUCTION

### Problem

Within the area of machinery reliability and analysis there is an abundance of information which relates to the monitoring and diagnosis of machinery problems. Many companies have well-developed machinery monitoring and diagnostic programs. As a result, a large knowledge base exists to aid an individual in the determination of what his machinery problem might be and how to rectify it.

There are published sources concerned with machinery problems related to various industries at many different technical levels. Regular diagnosis of rotating machinery defects, however, remains a major problem. While much of the information can be interpreted to make it useful to an individual of moderate understanding, it still remains out of reach of the majority of people concerned with machinery operation. Regardless of the benefits to be derived by using available published information, if there are any difficulties in using it most probably it will not be used.

Some companies have exceptional health monitoring programs. These progressive companies are active in many areas and have developed many advanced techniques for machinery reliability improvement and fault diagnosis. However, the majority of companies find this level of competence too expensive to develop and maintain.

Programs are needed to assist new companies or the less active companies in developing their ability to diagnose their machinery problems. A company that is beginning a machinery monitoring reliability program should be able to benefit from the knowledge and technology that already exist without having to go through the expense of re-creating those capabilities. Expert systems hold the potential for achieving this goal.

The programs developed to assist these less active companies should be tailored to their specific needs, and be flexible enough to allow incorporation of future developments. Since expert systems are knowledge-based, such a flexibility is built into even the most simple system.

With the belief that development of some form of an expert system would logically be the next step in a broad-base upgradation of machinery reliability programs to make diagnostic techniques available to everyone working with machinery, the problem boils down to the development of a vibration diagnostic expert system that:

1. should be able to manipulate measured vibration data for fault-diagnosis in "multiple-cause" situations;
2. should be able to indicate the relative importances of the probable causes;
3. should have a flexible knowledge base that can be extended or updated with the advance of diagnostic techniques;
4. should be able to operate under "insufficient-data" conditions that may arise when one or more of the data types required for diagnosis are unavailable;
5. should be able to give self-explanation on demand;
6. should have the ability to advise the user about the corrective measures to be taken.

The next two sections are devoted to reviewing the available literature on vibration diagnostic techniques and examining the suitability of existing expert systems approaches for using them.

### Literature on Vibration Diagnosis

Many systems generate a characteristic signature as a result of their operation [2] and their levels are



often a direct indication of the condition of the system [10]. Vibration monitoring and analysis is a process of monitoring the characteristic signature of a system to determine its condition and it can be used to diagnose faults in rotating machinery, or its components, and is indicative of the system during its operation [4].

The first step to implementing a successful machinery vibration monitoring and analysis is to select the parameters to be monitored. Three parameters — displacement, velocity and acceleration are available for monitoring. The other variables such as phase characteristics and noise characteristics can also be monitored [1] as useful data for analysis.

Mechanical signature analysis is a comparative process. Vibration signatures can be compared to the previous signatures obtained from the same system or to that from identical systems or machinery known to be in good condition or to established standards. The objective of this process is to predict whether the system has deteriorated to a point of failure.

A vast amount of information regarding various sources of vibration and their diagnosis techniques exists in the published literature. Criteria and standards have been developed to determine the acceptable vibration levels. Among several charts there exists IRD Mechanalysis general machinery vibration severity charts for causing vibration [1]. ISO charts are also of importance in this context. In addition to severity charts, tables correlating the vibration-producing signature characteristics, preferably quantized with relative probabilities are perhaps the most important type of information that is required for successful diagnosis. Outstanding work has been done by Sohre [8] to produce tables of such type with an exhaustive number of causes related to signature characteristics.

#### Expert Systems and Probabilistic Reasoning

An expert system is a computer program that can perform a specialized, usually difficult and complex professional task at the level of (or sometimes beyond the level of) a human expert. It produces high quality results in a minimal amount of time. The minimum accepted range of behaviour associated with the nature of expertise in expert systems consists of knowledge, public or private, about a narrow specialized domain, and skill at solving some of the domain problems.

The most important characteristic of an expert system is that it relies on a large database of knowledge. Because of its large knowledge-base and consequent problems of accessibility during use, organization becomes important. Moreover, it is important to separate a system's knowledge base, which must be able to grow and change, from its program part, which should be as stable as possible. As a result the most widely used way of representing domain knowledge in expert systems is as a set of facts and production rules. However, this simple structure fails to work when situations are encountered where it is impossible to state exactly the right thing to be done in each particular set of instances, i.e., where the certainty factor of the inferences are less than 1. In such domains inexact reasoning becomes unavoidable. One obvious way to handle this problem would be to treat the certainty estimates as probabilities and use Baye's theorem to compute the conditional probability of the conclusion given the assertion. But there are often several drawbacks to the use of Baye's theorem for a given problem.

