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TRENDS IN PREDICTIVE AND PROACTIVE MAINTENANCE OF MOTOR VEHICLES

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Abstract

Changes in maintenance approaches of more complex vehicles and related systems are closely associated with the development of motor vehicles and the ever increasing demand for mobility. Ever since the production of the first motorized vehicles started, engineers have been addressing maintenance issues, which aim to maximize the reliability of vehicles and eliminate unwanted failures. The purpose of this article is to show how proactive maintenance can be performed. Proactive maintenance is based on on-line diagnostic systems in motor vehicles. In this paper, the authors describe the possibilities of obtaining operational data on automatic transmission from on-board diagnostics and its subsequent processing. Furthermore, the article presents a model proposed for determining the amount of wear of individual machine parts in an automatic transmission. Finally, a comparison of the data from the proposed model and the data from the CAN bus is made. The authors show the possibility of access in the field of sustainability towards proactive maintenance and the effort to predict future wear of machine parts in an automatic transmission using modelling. In this case, Matlab & Simulink software was used, which is suitable for these processes. This approach to the sustainability of motor vehicles is in principle identical or very similar to the systems used under various designations in industry, aviation, computer science, etc.

Keywords: proactive maintenance, simulation of automotive gearbox, prognostics, condition based maintenance, prognostics methods

INTRODUCTION

Even if maintenance is a necessity, maintenance has a negative image and suffers from a deficiency of understanding and respect. It is usually recognised as a cost, a necessary evil, not as a contributor. Most people think that the role of maintenance is "to fix things when they break" but when things break down maintenance has failed (Blann, 2003). Moreover traditionally the scope of maintenance activities has been limited to the production vs. operation phase. But as the paradigm of manufacturing shift towards realizing a sustainable society, the role of maintenance has to change to take into account a life-cycle management oriented approach (Takata *et al.*, 2004) for enhancing the eco-efficiency of the product life (Voisin *et al.*, 2010). In that way, maintenance has to be considered not only in production vs. operation phase but also in product design, product disassembly, and product recycling… (van Houten *et al.*, 1998).

Generally, the motor vehicle is either in a usable state or an unusable state. Our goal is to keep the vehicle in a usable state, which means avoiding breakdowns and limit states of the motor vehicle. This objective is to be achieved on the basis of the lowest cost of the vehicle's life cycle, while maintaining inherent vehicle reliability throughout the period of use. This is reflected in the individual maintenance approaches from the 1930s to the present.

Condition based maintenance has come to the forefront in recent decades with the advancement of technical diagnostics. This is maintenance, which is based on monitoring the ongoing technical condition and the follow-up measures. Individual worn parts, parts at risk of failure or the whole groups are repaired or replaced in the optimal time. This means that the service life of the monitored components is fully utilized and the replacement takes place only when the component starts to exhibit abnormal behaviour but still performs its function. This maintenance system according to the technical condition can be divided into, as shown in Fig. 1:

a) predictive maintenance,

b) proactive maintenance.

Proactive maintenance is a preventive maintenance strategy that works to correct the root causes of failure and avoid breakdowns caused by underlying equipment conditions. The purpose of proactive maintenance is to see machine failures as something that can be anticipated and eliminated before they develop.

Proactive maintenance is considered the next higher level of maintenance. It is based entirely on previous predictive maintenance, which is further improved. Proactive maintenance requires the use of On Board Diagnostics (OBD) using the CAN data bus.

For more than half-century, the Box-Jenkins methodology using autoregressive moving average model (ARMA) linear models have dominated many areas of time series forecasting. In 1970, (Box *et al.*, 2015), made ARMA models popular by proposing a model building methodology involving an iterative three-stage process of model selection, parameter estimation and model checking. Recent explanations of the process e.g. (Makridakis *et al.*, 2008) often add a preliminary stage of data preparation and a final stage of model application or forecasting (Rojas *et al.*, 2008; Leitner and Figuli, 2018; Chovanec, 2012).

