Knowledge Base System for Predictive Maintenance of Gas Reforming and Turbo Machinery "Chemical Ammonia Plant at Talkha Egypt"

نظام قاعدة معرفة للصيانة التوقعية لمقطر الغاز والماكينات التوربينية بمصنع الأمونيا في طلخا بمصر

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ملخص البحث

يعتبر مصنع الأمونيا بطلخا واحدا من أكبر ثلاثة مصانع من الناحية الإنتاجية في مصر حيث يتضمن فرنين عملاقين ومحول ثاني أكسيد الكربون والميثان وبه مكثفات وتوربينات وضواغط بخار ضخمة.
تتوقف ديناميكا الآلات الدوارة على عوامل عديدة ويعتبر التأثير الاهتزازي للماكينات على محاورها وأسطح ارتكازها والاساسات وشبكات الأنابيب دليلا على حالة الماكينات. وتظهر حالة الماكينة بمعرفة مؤشرات أخرى علاوة على التأثير الاهتزازي مثل الضوضاء المنبعثة منها ودرجة حرارة وضغط الزيت والجزيئات الموجودة بداخل الزيت وغير ذلك. كما أن هناك كما من المعلومات يمكن الحصول عليه عند توقف الآلة لعمليات الصيانة كمعرفة آثار الاحتكاك والتاكل والشروخ التي قد تتواجد سواء كانت على الأجزاء الثابتة أو الدوارة وعلامات الحرق والنقر وعلى حالة صماويل الربط والتثبيت والتشوهات كل ذلك يعطى أعراضا للحالة الراهنة للماكينة ومن ثم يمكن معرفة الأسباب التي تولد الأعطال يجب إزالة تلك الأسباب بأسرع ما يمكن لكي تعمل الماكينة بحالة جيدة.
ترتبط الأعطال بالأسباب ارتباطا مباشرا ويؤدى التحليل الجيد للأعراض إلى اكتشاف طرق ووسائل التعرف على أسباب وأعراض العطل مما يساعد على إزالته.
تقدم هذه الورقة نظام قاعدة معرفة مختلط لتوقع الخلل في الآلات الدوارة وهو ما يعرف بنظام معرفي للصيانة التوقعية الأمر الذي يساعد مهندس الصيانة الوقائية في أداء عمله بعناية ويقلل من وقت تعطيل الماكينة ويجنبها الأعطال المدمرة والمكلفة. ويقصد بالنظام المختلط هنا هو استغلال الشبكات العصبية الاصطناعية جنبا إلى جنب مع نظام القواعد في بناء قاعدة معرفية تستخدم فيها لغة CLIPS للمعالجة واعطاء القرار. يطبق النموذج المبدئي على ضواغط وتوربينات مصنع اليوريا بطلخا

Abstract

The Urea plant at Talkha Egypt is the largest one among three SEMADCO factories from the production point of view. It includes two giant reformers (furnaces), converter of CO_2 (high and low temperatures), methanator, Benfield adsorbar process, condensate heat exchangers, steam turbine and compressor.

The behavior of the rotating machinery dynamics depends on various factors. The vibratory response of the machine on the shafting, bearings, housing, foundation, piping etc. depends on the condition of the machine. Beside the vibratory response, the condition of the machine is also reflected by other indicators, e.g. noise emanated from the machine, bearing oil temperature and pressure, bearing oil debris and particles, operating medium pressure etc. A lot of information is also available whenever the machine is stopped for maintenance such as, misalignment, rubbing and the wear of rubbed parts, cracks on the stationary and rotating parts, burn marks, pitting, fluid marks, loose bolts and nuts, loose assembly of bearings, permanent deformations. All these are symptoms of the machine and its condition. There are several causes in a machine that generate the symptoms mentioned above and the causes should be removed as far as possible to have the machine working in good order.

The symptoms of the machine and the causes are both related to each other. The analysis of the symptoms leads to find ways and means of identifying what causes the symptom so that the defect in the machine is removed.

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This paper presents a hybrid knowledge base system for predicting the defect of the rotating machinery (predictive maintenance) in the plant so that the preventive maintenance engineers can do their jobs carefully, to minimize the shut down periods and to avoid costly failures. The hybrid system means the utilization of the artificial neural network and the rule base. The rules are built using CLIPS language. The hybrid system is used for the compressor and turbine units at the UREA plant.

