ITM Web of Conferences **15**, 05003 (2017) DOI: 10.1051/itmconf/20171505003
CMES'17

Assessing the damage importance rank in acoustic diagnostics of technical conditions of the internal combustion engine with multi-valued logical decision trees

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Abstract. This paper presents possible applications of acoustic diagnostics in inspecting the technical condition of an internal combustion engine with autoignition on the example of the Fiat drive unit with the common rail system. As a result of measuring the sound pressure level for specific faults and comparing the noise generated by the motor running smoothly, the detailed maps of changes in the acoustic spectrum may be generated. These results may be helpful in future diagnostics of internal combustion engines. In the paper, we present the results from the scientific works in the area of research, design and operation of internal combustion engines, conducted at the Department of Automotive Engineering, in cooperation with the Laboratory of Hydraulic Drives & Vibroacoustics of Machines at the Wroclaw University of Technology. The broader study has so far allowed us to develop an authoritative method of identifying the type of engine damage using game-tree structures. The present works assess the possibility of using multi-valued logic trees.

1 Introduction

The fault diagnosis technique is used to prevent early faults in a mechanical system. Acoustic emissions and vibration signals are well known for their suitability for monitoring conditions of rotating machineries. Most of the conventional methods for fault diagnosis using acoustic and vibration signals are primarily based on observing the amplitude differences in the time or frequency domain. The non-invasive diagnostics of internal-combustion engines are an exciting method for determination of occurring problems, because of the fact that they do not involve interference in the structure or disassembly of construction to identify a given failure [1]. Several methods of non-invasive engine testing have been already proposed, including the measurements of pressure and vibrations [1-2]. It is important to test engine operating parameters during the manufacturing process as well as in its subsequent operation [3]. This enables determining the optimal parameters of engine operation. The development of acoustic diagnostics is a promises quick and simple identification of engine damage. Nowadays this method is widely used in a range of applications, especially in the field of machine testing [4-5].

For designers of internal combustion engines, one of the major problems is to design a reliable system of OBD (On-Board Diagnostics), which is the system of auto-diagnostic of a vehicle. Unfortunately, such systems contribute to an increasing size and overall production and operation costs of internal combustion engines. However, the OBD system is currently the only widely used non-invasive diagnostic system. Other diagnostic methods rely on visual assessment of the engine, which forces interference in its structure in order to disassemble the damaged and other components to gain the access to the damaged part. If the acoustic wave spectrum measurement systems, eliminating the impact of background noise and other noise sources, which do not affect operation of the engine, were developed, it would be possible for each user to carry out in-house acoustic diagnostics. In recent years, we may observe a growing interest in the development of non-invasive diagnostic methods, particularly regarding internal combustion engines [6-7]. This article focuses on reliability assessment of acoustic diagnostics methods of internal combustion engine and the preparation of accurate diagnostic maps for Fiat 1.3 JTD engine 70 horsepower model. The measurements consisted in comparing the sound pressure level of specific frequencies for motor operation with induced defects with the smooth operation of the engine. The paper includes the results from the scientific work in the area of research, design and operation of internal combustion engines, conducted at the Department of Automotive Engineering, in cooperation with the Laboratory of Hydraulic Drives & Vibroacoustics of Machines at the Wroclaw University of Technology. A detailed description of the acoustic diagnostic method and the results of measurements were described in

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previous articles [8-9]. In addition, the work [8] developed a decision system based on graphs and parametric game structures that identify the damage based on the spectral characteristics of sound emission. The game graph [9], taking into account the search algorithm, finds characteristic features, points and values (individual for each engine damage) by which the acoustical spectrum may be assigned to the specified type of damage. The present article takes into account the possibility of including multi-valued logic trees in an integrated decision system. An integrated decision system for logic machine learning was developed to test and identify the acoustic properties.

