An Expert System Approach for Diagnosis of Rough Ride Problems in Heavy Trucks

by

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"An Expert System Approach For Diagnosis Of Rough Ride Problems in Heavy Trucks"

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Abstract

The rough ride problem is one of the major problems in the maintenance of heavy trucks, and it often frustrates truck engineers due to the large number of vibration sources causing vibrations in the driver's cab and cargo space. However, the Knowledge Based Expert System (**KBES**) approach provides a framework for organizing diagnostic solutions to the problems that can currently be solved only by a handful of highly experienced human experts using large amounts of domain-specific knowledge. Therefore, the goals of my research are to extract and codify the knowledge of expert engineers for a better understanding of heavy truck dynamics and rough ride trouble-shooting, to design an expert system (**RE** - Ride Expert), capable of diagnosing rough ride trucks by identifying inherent vibration sources.

Two levels of knowledge are stored in RE's knowledge base, enabling it to find the problem sources from the symptoms and the fault signatures which are usually the results of analysis of vibration signals collected from various parts of the truck by a multi-probe system. Causal-level knowledge is extracted from Mechanical Signature Analysis, MSA, which manifests the signatures of trouble sources and hence finds the sources by using Spectrum Analysis techniques, whereas shallow-level knowledge is the heuristic knowledge extracted from expert engineers who accumulated this kind of knowledge by their own experience in trouble-shooting. The advantages of combining these two levels of knowledge are the capability of covering a wide range of rough ride problems, high diagnosis efficiency and better explanation features.

A set of MSA techniques capable of identifying the sources of rough ride problems have been investigated and tested on road, and the signal processing subsystem for these techniques has been implemented. The main KBES structure for rough ride diagnosis has been designed.

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1. INTRODUCTION

The rough ride problem is one of the major problems in the maintenance of heavy trucks, and it often frustrates truck ride engineers [Gillespie 85] due to the large number of vibration or other sources causing vibrations in the driver's cab and cargo space, and hence the difficulty of identifying those sources. This implies that the diagnostic task involves a large search space and a lot of uncertainty. Moreover, it can be done by only a handful of experienced engineers.

These characteristics of this diagnostic problem make it a typical candidate for applying Knowledge Based Expert Systems, **KBES** [Hayes-Roth 83].

This thesis describes an application of KBES to rough ride trouble-shooting, as a powerful diagnostic solution to the problem, owing to the combination of Mechanical Signature Analysis, **MSA**, and the heuristic methods used by expert ride engineers based on their own experience of trouble-shooting.

1.1 Motivation

In the modern truck design, higher priority is given to functional efficiency in order for the vehicle to be commercially viable, than to driver comfort and convenience. Such designs have forced the driver in a position that is less than optimum for good ride and that is sensitive to abnormal (even very small) vibrations from other parts of the truck [Gillespie 85]. These practices and the lack of vibration diagnosis expertise can therefore create major financial losses if the rough ride discourages potential buyers. Due to the countless combinations of vehicular components (various configurations) to best match consumer's needs, and the large number (30 - 40) of identifiable vibration modes (resonant modes) potentially affecting ride in the frequency range below 20 Hz and countless number of their combinations [SDRC 73], the task of diagnosing the vibration sources has been considered demanding and only a few human experts can currently do it. So, a diagnostic system with rough ride diagnosis expertise is needed.

Some research on the rough ride problem has been published [Gillespie 85], but none of it has suggested or supported a systematic approach for rough ride trouble-shooting. Power spectrum Density, **PSD**, has been suggested so that the vibration modes which cause the rough ride can be recognized, and hence the trouble sources with this modes can be identified, based on a good knowledge of vibration phenomena on heavy trucks. However, this is often difficult since some modes, with their harmonics and combinations, are too close to each other to be distinguished, and the mode frequencies are often not known accurately or are too costly to acquire in practice due to the variety of truck configurations. The only suggestion in the published research for truck ride engineers is to understand truck vibration responses of truck and to distinguish the sources at work [Gillespie 85]. Up to now, therefore, in practice of rough ride diagnosis, ride engineers use such knowledge of truck vibration responses and their accumulated experience in trouble-shooting. Due to their emphasis on heuristic methods, the practice is more art than engineering, and of course the efficiency is low.

In summary, some major characteristics of rough ride diagnosis on heavy trucks are listed here. First, due to the large number of trouble sources and their combinations, a large search space is involved in the diagnosis. Next, uncertainty is always involved due to the lack of information in the diagnostic procedure, which is usually the case in practice. Finally, human experts are necessary, and a variety of techniques, ranging from heuristic to in-depth analysis of vibration data, are involved. Such a large search space and the uncertainty involved make it impossible for us to create a single analytical model of a truck so as to find the abnormal vibration sources causing rough ride with conventional algorithmic methods. Therefore, a KBES approach was chosen for the diagnostic problem.

1.2 Problem Statement

The aim of the research in this thesis is to examine how expert engineers diagnose rough ride problems by using various techniques ranging from heuristic to analytical, and to design a knowledge based expert system, **RE** (Ride Expert), as capable of coping with rough ride diagnostic problem as an expert engineer.

Some special considerations have been given to the areas such as diagnosis coverage and economic efficiency of RE. RE is so designed that up to 90 percent of rough ride problems would be covered by RE with the help of an average truck mechanic. The cost of rough ride trouble-shooting would be reduced considerably with RE, by its powerful focus ability to reduce mechanical check-up. Computation efficiency has also been considered due to the computing cost of spectrum analysis.

1.3 Approach

A two-level diagnostic architecture combining heuristic and causal (shallow and deep) reasoning [Torasso 89] has been adopted in RE. The use of two levels of knowledge and reasoning scheme is largely because of the diversity of the techniques used in rough ride trouble-shooting. Most of the knowledge extracted from MSA (Mechanical Signature Analysis) is codified as causal-level knowledge, which usually represents the cause-effect relationship between rough ride trouble sources and observable facts, describing the faulty behavior of the modelled truck in a very precise way (causal model). A causal network, (a kind of semantic network), has been used to represent the causal-level knowledge, and a hypothetical reasoning scheme has been used in this level. Heuristic knowledge serves as shallow-level knowledge, which is extracted, through a series of interviews, from expert engineers who accumulated this kind of knowledge by their own experience in trouble-shooting.

There are several advantages of using such a two-level reasoning architecture. Many techniques (diagnostic knowledge) can be used in rough ride troubleshooting, depending on the situation and the type of problem. They can be grouped into two, heuristic and analytical, and each of them model the truck in quite different ways. Expert ride engineers tend to solve problems using experience knowledge first, by directly associating their observations (findings, symptoms) with diagnostic hypotheses (trouble sources). In this way, less effort (measurements, check-up) will be involved. However, this can only solve a limited number of problems, and usually can not give satisfactory explanations for the diagnostic solution, due to the direct association used. In analytical methods, more observations (vibration signals and even its in-depth analysis) are taken and the correlation of the observation and the possible trouble sources is analyzed with the emphasis on their cause-effect relationship. This method can usually solve more problems and provide good explanations, But due to their higher costs, analytical methods are usually used after the heuristic methods fail. The combination of these two can provide the power of both and avoid their drawbacks.

A set of MSA techniques capable of indicating vibration sources have been investigated, and the conditions or situations in which these techniques should be applied have been identified. A series of road tests have been carried out to verify these MSA techniques. The signal processing subsystem for these MSA techniques to be used in the KBES in RE has been implemented. The main KBES structure for RE has been designed, and initial knowledge acquisition has been done by a series of interviews with expert engineers from Freightliner of Canada Ltd. in Burnaby.

2 . DIAGNOSIS OF ROUGH RIDE TRUCKS

In this chapter, the major techniques for rough ride diagnostics are presented, with a brief introduction of the truck ride problem as the beginning. MSA provides some good tools for truck dynamic analysis, and hence can be helpful in rough ride trouble-shooting.

2.1 Rough Ride Problems of Heavy Trucks

A truck can be considered as a dynamic system, exhibiting vibration in response to excitation inputs, as shown in Figure 2.1-1

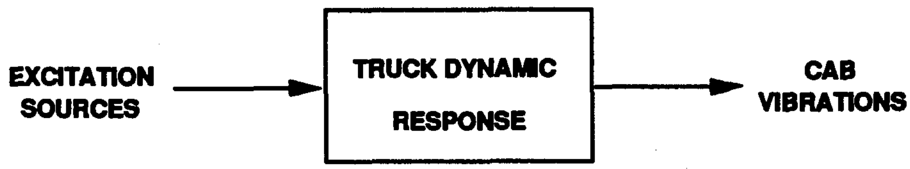


Figure 2.1-1, The truck dynamic system.

Because the minimum tolerance (maximum sensitivity) of human body is in the frequency range of 0 to 20 Hz [Lee 68, ISO 78], the primary focus of rough ride diagnosis is on the sources causing excessive cab vibrations in this frequency range.

The excitation sources and the truck dynamic response properties determine the ride vibration at the driver's cab and ultimately determine the driver's perception of the cab as a work place.

The major excitation sources by which truck ride vibrations may be excited can be classified as shown in Table 2.1-1.

Table 2.1-1, Vibration excitation sources

CLASS	RESPONSIBLE PART
Road Roughness	road
On-Board Sources	tire/wheel assembly driveline engine/transmission

Road roughness is described by the elevation profiles [Sayers 84], which fit the general category of broad-band random signals [Gillespie 85]. A different combination of a road and a truck can give quite different ride. An interesting example is that some trucks give better ride on a rough road than on a smooth road (see example in Section 2.5).

The vibrations attributed to tire/wheel assembly are usually caused by nonuniformities of the tires, wheels, hubs, brake drums, and other rotating parts, owing to imperfections in manufacture. Table 2.1-2 lists the major causes and their effects.

The driveline is the third major source of vibration excitation. The major forms are shown in Table 2.1-3.

As shown in Figure 2.1-1, the ride quality is also determined by the truck's dynamic response properties. Some subsystems of the truck have a major influence on the response properties and hence cause rough ride if faults are present in these subsystems. Some of them are listed in Table 2.1-4.

Table 2.1-2, Excitations of tire/wheel assembly

CLASS	TYPE	PARTS	VIBRATION FREQUENCY	VIBRATION DIRECTION
Dimensional Variations	eccentricity	t,w,h	*rps*	vertical,longitudinal
	ovality	t,w	2*rps*	vertical,longitudinal
	high-order radial	t	n*rps*	vertical
	wobble	t,w	*rps*	lateral
	high-order lateral	t	n*rps*	lateral
Imbalance	static	t,w,h,b	*rps*	vertical,longitudinal
	dynamic	t,w,h,b	*rps*	aligning torque
Stiffness Variations		t	$\geq$ *rps*	vertical

where

rps - the rotational speed of wheel (*revolutions per second*);
n - 2,3,...;
t - tires;
w - wheels;
h - hubs;
b - brake drums.