Key Words: – rotating machinery dynamics, vibratory response, knowledge base, artificial neural networks, and predictive and preventive maintenance

1 Introduction

Major rotating machinery may cost hundreds of millions of dollars. Once commissioned, many feel that their role comes to an end, but in fact their real mission has just started. Just one-day shutdown in operation may generate a loss in millions of dollars, a failure of a machine may cost more and in the case of catastrophic accidents, the whole plant may be lost causing heavy financial losses.

It is essential to manage these assets and equipment in which millions of dollars were invested so that their return on investment is maximized. Available experience for failnre diagnosis in turbo-machinery can be utilized for bnilding knowledge base, developing expert systems and computerized maintenance management system for planned maintenance and material management [1]. All can achieve the following objectives.

- Increasing productivity and maximizing revenues,
- Redncing the operation expenditure,
- Extending the useful life span of equipment and hence reducing the capital expenditure.

The need for high reliability and avnilability is not just restricted to safety critical systems [2]. Telephone switches, airline reservation systems, process and prodnction control, stock trading systems, computerized banking, etc all demand very high availability. The management of operations and associated risks has become a critical task. The goal of management systems is to monitor, interpret and control system operations, optimizing costs and reducing risk [3]. Knowledge base for a machine requires time and data collection over a period of different conditions of operation. The relationship may be similar between identical designs and therefore, it may be assumed at the beginning of operation of a new machine of proven design. However, the machines designed and manufactured by the same gronp may operate differently under different conditions and exhibit a different cause – symptom relationship. In other words, there is no single knowledge base for rotating machines, there are only guidelines that can be available for the purpose of nnderstanding the behavior of a machine [4]. This paper presents a predictive maintenance knowledge base (PDMKB) system for compressor – turbine section (K102 &KT102) at the society of EL-Naser for fertilizers and chemical industries (TALKHA – EGYPT). The PDMKB has to enable the operator to minimize the shut down time of faulty equipment and hence increases the productivity. Furthermore the system will minimize the probable human faults and reduce production costs.

2 Independent events

The notion of the independence of events plays a significant role in the probability theory and its applications [5]. For practical determination of the independence of any events, one rarely checks to see that:

$P(A/B) = P(A)$ (1)

$P(A)\,P(B/A) = P(A)*P(B)$ (2)

Where:

$P(A/B)$, $P(B/A)$ are the conditional probabilities.

$P(A)$, $P(B)$ are the unconditional probabilities

For independent events, the multiplication theorem takes on a particularly simple form, namely, if events A and B are independent, then

$P(AB) = P(A)*P(B)$ (3)

The notion of independence of two events can be generalized to a collection of several events

Events $B_1, B_2, \ldots, B_s$ are collectively independent if for any event B_p of them and arbitrary $B_{i1}, B_{i2}, \ldots, B_{ir}$ ($i_h \neq p$) of that same number, events B_p and $B_{i1}, B_{i2}, \ldots, B_{ir}$ are mutually independent. By virtue of the foregoing this definition is equivalent to the following

For any $1 \le i_1 \le i_2 \ldots i_r \le s$ and r ($1 \le r \le s$)

$P(B_{i1} B_{i2} \ldots B_{ir}) = P(B_{i1})P(B_{i2}) \ldots P(B_{ir})$ (4)

For several events to be collectively independent it is not sufficient for them to be pair-wise independent
In the case of turbomachinery some features used into the diagnosis process are assumed to be independent so, the multiplication of probability can be applied on them.