- \* It is often difficult to collect all the a priori conditional and joint probabilities required. Doing so would require accumulating a great mass of data. Doing so would also be very expensive.
- \* It is very difficult to modify the database of a Bayesian system because of the large number of interactions between its various components. For example, the probabilities of all the possible outcomes must sum to 1. Suppose they do, now what happens if we want to add knowledge about a new outcome to the database. Many of the existing entries will have to be modified to keep the sum of the probabilities constant. This is a serious weakness in a system designed to work in a task that is too complex.



ever to be described completely even it would stand still which it often will not.

- Evaluating Baye's formula in a complex domain requires a lot of computing since so many probabilities must be considered, many of which may contribute very little to the accuracy of the answer. However, the accuracy of the final answer is going to be limited anyway by the accuracy of the probabilities used to compute it, and as we have already discussed, that accuracy may not be very high. So such detailed computation may be a waste of effort.

- In order for Baye's formula to give an accurate estimate of the probability of a particular outcome, all of the possible outcomes must be disjoint. It can never happen that two of them occur at once. This is often not the case.

- The accuracy of Baye's formula also depends on the availability of a complete set of hypotheses. In other words, one of the known hypotheses must be true. Unless we introduce a dummy hypothesis "none of the above", this may often not be true.

For all of these reasons, Baye's theorem does not appear to solve all the problems that arise in real world situations.

An alternative approach that attempts to avoid these problems is to associate with each rule a number between 0 and 1 representing the certainty of the inference contained in the rule. These numbers are similar to probabilities but not identical. What is important is that by using these numbers a program can combine several sources of inconclusive information to obtain a conclusion of which it may be almost certain, as in the case of MYCIN [7].

The problems associated with this approach are [6]:

- How to convert from human terms to numeric certainty factors. For example, what does "it is very likely that" mean?

- How to normalize across different individual's scales, particularly if the solution to the question above is to get people to provide numbers directly.

#### Problem Revisited

The present problem of building a vibration diagnostic expert system can now be revisited in the light of the above literature survey.

The most organized knowledge that we have is in the ISO charts (containing the allowable vibration limits for different machine categories grouped according to their HP ranges) that enable us to estimate the vibration severity in machines, and in the Sohre's chart (containing various vibration-producing causes with relative probabilities of occurrence of their possible signatures) that provides us with a valuable, organized database for probabilistic reasoning. The availability of such an organized knowledge base and standardized reasoning process makes the application of rule-based approach inefficient, as cited by Georgeff [3] and Kak *et al.* [5]. In TURBOMAC [9], probably the only available expert system on vibration diagnosis other than the present system, the problem has been attempted to be solved by making simplifying assumption of "single-cause" situations and treating the statistical data merely as qualitative indicators (for instance, to infer that a particular cause is present, likely to be present or not present depending on whether the certainty factor corresponding to it is 1, any non-zero value less than 1 or 0 respectively). This, however, is far from reality in most of the practical instances, where more than one cause is involved. The shortcomings of other conventional approaches have been discussed before.

In the light of the above discussion, the problem can be reframed as follows:

We need to develop an expert system that can

- diagnose vibration-producing problems under "multiple-cause" situations,



- \* overcome the inefficiency of conventional expert system techniques by some other means,
- \* focus light on the relative probabilities of probable causes,
- \* provide flexibility in the knowledge base for updating it with upcoming knowledge, and
- \* work even in inadequate-data conditions.

## DESCRIPTION OF THE PRESENT EXPERT SYSTEM

### Knowledge Representation

The present expert system SIGNOSE exploits the Sohre's table and the ISO charts as its main sources of knowledge. To get around the problems associated with conventional approaches, an essentially table-driven exact matching procedure has been chosen. The ISO chart has been represented in the form of a set of LISP functions and Sohre's table has been transformed into a table written in 'C' where the causes are codified as row numbers, and stored in the columns corresponding to each cause are the probabilities of occurrence of various signature characteristics if that cause occurred. Another table, which correlates each machine to all the machine-faults that are relevant to it, has also been created (using 'C' language). This machine-cause table is interactively updatable. The block diagram of the expert system has been shown in Fig. 1.

