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# PREVENTION OF ENGINE FAILURE WITH MISFIRE DETECTION SPREČAVANJE KVARA MOTORA SA DETEKCIJOM IZOSTANKA PALJENJA

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<ul> <li>Keywords</li> <li>statistical analysis</li> <li>engine rotation</li> <li>fault diagnosis</li> <li>data visualisation</li> </ul>	Ključne reči • statistička analiza • rotacija motora • dijagnoza nepravilnog rada • vizuelizacija podataka		
Abstract Increasing requirements for a fuel economy, prevention of engine failure with misfire detection, exhaust emissions	Izvod Porast zahteva za ekonomičnošću goriva, sprečavanje kvara motora usled izostanka palienia, emisije izduvnih		

of engine failure with misfire detection, exhaust emissions and the output performance and also the complexity of automotive engines necessitate the development of a new generation of engine control functionality. It is known that engine revolution analysis is an excellent tool for this purpose. The main goal in this paper is in defining the function of machine members for value distribution of crank shaft signal for a fault decision expert system, based on fuzzy logic. In combination with another data (i.e.  $O_2$ sensor or intake manifold embedded sensors) the quality decision process may be enhanced.

#### INTRODUCTION

Increasing requirements for fuel economy exhaust emissions and the output performance, and also the complexity of automotive engines necessitate the development of a new generation of engine control functionality. Engine torque estimation function is an important function for an engine torque model, misfire diagnostics, and dependability. The engine torque estimation function is based on monitoring of the cylinder individual fluctuations in the high resolution engine speed signal, /1/.

The engine speed signal is based on measurements of a passage time between two subsequent teeth on a crank wheel. The passage time decreases as the rotational speed increases, thus the time interval errors increase. Moreover, low frequency oscillations from the power train and high frequency oscillations due to the crankshaft torsion, together with vibrations induced from the road, act as disturbances on the crankshaft. These disturbances influence directly the performance of the engine speed signal and consequently the torque monitoring function. Many misfire diagnostic functions utilize a low rate sampling of the engine crankshaft speed. Typically, the crankshaft speed is Porast zahteva za ekonomičnošću goriva, sprečavanje kvara motora usled izostanka paljenja, emisije izduvnih produkata sagorevanja, krajnje performanse, kao i složenost automobilskih motora iziskuju razvoj nove generacije kontrolisanja rada motora. Poznato je da analiza obrtaja motora predstavlja odličan alat za ovu svrhu. Osnovni cilj rada je u definisanju funkcionalnosti delova za ocenu raspodele signala sa kolenastog vratila radi primene ekspertnog sistema u ocenjivanju nepravilnog rada, koji se zasniva na fazi logici. U kombinaciji sa drugim podacima (na primer, sa senzora  $O_2$  ili senzora na usisnoj grani) kvalitet ocenjivanja se može poboljšati.

sampled once per cylinder firing event. The engine speed can be approximated by a trigonometric polynomial due to the periodic nature of both engine rotational dynamics and combustion forces as functions of a crank angle, /2/. Misfire is the state of an engine where the combustion does not occur due to the errors in fuelling or ignition. As a consequence, such misfires affect long term performance of the exhaust emission control system. Misfires cause changes in the crankshaft rate of rotation, because the misfired cylinder is not able to provide the torque. Engine misfire diagnostic functions are based on monitoring of the cylinder individual fluctuations of the high resolution engine speed signal or a passage time between subsequent teeth on a crank wheel. The high resolution engine speed signal is calculated as a ratio of the length of the angular segment on the crank wheel and the passage time for this segment. The passage time becomes less as the rotational speed increases, thereby the time interval errors rise. Usually, the measured signals in most cases are transformed to frequency signals. In this paper we had analysed the measured signals directly, without any transformation.



Figure 1. Types of sensors: a) variable reluctance sensor; b) Hall-effect sensor. Slika 1. Tipovi senzora: a) promenljive reluktanse; b) senzor Hal-efekta

In Figure 1 are shown different types of sensors which can be used for measuring the misfire in the engine. Figure 2 shows the estimated circular velocity on the basis of data from sensors, idle speed.

The analytical method can be applied to the study of any rotating machine with an appropriate calibration procedure.



## PROBLEM STATEMENT

The passage time between two teeth on a crank wheel is measured in production engines. The high resolution engine speed signal is then calculated as a ratio of the length of the angular segment on the crank wheel and the passage time for this segment.

We have prepared the hardware for measuring the signal value in voltage from the engine crankshaft sensor on a real engine. For this, we have used an universal measurement tool QUANTUM MX-840 and an engine embedded crank shaft speed sensor, /3/. The sampling rate need to be very high because of interest for high resolution of measurement.