3 History analysis

Logically, if maintenance problem can be eliminated or if service life of units or components can be extended, corrective actions should be considered.. In some cases, particularly when non-critical equipment is involved, repairing equipment, as the need becomes evident could be a logical course of action. Fig 1 shows the actions that should be considered in the repair analysis

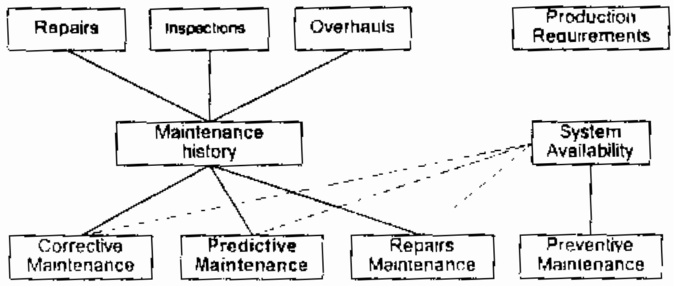


Figure 1 Block Diagram for Maintenance Operating Procedures

4 Predictive maintenance

Recognizing that a change in physical condition is the principal reason for maintenance, it is logical to consider the use of sensing, measuring, or monitoring devices to determine significant changes. This technique can minimize the need for disassembly and inspection of internal parts Just as important, though periodic measurement or monitoring it is possible to identify conditions that require correction before a major problem develops Predictive maintenance takes advantage of the fact that commercial equipment is available such as portable vibration analyzers and amplitude meters etc [6] With such equipment, conditions can be measured and recorded periodically or when justified, continuously monitored with alarms or cutoffs set at pre-established levels

4. 1 Maintenance of machines by a team of repairmen

Assume a team of r repairmen services n machines of the same type ($r \leq n$) Each one of the machines may demand the attention of a repairman at random moments. The machines go out of commission independently of one another The probability of dropping out of operation during the time interval $(t\ ,\ t+h)$ is equal to $\lambda h + o(h)$. The probability that during time $(t\ ,\ t+h)$ a machine will be put into operation again is equal to $\nu h + o(h)$. Each repairman can repair only one machine at a time, each machine handle by only one repairman The parameters λ and ν are independent of t and n and also of the number of machines undergoing repair The probability P_k that in a steady state process of service their will be a certain number of machines idle at a given time can be given as follows,
Let E_k the event that k machines are out of commission at a given instant It is obvious that the system can thus be in the states E_0, E_1, ... E_n Using the birth and death process for which [5]

$\lambda_k = (n - k)\lambda$ for $0 \leq k \leq n$,
$= 0$ for $k \geq n$ (5)
$\nu_k = k\nu$ for $1 \leq k \leq r$,
$= r\nu$ for $k \geq r$ (6)
Then for $1 \leq k \leq r$ ($\rho = \lambda/\nu$)
$P_k = (n!/(k!\,(n-k)!))\ \rho^k p_0$
And for $r \leq k \leq n$
$P_k = (n!/(\ r^{k-r}!(n-k)!))\ \rho^k p_0$ (7)
And

$$P_o = \left[\sum_{k=0}^{r} n!/k!(n-k)!\rho^k + \sum_{k=r+1}^{n} (n!/r!r^{n-k}(n-k)!)\rho^k \right]^{-1} \quad (8)$$

4.2 Critical Speed

The fundamental critical speed of a shaft carrying a number of components can be determined by the method proposed by Rayliegh [4]. It is based on the fact that the maximum kinetic energy must be equal to maximum potential energy for a conservative system under free vibration conditions. The fundamental frequency can be obtained from :

$$\omega^2 = g\,(\Sigma M_y / \Sigma M_y 2) \quad (9)$$

Where M_1 , M_2 ,. .... are masses of different components and y_1, y_2 . are deflections of the shaft at the locations of these components. Since the frequency is maximum, it is always an upper bound value The external torque on any cylinder has several harmonic frequencies , $j\omega/l$ where $j = 1, 2,..$ and l is the length of the crank If the j^{th} harmonic excitation frequency coincides with any one of the natural frequencies F_k of the system, then response occurs at the critical angular velocity ω_c.

4.3 Symptoms and distress of turbo machinery

It is possible to come to a conclusion on the behavior of a machine from its observed and measured symptoms Charts produced by turbomachinery international publications show the symptoms and distress that can be used as a basic guide for building a knowledge base [7]. They are; vibration analysis (predominant frequencies, direction and location of predominant amplitude, amplitude response to speed variation during vibration test runs), operational evidence (effect of operating conditions, effect of oil pressure (P) & temperature (T)) and flow, predominant sound, damage or distress signal), installation (fonndation, piping).