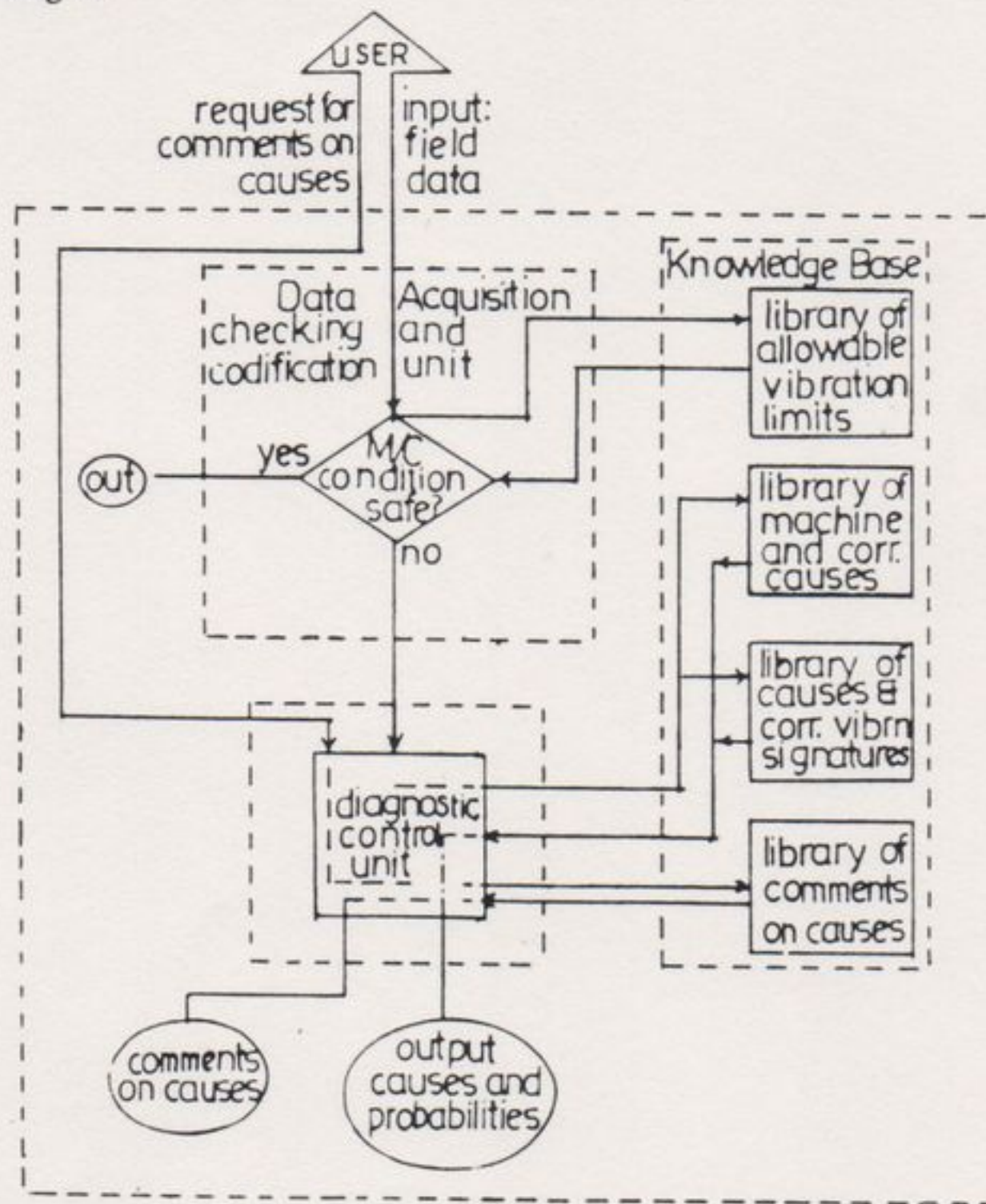


Fig. 1 Block Diagram of the Expert System

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The above simplified structure, though not written in the conventional AI approach, still retains the flexibility for upgradation. A few simple LISP functions could be written that would essentially take each instance of an actually occurred machine-fault and the corresponding generated signature and simply increase the number of entries of that signature for that particular cause in the Sohre's table, thereby eventually reflecting a probabilistic database characteristic to the particular plant it is installed for.

### Control Structure for Diagnosis

The control structure (Fig. 2) for diagnosis consists of four principal parts:

1. Random Number Generator.
2. Test-cause Situation Simulator.
3. Data Modifier.
4. Matcher.

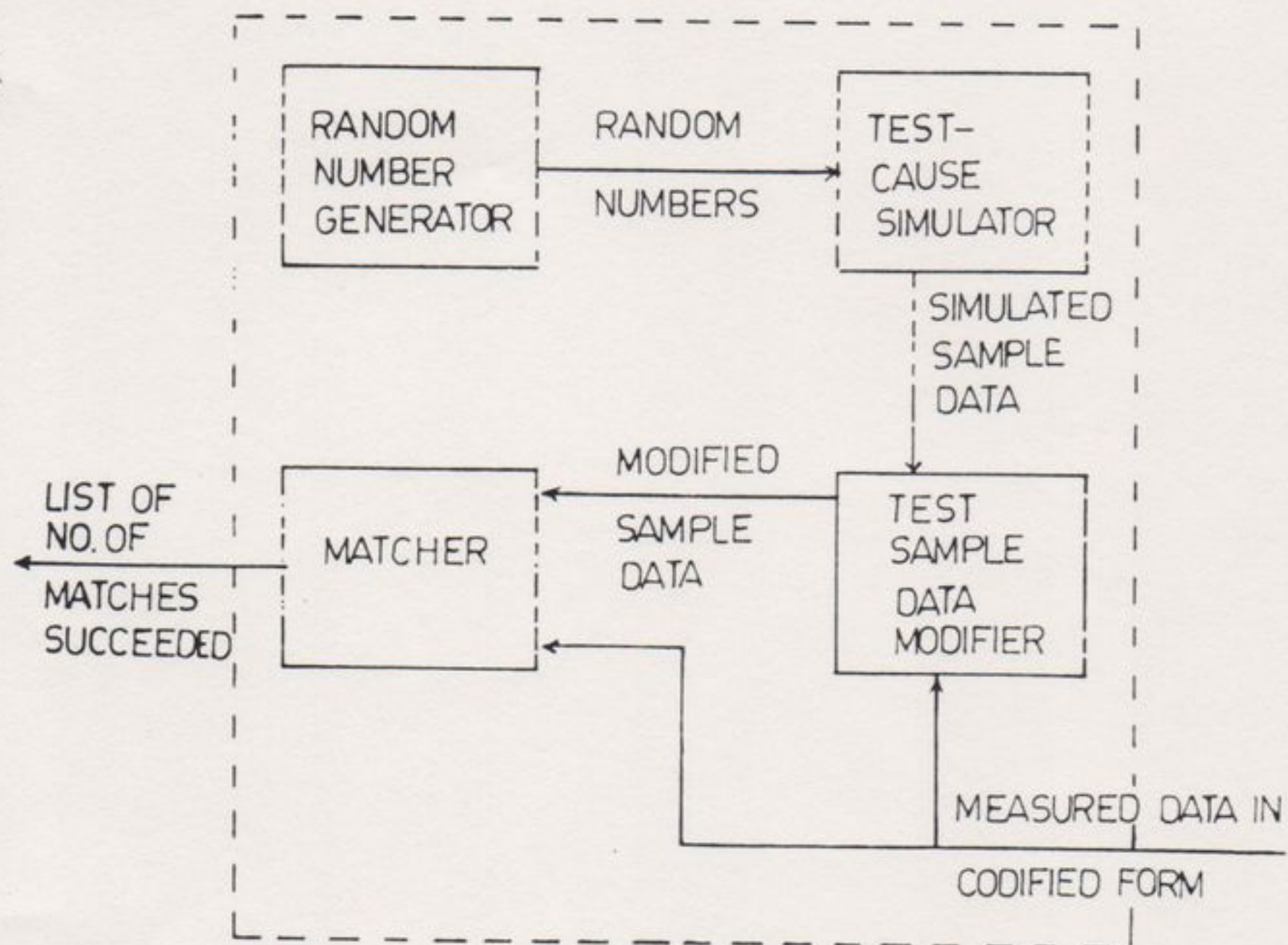


Fig. 2 Control Structure of the Expert System

The random number generator generates random numbers between 0 and 1 with uniform probability distribution and hands them to the test-cause situation simulator. The test-cause simulator when run for a particular machine converts the random numbers into 100 sample signatures (represented by five characteristic data-types) for each cause relevant to that machine and hands them over to data-modifier. The simulator is constructed on the following principle:

There are precisely five types of data presently required for diagnosis: amplitude vs. frequency data, direction(s) of predominant vibration, location of predominant vibration, phase data and noise data. For



each particular cause of vibration, a discrete probability distribution showing the relative probabilities of occurrence of the characteristics of each datatype has been given (in Sohre's table). Thus each cause consists of five probability distributions, one corresponding to the characteristics of each data-type.

Now, with the help of a discrete probability distribution simulation technique, we can generate weighted random numbers and as a result, can modify every five random numbers to five characteristics of a signature, where each characteristic corresponds to one separate data-type.

Thus every five random numbers after going through the simulator gets converted to a list of five numbers, i.e. (x1, x2, x3, x4, x5), each of which corresponds to one possible characteristic of a separate data-type. For each cause of vibration, 100 such samples (representing all signatures possible for that cause) would be created and fed to the modifier unit.