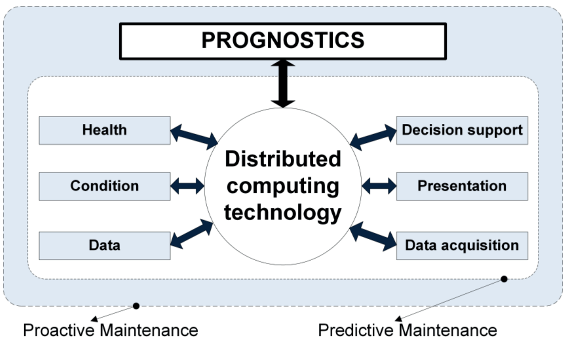
In the aeronautical industry, health management and maintenance processes are among the main research topics for economical, ecological and industrial reasons (Inman *et al.*, 2005; Vachtsevanos *et al.*, 2006). However, the first challenge is to model industrial systems and their degradations. The variety and number of sources of uncertainty (e.g. forecast, complex system, unknown degradation process) encourage a probabilistic approach. System modelling can take various forms: macroscopic considerations (e.g. interacting components in or precise physical modelling (Daigle and Goebel, 2010; Guan *et al.*, 2009). This paper adopts a probabilistic method which considers both standpoints: the Piecewise Deterministic Markov Processes (PDMPs) introduced by (Davis, 1993) and studied by (Jacobsen, 2006).

An interesting maintenance approach consists in using condition-based maintenance (CBM) to act on the system based on its current state and before its failure (Jardine *et al.*, 2006). In the framework of control-limit decision rules, the CBM decision depends on an indicator associated with some thresholds (Jardine *et al.*, 2006). It is often a degradation indicator as in (Dieulle *et al.*, 2003). (Huynh *et al.*, 2012) compare CBM strategies using degradation or age indicators.

A third indicator appeared recently: the Remaining Useful Life (RUL) of the system (Saxena *et al.*, 2010; Vachtsevanos *et al.*, 2006). It represents the remaining time before a failure occurs.

Its definition ina CBM context remains unclear (Jardine *et al.*, 2006) for a partial definition). Moreover, in the literature, the RUL is computed using data only (Jardine *et al.*, 2006), time-series forecasting (Yan *et al.*, 2007), neural networks (Zemouri *et al.*, 2003) and (Yu *et al.*, 2006) or neuro-fuzzy systems (Wang *et al.*, 2004) but never using models nor physics of failure.

Simulations often incorporate analytical models of the bearings in the gearboxes. However, only the very simple shapes of the working surface of the bearing segments can be used for the analytical lubrication solution (Novotný *et al.*, 2019). Such a model can incorporate the analytical solution to the Reynolds equation under the assumption of an infinitely long bearing presented by, for example, (Stachowiak and Batchelor, 2013). This theory can be further expanded; for example, (Liu and Mou, 2012) present an approach for the analytical solution, assuming the rectangular shape of the working surfaces.



1: *Maintenance based on technical condition (Furch and Nguyen, 2016; Vachtsevanos et al., 2006)*

MATERIALS AND METHODS

Telemetry Monitoring

The essence of telemetry is the wireless transmission of vehicle technical data. It is a process of measuring certain data and sharing data remotely without a direct physical connection. The basic prerequisite is that the vehicle is equipped with on-board diagnostics and a CAN bus. When meeting these requirements in conjunction with maintenance we can talk about telemaintenance.