The phase 1 of the project [8] has completed the installation of the BENTLY NEVADA measuring system to the machines in the plant.

The goal was to obtain the vibratory signatures at very frequent intervals or on a real time. The frequency content of a signature has a very useful information and it can be broken down usually into different frequencies related to the machine rpm

5 Expert system general frame work

The predictive maintenance knowledge base schematic diagram for the compressor - urbine section (K102 &KT102) is shown in Fig. 2

The algorithm can be illustrated as follows:

- The data collected from the sensing devices passes through the FFT program file.
- Unsupervised artificial neural network program for extracting the effective features is used to prepare the feature vector in order to feed supervised neural network for the purpose of diagnosis [9],
- The data is passed through on line storage system to feed the fault file.
- Integration of decisions (from the supervised neural net and the rule base system) is performed into general knowledge base so that the CLIPS inference engine can access it [10].
- A program for fault coding is used to help the user in the case of HOW the decision is achieved
- If the symptoms are new (new fault) then the program gives the operator facility to add it into the knowledge base. The decision is displayed, reported and stored for the further analysis

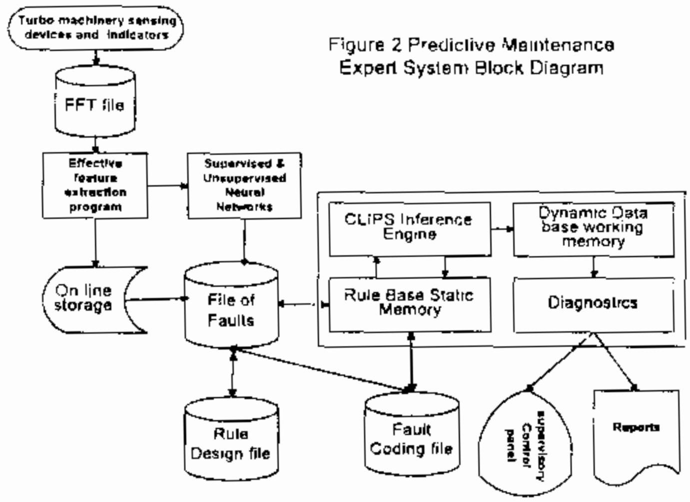


Figure 2 Predictive Maintenance Expert System Block Diagram

3.1 Computer Assisted Vibration Monitoring System

Fig. 3 shows a schematic diagram of the computer assisted vibration monitoring system [11]

The transducer is responsible for accurately converting mechanical vibration into an analog electrical signal in terms of phase, frequency and amplitude. A computer with analog to digital converter (ADC) stores the incoming vibration signal from the transducer and processes the waveform using Fast Fourier Transform (FFT) technique. Analysis software of this system allows

- Creation of a machine database containing information for each machine to be monitored
- Definition of data analysis parameters, which allows more flexibility in selecting the vibration analysis method to be used for individual machine parts.
- Scanning data for exceptional values which may indicate machine part deficiencies or problems
- Generation of graphical display in order to facilitate the vibration analysis
- Compilation of data in a historical manner for trending, archiving and allowing of justification of program continuity

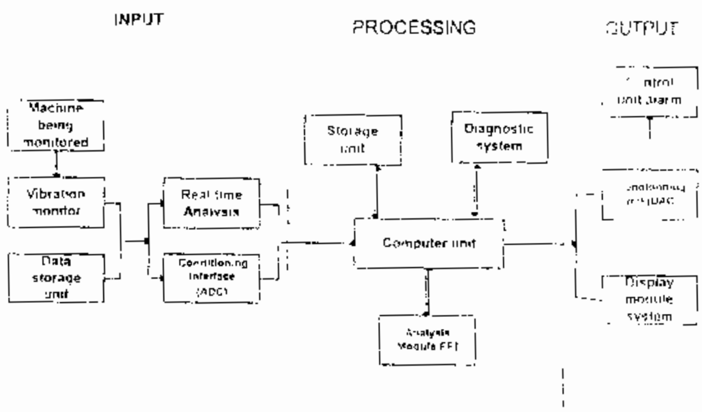


Fig. 3 Block diagram of the computer assisted vibration monitoring system

5.2 Filter Bank Based Composite

The filter bank based strategy relies on a filter bank (FB) containing a set of analysis filters $H_l(z)$ and synthesis filters $F_l(z)$