The modifier consists of a set of 'C' functions that have been created to take care of the "insufficient-data" conditions. It gets as input the list of measured data in modified form (essentially the list of vibration signatures obtained from the machine) at one end, and, the list of simulated signatures at the other. It then works in the following way:

The measured data in the modified form is a list consisting of five sublists, each of which lists all the characteristics found for a separate data-type. Thus the list of possible sample signatures for a modified data of the form

$$((y_{11}, y_{12}) (y_{21}, y_{22}) (y_{31}) (y_{41}) (y_{51}))$$

would be the following:

$$\begin{aligned} &((y_{11}, y_{21}, y_{31}, y_{41}, y_{51}) \\ &\quad (y_{11}, y_{22}, y_{31}, y_{41}, y_{51}) \\ &\quad\quad (y_{12}, y_{21}, y_{31}, y_{41}, y_{51}) \\ &\quad\quad\quad (y_{12}, y_{22}, y_{31}, y_{41}, y_{51})). \end{aligned}$$

The first part of the modifier creates all possible combinations of the elements of the sublists of modified data to yield a list of all the signatures obtained from the machine.

The second part checks whether any data-type is unavailable. This can be identified by checking whether the number corresponding to an element of an obtained signature is equal to a specific number that corresponds to the unavailability of that data-type. For each of the obtained signatures of modified data, the unavailable data-types are identified and the corresponding elements in the test-cause-samples are also changed to the 'unavailability number' of the corresponding data-type. This procedure is done for each of the obtained signatures of modified data. The obtained signatures and the simulated signatures are then passed to the matcher.

The matcher takes one obtained signature from the modified data, performs exact matching of it with each of the simulated signatures for a particular cause, stores in a list the number of times the matching succeeded and does the same operation for each of the other possible causes to create a match-list, each element of which shows the number of times the matching has succeeded for the particular cause which has as its code number the serial number of that element in the list. The above operation is done for each of the obtained signatures, yielding a list of match-lists.

The matrix addition of all the match-lists yields a final match-list. A list containing each element of the final match-list divided by the total number of matches gives the probabilities of occurrence of the corresponding causes (stored in terms of their code numbers in the same order in a separate list). Mathematically speaking, if there are two obtained signatures of modified data:

$$\begin{aligned} Y_1 &= (y_{11}, y_{12}, y_{13}, y_{14}, y_{15}) \\ Y_2 &= (y_{21}, y_{22}, y_{23}, y_{24}, y_{25}) \end{aligned}$$



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and (assuming that only three probable causes exist for the machine) their corresponding match-lists are

$$M1 = (m11, m12, m13)$$

$$M2 = (m21, m22, m23)$$

then the final match-list is

$$M = M1 + M2 = ((m11 + m21), (m12 + m22), (m13 + m23))$$

and the probability list is

$$P = ( ((m11 + m21)/\sigma_m), \\ ((m12 + m22)/\sigma_m), \\ ((m13 + m23)/\sigma_m) )$$

where

$$\sigma_m = m11 + m21 + m12 + m22 + m13 + m23 .$$

A reconditioner function changes the code-list of the possible causes into their actual names and a printing function displays the probability of occurrence of each vibration cause against its name.

### Supporting Facilities

The supporting facilities include ability to give short explanation and to comment on the vibration producing causes on demand.

Short explanations include ability to explain its conclusions during initial phases of severity checking. The system can also locate and emphasize the inadequacy of supplied data as a feedback to the user for improving the efficiency of diagnosis.

The comments on vibration-producing causes, displayed by the system on demand, contains valuable points regarding their root, nature and/or suggested remedial measures to be taken.

### PERFORMANCE EVALUATION

In Bloch *et al.* [1], a number of case-studies on vibration producing problems in various machines have been discussed. In SIGNOSE expert system, the measured vibration signatures for those case-studies have been converted into the input data-form required by the system and fed subsequently for diagnosis. The comparative study of the output of SIGNOSE and the machine-faults actually detected to have occurred gives a measure of the performance of the system as a diagnostic consultant in real world situations. A sample graph containing probable causes, their estimated probabilities of occurrence and the actual causes has been shown in Fig. 3. The comparative study reveals the following:

1. In all of the cases, all the causes detected to have actually occurred have been identified by the system.
2. In many of the cases, the system identified a larger number of causes than that actually occurred.
3. In most of the cases, the probabilities of occurrence of actually occurred causes, as estimated by the system, are reasonably appreciable even in most inadequate-data conditions.
4. It is important here to note that the input-data supplied was quite inadequate for efficient diagnosis due to the unavailability of location data, phase data and noise data.