Table 2.1-3, Excitations of driveline

TYPE	CAUSING PARTS	VIBRATION FREQUENCY	VIBRATION DIRECTION
Imbalance	rotating parts	*rps*	vertical,lateral
Second Coupling	universal joints	2*rps*	longitudinal

Table 2.1-4, Subsystems affecting truck response properties

PART	TYPICAL FAULT EFFECTS
Suspension System	fail to damp out the roughness of road, due to flat-leaf spring friction, incorrect air bag height, spring damage, incorrect shackle angle, insufficient travel on shock absorbers, etc.
Tire/Wheel	fail to damp out the roughness of road, due to overinflation, severe tire wear, aggressive tread pattern, etc.
Cab Mounting	fail to isolate vibrations, due to loose or worn cab isolators, excessive cab movement allowed by cab mount, too rigid exhaust mounts or sleeper boot,etc.
Driver's Seat	fail to isolate vibrations, due to damaged seat mounting base and structure.
Frame	vibration or large frame bending, due to failed welds, cracks at stress points, loose components and cross members, etc.
Fifth Wheel	improper position causes large frame bending.

Besides the primary vibration sources and truck response properties, there are two factors having an impact on the ride, the truck travelling **speed** and the **load**. Most excitations, either inherent or road oriented, are speed dependent, thus the speed has direct impact on the ride. The load on the truck changes the response properties to some degree, depending on the load distribution, the suspension and frame configuration.

As a summary, the major factors affecting ride are listed in Table 2.1-5.

Table 2.1-5, Factors affecting ride

TYPE	FACTORS
ON BOARD	on board excitations truck dynamic response properties
OPERATING CONDITION	road roughness travelling speed loading

Any significant change of on-board factors is considered to be caused by a fault in the truck, which is to be found by RE. As shown by the examples we will see in Figure 2.4-3 and Figure 2.5-3, any combination of the three operating conditions in Table 2.1-5 (as a trigger) determines the presence of a ride problem, and hence should be carefully chosen during the road test in a diagnostic procedure.

2.2 Heuristic Methods

The heuristic method has been used for rough ride diagnosis since this problem became of concern. Truck ride engineers have accumulated a considerable amount of knowledge of ride problems, by their experience on trouble-shooting. The ride perception for a problematic truck by experienced ride engineers is usually classified into four categories, as shown in Table 2.2-1.

The connections between these expert engineers' perception of the ride and the vibration spectra taken from the truck sometimes can be found. For example, the perception of harmonic ride is usually related to an excessive strong peak on the PSD, such as that at 6.6 Hz in Figure 2.4-3. This implies that the vibration is dominated by one frequency component, and is most likely a rotating vibration (a heuristic rule).

Table 2.2-1, Ride perception with possible causes

RIDE	MAIN SYMPTOMS	MAJOR CAUSES	RESPONSIBLE PARTS
Harsh Ride	The road feels too rough.	suspension system is transmitting rather than damping road shocks.	tire, suspension, cab isolators, fifth wheel.
Harmonic Ride	The truck moves in a bucking or bouncing motion at a particular speed.	nonuniformities of rotating parts.	tire/wheel, driveline, cab mounting, fifth wheel.
Vibration Ride	Quiver or trembling, oscillation; rotating vibration with higher harmonics.	damaged joints of rotating parts; improper rotating part mounting; worn out engine part.	driveline, clutch, engine, transmission, frame parts.
Shimmy Ride	Lateral oscillation.	looseness or springiness in the steering system, dynamic imbalance.	steering system, tire/wheel, axle/suspension.

Such a classification as shown in the above table usually helps ride engineer very little in reducing the search space for a rough ride problem without some other heuristic rules (either searching strategies or classification), which are very difficult to organize in a table or on paper. Some major truck manufactures have made several ride manuals to collect ride diagnostic knowledge to help in trouble-shooting, like [Freightliner 84]. Usually such a manual lists all the faults on a truck which could cause ride problems, but with very little knowledge which can be used to conduct an efficient search. Thus such a book can offer very little but exhaustive search guide, and hence inexperienced engineers might find them little use.

2.3 Mechanical Signature Analysis

MSA deals with the extraction of information from measured signal patterns, which characterizes a specific system state. In our application, vibration signals are used as an information carrier, and the name "signature" denotes the signal pattern characterizing a specific trouble source causing ride a problem.

MSA has applications within the field of mechanical engineering, including machinery condition monitoring, diagnostics, modal testing, noise/vibration abatement, and production quality control.

Three main steps are involved in MSA. The first is **data acquisition** which includes signal collection and signal condition. A multi-probe system [Rawicz 90] is used to collect vibration (acceleration) signals on several locations on the truck simultaneously for the ride diagnosis. Next, **data reduction** is used to reduce the previously acquired data which usually reach an overwhelming number of points in a very short period. It can be done by various techniques, including transformations to other domains, filtering and parametric modelling techniques, in various domains: time, frequency, amplitude, etc. We mainly use frequency domain for ride diagnosis. Finally, **signature analysis** is performed to reveal the characteristics of interest so that a classification can be carried out to recognize the system state of interest. The techniques and classification strategies used for this step vary with application domains, and those used for rough ride diagnosis are the main topics for the rest of this chapter.

2.4 PSD Analysis

The power spectral density (PSD) [Jenkins 68], has been a useful representation of vibration strength in truck dynamic analysis. For a vibration signal $x(t)$, the PSD gives the distribution of the power of $x(t)$ with frequency and is defined as

$$S_{xx}(f) = \int_{-\infty}^{\infty} R_{xx}(\tau) \cdot e^{-j2\pi f\tau} \cdot d\tau, \qquad R_{xx}(\tau) = \lim_{T \to \infty} \frac{1}{T} \int_0^T x(t) \cdot x(t+\tau) \cdot dt. \tag{2.4.1}$$

where R_{xx} is the autocorrelation function. For discrete signal $x(k)$ with N samples separated by interval T, we have

$$S_{xx}(k \cdot \Delta f) = \frac{T}{N} X^*(k \cdot \Delta f) \cdot X(k \cdot \Delta f). \tag{2.4.2}$$

where $\Delta f = 1/NT$ and $X(k \cdot \Delta f)$ is the Discrete Fourier Transform (DFT) of $x(k)$.

In our application, PSD is applied to the acceleration amplitude of the vibrations on a truck, since excessive acceleration causes discomfort and human body damage and hence is of main concern. The vibration signals collected by accelerometers [Rawicz 90] and the PSD's are estimated (see Section 4.2). Then, these PSD's can be used in several ways in the diagnostic procedure.

<u>Resonant mode: peaks on PSD</u>

This is a method based on the identification of the modal resonances responsible for the peaks on the PSD. There are 30 - 40 identifiable resonant modes potentially affecting ride in the frequency range below 20Hz. Some of them are simple, such as "rigid-body" mode produced by the overall tire-suspension-body system with the resonant frequency of 1 - 2 Hz. Others are quite complicated, like frame-bending mode with not only the fundamental resonant frequency but also visible higher harmonics owing to the frame's thin beam structure. Some of these resonant modes on a truck are produced by certain vibration sources and hence can be used as the signatures of these sources. Thus, with a good knowledge of what vibrations are present at every point on a truck and the resonant modes involved, the trouble source for some rough ride problems can be identified. For example, a strong peak at the axle vertical (hop) mode implies excessive excitation from tire/wheel assembly with some kinds of nonuniformities. Figure 2.4-1 shows typical spectral components of cab vibration with the identification of the major modes of interest.

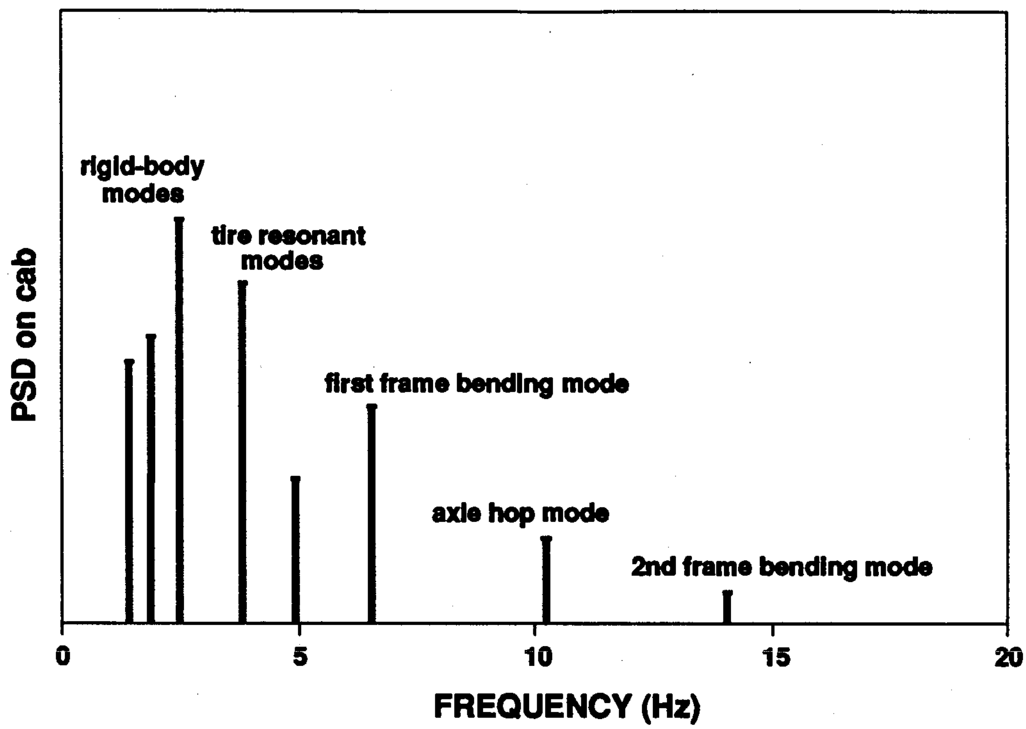


Figure 2.4-1, Typical modes of cab vibration.

<u>Spectral pattern</u>

Some of the ride-related faults shift frequency components on the PSD.

For example, low height of the air-bag in suspension system causes strikes on the bumper stop inside the bag when a large deflection of the suspension happens, thus the suspension system loses damping capability at this point. This leads to the up shift of the low frequency components on the PSD, because high-amplitude road roughness is concentrated in a range of long wavelength (low frequency). The envelop of a typical PSD of cab vibrations [Gillespie 85] and the anticipated effect of low height air bag suspension are illustrated in Figure 2.4-2. This can happen on a shock absorber when it bottoms out due to insufficient travel.