The analysis filters decompose the input vibration signal x(n) into M uniform frequency subbands and subsample by a factor of M Processing can be performed on each subband independently. The synthesis filters combine the processed subbands to reconstruct the input signal. Thus, a FB-based algorithm involves decomposing a signal into frequency subbands, processing these subbands according to the application, and reconstructing the processed subbands [12]

Assume that the FB contains M analysis and synthesis filters, each of length L The analysis filters $H_l(z)$, $l=0,1,\ldots,M-1$ bandpass the input signal X(z) to produce the subband signals $U_l(z)$:

$U_l(z)=H_l(z)X(z)\quad l=1,2,\ldots M-1$

Since the effective bandwidth of $U_l(z)$ is $2\pi/M$,

it can be down sampled to reduce the total rate. The down sampling process keeps one sample out of M samples The down sampled signal $W_l(z)$ is:

$$W_l(z) = 1/M \sum^{M-1} U_l(z^{1/M} e^{-j2\pi l/M}) \qquad (10)$$

for $l = 0, 1, \ldots M-1$

Taking advantage of the down sampling we can efficiently apply the filtering process at 1/M the input rate This implementation is referred to as polyphase implementation and contributes to the computational efficiency of the FB-based algorithm. Time and frequency dependent processing can now be performed on some or all of the subband signals to result in a processed and down sampled subband signal, $W_{pl}(z)$ The reconstruction is achieved by upsampling and interpolating the subband signals using a set of band pass filters, $F_l(z)$. Similar to the analysis bank, the filtering process in the synthesis bank can be efficiently implemented by taking advantage of the M-1 zeros in the upsampled sequence, $V_l(z)$ [12].

For vibration signature enhancement it is useful while processing each subband to have a fixed or deterministic relationship between data in the processed subbanda and data at the input. This requirement implies that the analysis filters have linear phase frequency characteristics or constant group delay for all frequencies in the passband The linear phase requirement ensures that the input will have the same sample delay through the analysis filters. It is then possible for example to determine the exact location of the 1 X rpm or resonant frequency and other fiducial points in the subband. Moreover, this linear phase requirement on each filter should be distinguished from the linear phase property of the whole FB system.

5.3 Vibration Predominant Amplitude Detection Criteria

There exist a number of vibration predominant amplitude detection schemes Two main basic criteria were used in such scheme selection algorithms, the complexity and performance [13] Each algorithm employs one or more preset constants, either as multiplier or as thresholds. The detection algorithms are based on first derivative only, first and second derivatives and digital filters. The detection algorithm used here is based on the first an second derivatives It was adopted from the QRS detection scheme developed by Ahlstrom and Tompkins [14] The rectified 1^{st} derivative of sample points (SN) is calculated from the vibration spectrum as

$$Y_0(n) = ABS\,(X(n+1)-X(n-1)) \qquad (11)$$
$$3 < n < SN$$

The rectified 1^{st} derivative is then smoothed as:

$$Y_1(n) = (Y_0(n-1) + 2\,Y_0(n) + Y_0(n+1))/4 \qquad (12)$$
$$3 < n < SN$$

The rectified 2^{nd} derivative is calculated as

$$Y_2(n) = ABS\,(X(n+2)-2X(n) + X(n-2)) \qquad (13)$$
$$3 < n < SN$$

The rectified, smoothed first derivative is added to the rectified second derivative as

$$Y_3(n) = Y_1(n) + Y_2(n) \qquad (14)$$
$$3 < n < SN$$

The maximum value of this array is determined and scaled to serve as primary and secondary thresholds

Primary threshold = 0.8 max $[Y_3(n)]$

$3 < n < SN$

Secondary threshold = 0.1 max $[Y_3(n)]$

$3 < n < SN$

The array of the summed 1st and 2nd derivatives is scanned until a point exceeds the primary threshold. In order to be classified as a vibration peak, the next six consecutive points must all meet or exceed the secondary threshold:

$Y_3(i)$ >= primary threshold and,

$Y_3(i+1)$, $Y_3(i+2)$, ... $Y_3(i+6)$ > secondary threshold

6 The knowledge base dissection

Phase II of the project concentrates on the utilization of the vibration analysis and data measured from the machines to build the predictive maintenance knowledge base. A threshold level can be determined for each measuring point at the machine. The specified threshold should depend on the frequency mode (i.e. form low frequencies to high frequencies) so that the peaks at different frequencies keep the actual signature. An inspection program is used to detect ***if*** a peak or peaks are detected and their causes of vibration ***then*** determine their corresponding frequencies. Make an instance from the disorder class with the cause of vibration and calculate the corresponding probability. The following is pseudo code of a sample in the diagnose process:

<u>defclass</u> *VIBRATION (is-a USER)*

(slot dis_code ,slot machine_ID, slot measuring_date , slot period, slot probability
slot how)

<u>Diagnosis Rules</u>

IF there exists *a* ***frequency spectrum*** *at a* ***given measuring point and it has the peaks that may show symptoms of cause (S) OF VIBRATION then***

Begin

Determine the set of vibration causes (1,2,4,9,...,n), their probability of occurrences $P_{(1,2,4,9,...,n)}$, the time and date and the location

Begin

$P_{(1,2,4,9,...,n)}$ initial = 1

Make instance of the VIBRATION class and put the code of cause of vibration in its corresponding slot

Update the probability according to

*$P_{(1,2,4,9,...,n)}$ new = $P_{(1,2,4,9,...,n)}$ old * $P_{(1,2,4,9,...,n)}$*

Put the peaks at frequencies in the HOW slot for the explanation

End

End.

<u>Arrange instances</u>

Do for all instances

Arrange instances according to their probabilities and
display them in descending way.

<u>Collect and make decision</u>

Do for all measuring points (horizontal, vertical and axial) $P_{tot} = P_H + P_V + P_A$

Where

P_{tot} total probability of cause of given signature

P_H the horizontal probability

P_V the vertical probability

P_A the axial probability

<u>Display diagnosis</u>

Display the causes of vibration according to their probabilities of occurrences

If HOW is needed then display the HOW content

7 Implementation

The Ammonia loop parameters affecting the production process consists of five sections. Each section consists of different service at specific design conditions and within the limits of operation. These sections are [15]

#1 Natural gas, control heater and primary reformer,

#2 De sulphurization and secondary reformer

#3 Waste heat boilers
#4 Syn. Gas CO_2 removal, Benfield system &Methanation
#5 Compressor Turbine (K102 & KT 102

The computer-assisted vibration monitoring system includes a non-contact proximity transducer system that measures vibration displacement between the probe tip and the observed target. A PC- computer is used to capture and process the vibration signal through the transducer system and analog to digital converter [11].

The vibration analysis hardware which automatically perform the frequency measurements are

- Bently Nevada 7200 proximity transducer system offers 2mm of linear measurement with scale factor of 8v/m. The system can be used to measure radial vibration, axial thrust position and vibration amplitude and phase angle
- A PC computer
- A signal conditioning module (an analog to digital converter) with the following specifications:-

input range (0 – 5)V DC, 12 bit * output range + 5 V DC, 16 input A/D, Band width (4Hz – 20 K Hz),2 output D/A Conversion times 12 μ sec.

The knowledge base was tested off line first. The causes of vibrations were;

- initial unbalance , permanent bow , temporaty rotor bow , casing distortion . foundation distortion
- seal rub, rotor axial rub, misalignment, piping forces, journal and bearing eccentricity. bearing damage. bearing and support excited vibration,
- unequal x and y bearing stiffness, thrust bearing damage, insufficient tightness in assembly of rotor, bearing linear, bearing case, casing and support
- gear inaccuracy or damage, critical speed, structural resonance, pressure pulsation

The PDMKB is then interfaced with the BENTLY NEVADA measuring system There were 15 measuring points (15 Files) A sequential process for each three files (horizontal, vertical and axial) which correspond to one part or unit was adjusted to facilitate the diagnoses for each one at a time.