2 Measurements

The measurements were made on a Fiat diesel engine with the common-rail system. The tested model was Fiat 1.3 JTD, series designation - 188A9000. In total, 13 measurements of the acoustic wave spectrum for different cases of induced engine faults were conducted. The average L_{am} [dB], the maximum L_{Amax} [dB] and the minimum sound level L_{Amin} [dB] were measured by means of the following instrumentation: a modular sound pressure level meter with the record time history and analysis of the frequency (sound level meter, accuracy class I) from B&K type 2250 serial No. 2506429 with preamplifier type ZC 0032 serial No. 4112 and microphone type 4189 serial No. 2519832. The sound level meter meets the requirements set out in Regulation of Polish Tripartite Commission for Social and Economic Affairs from 28 May 2007 (Journal of Laws from, No. 105, item 717) and is confirmed by the current calibration certificate of the Regional Office of Weights and Measures in Wroclaw [8-9].

The test rig consists of eddy-current brake comprising the cooling system, the coil and the magnetic plate mounted on a shaft which is connected to the crankshaft of the engine. At the exit of the cooling channels two temperature sensors are provided. The rotational speed is measured by the rotation sensor and the torque is determined by the strain gauge force transducer attached to the arm of a known length to the brake housing, which is located on the bearings to obtain free rotation in the axis of the torque. The sound level meter was placed at a distance d equal to 1 m from the cuboid surrounding the motor housing with accordance to the standard (Fig. 1).

Fig. 1. Test rig for acoustic measurements [8-9].

The first study was to measure the background noise on the test bench, which is mainly caused by the flow of the coolant system of eddy current brake. Another 12 measurements were carried out for 6 different cases of the engine diagnostic condition during the load of 80Nm for two engine speeds - 1,000 rpm and 2,000 rpm. The time of each measurement was t = 10 s. These included the following cases [8-9]:

- engine in the perfect diagnostic condition, not warmed-up,
- engine in the perfect diagnostic condition after reaching the proper operating temperature,
- disconnected boost pressure sensor,
- disconnect the camshaft position sensor,
- disconnected injector No. 2,
- disconnected fuel pressure sensor.

2.1 Results of measurements

The results are presented in the form of spectral characteristics of acoustic pressure. The sound pressure level difference compared to the reference sound pressure level is depicted in the bar charts (Fig. 2, Fig. 3). An important parameter is the actual difference in sound pressure level, which specifies the real difference in the energy of the acoustic wave (Fig. 4, Fig. 5) [8-9].

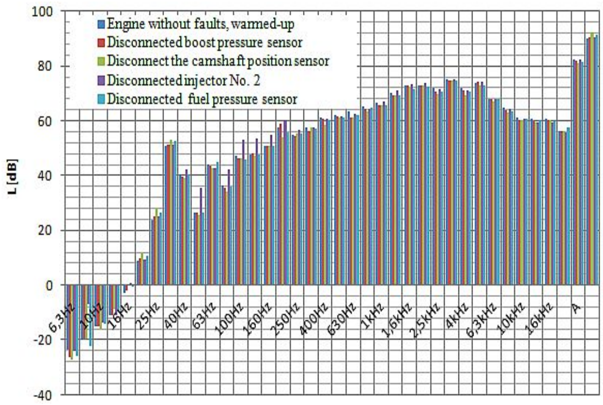

Fig. 2. Graph of the average sound pressure level L_{mA} for the speed of 1,000rpm.

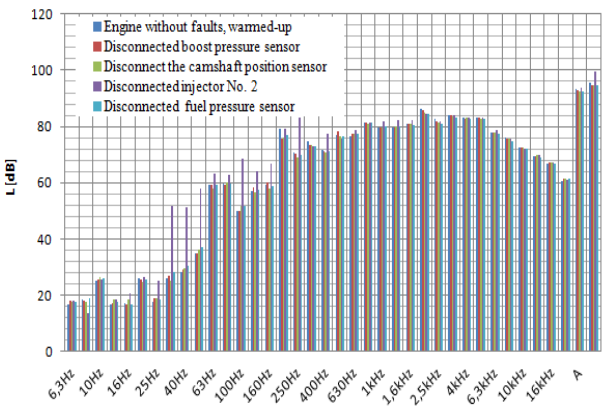

Fig. 3. Graph of the average sound pressure level L_{mA} for the speed of 2,000rpm.