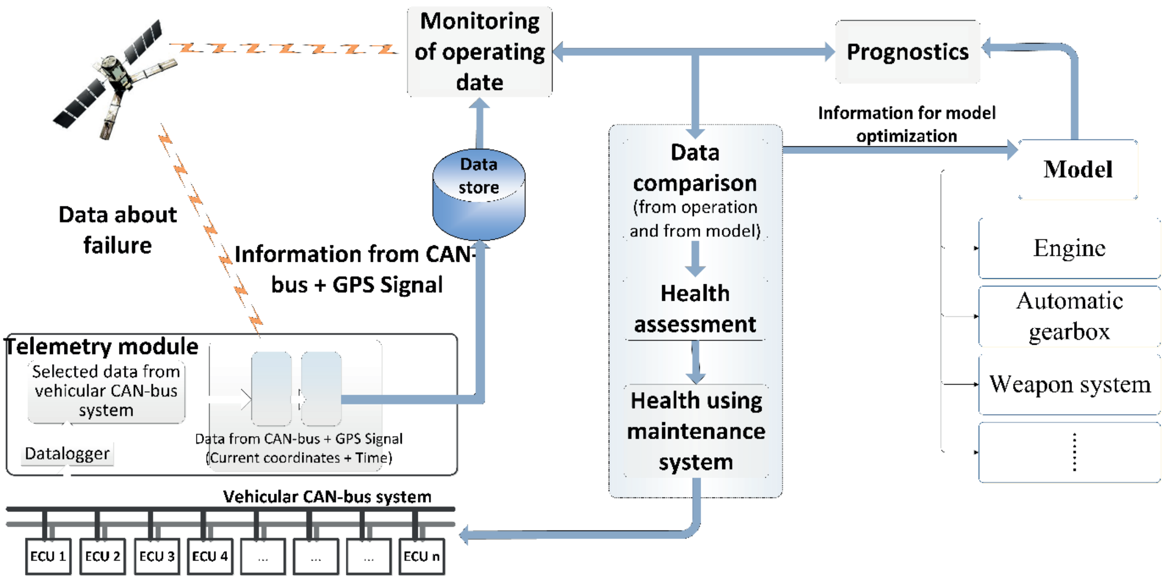
Transmission using a telecommunications network, radio or infrared signal may be used to send data. The data can be also sent via computer or telephone networks.

Modern vehicle tracking systems are designed to provide comprehensive vehicle information to several levels (operator information, service information, logistical support information, etc.). In companies that deal with transport or operate a large number of motor vehicles, the emphasis is mainly on reducing operating and maintenance costs. In general, when the vehicle is in operation, it means that it is involved in generating profits. If the vehicle is idle or maintenance is in progress, the vehicle does not make a profit. Therefore, the aim is to monitor the technical condition of the vehicle on-line using on-board diagnostics and the CAN bus. In addition to this approach, attempts are made to create models for predicting the failure of complex systems, as shown in Fig. 2.

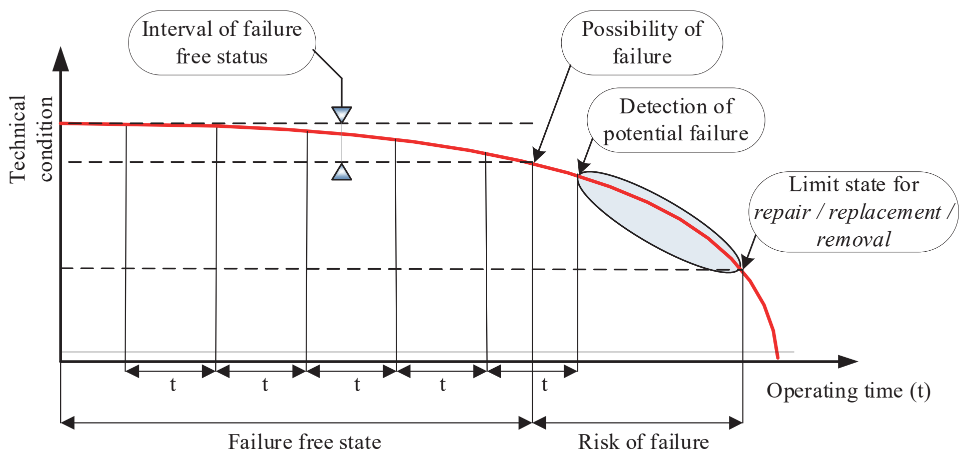
Possible Approaches to Signal Prediction, Processing and Analysis in Proactive Maintenance

Modern vehicle maintenance systems based on parameter monitoring from motor vehicle sensory networks are increasingly focusing on the forecasting options of technical conditions. Forecasting in the technical field means the ability to predict the remaining useful life of specific components or subsystems of a given unit, see Fig. 3. The forecast is evaluated by the degree of reliability. Modern maintenance systems aim to enable long-term prediction of failure development and to increase the reliability of such prediction by various methods. In this case it is called proactive maintenance.