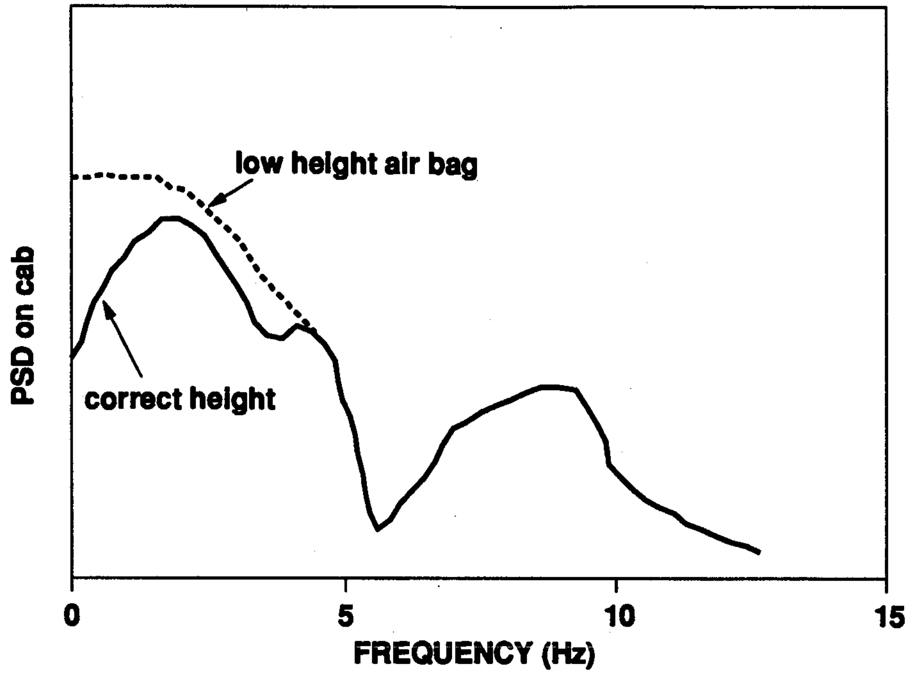


Figure 2.4-2, Effect of incorrect air bag height.

Speed dependency

The frequency and amplitude of some of the vibration excitations on board are dependent on truck travelling speed. Thus, a strong peak on PSD at a resonant mode can take place on a truck at a specific speed and disappear after the speed changes. Figure 2.4-3 shows two PSD's taken from the driver's cab of a truck at speed of 80 and 90 Km/h, respectively. At the speed of 80 Km/h, the imbalanced wheel produced an excitation at 6.8

Hz, which is the same as the axle hop mode frequency. Hence a strong peak on the PSD at 6.6 Hz is present. At 90 Km/h, the excitation produced by the wheel shifts to 7.4 Hz, away from the axle hop mode, thus no strong peak is found on the PSD at this frequency range.

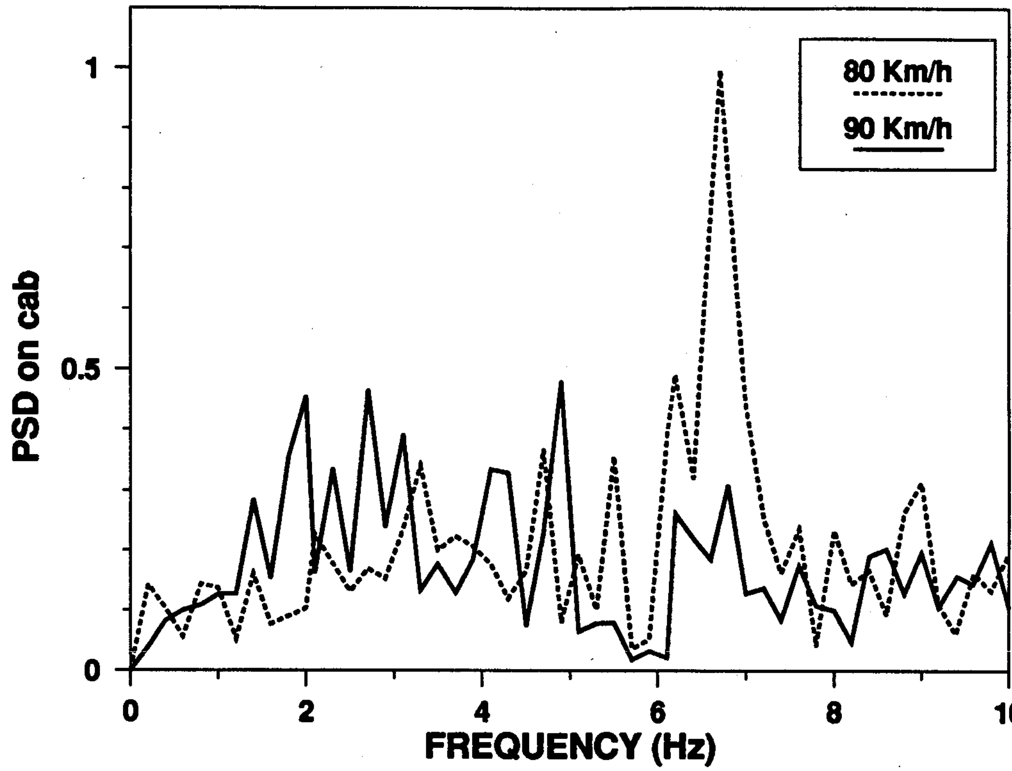


Figure 2.4-3, Speed dependency.

2.5 Coherent Power and Transfer Function

Power spectrum analysis is useful for resolving the frequency and strength of the components of a given signal, but has several limitations in identifying the source of a particular component vibration. When two vibration modes are present with their frequencies very close to each other, PSD becomes of little use. This is worse when the accurate mode frequencies for some modes on heavy truck are hardly known due to the variety of truck configurations. The use of multi-probe sensing scheme and coherent power analysis [Braun 86] provides a further aid in the identification and monitoring of subsystems.

The major concern here is the portion of vibration power at an observed point, which is usually the driver's seat, that comes from a vibration source. The power contributions from different sources thus can be compared so that the sources causing the most trouble at this point can be identified. A least-square regression method [Bendat 86] can be used to estimate portion of vibration power at an observed point y (usually the driver's cab) which is contributed by a source x, by means of two vibration signals, $x(t)$ and $y(t)$ which are collected simultaneously by the accelerometers attached to x and y, respectively.

This method is based on the closeness or commonality of $x(t)$ and $y(t)$ (the input and output), by splitting $y(t)$ into two components, one having commonality with $x(t)$ and the other not. In linear situation, we try to find $h(t)$ and $n(t)$ minimizing S_{nn}, where

$$y(t) = h(t) \otimes x(t) + n(t), \tag{2.5.1}$$

where $S_{nn}(f)$ is the power spectrum of $n(t)$, and $\otimes$ is convolution. By minimizing S_{nn}, the maximum power due to the part of $y(t)$ that is linearly related to $x(t)$ can be found. Figure 2.5-1 depicts this model.

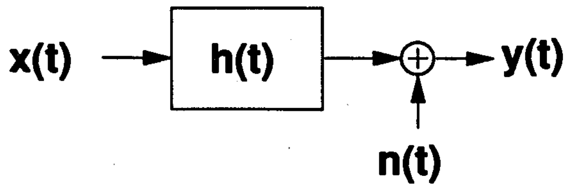


Figure 2.5-1, Linear model of relationship between $x(t)$ and $y(t)$.

In this model, $y(t)$ is split into two components: $h(t) \otimes x(t)$, which is linearly related to $x(t)$; and the residual, $n(t)$, which is due to other sources including noise and/or the nonlinearity in the actual physical relationship between $y(t)$ and $x(t)$. Following [Bendat 86], the solution of the above equations is given by

$$H(f) = \frac{S_{xy}(f)}{S_{xx}(f)}. \tag{2.5.2}$$

where $H(f)$ is the Fourier transform of $h(t)$:

$$h(t) = \int_{-\infty}^{\infty} H(f) \cdot \exp(j2\pi ft) \cdot \mathrm{d}f.$$

and $S_{xy}(f)$ and $S_{xx}(f)$ are the cross spectrum and power spectrum [Jenkins 68], respectively

$$S_{xy}(f) = X^*(f) \cdot Y(f), \tag{2.5.3}$$

$$S_{xx}(f) = X^*(f) \cdot X(f). \tag{2.5.4}$$

where * denotes complex conjugate, and $X(f)$ and $Y(f)$ are the Fourier transforms of $x(t)$ and $y(t)$, respectively. It can be readily seen that $h(t)$ is chosen so that $x(t)$ and $n(t)$ are uncorrelated or orthogonal to each other, as shown below

$$
\begin{aligned}
S_{nx}^*(f) = S_{xn}(f) &= X^*(f) \cdot N(f) \\
&= X^*(f) \cdot [Y(f) - H(f) \cdot X(f)] \\
&= S_{xy}(f) - H(f) \cdot S_{xx}(f) = 0.
\end{aligned} \tag{2.5.5}
$$

where $N(f)$ is the Fourier transform of $n(t)$. With this, the power components at y can be easily derived by

$$
\begin{aligned}
S_{yy}(f) &= Y^*(f) \cdot Y(f) \\
&= [H^*(f) \cdot X^*(f) + N^*(f)] \cdot [H(f) \cdot X(f) + N(f)] \\
&= |H(f)|^2 \cdot S_{xx}(f) + S_{nn}(f) + H(f) \cdot S_{nx}(f) + H^*(f) \cdot S_{xn}(f) \\
&= |H(f)|^2 \cdot S_{xx}(f) + S_{nn}(f).
\end{aligned} \tag{2.5.6}
$$

It is now clear that with this linear model in Equation (2.5.1), the vibration power at y can be split into two uncorrelated components due to $x(t)$ and $n(t)$ respectively, as given by above equation. Thus the **coherent power**, which denotes the portion of vibration power at y due to x, is given by

$$
\begin{aligned}
P_{xy}(f) &= S_{yy}(f) - S_{nn}(f) \\
&= |H(f)|^2 \cdot S_{xx}(f).
\end{aligned} \tag{2.5.7}
$$

and the **coherence function**

$$
\begin{aligned}
\gamma_{xy}^2(f) &= \frac{\text{coherent output power}}{\text{total output power}} \\
&= \frac{P_{xy}(f)}{S_{yy}(f)} = \frac{|S_{xy}(f)|^2}{S_{xx}(f) \cdot S_{yy}(f)}.
\end{aligned} \tag{2.5.8}
$$

represents the fraction of the power of $y(t)$ due to $x(t)$.