 DOI: 10.1051/itmconf/20171505003

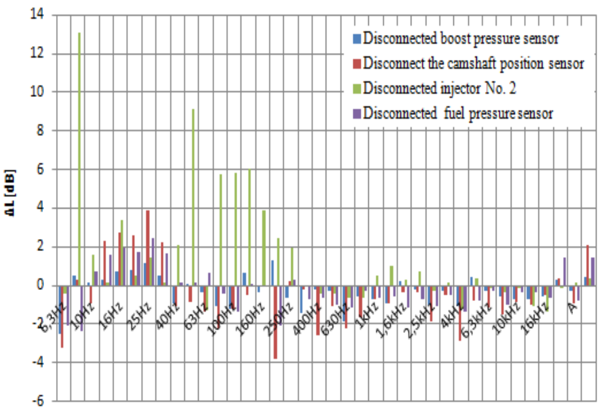

Fig. 4. Graph of differences in sound pressure level *ΔL* at the speed of 1,000rpm.

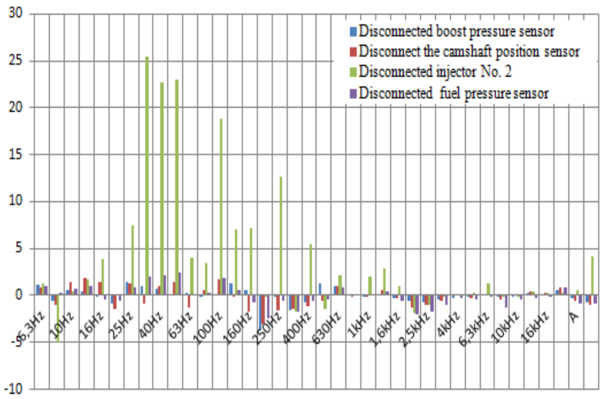

Fig. 5. Graph of differences in sound pressure level *ΔL* at the speed of 2,000rpm.

2.1.1 Results analysis

On the basis of Figs (2-5) failures occurring in the test engine can be clearly identified without the need of OBD system application. As the comparison of the sound level at all frequencies for each fault is time-consuming it is worth paying attention only for the characteristic changes in the acoustic spectrum for specific faults that are described below [8-9].

Boost pressure sensor disconnected - the main changes concern the frequency of 315Hz and 2.5 kHz, because there occurs a clear decline in the sound pressure level at the both the speed of 1,000 rpm and 2,000 rpm. These differences are about -1.5dB for 315Hz for both speeds, -1.01dB for 1000rpm and -0.66dB for 2,000rpm for a wave frequency of 2.5 kHz.

Disconnected camshaft position sensor - the best picture of the spectrum changes is produced during the test at a rotational speed of 1000 rpm. For higher speed, there were no significant differences.

Disconnected injector No. 2 - the only type of fault, which can be determined with an unaided ear. The strong increase in the noise level at low and medium frequency. It is worth pointing out here a correlation of enhancement for 1,000rpm and 2,000rpm, where increase of the pressure level of the first speed occurs at the doubled frequency values of higher speed.

Disconnected fuel pressure sensor - a situation similar to the one with disconnected camshaft position sensor, however, both strengthened and damped waves are smaller.

3 Discrete decision model

In order to create the method of decision trees it is possible to use heuristic search methods [10-11]. Actions undertaken in finding the solution can be classified as searching of objects of specified characteristics. For the identification of the type of engine damage, rules of procedure by the generate-and-test method focused on testing of a given property of an acoustic signal having been used.

It can be assumed that elements of the system form the set Q, relations – the set Ω, properties of elements – the set Γ, the objective function- F. It can be assumed that states of the engine are elements of the set:

$$Q=\{X_o, X_1, X_2, ..., X_i ..., X_m\} \qquad (1)$$

where: X_i- i-th engine damage, if Q is a finite set.

For a given object $X_i \in Q$ it is possible to differentiate a certain level of sound pressure $\tilde{A}_i$. Then, sound pressure values, as possible states of the analysed damage X_i will be a finite set in this domain.

$$^{+}\tilde{A}_i=\{a_{i,1}, a_{i,2}, ..., a_{i,j}, ..., a_{i,w}\} \qquad (2)$$

where: elements $a_{i,\ j,}$ for $i=const$ and $j=$ 1, 2, mean highlighted values in this domain (frequency) $\tilde{A}_i$. Values of differences in the level of sound pressure ΔL for the frequency f [Hz]: {6.3Hz, 8Hz, 10 Hz, ..., 20kHz, A, Z} will be included in the analysis.