In a system based on the proactive maintenance principle, emphasis is placed on obtaining the maximum set of information, increasing the ability to detect failures and minimizing false failure alarms using on-board diagnostics.



2: *Design of data transmission from the CAN bus of a motor vehicle including proactive maintenance (Furch et al., 2017)*



3: *Failure prediction depending on technical condition and time of operation (Furch et al., 2017)*

Modelling – Based Forecasting Methods

Modelling-based forecasting methods use simplified processes that are subject to prediction. Models based on physical principle, autoregressive modelling, empirical methods and Kalman filter are used as prediction tools.

Modelling-based methods are used to elucidate the failure process of a part. Models based on physical principle can serve as a means of detecting critical component damage as a function of operating conditions and evaluating cumulative effects over time of use. By extending the physical models by stochastic modelling methods, it is possible to use the model to evaluate the distribution of the remaining life of a part as a function of the uncertainties in partial properties of the components (strength, stress, lubrication conditions) for specific failures. Statistical representation of operational events serves as a basis for calculating the frequency of failures in further operation.

Models Based on Physical Manifestations of Material Fatigue

In models that focus on material fatigue investigation, it is necessary to determine the origin of damage (fracture, crack) and its manifestations for effective forecasting. In the aerospace industry, attention is paid to models that are able to detect the propagation of cracks in the material and recognize their manifestations.

Fatigue cracks are typical of machine parts such as gears, shafts, and vehicle body parts and are influenced by a number of factors (material properties, stress characteristics, temperature, lubrication, etc.). Due to the prognosis determination, crack propagation models can be divided into two categories, namely deterministic models and stochastic models. The basis for deterministic models investigating crack propagation in a material is the Paris-Erdogan relationship (Tomaszek *et al.*, 2013):

$$\frac{dl}{dN} = C(\Delta K)^m, \quad (1)$$

where

l ....crack length,
N ....number of cycles,
C, m.....material-dependent constants,
ΔK ....range of stress intensity factor.

Model parameters are usually determined using a non-linear recursive least squares method with the so-called forgetting factor.

In stochastic crack propagation models, all parameters are taken as random variables. The resulting crack propagation equation has a differential shape and simulations using Monte Carlo methods, neural networks and other methods are used as a means for parameters estimation (Furch *et al.*, 2017).

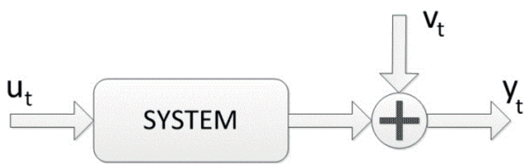
Autoregressive Moving-average Model ARMA and ARMAX

In practice, there are many cases of complex systems where it is very difficult or even impossible to derive dynamic models based on all the physical processes that affect the system. In similar cases, it is possible to use the simplified basic model of the system and use the input and output data of the real system to determine additional required parameters of the model.

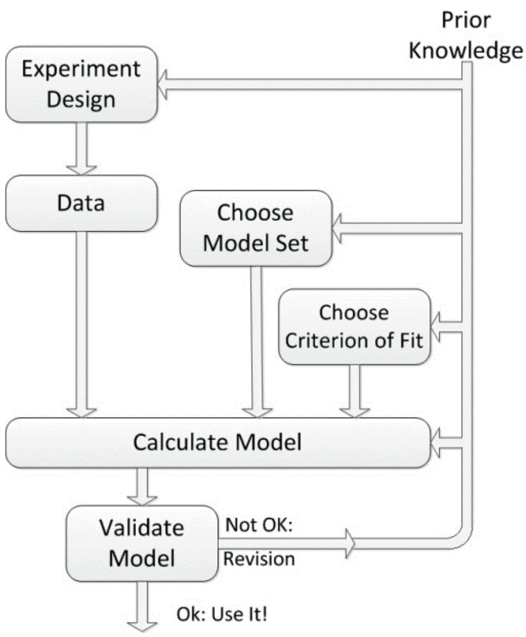
Data from the system are obtained by performing a series of test measurements. The basic model of the system is set according to the input criteria of the system and is used for calculating the parameters. After calculating, model output data and system output data are verified. The test loop is terminated if the last step (model verification) gives satisfactory outputs. Otherwise, the loop is not terminated. The scheme of the loop is shown in Fig. 5.