In this model, $h(t)$ simply constitutes a mathematical function that defines the best linear relationship between $x(t)$ and $y(t)$ in the least-square sense. Several comments are worth making. First, since $x(t)$ and $y(t)$ are collected simultaneously from one truck with the same sampling parameters [Rawicz 90] in our application, $h(t)$ obtained by using this model has strong physical meaning in regarding to the actual relationship between $x(t)$ and $y(t)$, rather than has only purely mathematical meaning [Braun 86]. Next, owing to the orthogonality of $x(t)$ and $n(t)$, this model can discern vibration sources with quite different vibration patterns (uncorrelated or weekly correlated), such as excitation from road roughness and the power line on a truck. But it becomes of little use when the problematic path among several paths connecting x and y is to be identified. Finally, although nonlinear characteristics of the vibration propagation path on heavy truck do exist, because the small neighborhood of the operating point at which the sampling of $x(t)$ and $y(t)$ takes place is the only range we are interested in, linear approximation does not give much discrepancy in such a small neighborhood, for our diagnostic purpose. In summary, coherent power can be used as a good approximation of the power due to the part of $y(t)$ contributed by $x(t)$ for the purpose of identifying uncorrelated or weekly correlated vibration sources in our application.

As an example, Figure 2.5-2 shows the coherence functions between the front axle and cab vibrations at the same situations as those in Figure 2.4-3. The vibrations at the front axle (caused by a imbalanced wheel) accounts for the most vibration power (87%) at frequency of 5-7 Hz on the cab when the truck traveled at speed of 80 Km/h, but not at speed of 90 Km/h. Therefore, the source (this imbalanced wheel) causing the rough ride problem in this particular case is identified.

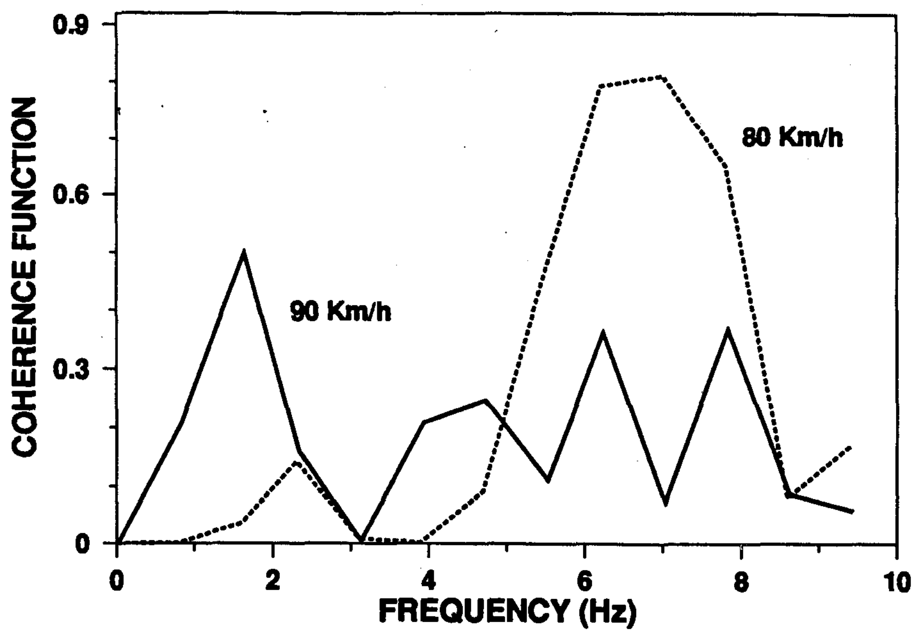


Figure 2.5-2, Coherence function between the front axle and cab vibrations.

Some faults on a truck can change certain transmissibilities (input-output gain [Gillespie]) between points on the truck, and hence cause ride problem (see Section 2.1). As the best (in least-square sense) estimate of the transmissibility, the transfer function given by Equation (2.5.2) can be used to monitor such a change and to identify the faults. As an example, Figure 2.5-3 gives two transfer functions between the front axle and the frame of a truck on two different road (rough, smooth). Due to the old flat-leaf suspension and the lack of lubrication on the spring pin, the suspension system exhibits a severe hysteretic behavior [Sayers 81], a type of nonlinearity between the force and displacement on the spring which causes higher effective stiffness when the displacement on the spring is small. On the smooth road, the displacement is small, and the higher effective stiffness of the suspension causes a peak on the response gain (absolute value of transfer function) at 10

Hz, which is absent on the rough road.

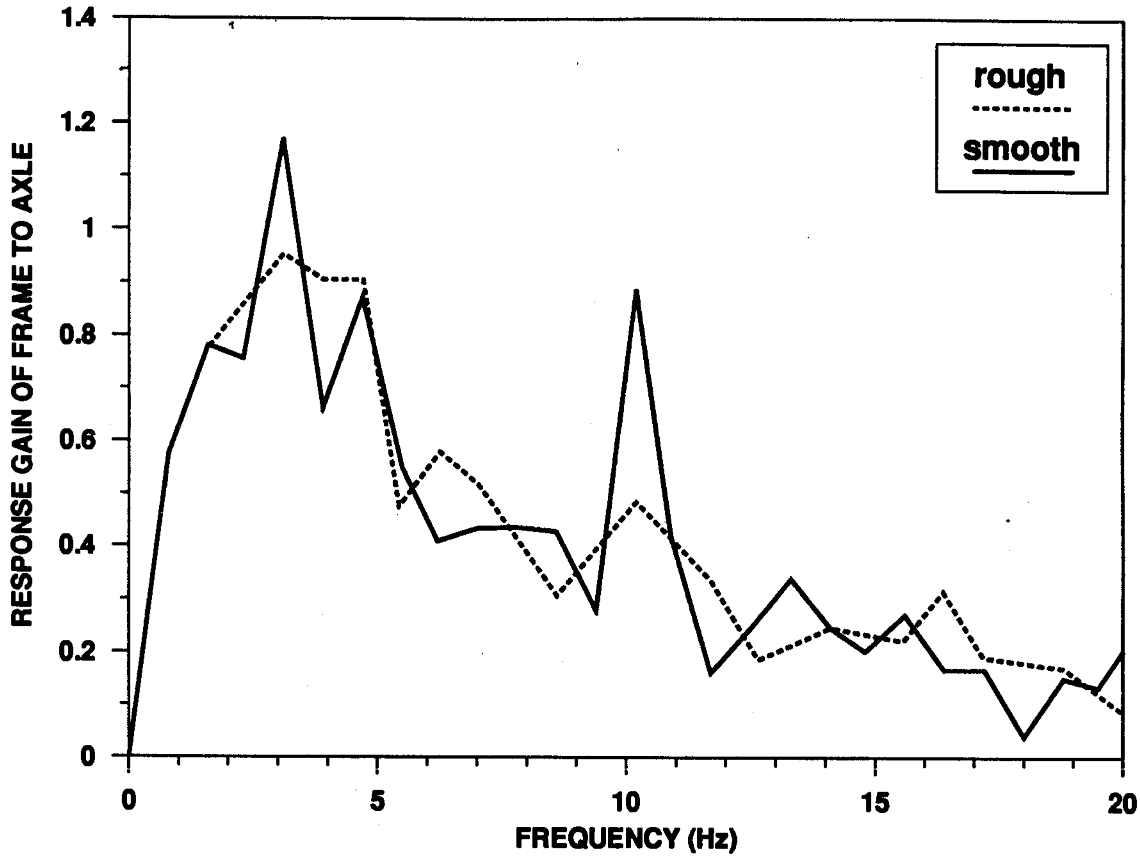


Figure 2.5-3, Better ride on rougher road.

3 . EXPERT SYSTEM APPROACH FOR DIAGNOSTIC PROBLEM SOLVING

3.1 Knowledge Based Expert System

A KBES differs from algorithmic problem-solving, in using domain-specific knowledge to cope with the enormous search space of alternatives found in real-world problems. An expert system can generally be characterized as including the following:

- extensive specific knowledge from the domain of interest;
- application of search techniques;
- support for heuristic analysis;
- capability to infer new knowledge from existing knowledge;
- an ability to explain its own reasoning.

Most KBES's have three components in common: a **working memory**, a **knowledge base** and an **inference engine**. The separation of these three components is a major difference from conventional algorithmic programs. Three major formats for knowledge representation are rule, frame-based and semantic network.

3.2 ES Architecture in RE

3.2.1 The Overall Structure

Figure 3.2.1-1 depicts the KBES structure used in RE. The consultation system asks the user to provide the truck's conditions and configuration, and the symptoms of the rough ride problems observed by the user. This information is put in the working memory, along with the information (vibration signatures) provided by the vibration data collection and analysis system. The inference engine conducts an inference trying to find the trouble sources accounting for the symptoms in the working memory, by using the knowledge in the knowledge base. The inference engine also send out, directly or through consultation system, control signals to obtain more information for the diagnostic procedure. These signals could be

- suggestion for a mechanical check-up, to either support or reject a diagnostic hypothesis;
- suggestion for the allocation or re-allocation of vibration sensors, to focus the possible problem areas and hence to reduce the search space;
- types of mechanical signature analysis, to avoid unnecessary computation of vibration signal processing involved, which is usually very costly.

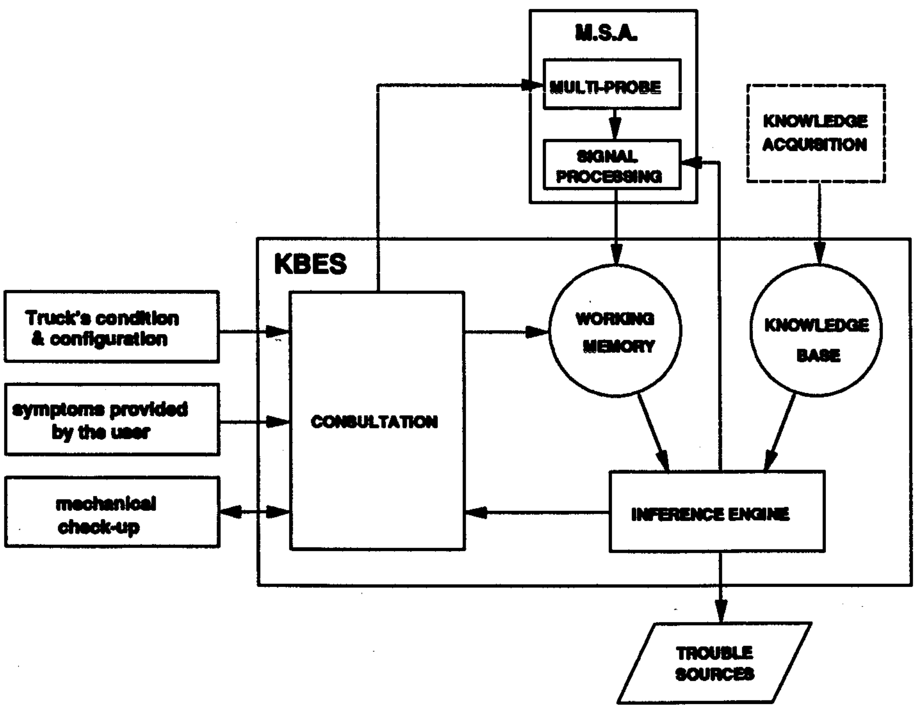


Figure 3.2.1-1, The Overall Structure.