It is necessary to define the relation of the measured values of sound pressure levels values of given damages X_i in order to differentiate damages. The set Π_s composed of the ordered pairs (X_i, X_j) may be called the relation on the set Q. The set Π_s is a subset of the Cartesian product QxQ and takes the following form [8, 9, 12].

$$\Pi_S=\{(X_{i1}, X_{j1}), (X_{i2}, X_{j2}), ..., (X_{is}, X_{js})\} \qquad (3)$$

where i_s, j_s are specific values of the sound pressure level of a given damage.

When searching a game graph, there will be a possibility of determining the kind of damage X_i in the scope of the relation of the Π_s type by means of defining highlighted values. Such a state can be presented in the following form of a vector:

$$\Pi_s^i=[\delta_s^i(j_1), \delta_s^i(j_2), ..., \delta_s^i(j_n)] \qquad (4)$$

In the case of our analysis, there is the following combination table: X_1 - disconnected boost pressure sensor, X_2- disconnected shaft position sensor, X_3- disconnected injector No. 2, X_4 - disconnected fuel

DOI: 10.1051/itmconf/20171505003

pressure sensor. For example, Figures 6 and 7 show acoustic sound levels of specified failures: disconnected boost pressure sensor (failure I), disconnected camshaft position sensor (failure II), disconnected injector No. 2 (failure III), disconnected fuel pressure sensor (failure IV) in comparison to proper operation of engine.

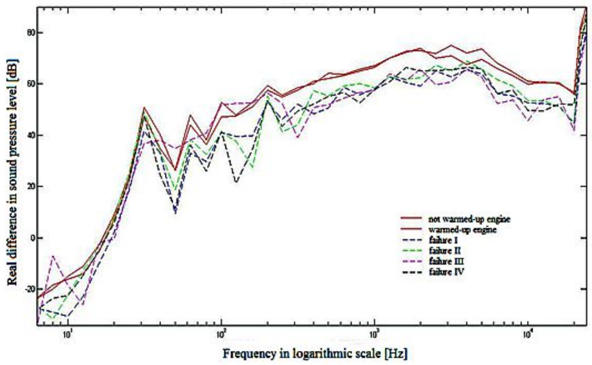

Fig. 6. Graph of sound pressure level for the speed of 1,000 rpm – comparison of all failures.

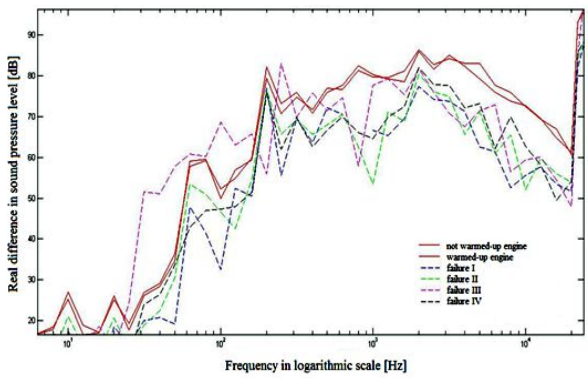

Fig. 7. Graph of sound pressure level for the speed of 2,000 rpm – comparison of all failures.

4 Multi-valued logic decision trees

Complex, multiple-valued logic functions determine the degree of importance of logic variables by changing the levels of the logic tree, from the most important (near the root) to the least important (on the top) because there is a generalisation of a Boolean quality index into a multiple-valued one: $(C_k - k_i m_i) + (k_i + K_i)$, where C_k – the number of branches of k- level, k_i – multiplicity of simplification on k-level, m_i – value of i- variable, K_i – the number of branches (k-1) – level, out of which branches of k-level were formed which cannot be simplified. In this way it is possible to obtain the minimum complex alternative normal form. All transformations are described by the so-called Quine–Mc Cluskey algorithm based on the minimization of individual partial multiple-valued logic functions.