Suppose there is a set of crank angle synchronized data,  $y_l$ , l = 1,..., n (n < 15000) measured at the following points: x,  $x_1 = \Delta$ ,  $x_2 = 2\Delta$ , ...,  $x_n = n\Delta$ ,  $\Delta = 0.000417$  s. The misfire state is controlled manually, for any cylinder (1<sup>st</sup> to the 4<sup>th</sup>).

Table	1.	Measured	data.
Tabala	1	Izmoroni r	odooi

rabera 1. izmereni podaci.									
norma	al state	1st cyl disabled		2nd cyl disabled		3rd cyl disabled		4th cyl disabled	
0	-0.34135	0	3.025295	0	-6.24184	0	-2.08619	0	-2.22722
0.000417	3.674666	0.000417	1.620199	0.000417	-11.3549	0.000417	-3.41265	0.000417	-5.53553
0.000833	0.289516	0.000833	-1.45069	0.000833	-2.03844	0.000833	-4.56775	0.000833	-3.39072
0.00125	-1.05096	0.00125	4.253419	0.00125	1.352602	0.00125	-0.94344	0.00125	-3.59625
0.001667	3.290856	0.001667	-0.63544	0.001667	10.69681	0.001667	-6.3695	0.001667	-4.99481
0.002083	0.85035	0.002083	1.482191	0.002083	3.597733	0.002083	-0.25947	0.002083	-2.19339
0.0025	-0.86523	0.0025	2.984	0.0025	2.470534	0.0025	-6.91866	0.0025	-6.96948
0.002917	3.151368	0.002917	-1.86904	0.002917	-3.30137	0.002917	-0.93836	0.002917	-0.89454
0.003333	1.211538	0.003333	3.738023	0.003333	3.078322	0.003333	-5.12115	0.003333	-7.48536
0.00375	-1.40347	0.00375	0.649114	0.00375	-2.19125	0.00375	-3.04726	0.00375	-0.53651
0.004167	3.067888	0.004167	0.193866	0.004167	0.889037	0.004167	-2.96356	0.004167	-6.83391



In Table 1 are presented measured data time vs voltage value, of normal state, when the  $1^{st}$  cylinder is disabled, when the  $2^{nd}$  cylinder is disabled, in respect, and finally when the  $4^{th}$  cylinder is disabled.

Figure 3. Interpret. of signals. Slika 3. Interpretacija signala.

# ANALYSIS RESULTS AND DISCUSSION

The measured signal is not transformed in rotation speed or frequency signal, and is evaluated directly.

Figure 3 shows the interpretation of the signal, obtained on the basis of measured results, in Table 1.

Based on obtained data, Figure 4 presents the signal in normal working mode and when one of the cylinders is disabled.





Figures 4-6 show histograms of data, data in terms of the value of the voltage signal, distribution in normal mode or when some cylinders are disabled (meaning an intentionally disabled ignition). The aim is to analyse and visualize the value of the voltage signal and the statistical behaviour.

Figure 4 presents the data signal distribution in normal mode, where samples/degree of crank shaft and the data structure for the signal value in Volts are shown. Data distribution for different variants of the engine regime, for normal mode and in the mode when a cylinder is disabled. Also presented in this paper is the normal regime analysis for different sample data, and data distribution for different sample sizes.



Figure 6. Data distribution for different sample sizes. Slika 6. Raspodela podataka za različite veličine uzorka

In this sense one problem exists. When the rotation speed rises, the signal amplitude and frequency are also raised, /3/, and normally the distribution may be different.

#### VERIFYNG THE DATA

First of all, we have evaluated the signal, voltage value, distribution for different sample lengths, /4/. Normal operating conditions are shown in Fig. 7, and also the analysis of different sample size (data) – function density for the normal distribution.



Figure 7. Analysis of different sample size (data) – function density for the normal distribution. Slika 7. Analiza različitih veličina uzoraka (podataka) – funkcija

verovatnoće za normalnu raspodelu

It is clear that function density for the normal distribution is same for different samples (3 groups).

Mean values and the variance of the measured signal are shown in Fig. 8.

Table 2. Normal	working condition.
Tabela 2. Nori	nalni radni uslovi

A1: Mean:	0.100009	Variance:	6.5596
A2: Mean:	-0.121623	Variance:	7.46086
A3: Mean:	-0.120445	Variance:	7.08218

According to Table 2 and experimental results, working conditions for the engine are:

- normal working condition:
- Mean -0.118227 Variance 6.80575 • 1<sup>st</sup> cylinder disabled:
- Mean -0.978992 Variance 7.69948
- 2<sup>nd</sup> cylinder disabled: Mean -0.194629 Variance 8.35745
- 3<sup>rd</sup> cylinder disabled:
- Mean -0.529648 Variance 8.44994
  4<sup>th</sup> cylinder disabled:





Figure 8. Function density distribution data for all variants of the engine regime.