3.2.2 Two-Level Diagnostic Architecture

Diagnosis is a process of fault-finding in a system based on the observed system behavior, using knowledge of the correlation between the faults and behaviors. Heuristic knowledge, which is the heuristic relationship between diagnostic hypotheses (system faults) and observed data (system behaviors), is the only type of knowledge used in earlier diagnostic expert system, such as MYCIN [Shortliffe 76]. Such a relationship is a shallow correlation between the faults and behaviors, and usually represented by means of **IF...THEN...**, Production rules. Figure 3.2.2-1 shows an example of such a kind,

---

IF

spring suspension used, and

it is two or three years old, and

the truck is travelling on a smooth road

THEN

harsh ride at 6-12 Hz could be felt at driver's seat,

with probability 0.2.

Figure 3.2.2-1, A simple rule for spring suspension.

Such an approach, regarded as the first generation of KBES [Steels 85] and classified as "Heuristic Classification" [Clancey 85], corresponds to the behavior of a domain expert who can solve most of the problems that he faces simply by using the experience gained in solving similar cases. This experience knowledge is necessary for solving diagnostic problems, but it is not sufficient for several reasons [Steels 85a, Partridge 87]. First, heuristic systems have good performance on typical cases but degrade rapidly when different cases are met. Next, it does not permit the generation of useful explanation, because the reasoning path followed to find a solution usually differs from a convincing rational argument why the solution is valuable. As an example, the interleaf friction of spring suspension actually causes the harsh ride on smooth road when old and poorly maintained springs are used, but the rule in Figure 3.2.2-1 does not reveal this. It provides the "correlation" (connection) but does not provide "why". Finally, finding heuristic rules has turned out to be extremely difficult, and there are always problems of incompleteness and inconsistency. These reasons led us to use knowledge at a deeper abstract level.

Causal model [Bobrow 84, Reggia 83, Console 90], which models the system under consideration by cause-effect relationships between system states, is an answer. Such a causal relationship can be effectively used to describe the behavior of the modelled system in a very precise way. Figure 3.2.2-2 shows a causal model of the spring suspension problem in corresponding to the rule in Figure 3.2.2-1.

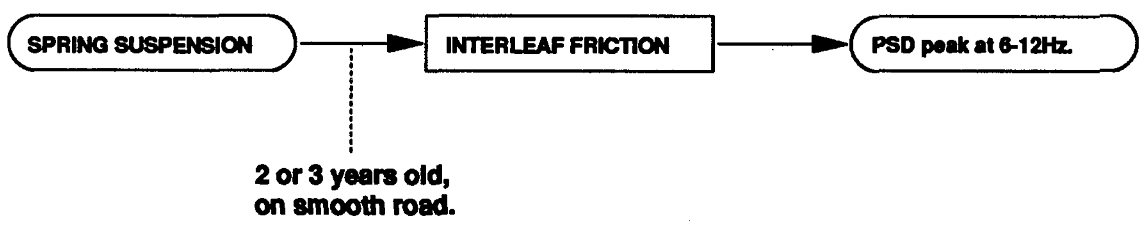


Figure 3.2.2-2, A simple cause-effect in spring suspension.

However, for several reasons, some systems can not be modelled purely by causal model. Since a deep causal model is built at a lower level of abstraction with more details involved, the complexity (computational and spatial) might be prohibitive [Kahn 84] in some case for large systems. Reasoning purely on a causal model does not produce the behavior of a human expert who certainly uses some forms of experience, at least to focus deep reasoning. Human experts tend to solve problems using experience knowledge first, that is, by directly associating observations with diagnostic hypotheses so that they can find the solution quickly or at least reduce the search space quickly. When this attempt fails, they start to consider the problem in a different and deeper way. The consequence of these observations about heuristic and causal reasoning suggests that a good scheme for a diagnostic system might be to represent domain knowledge at different levels, so that reasoning can be performed at different levels of abstraction to optimize system performance [Fink 85, Sticklen 88, Koton 88, Milne 87].

Therefore, an architecture combining heuristic (shallow) and causal (deep) reasoning [Torasso 89] is proposed for the KBES for RE. There are two sources of diagnostic knowledge for RE. One is extracted from MSA, the other is extracted from expert experience. Most of the knowledge from MSA is codified in causal-level, whereas the major of knowledge at shallow-level comes from expert experience (Figure 3.2.2-3).

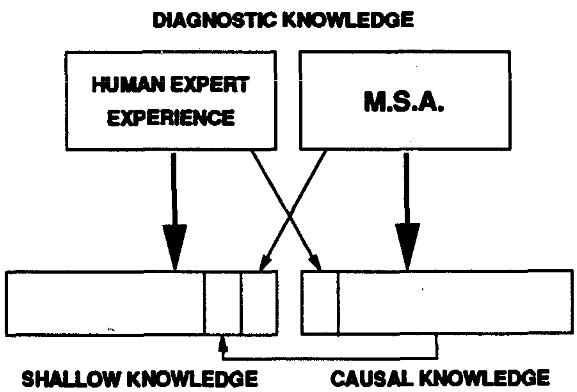


Figure 3.2.2-3, Knowledge sources for RE.

In Figure 3.2.2-3, we can see that the shallow knowledge also can be generated directly from knowledge at causal-level, an inherent learning mechanism [Steels 85b, Pazzani 87] (for future research).

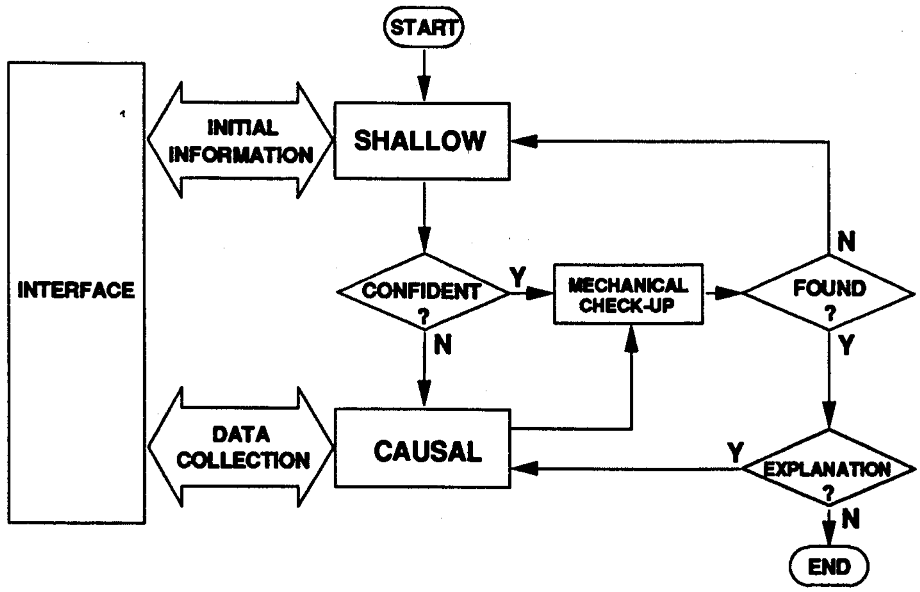


Figure 3.2.2-4, Inference control for two-level reasoning.

Figure 3.2.2-4 depicts inference control for the two-level reasoning in INFERENCE ENGINE in Figure 3.2.1-1. The shallow-level is involved first to gather the initial information and to generate initial diagnostic hypotheses. In the cases when the certainty factors of these generated hypotheses are not high enough or these hypotheses are not focused enough to suggest a mechanical check-up usually leading to a solution, or when a confirmation of these hypotheses is requested by the user, the causal-level is activated to confirm these hypotheses. This usually invokes more data gathering activities (vibration data collection and analysis). If an explanation is desired, the causal-level is invoked to give an explanation for the solutions RE has found.

A brief description of a two-level diagnostic architecture will be given in the remainder of this chapter.

3.3 Heuristic Level

The knowledge at the heuristic-level is represented by production rules, such as one in Figure 3.2.2-1. Such rules can be easily implemented in Prolog [Borland 88]. A certainty factor is attached to each rule which gives certainty for this rule. MYCIN's certainty combination scheme [Shortliffe 84, Adams 84] is used, and it is readily implemented in Prolog [Sterling 86, Clark 82].

As an example, the implementation of the rule in Figure 3.2.2-1 is given below.

```
suspension(fault, CF) :-
        suspension(flat_leaf_spring),
        suspension(age, 3),
        road(smooth, CF_smooth_road),
        ride(harsh, CF_harsh_ride),
        retract( cf(suspension_fault, CFsusp) ),
        combine_cf(CF, CFsusp, [CF_harsh_ride,CF_smooth_road], 0.2),
        assert( cf(suspension_fault, CF) ).
```

Figure 3.3-1, Prolog implementation of a heuristic rule.

3.4 Causal Level

3.4.1 Knowledge Representation

The knowledge at causal-level is represented in a formalism of "causal network" [Patil 81, Console 90], which is a type of semantic network. A causal network is made up of a set of nodes representing various entities (such as system states, diagnostic hypothesis and findings), connected by different kinds of relationships.

Five types of nodes can be used to form a causal network: **HYPOTHESIS, STATE, ACTION, INITIAL-CAUSE** and **FINDING**, as listed in Figure 3.4.1-1.

NODE	GRAPHICS	REPRESENTATION
HYPOTHESIS	H	Diagnostic Hypothesis
STATE	S	System State
INITIAL-CAUSE	C	Initial Cause
ACTION	A	Event Causing State Transition
FINDING	F	Observable State

Figure 3.4.1-1, Nodes used in causal network.

HYPOTHESIS nodes correspond to the diagnostic hypotheses considered by RE. The causal-level shares some hypotheses with the shallow-level. A STATE node represents a possible situation in which the modelled system can be at a given time. A FINDING node corresponds to an observable state of the modelled system, in comparison with internal states which are usually not observable. Two kinds of finding are used: easily observable states and those valuable only after a sort of in-depth analysis, such as spectrum analysis in MSA.

These nodes are connected by "arcs" representing the relationships among the nodes. Six types of arcs can be used in RE, namely **CAUSAL, HAM** (Has As a Manifestation), **SUGGEST, DEFINED-AS, FORM-OF** and **LOOP,** as listed in Figure 3.4.1-2. A CAUSAL arc represents a cause-effect relationship (between system states) which is augmented with information about the events causing the state transitions. A condition can be attached to an arc under which the state transition can take place, as shown by the formula for CAUSAL arc in Figure 3.4.1-2. A HAM arc represents the relationship that the finding is an external manifestation of the state. A DEFINED-AS arc represents the fact that the diagnostic hypothesis is defined as the presence of the state. A SUGGEST arc represents that presence of the state suggests the analysis of the hypothesis as a collateral or an alternative one. FORM-OF arcs connect HYPOTHESIS nodes to form the hierarchy of the diagnostic hypotheses in a causal network.