4.1 Quine-McCluskey algorithm for the minimization of multi- valued logic functions

The Quine-McCluskey algorithm is capable of finding all prime implicants of a given logic function, *i.e.* there is a shortened alternative, normal form SAPN [13, 14]. The terms of incomplete gluing and elementary absorption play the main role in the search of prime implicants and are used for the APN of a given logic function.

The following transformation is called the consensus operation:

$$Aj_o(x_r) + \dots + Aj_{m_r-1}(x_r) = A \qquad (5)$$

where: $r = 1, \dots, n$ and A- a partial elementary product, the literals of which possess variables belonging to the set: $\{x_1, \dots, x_1, x_1, \dots, x_n\}$.

$$w_o Aj_o(x_r) + \dots + w_{m_r-1} Aj_{m_r-1}(x_r) = \\ = \left(min\{w_o, \dots, w_{m_r-1}\}\right) \cdot A + \sum_{s=i_o,\dots,i_{m_r-2}} w_s \cdot A \cdot j_s(x_r) \qquad (6)$$

where: w_i - polyvalent weighting factor.

For example using the formula:

$$Aj_0(x_r) + \dots + Aj_{m-1}(x_r) = A, \quad Aj_u(x_r) + A = A, \qquad (7)$$

where: $A = A(x_1, \dots, x_{r-1}, x_{r+1}, \dots, x_n)$,

$$j_u(x_r) = \begin{cases} m-1 & , \quad u = x_r \\ 0 & , \quad u \neq x_r \end{cases} \qquad 0 \le u \le m-1 \qquad (8)$$

For example multiple-valued logical function f(x_1, x_2, x_3), where $x_1, x_2, x_3 = 0, 1, 2$, written by means of numbers KAPN (Canonical Alternative Normal Form): 100, 010, 002, 020, 101, 110, 021, 102, 210, 111, 201, 120, 022, 112, 211, 121, 212, 221, 122, there is one MZAPN (Minimal Complex Alternative Normal Form) after the application of the Quine– Mc Cluskey algorithm based on the minimization of individual partial multi-valued logical functions having 13 literals (Figure 8) [13, 14].

$$f(x_1, x_2, x_3) = j_o(x_1)\left(j_o(x_2) j_2(x_3) + j_1(x_2) j_o(x_3) + j_2(x_2)\right) + \\ + j_1(x_1) + j_2(x_1)\left(j_o(x_2) j_1(x_3) + j_1(x_2) + j_2(x_2) j_1(x_3)\right). \qquad (9)$$

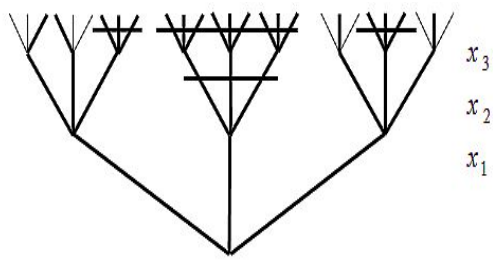

Fig. 8. A multi-valued decision tree for the parameters x_1, x_2, x_3 with an appropriate layout of levels.

4.2 Application of multi-valued logic decision trees

Based on the obtained measurements results (Figures 2-5) the morphological table for this specific case was prepared, as shown in Tables 1-2.

Table 1. Morphological table of measurement results and logic values for *n* = 1000 [rpm].

Frequency [Hz]	X_1	X_2	X_3	X_4	Logic values
	n= 1000 rpm				
	0	0	0	0	
6.3Hz	-2.53	-3.27	-0.42	-2.06	0
8Hz	0.51	0.28	13.07	-2.35	
10Hz	0.12	-0.95	1.56	0.72	
12.5Hz	0.28	2.33	0.14	1.58	
16Hz	0.72	2.75	3.41	1.96	
20Hz	0.78	2.6	0.47	1.7	
25Hz	1.13	3.88	1.43	2.46	1
31.5Hz	0.5	2.24	0.17	1.66	
40Hz	-0.91	-1.08	2.07	0.11	
50Hz	0.09	-0.86	9.11	0.14	
63Hz	-0.35	-1.35	-1.28	0.67	
80Hz	-1.05	-2.21	5.77	-0.4	
100Hz	-1.2	-1.2	5.81	-1.37	2
125Hz	0.64	-0.47	6.06	0.01	
160Hz	-0.34	-0.02	3.9	-0.1	
200Hz	1.3	-3.84	2.44	-2.07	
250Hz	-0.62	0.19	1.93	0.29	
315Hz	-1.41	-0.19	-0.06	-0.73	

Table 2. Morphological table of measurement results and logic values for *n* = 2000 [rpm].