7.1 Off Line Program Operation

Fig.5 shows the predictive maintenance knowledge base main menu screen. The program enable the user either to read data from previous case (Off line file system) or on line data. In the Off line case the user should determine the horizontal, vertical and/or the axial measuring data file as shown in fig 6 The signal FFT waveforms will be displayed as shown in fig. 7

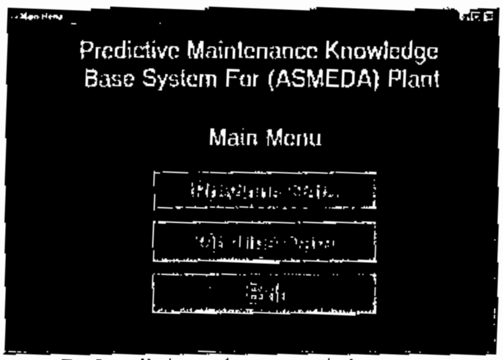


Fig.5 predictive maintenance window

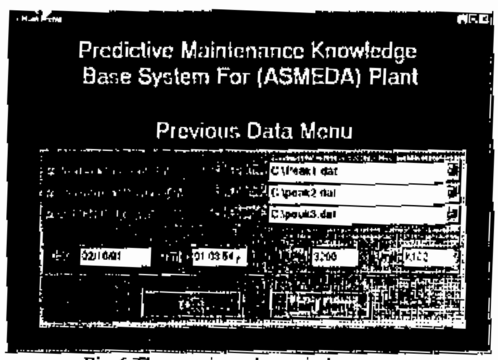


Fig 6 The previous data window

The screen includes some important data such as time, date , and the RPM of the rotating unit The possibility of increasing the horizontal and vertical scales (scaling of the waveform) is already exist When the user click the Diagnosis control button the inference begins. The click on the Show Diagnosis control button immediately displays the causes of vibration as shown in fig.8 The turbo machinery diagnosis window (fig. 8) mainly displays the causes of vibration and there possibilities numerically and graphically. In order to print reports the user can click on the Print control button.