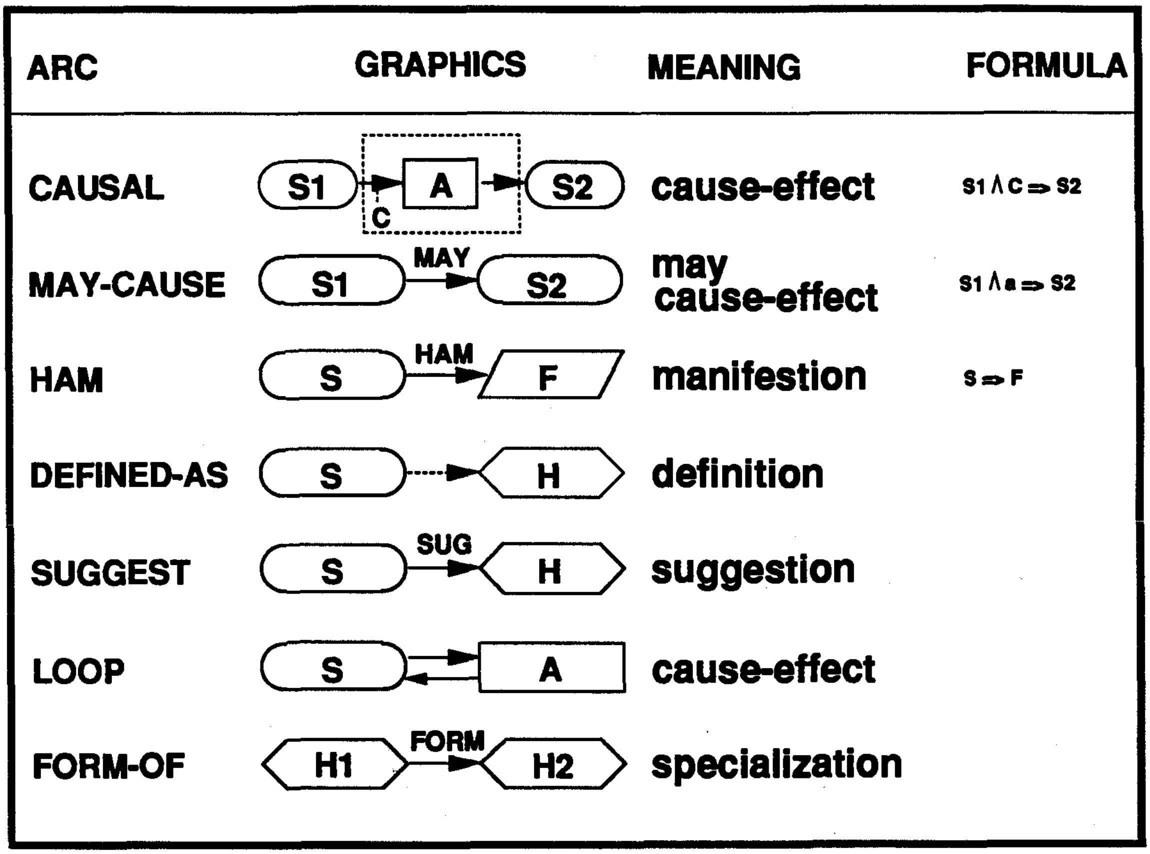


Figure 3.4.1-2, Arcs used in causal network.

As an example, Figure 3.4.1-3 illustrates a causal model for air bag suspension system.

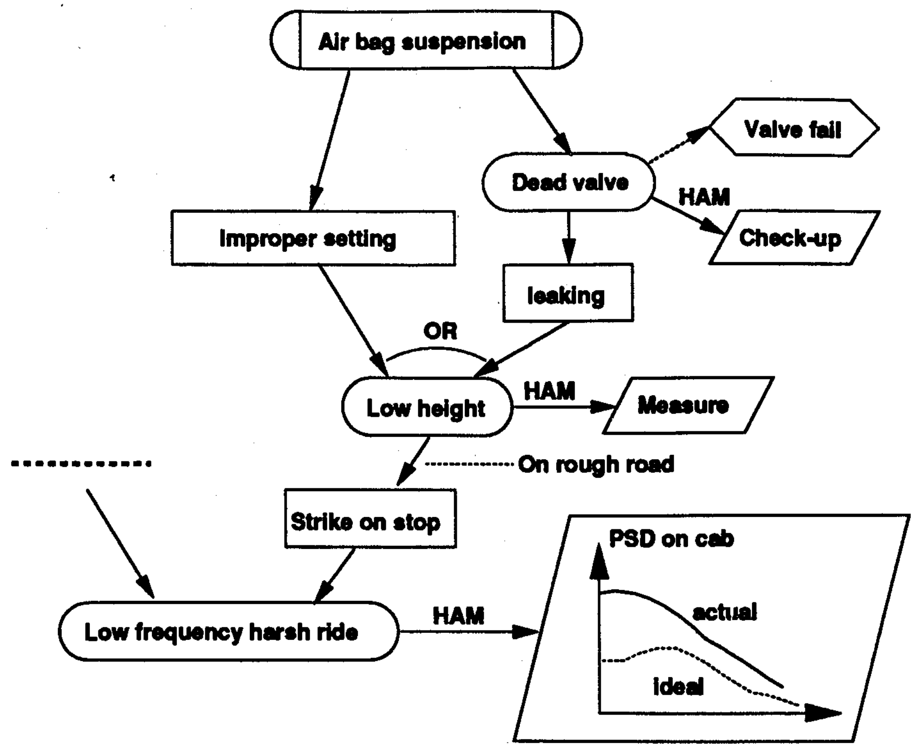


Figure 3.4.1-3, A causal model for air bag suspension system.

3.4.2 Hypothetical Reasoning

Causal-level reasoning can be used to confirm a diagnostic hypothesis generated by shallow-level, or to provide deeper explanation. The main reasoning strategy for this confirmation purpose is discussed in this section.

Suppose that a diagnostic hypothesis, H, is to be confirmed in a causal network. The following is the general reasoning procedure.

I. A backward search is conducted for all STATE nodes, Sd_i (i=1,...,n), defining H, and a confirmation for each Sd_i is attempted, which comprises of 3 steps (II, III and VI below). If every Sd_i is confirmed (present), H is confirmed.

II. A forward search for all the FINDING nodes connected from Sd_i by HAM arcs is performed. Then, each of these nodes is checked for its presence. This could involve the consultation with the user and/or acquisition for vibration data. If one of these FINDING nodes is ***absent*** (certainly not present, see explanation below), we say that the STATE node Sd_i is rejected, and the attempted confirmation for H fails. Otherwise, the reasoning procedure goes on.

III. If the conditions attached to each causal arc entering Sd_i are satisfied, go on to next step. This might demand more input information.

IV. A backward search for all the causing STATE nodes connected to Sd_i by causal arcs is conducted, and confirmation for each of these STATE nodes is attempted. If all these causing STATE nodes are confirmed, Sd_i is confirmed.

Figure 3.4.2-1 illustrates the chain of such a reasoning. If H is confirmed, any suggested hypothesis connected by SUGGEST arc to any confirmed STATE nodes in the above procedure will be a candidate to be analyzed or confirmed.

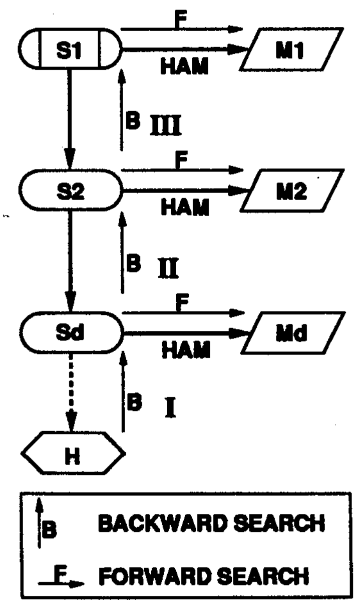


Figure 3.4.2-1, An example of causal reasoning chain.

This reasoning scheme (modified version of a hypothetical reasoning scheme [Console 90]) has been designed with two main concerns. First, in MSA, the data, which are either direct measurement or a result of in-depth analysis (such as transfer function analysis), usually have some degree of ambiguity, and sometimes the analyzed fault signatures are masked by noise or the signals of other effects on the truck. Therefore, when the status of a FINDING node is to be determined based on input data, three linguistic value are used: ***present***, ***absent*** and ***uncertain***, with meanings of certainly present, certainly absent and uncertain, respectively. In step I, when one of the FINDING nodes is *absent*, the implication formula for HAM arc (Figure 3.4.1-2) does not hold if the STATE node is present (confirmed), and hence an **inconsistency** is found. This implies that certain assumptions (see below) previously made along the reasoning chain do not hold any more and the reasoning chain should be entirely or partially abandoned. One the other hand, when none of these FINDING nodes is *absent*, the reasoning process should continue, under an assumption that they are *present* if some of them are *uncertain*. Then, the reasoning is continued in a (hypothetical) reasoning world [Kripke 59, Console 90] with this assumption present. If an inconsistency is found in this hypothetical world, it is rejected and the reasoning is continued in the previous world, by looking into other search branches. The similar hypothetical reasoning can be applied to MAY-CAUSE arcs [Console 90].

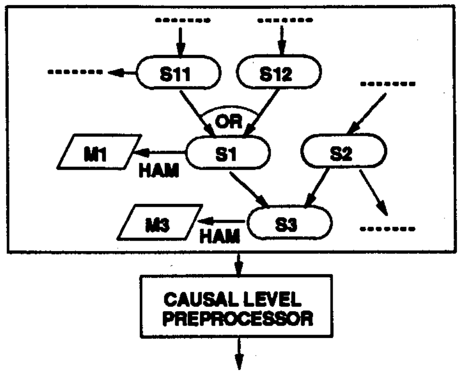
The causal network should be so structured that the FINDING nodes closest to INITIAL-CAUSE nodes (e.g. M1 in Figure 3.4.2-1) have no or very little uncertainty in terms of determining their presence, such as the result from an accurate transfer function analysis (Section 2.5) or a mechanical check-up. Mechanical check-ups usually serve as the last resort of rough ride diagnosis because of the cost, but are always able to explain the observed facts with no or little uncertainty. In such a way, when the reasoning finally reaches the INITIAL-CAUSE, there is little uncertainty left for the acceptance or rejection of the hypothesis being confirmed. Such a (qualitative reasoning) characteristic of this hypothetical reasoning makes it, in some cases, certainly superior to shallow reasoning with certainty factor combination scheme when it provides the user with several competing diagnostic hypotheses with similar certainty factor.