Frequency [Hz]	X_1	X_2	X_3	X_4	Logic values
	2000 rpm				
	1	1	1	1	
6.3Hz	1.09	0.87	1.31	0.96	0
8Hz	-0.58	-1.05	-4.99	0.25	
10Hz	0.51	1.4	0.42	0.67	
12.5Hz	0.44	1.85	1.75	1	
16Hz	-0.14	1.47	3.93	-0.43	
20Hz	-0.84	-1.39	0.2	-0.56	
25Hz	1.45	1.35	7.4	0.78	1
31.5Hz	0.96	-0.89	25.4	2.07	
40Hz	0.7	1	22.65	2.16	
50Hz	0.12	1.4	23	2.49	
63Hz	0.32	-1.36	3.97	0.1	
80Hz	-0.07	0.56	3.38	0.24	
100Hz	0.08	1.7	18.88	1.91	2
125Hz	1.31	-0.16	7.03	0.52	
160Hz	0.52	-1.7	7.18	-0.73	
200Hz	-3.76	-3.1	-0.02	-2.48	
250Hz	-0.14	-1.63	12.65	-0.64	
315Hz	-1.54	-1.4	-1.67	-1.68	

In the first step decision trees were used for the frequency range: up to 315 Hz. Arithmetic values of analysed parameters have been chosen in order to make an analysis in accordance with a table. In case of our analysis, there is the following combination table:

X_1 - disconnected boost pressure sensor;
X_2 - disconnected shaft position sensor;
X_3 - disconnected injector No. 2;
X_4 - disconnected fuel pressure sensor.

These values had been coded by means of logic decision variables for the needs of logic decision trees.

$$\begin{cases} X_1, X_2, X_3, X_4 = 1000\,[rpm] \sim 0 \\ X_1, X_2, X_3, X_4 = 2000\,[rpm] \sim 1 \end{cases};$$

$$f \in \langle 6{,}3 - 20 \rangle\,[\mathrm{Hz}] \sim 0;\ f \in \langle 25 - 80 \rangle\,[\mathrm{Hz}] \sim 1;$$

$$f \in \langle 100 - 315 \rangle\,[\mathrm{Hz}] \sim 2.$$

Based on the acquired measurements results, the morphological table for this specific case (and logic values) was prepared as shown in Table1 (for n = 1000 [rpm]) and Table 2 (for n = 1000 [rpm]).

The sets of highlighted values presenting features of sound pressure values for a given damage have been obtained from the analysis. The above summaries allow us to create a measuring ladder, which will make it possible to determine the type of engine damage on the basis of sound pressure measurements on chosen frequencies. For values in Table 1, according to the Quine-Mc Cluskey algorithm we obtain the following solution:

For Table 1:

X_1	X_2	X_3	X_4				
N	N	N	N				
C	C	C	N	*			
C	N	C	C		*		
C	C	C	C	*	*		
C	C	C	C				*
N	N	C	C	*	*	*	
C	N	C	C	*			*
N	N	N	C		*		
N	N	C	N			*	
N	N	C	N	*			
C	N	C	C	*			
C	N	C	N	*			
N	C	C	C				
N	N	N	N	*			

$$\begin{matrix} 1_0 \\ 2_0 \\ 3_0 \end{matrix} \begin{cases} N\ N\ N\ N \\ C\ C\ C\ - \\ C\ -\ C\ C \end{cases} 0 \qquad \begin{matrix} 1_1 \\ 2_1 \\ 3_1 \\ 4_1 \end{matrix} \begin{cases} -\ N\ N\ N \\ N\ N\ -\ C \\ N\ N\ C\ - \\ C\ -\ C\ C \end{cases} 1$$

$$\begin{matrix} 1_2 \\ 2_2 \\ 3_2 \end{matrix} \begin{cases} N\ N\ -\ N \\ C\ N\ C\ - \\ N\ C\ C\ C \end{cases} 2$$