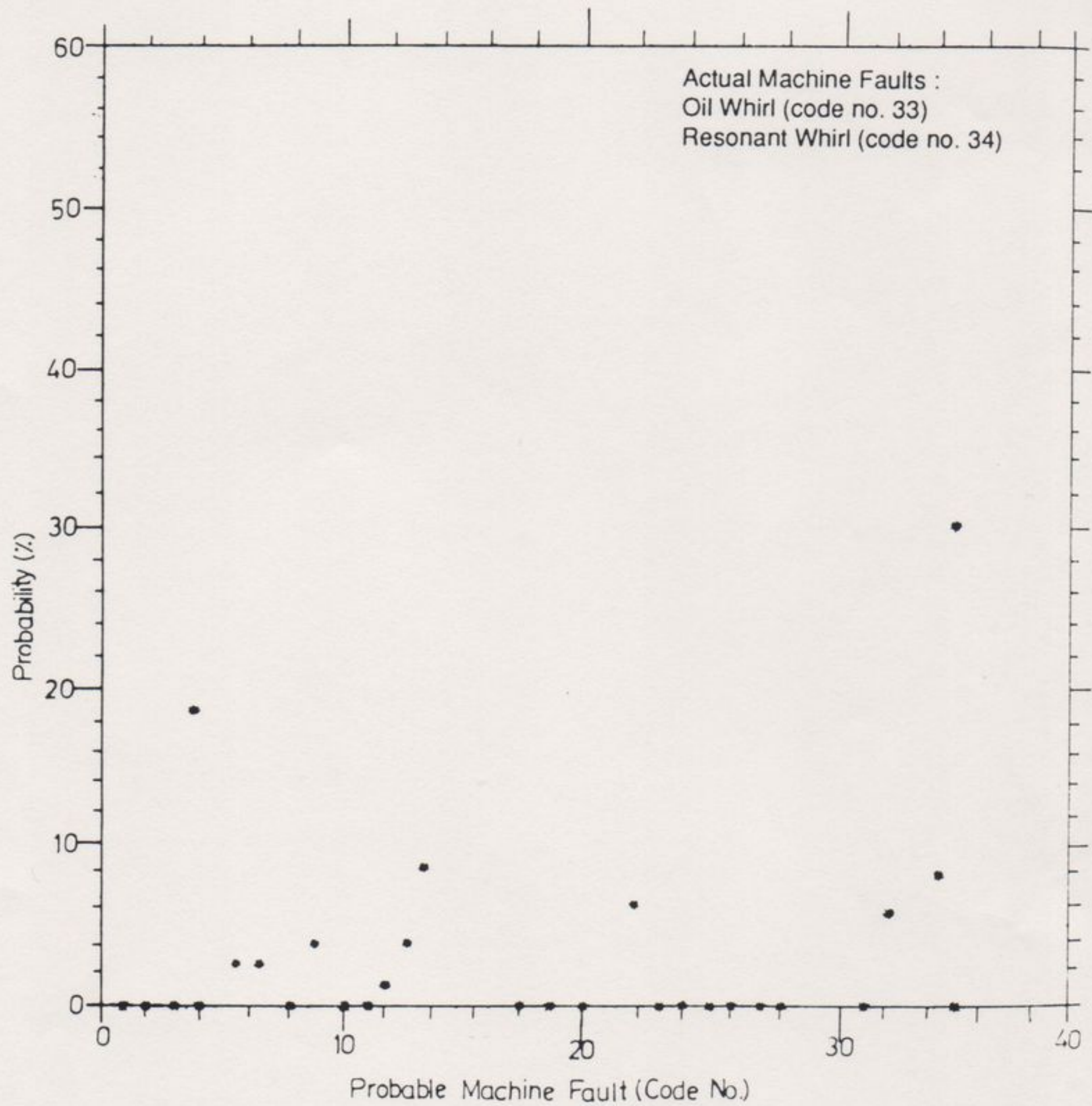


Fig. 3 Graph Showing Probable Causes and Their Probabilities of Occurrence as Estimated by SIGNOSE



The above observations demonstrate a number of significant points on the performance of the system, as is discussed below:

1. Observation 1 implies that the actually occurred causes are in no case missed by the system.
2. Observations 2 and 4 in a way reveal the effect of the inadequacy of supplied data on the performance of the system. Though the system can identify the root causes (that actually occurred), it cannot highlight those causes very prominently due to the effect of "insufficient-data" conditions.

But here a question may arise: does the system improve its efficiency with the increase in the number of data-types supplied to it?

The answer is Yes. To clarify the answer, or rather to find it out, the system has been tested through a number of test situations simulated for a few particular causes, and the performance of the system has been observed by examining the change in relative importance given by the system to the simulated causes as the number data supplied has been increased. It has been noted that an increase in the number of data-types supplied clearly improves the efficiency of the system towards identifying the actually relevant causes. Figure 4 shows the change in system performance with the increase in the number of data-types supplied for a sample case.

The above discussion can be summarized as follows:

The system works reasonably satisfactorily in an inadequate knowledge domain to the point that it does not miss any of the actually relevant causes, as is reflected by its relatively general conclusions in such situations. However, the system can very efficiently identify the relevant causes under sufficient or nearly sufficient data conditions. In "multiple-cause" situations, the performance of the system is equally good.