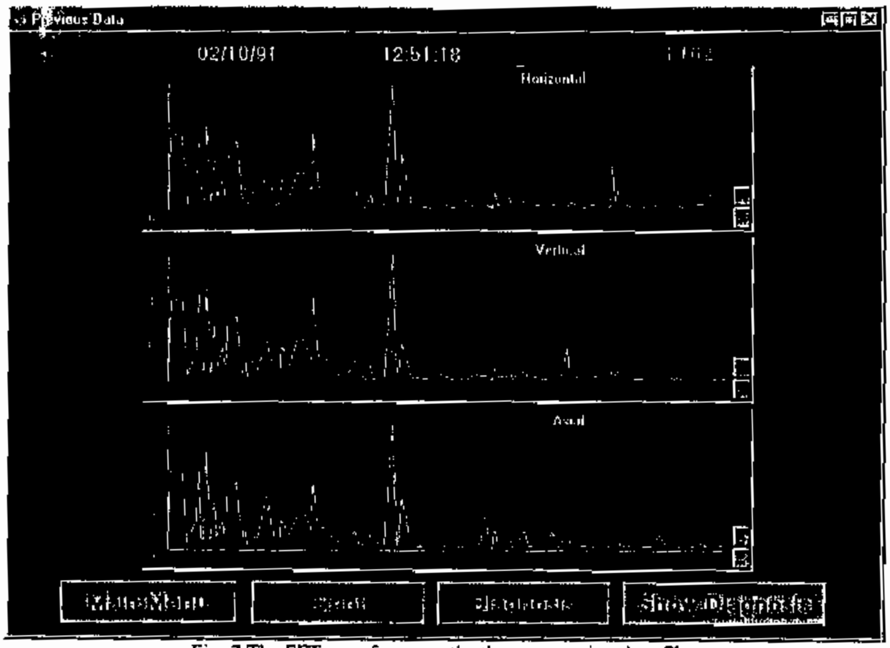


Fig. 7 The FFT waveforms on the three measuring data files

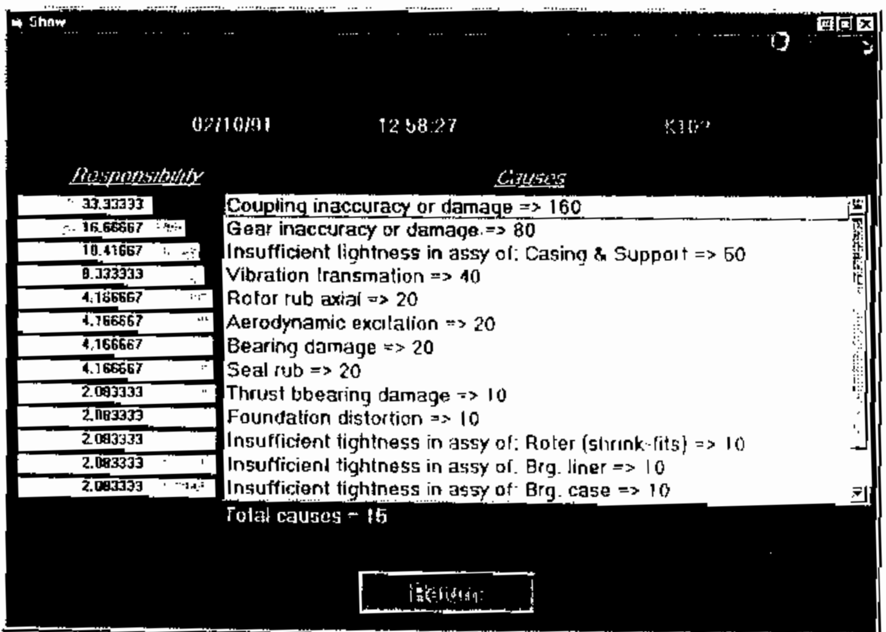
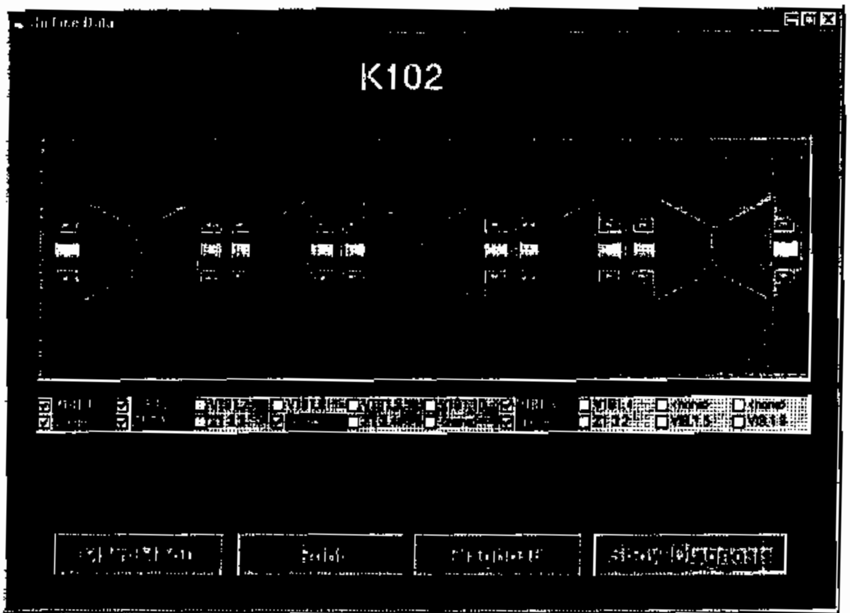


Fig. 8 The turbo machinery diagnosis screen

7. 2 On Line Program Operation

When the user chooses the ON line data, the measuring points on the rotating unit will appear and their number will be lightened as shown in fig. 8. The same process of diagnosis will be executed.



Fig, The ON LINE unit appearance

8 Conclusions

Vibration measurements of the external surface of a machine contain a great deal of information on the internal process and have become an established method of judging the machine condition The utilization of unsupervised neural network for measuring data that causes vibration is helpful tool in the diagnosis process The predictive maintenance overall objective is to provide a system that would continuously monitor vibration levels of equipments, automatically analyze, storage and update vibration information and generate alarms that would indicate the source of trouble

This paper has described the design principles and the considerable advantages that can arise from the incorporation of an expert system within the framework of a condition monitoring system

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