The other concern when this reasoning scheme was designed was computation complexity. In the reasoning procedure, the search space should be reduced as early as possible and as much as possible, with less expensive information. The further the reasoning proceeds, the more effort should be involved to obtain the solution, i.e. the more expensive is acquiring further information for the inference procedure. This is like the way a human expert works on a problem. In a similar way, the reasoning scheme discussed above searches a causal network backwards from the final effects to the initial causes (can be considered as a kind of *abductive inference* [Charniak 85, Pople 82, Reggia 85]), so as to minimize the cost along the reasoning path. The final effects are usually observable at an early stage of the diagnosis and hence the acquisition for their manifestation is the least expensive (e.g. from consultation with the user), whereas the initial causes are usually revealed ultimately by a mechanical check-up, the most expensive one.

3.4.3 Implementation

The expert system is to be implemented in Prolog for several reasons. Some of available expert system shells support multiple schemes of knowledge representation and object-oriented programming which are necessary for RE implementation, but they are quite expensive (above $5,000) and none of them runs on IBM PC [Harmon 88]. Turbo Prolog [Borland 88] is inexpensive and has a good interface with Turbo C which is used for implementation of signal processing subsystem of RE. Moreover, as we will see in the remainder of this section, by using an object-oriented programming scheme in Prolog [Torasso 89], the causal level can be implemented in Prolog, and the integration with the shallow level can be readily achieved.

Each node in a causal network is considered as an object which is characterized by a set of local variables and a set of reasoning methods, and represented by a set of Prolog clauses. The name of the predicate of these clauses' left hand side is the same with the name of this node. Local variables are represented by assertions (facts), whereas reasoning methods are represented by complex clauses (rules). As an example, the implementation of a causal work is illustrated in Figure 3.4.3-1.



S11 ...	
S12 ...	
S1 (confirm, ...) :-	S1 (forward, ...), S1 (backward,...).
S1 (forward, ...) :-	M1 (presence,...).
S1 (backward,...) :-	S11 (confirm, ...).
S1 (backward,...) :-	S12 (confirm, ...).
S2 ...	
S3 (confirm, ...) :-	S3 (forward, ...), S3 (backward, ...).
S3 (forward, ...) :-	M3 (presence,...).
S3 (backward,...) :-	S1 (confirm, ...), S2 (confirm, ...).

Figure 3.4.3-1, Implementation of a causal network.

3.5 A Complete Example

In this section, we shall consider a simple hypothetical example of rough ride diagnosis by using the diagnostic techniques and the reasoning mechanism presented so far.

At first, a symptom (a complaint from the driver) of harmonic ride (see section 2.2) is input into the expert system, and the shallow level generates a diagnostic hypothesis: *rotating vibrations*, by using a heuristic rule in the shallow level knowledge base:

IF

harmonic ride

THEN

rotating vibrations (cf=0.6).

Then, the causal level is invoked to confirm this hypothesis and to look further for the trouble source, by reasoning on the causal network of rotating vibrations as illustrated in Figure 3.5-1.

The confirmation of hypothesis, *rotating vibrations*, starts from HYPOTHESIS node of *rotating vibrations*. First, the confirmation of STATE node of *rotating vibration*, which defines this hypothesis, is attempted. In the FOUNDING node connected from this STATE node, a PSD of vibrations in the driver's cab is acquired at truck speeds of 80 Km/h (at which the rough ride occurs according to the driver's complaint) and 90 Km/h. This PSD shows a strong peak at 6.6 Hz at speed of 80 Km/h, but does not at speed of 90 Km/h, and hence the speed dependency of vibration amplitudes (see section 2.4, Figure 2.4-3) is identified which confirms the existence of rotating vibrations. To find the initial cause, the reasoning goes on to confirm STATE nodes of *front rotating vibrations* and *rear rotating vibrations*. Node of *front rotating vibrations* is rejected by its FOUNDING node, in which

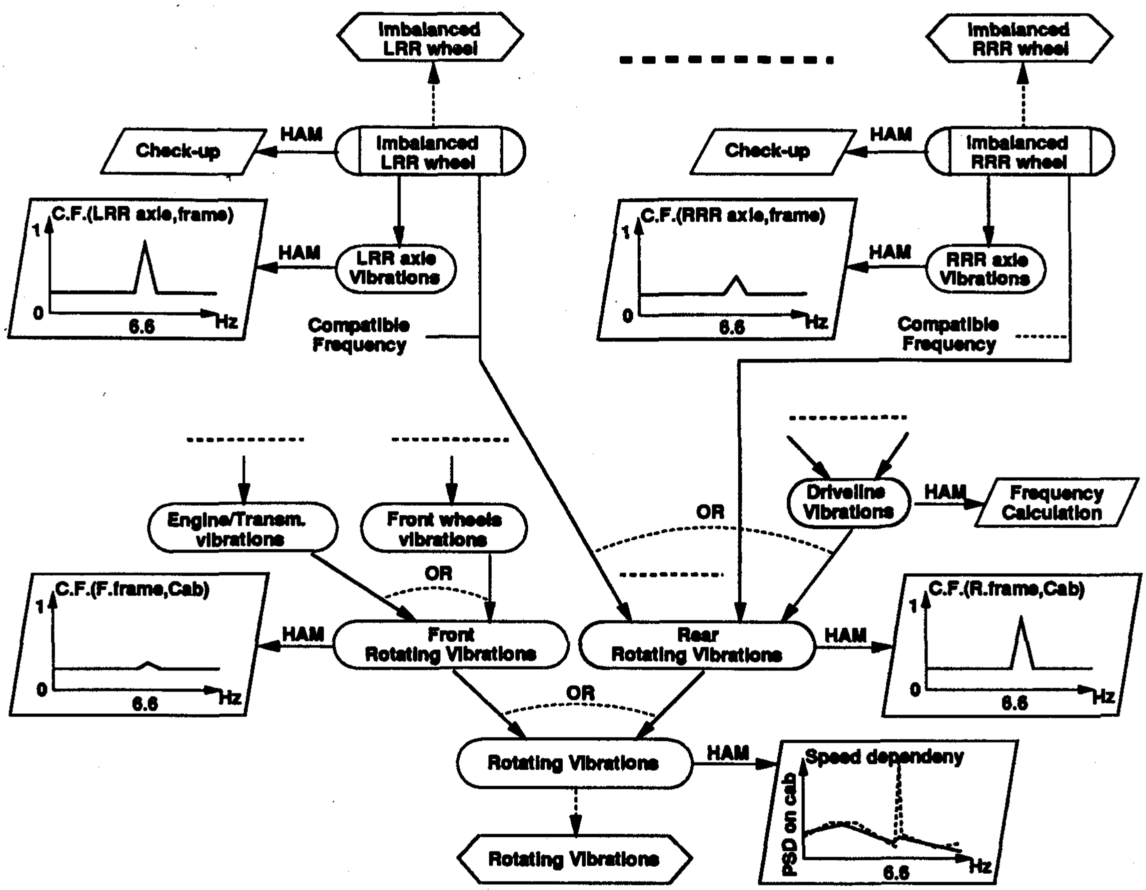


Figure 3.5-1, A causal network of rotating vibrations.

the coherence function between the vibrations of the front frame and the cab shows that a very small fraction of cab's vibration power comes from front part of the truck and hence the excessive vibrations comes from somewhere other than the front. The coherence function in the FOUNDING node connected from STATE node of *rear rotating vibrations* supports the presence of this STATE node (a peak at 6.6 Hz on this coherence function), and hence the reasoning continues in the branch of this causal network started from node of *rear rotating vibrations* to search back for the cause. In the FOUNDING node connected from STATE node of *driveline vibrations*, the frequency calculation shows that the frequencies of the vibrations generated by driveline at current speed (80 Km/h) are 28 Hz and its multiples (harmonics), far away from the frequency (6.6 Hz) at which the rough ride occurs. This STATE node is thus rejected. In the FOUNDING node connected from STATE node of *LRR axle vibrations* (the consequence of the INITIAL-CAUSE node of *Imbalanced LRR wheel*), the coherence function between the vibrations of the left end of rear rear-axle (*LRR axle*) and the frame shows this part of this axle contributes the most of vibration power at rear frame, implying that the left rear rear-wheel (*LRR wheel*) has imbalance problem (the initial cause: trouble source). This is finally proved by a mechanical check-up.

4 . RE DEVELOPMENT

4.1 Vibration Data Collection

The vibration data are collected by a multi-probe system [Rawicz 90] and transferred to a PC. The sample interval is 5 milliseconds, which gives us the undistorted signal under 100 Hz (Nyquist sampling theorem), enough for our application: low frequency range. This sample interval also gives the necessary 0.38 Hz frequency resolution with only 512 point-DFT ($\Delta f = 1/NT$), that is - less computation. Each sample record has 16,384 points, which is enough for 32-segment averaging to get good quality PSD estimates (see next section). This is only suitable for a good surface road because it takes 82 seconds to acquire this lengthy record, and it does not change characteristics within this distance. By using Reverse Arrangements Test method [Bendat 86], stationarity tests of the smooth road with this length have been carried out and no evidence has been found to reject the stationary assumption [Nigam 83].

4.2 Spectral Estimation

The segment-averaging method [Nuttall 80] is used to estimate the auto-spectrum (PSD) and cross-spectrum. This method is based on dividing the signals, *x(i)* and *y(i)* with length of *N*, into *M* segments

$$x_j(i) = x \cdot [i + (j-1)N_1], \qquad \textbf{(4.2.1)}$$

$$y_j(i) = y \cdot [i + (j-1)N_1], \qquad (j = 1, \ldots, M)$$

where $N_1 = N / M$ is the length of each segment. We now compute the estimates of either auto-spectrum S_{xx} or cross-spectrum S_{xy} for each segment as

$$\hat{S}_{xxj}(k) = \frac{T}{N_1} X_j^*(k) \cdot X_j(k), \tag{4.2.2}$$

$$\hat{S}_{xyj}(k) = \frac{T}{N_1} X_j^*(k) \cdot Y_j(k), \tag{4.2.3}$$

where $X_j(i)$ and $Y_j(i)$ are the Discrete Fourier Transform (DFT) of $x_j(i)$ and $y_j(i)$, respectively. Then, we can get the estimate of either S_{xx} or S_{xy} by ensemble averaging

$$\hat{S}_{xx}(k) = \frac{1}{M} \sum_j^M \hat{S}_{xxj}(k), \tag{4.2.4}$$

$$\hat{S}_{xy}(k) = \frac{1}{M} \sum_j^M \hat{S}_{xyj}(k). \tag{4.2.5}$$

The normalized random error (coefficient of variation) of these estimates is inversely proportional to the square root of M [Bendat 86]. Because of our accelerometer's low response at high frequency range [Rawicz 90], the signals from these sensors are considered as low-passed signals and hence low-pass filtering to prevent aliasing errors [Bendat 86] is no longer necessary. But a time weighting function (window) [Nuttall 81] is applied to each time segment in Equation (4.2.1) before the DFT, to reduce the leakage error. Time weighting is preferred here to lag weighting [Bendat 86], since the frequency resolution which can be possibly achieved by using data records with a limited length is of main concern.