A simplified scheme of the system is shown in Fig. 4. The input values of the system are determined as u_t, the output values as y_t, which represent the measured values. The model of this system can be expressed by the relationship (Lennart, 1999):

$$v_t + a_1 v_{t-1} + \ldots + a_{n_a} v_{t-n_a} = e_t + c_1 e_{t-1} + \ldots + c_{n_c} e_{t-n_c}. \quad (2)$$



4: *Simplified scheme of the system (Vachtsevanos et al., 2006)*



5: *Model test loop (Vachtsevanos et al., 2006)*

Autoregressive Moving-Average Models (ARMA) represent dynamic systems that are characterized by the dependence of the functions v_t at time t on their previous values as well as on the time course of noise e_t up to time t.

Mathematically, the system can be expressed using coefficients that represent "unknown" model parameters and must be appropriately set to match the output behaviour of the model to the input/output data of the system. The relation between inputs and outputs is defined by the model error equation (Lennart, 1999):

$$y_t + a_1 y_{t-1} + \dots + a_{n_a} y_{t-n_a} = b_1 u_{t-1} + \dots + b_{n_b} u_{t-n_b} + e_t. \quad (3)$$

Parameters (a_1, a_2, ..., a_{na}, b_1, ..., b_{nb}) can be expressed using a vector of unknown variables $\theta = [a_1, a_2, \dots, a_{na}, b_1, \dots, b_{nb}]^T$ and after substituting into equation (3) we get:

$$y_t = [-y_{t-1} - y_{t-2} \dots -y_{t-n_a} u_{t-1} \dots u_{t-n_b}]\theta + e_t = h_t^T\theta + e_t, \quad (4)$$

where

u_t ....input data,

y_t ....output data,

e_t..........disturbance,

t ....time,

h ....regression vector that contains all monitored data, including past values u_t, y_t.

The model error equation lacks the possibility to fully describe the properties of unmeasured values vt as required by the ARMA model, where it is necessary to know both the current and the previous noise values et. The extended variant of the ARMA model under the name ARMAX describes the equation of model errors by the relationship (Lennart, 1999):

$$y_t + a_1 y_{t-1} + \dots + a_{n_a} y_{t-n_a} = b_1 u_{t-1} + \dots + b_{n_b} u_{t-n_b} + e_t +$$
$$+ c_1 e_{t-1} + \dots + c_{n_c} e_{t-n_c}, \quad (5)$$

where the adjustable unknown parameters are given by the vector (Lennart, 1999):

$$\theta = [a_1 \dots a_{n_a}, b_1, \dots b_{n_b}, c_1 \dots c_{n_c}]^T. \quad (6)$$

The ARMA, ARMAX models are used in a number of applications as a means of predicting the future state of the system, which is based on the monitoring of the previous data. Precisely for this reason they are used in forecasting systems in which one of the main objectives is to predict a failure and to follow the failure process.

Particle Filter Framework for Failure Prognosis

Bayesian estimation techniques are finding application domains in machinery fault diagnosis and prognosis of the remaining useful life of a failing component/subsystem (Orchard *et al.*, 2005). This method is used to accurately and reliably predict failures of parts that are based on particle filtration using known techniques that have been developed at the Institute of Technology in Georgia. For mathematical processing Bayesian estimates are used. They deal with the application of fault diagnostics in the field of mechanical engineering as well as detecting the remaining useful life of subsystems or individual components. This innovative approach to the use of the static-dynamic model and measurement model is applicable for the subsequent determination of the probability density of states, which is used to predict the occurrence of the system damage due to wear or its total failure.