The final solution is:

$$3_0 \wedge 1_1 \wedge 2_2 = C\,N\,C\,C\ .$$

For Table 2:

X_1	X_2	X_3	X_4				
C	C	C	C				
N	N	N	C				
N	C	C	N	*			
N	N	C	N	*			
C	C	C	C	*	*		
C	N	C	C	*			
N	C	C	C		*		
C	C	C	C	*			
C	N	C	C	*	*		
C	N	C	N		*	*	
N	N	N	N				*
N	N	C	N			*	*

$$\begin{matrix}1_0\\2_0\\3_0\end{matrix}\begin{cases}N\ -\ C\ N\\ C\ C\ C\ C\\ N\ N\ N\ C\end{cases} 0 \qquad \begin{matrix}1_1\\2_1\end{matrix}\begin{cases}C\ -\ C\ C\\ -\ C\ C\ C\end{cases} 1$$

$$\begin{matrix}1_2\\2_2\\3_2\\4_2\end{matrix}\begin{cases}C\ -\ C\ C\\ C\ N\ C\ -\\ -\ N\ C\ N\\ N\ N\ -\ N\end{cases} 2$$

The final solution is:

$$2_0 \wedge 1_1 \wedge 1_2 = C\,C\,C\,C$$
$$2_0 \wedge 2_1 \wedge 1_2 = C\,C\,C\,C\ .$$

It should be noted that a similar analysis should be made for the frequency range: $f \in 400$ [Hz] - 20 [kHz].

The sets of highlighted values presenting features of sound pressure values for a given damage were obtained from the result of an analysis. The summaries above may be employed to create a measuring ladder, which will make it possible to determine the type of engine damage on the basis of sound pressure measurements on chosen frequencies.

5 Conclusions

The most advanced form of a substantially integrated system can be an integrated system, resulting from the integration of complex system-aided management of complex systems supported decision-making. (Fig. 9).

All operations were made in the real time during normal use of the motor housing. On the basis of the results received from the inference mechanism, resulting from the correlation between acoustic signals measured in a continuous manner and model signals placed in the data base, there would be an identification of the influence of particular signals from microphone on the chosen parameters of motor housing integrated logic system may be used for the integrated decision system. Proposed in the paper decision method for identifying engine failure based on sound emission spectral characteristics allows fast identification of specific damage. The complete procedure of fault engine diagnostics proposed by authors includes several steps [15, 16]. Firstly, the precise sound pressure level characteristics of an operating engine need to be obtained for efficient and damaged engine in order to gain engine acoustic maps. The next step is to create a morphological table with logical coding. The proposed decision method of identifying engine failure based on sound emission spectral characteristics, will allow the quick identification of particular damage.

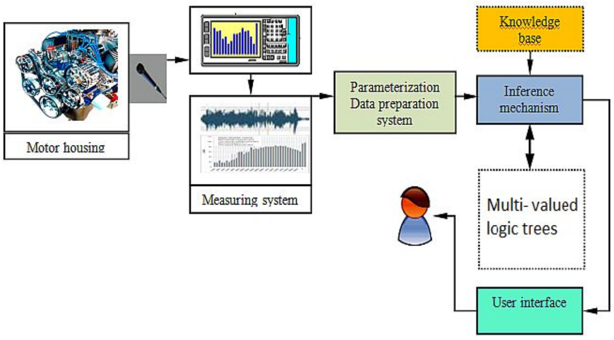

Fig. 9. Decision support system.

The method may be successfully used for subsequent measurements on the same engine and engines of the same kind. In the case, where a greater number of measurements are made, it may occur that a better classification system based on the tools with the reversed correlation matrix generated by the motor running smoothly may be proposed, which enables generating more detailed maps of changes in the acoustic spectrum. These results may be helpful in the future diagnostics of internal combustion engines. In the paper, the results of scientific work in the area of research, design and operation of internal combustion engines, conducted at the Department of Automotive Engineering, in cooperation with the Laboratory of Hydraulic Drives & Vibroacoustics of Machines at the Wroclaw University of Technology are included. The ongoing research works have already developed an authoritative method for identifying the type of engine damage using game-tree structures and induction machine [17].

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