Slika 8. Funkcija raspodele verovatnoće za sve varijacije rada motora

The estimation (simulated) for different rotating speed in respect to the crank shaft sensor signal nature (induction sensor), is given in Table 2 as a *mean* value.



Figure 9. Simulated signal from the engine crankshaft sensor for different working conditions. Slika 9. Simulirani signal senzora radilice motora za različite

radne uslove

The simulated signal from the engine crankshaft sensor for different working conditions can be described with these functions:

sin(x), mean:  $-1.72582e-005 \approx 0$  Variance: 0.500253

 $5\sin(2x)$ , mean:  $-0.000172676 \approx 0$  Variance: 12.5063

After fitting the data distribution histogram, it is clear that the mean value and form of fitting curve are a good start point for defining the membership function (MF) for fuzzy sets which may be used in the expert system /5, 6, 7/. This expert system then must be capable to make a decision in case of misfire. One of major problems is the calibration, especially when we see Fig. 8.



Figure 10. Function density distribution data for simulated modes of the engine working regime.

Slika 10. Funkcija raspodele verovatnoće za simulirane modove rada motora

# FUZZY INFERENCE SYSTEM (FIS)

An intelligent inference procedure based on fuzzy logic can then be used to classify the engine faults (misfire). Fuzzy logic seeks to reach a decision following linguistic rules as an experienced human dealing with *fault diagnosis* problems. Membership functions and fuzzy rules must be established before the condition of the engine is diagnosed. To characterize the parameters of the membership functions, statistical data analysis is required to find the mean value and standard deviation. Next, the fuzzy rules must be established.



Figure 11. Model systems for the detection of misfire. Slika 11. Model sistema za određivanje izostanka paljenja smeše

The nature of fuzzy logic requires very good engineering knowledge about the technical system and understanding of processes in the system. Linguistic rules are based on expert knowledge. In the next simulation, as input variables for the FIS (Fuzzy inference System), we use the throttle position state and engine rotation signal state, Fig. 11.

The FIS system is not perfectly calibrated and we do not discuss the programming of the engine central processor unit (CPU) or the separate fuzzy controller.



Figure 12. Simulated fault detection (> 0.5). Slika 12. Simulacija otkrivanja grešaka (> 0.5)

#### DATA VISUALISATION

For the tasks of diagnosis or supervision, it is often enough to display the measured value of a parameter – key performance indicators (KPIs) in a convenient visual form, /10/. This is especially useful for technical personnel of lower expert knowledge. For them it is enough to watch the go-off (departure) from the normal behaviour of the technical system. Software development in a class of statistical tools and data mining, although are not intended mainly for this purpose, provides new possibilities in the diagnosis and analysis of technical systems. The most important feature of these tools is the transformation and analysis of data and their storage in the form of CSV, XML, Excel form or in some other database file, Fig. 13.



Figure 13. Predictive maintenance, source: IBM Predictive Maintenance and Quality Technical Overview, 2013. Slika 13. Prediktivno održavanje, izvor: IBM Predictive Maintenance and Quality Technical Overview, 2013

In the advanced CMMS software such files can be used for programming of maintenance tasks and prediction of failure.

What do Figs. 14-16 show? For example, when the engine runs unevenly, there are holes in a cloud of graphic displayed values, and we can use these data to predict the failure.





Figure 16. 3<sup>rd</sup> cylinder disabled. Slika 16. Treći cilindar onemogućen

### CONCLUSIONS

Algorithms for evaluating the proper or improper engine work are complex. It is known that engine revolution analysis is an excellent tool for this purpose. The capability for capturing the real data in working regimes, and analysing them with existing software (e.g. Matlab) in combination with a simulation of failures has enabled the possibility for education, scientific and other tasks. Measurement data (signals) can be analysed, transformed, filtered, and combined (stored) with commercial software.

The main goal in this paper it is how to determine the membership function (MF) for the data distribution signal for a fault decision expert system based on fuzzy logic. In combination with other data (for example the  $O_2$  sensor or the intake manifold embedded sensors).

One of the key techniques used in this paper are statistical techniques. A periodic nature of engine rotational dynamics and a cycle-to-cycle variability allows the presentation of engine signals as statistical signals utilizing such statistical variables as mean values and standard deviations. These statistical methods are the future prospective methods for a new generation of robust engine functionality.

Alternatively, further research can provide full integration of the measured data into systems of CMMS, maintenance benchmarking, FMECA and maintenance optimisation.

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