The estimate of transfer function is given below [Bendat 86], by using the results obtained above

$$\hat{H}(f) = \frac{\hat{S}_{xy}(f)}{\hat{S}_{xx}(f)}. \tag{4.2.6}$$

4.3 Data Structure for spectra

As we have seen earlier, vibration spectra are heavily used in RE as the diagnostic information carriers. Computation of these spectra is very costly, as seen in the previous section. The storage space for these spectra is also large, due to the overwhelming number of data points. So, compromises often have to be made between necessary re-calculation when the same data is requested more once in a diagnostic procedure, and overwhelming storage space needed to prevent re-calculation. As a solution, a multilevel signal abstraction scheme [Milios 89] is used in RE to carry spectral information.

Spectral information is expressed at three levels of abstraction: the **numeric spectrum level**, the **peak level**, and the **harmonic peak set level.**

The numeric spectrum level is the lowest level of abstraction, and is described as a set of pairs: **(frequency, amplitude)**, carrying all the detail information of a discrete frequency spectrum. This level is usually used to carry the raw spectra for further abstraction or analysis, and those spectra which can not be properly characterized by their peaks.

In the peak abstraction level, spectra are characterized by their peaks by losing some detailed information, and are described as a set of peaks, each of which is described by **(frequency, amplitude, characterization)**. Here, the "characterization" is used to characterize the peak in terms of peak strength. A spectrum at this level is considered carrying almost the same amount of information if the peaks are of only interest in the analysis, such as the example shown in Figure 2.4-3, but needs much less storage space than the numeric spectrum level.

The harmonic set abstraction level is used to describe a spectrum by a set of harmonic sets, each of which is described by the fundamental frequency and a set of harmonically related peaks (at the multiples of the fundamental frequency) and the characterization. This is the highest level and is useful when high level description of the harmonic set is needed, such as the frame-bending modes: a harmonic set, shown in Figure 2.4-1. A set of harmonically related peaks can be found from a vibration spectrum by using Cepstrum technique [Randall 80, Rawicz 90].

4.4 Program Organization

RE comprises two major subsystems, the signal processing and the expert system. The signal processing subsystem is written in Turbo C, whereas the expert system is to be written in Turbo Prolog. Turbo Prolog has a good interface with Turbo C and they both provide good graphics facilities. As discussed in Section 3.2.1, the signal processing subsystem accepts the control signal from the expert system and returns the data requested by the expert system. This can be implemented by calling C functions (as predicates) from Prolog, to allow the expert system to be in main control.

5. CONCLUSION

The diagnostic problem for rough ride on heavy trucks is a difficult problem, and has no systematic solution with conventional algorithmic methods. A variety of techniques with quite different characteristics can be used in the diagnosis, ranging from heuristic to analytical. These motivated this thesis. More specifically, this thesis studied the techniques, heuristic and analytical, which have good performance on this diagnostic problem <u>and</u> can be unified under the roof of a Knowledge Based Expert System. The KBES for RE has been conceptually designed based on a good understanding of these techniques.

The success of RE depends on several points which highlight some contributions of this thesis. These points are:

1. A broad range of technologies must be used to cope with the difficulties in ride diagnostic problem.

2. Mechanical Signature Analysis provides powerful tools for vibration analysis and hence for rough ride trouble-shooting. Coherent power is proved to be powerful enough to distinguish the trouble source from other vibration sources with considerably different characteristics.

3. Two-level diagnostic architecture combines two kinds of knowledge and their advantages as well, providing the capability of covering a wide range of rough ride problems, with high diagnosis efficiency and better explanation features.

The research in this thesis is the beginning of a large project: building RE with real practical value. Future research will include the implementation of the prototype of this KBES to validate the major concepts in the design, to clear the road for the final system design and implementation. More techniques for higher diagnostic resolution, such as Cepstrum [Randall 80], are also worth being studied to improve the diagnostic resolution.

REFERENCES

[Adams 84] J.B. Adams: "Probabilistic reasoning and certainty factors", in (B.G. Buchanan ed.): Rule-Based Expert Systems, 1984, pp.262.

[Bendat 86] J.S. Bendat, et al: *Random Data, Analysis And Measurement Procedures*, John Wiley & Sons Inc., 1986.

[Bobrow 84] D.G. Bobrow (ed): "special issue on qualitative reasoning", Artificial Intelligence, 1984(24).

[Borland 88] Borland International: *Turbo Prolog Manual*, 1988.

[Braun 86] S. Braun (Ed.): *Mechanical Signature Analysis, theory and applications*, Academic Press, 1986.

[Charniak 85] E. Charniak, et al: *Introduction to Artificial Intelligence*, Addison-Wesley, 1985.

[Clancey 85] W.J. Clancey: "Heuristic classification"; Artificial Intelligence, 1985(25), pp.289-350.

[Clark 82] K.L. Clark, et al: "PROLOG: a language for implementing expert systems", Machine Intelligence, 10, 1982, pp.455.

[Console 90] L. Console, P. Torasso: "Hypothetical Reasoning in Causal Models", International Journal of Intelligent Systems, vol.5, 1990, pp.83.

[Fink 85] P. Fink, et al: "A general Expert system design for diagnostic problem solving", IEEE Trans. on Pattern Analysis and Machine Intelligence, PAMI-7, 1985, pp.553.

[Freightliner 84] Freightliner of Canada Ltd.: *Ride Manual*, 1984.

[Gillespie 85] T.D. Gillespie: "Heavy truck ride"; Society of Automotive Engineers, Inc., 1985.

[Harmon 88] P. Harmon: *Expert System Tool and Applications*, John Willey & Sons, 1988.

[Hayes-Roth 83] F. Hayes-Roth, et al (Ed.): *Building Expert Systems*, Addison-Wesley Publishing Company, Inc. 1983.

[ISO 78] "Guide for the evaluation of human exposure to whole-body vibration", International Standard ISO 2631-1978(E), International Organization for Standardization, 1978.

[Jenkins 68] G.M. Jenkins, et al: *Spectral Analysis and its applications*, Holden-Day, Inc. 1968.

[Kahn 84] G. Kahn: "On when diagnostic systems want to do without causal knowledge", Proceeding of ECAI 84, Pisa, 1984, pp.21.

[Koton 88] P. Koton: "Integrating causal and case-based reasoning for clinical problem solving", in Proceeding of AAAI Symposium on Artificial Intelligence in Medicine, Stanford, 1988, pp.53.

[Kripke 59] S. Kripke: "A completeness theorem in modal logic", Journal of Symbolic Logic, 1959(24), pp.1.

[Lee 68] R.A. Lee, et al: "Analytical Analysis of Human Vibration", SAE Paper No. 680091, Jan. 1968.

[Milios 89] E.E. Milios, et al: "Signal Abstractions in Signal Processing Software", IEEE Trans. ASSP-37, No.6, 1989, pp.913.

[Milne 87] R. Milne: "Strategies for Diagnosis", IEEE Trans. on System, Man, and Cybernetics, SMC-17, No.3, 1987, pp.333.

[Nigam 83] N.C. Nigam: *Introduction to Random Vibrations*, The MIT Press, 1983.

[Nuttall 80] A.H. Nuttall, et al: "A generalized framework for power spectral estimation", IEEE Trans. Acoust., Speech, Signal Processing, ASSP-28, 1980, pp.334.

[Nuttall 81] A.H. Nuttall: "Some Windows with Very Good Sidelobe Behavior", IEEE Trans. ASSP-29, No.1, 1981, pp.84.

[Partridge 87] D. Partridge, "The scope and limitation of first generation expert systems", Future Generation Computing Systems, 1987 (1), pp.1.

[Patil 81] R. Patil: "Causal representation of patient illness for electrolyte and acid-base diagnosis", Cambridge: MIT 1981. MIT/LCS/TR-267.

[Pazzani 87] M.J. Pazzani: "Failure driven learning of fault diagnosis heuristics", IEEE Trans. Syst. Man, Cybern., SMC-17, No.3, 1987, pp.380.

[Pople 82] H. Pople: "On the Mechanization of Abductive Logic", IJCAI82, 1982, pp.147.

[Randall 80] R.B. Randall: "Advances in the Application of Cepstrum Analysis to Gearbox Diagnosis", Vibration in Rotating Machinery: 2nd International Conference, 1980, pp.169.

[Rawicz 90] A.H. Rawicz, et al: "Multi-Probe Vibration Analysis for Reliability"; Annual Reliability and Maintainability Symposium, 1990, pp.331-335.

[Reggia 83] J.A. Reggia, et al: "Diagnostic expert systems based on a set covering model", International Journal of Man Machine Studies, vol.19, 1983, pp.437.

[Reggia 85] J. Reggia: "Abductive inference", Proc. Expert Systems in Government Symp., Oct. 1985, pp.484.

[Sayers 81] M. Sayers, et al: "The effect of suspension system nonlinearities on heavy truck vibration", Proc. 7th IAVSD Symposium on Dynamics of vehicles on roads and tracks, Cambridge, England, 1981.

[Sayers 84] M. Sayers, et al: "Guidelines for the conduct and calibration of road roughness measurements", Report to the World Bank, Transportation Res. Inst., University of Michigan, Rept. No. UMTRI-84-13, 1984.

[SDRC 73] "System Simulation of a WT-9000 Tractor/Trailer." Final Report, Structural Dynamics Research Corporation, October 19, 1973.

[Shortliffe 76] E.H. Shortliffe: *Computer-Based Medical Consultation: MYCIN*; Elsevier, 1976.

[Shortliffe 84] E.H. Shortliffe, et al: "A model of inexact reasoning in medicine", in (B.G. Buchanan ed.): Rule-Based Expert Systems, 1984, pp.232.

[Steels 85a] L. Steels: "Second generation expert systems"; Future Generation Computing Systems, 1985 (1), pp.213-221.

[Steels 85b] L. Steels, et al: "Learning in second generation expert systems", in (R.Kowalik ed.): Knowledge-based Problem Solving, Prentice Hall, 1985.

[Sterling 86] L. Sterling, et al: *The Art of Prolog*, The MIT Press, 1986.

[Sticklen 88] J. Sticklen, et al: "MDX2: An integrated medical diagnostic system", in Proceeding of AAAI Symposium on Artificial Intelligence in Medicine, Stanford, 1988, pp.90.

[Torasso 89] P. Torasso, et al: *Diagnostic Problem Solving*, North Oxford Academic, 1989.