#### SUMMARY AND CONCLUSION

In the previous chapters, an attempt to develop a plausible vibration-diagnostic expert system has been elaborated. The present work has succeeded in developing some capabilities in which it is the first of its kind in the field of expert systems for vibration diagnosis. Included amongst those capabilities are

1. Ability to manipulate measured vibration data for fault-diagnosis in "multiple-cause" situations.
2. Ability to avoid the inefficiency of conventional approaches by adoption of a simulation and simple matching technique using essentially tabular database.
3. Ability to operate under most "inadequate-data" conditions.
4. Retention of the potential of achieving an updatable database.

A standard SIGNOSE diagnosis session takes between five and ten minutes, depending on the complexity of the problem.

The system, notwithstanding the potential it holds, needs a number of extensions and modifications to be able to work satisfactorily in real-world situations:

1. The present system does not have complete information at hand about the general allowable vibration limits for some of the machines, particularly on filter-in amplitude vs. frequency data and noise data. This has made the system to some extent dependent on the judgement of the user in cases where standard vibration limits are unavailable (e.g., disc cutters).

Some standardized techniques for quantification of vibration limits for any given machine, given its HP, supports, etc., as arguments, has to be thought of. This would enable the system to generate the allowable vibration limits and provide check functions with more self-dependence, and as a result, would improve the accuracy of diagnosis.



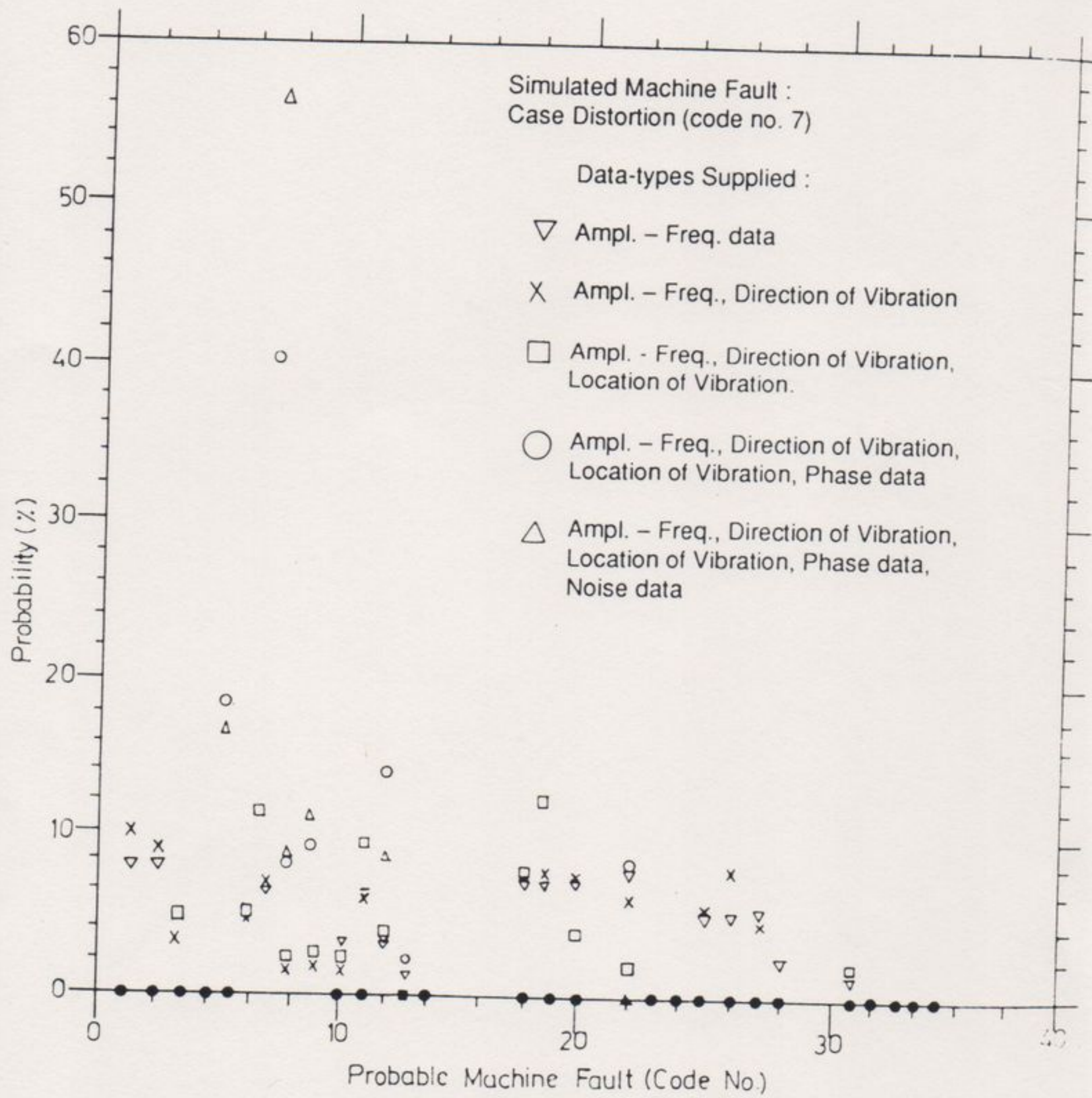


Fig. 4 Change in System Performance with the Change in Number of Input Data Supplied

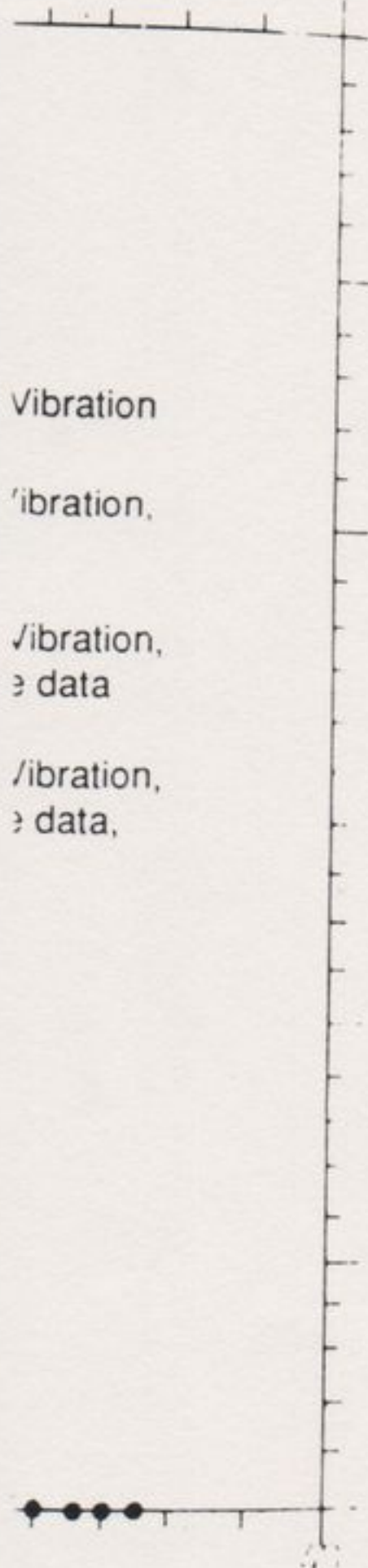


2. Some kind of interface has to be developed that would continually monitor the machine, dress up the crude measured data, feed it into the expert system and act according to the result of its analysis. This would obviate the need for continuous manual monitoring and the time lag involved with it.

The present work at least shows that an expert system for vibration diagnosis with some, if not all, of the facilities described at the time of defining the problem is possible to achieve. We believe that the system can go quite far from where it has just started.

#### REFERENCES

1. Bloch, H.P. and Geitner, F.K., *Practical Machinery Management for Process Plants*, Vol. 2, 1983, Gulf Publishing.
2. Catlin, J.B., *Journal of Engineering for Industry*, April 1973, 5(4), pp 913-918.
3. Georgeff, M.P., "Procedural Control in Production Systems", *Proc. IEEE*, 1982, Vol. 18, pp. 175-201.
4. Gibbs, J.A., *Instrument Control Systems*, May 1981, 54(5), pp. 51-55.
5. Kak, A.C., Boyer, K.L., Chen, C.H., Safranek, R.J., and Yang, H.S., "A Knowledge-based Robotic Assembly Cell", *IEEE-Expert*, Spring 1986, Vol 1, Number 1, pp. 63-83.
6. Rich, E., *Artificial Intelligence*, 1983, McGraw-Hill.
7. Shortliffe, E.H., *Computer-based Medical Consultations: MYCIN*, 1976, Elsevier, New York.
8. Sohre, J.S., Machinery Vibration Monitoring and Analysis Seminar and Mtg., *Proc. Sponsored by Vibration Inst.*, New Orleans, Louisiana, April 1979, pp. 129-137.
9. Stuart, J.D. and Vinson, J.W., *TURBOMAC: An Expert System to Aid in the Diagnosis of Vibration-producing Problems in Large Turbomachinery*.
10. Taylor, J.I., Machinery Vibration Monitoring and Analysis Seminar and Mtg., *Proc. Sponsored by Vibration Inst.*, Houston Texas, February 1979.
11. Winston, P.H. and Horn, B.K.P., *LISP*, 1981, Addison-Wesley.



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