Damage prediction and failure indicators result in gross uncertainty. Accurate determination of the failure time of a component or subsystem shall take into account critical state variables such as crack length, pitting, etc. in the form of random variables with associated probability distribution. Where the probability distribution has already been determined, other necessary attributes, such as confidence intervals, should continue to be envisaged. Based on the above facts, it is possible to solve a prognosis based on the recursive Bayesian estimation theory, which combines both the use of information obtained from probability models and the data measured by sensors that monitor the main wear parameters.

Long-term failure prediction is based on a very accurate estimation of the current state of a component (system) as well as a model that describes the development of the damage. If damage is detected and isolated in the initial phase, it is advisable to perform measurements more frequently and analyze and process the data acquired from the sensors. Subsequently, the newly acquired data is added to the model, which allows for more accurate prediction of time to failure. We measure and verify the model until we determine the limit state of the component/system damage. To prevent catastrophic events (system failure), maintenance must be performed.

The available and recommended CBM/PHM sensors and the property extraction module allow sequential observation and measurement of damage evolution data zk at the current time k. The damage status can be described using the status and measurement models (Vachtsevanos *et al.*, 2006) and (Orchard *et al.*, 2005):

$$x_k = f_k(x_{k-1}, \omega_k) \leftrightarrow p(x_k \mid x_{k-1}), \quad (7)$$

$$z_k = h_k(x_k, v_k) \leftrightarrow p(z_k \mid x_k), \quad (8)$$

where

x_k..........is failure state or size (such as crack size), variable conditions directly affecting the development of failure,

ω_k, v_k...are non-Gaussian noises,

f_k,h_k......are nonlinear functions.

In the first part of the approach, the state estimation is performed, which can be described as an estimate of the current range or extent of the damage, as well as other important environmental variables. In the second part of this approach it is based on a long-term forecast, resulting from an estimate of the extent of damage and a model of damage development with parameters. The values are further refined throughout the observation period on the basis of the actual state of the observation. The innovative process of recursive integration is based on both the importance of sampling and the approximation of the distribution density function using Kernel functions. It is then applied to create the state forecast for the time interval (k + 1) to (k + p) (Vachtsevanos *et al.*, 2006; Orchard *et al.*, 2005):

$$p(x_{k+p}|z_{1:k}) = \int p(x_k|z_{0:k})\prod_{j=k+1}^{k+p} p(x_j|x_{j-1})dx_{kk+p-1}, \tag{9}$$

$$p(x_{k+p}|z_{1:k}) = \sum_{i=1}^{N}\tilde{w}_k^{(i)}\int\ldots\int p(x_{k+1}|x_k^{(i)})\prod_{j=k+2}^{k+p} p(x_j|x_{j-1})dx_{k+1:k+p-1}. \tag{10}$$

Long-term prediction can be used to estimate the probability of failure during use. For this purpose, a risk zone is designed, which is defined by its minimum h_{lb} and maximum limit values H_{up}. The predicted confidence interval as well as the estimated time to failure (TTF) can be derived from the mean time to failure of the probability density function (Vachtsevanos *et al.*, 2006; Orchard *et al.*, 2005):

$$p_{TTF}(TTF) = \sum_{i=1}^{N}\Pr\left\{H_{lb} \le x_{TTF}^{(i)} \le H_{up}\right\}\tilde{w}_{TTF}^{(i)}. \tag{11}$$

The uncertainty of the forecast accuracy usually increases with the length of the forecasting period. To reduce the uncertainty of the failure forecast, which is based on particle filtering, a model capable of correcting the estimated time to failure is used. The model calculates the expression C_n, which consists of the difference between the current estimated time to failure and the previous time to failure as determined in the previous iteration step. After obtaining the correction expressions p, a linear regression model is constructed, which defines the relationship between the individual correction expressions that were used in the previous calculations. The constructed linear correction model is then used to estimate future corrections that would be used if the procedure had a wide sense stationary (WSS). Its use will improve the accuracy of long-term predictions.

Forecasting Methods Based on Probability

In situations where records of previous system failures are maintained, probability-based methods are often used for forecasting options. These methods require less detailed information than model-based methods because the necessary information for forecasting needs is contained in various probability density functions. The advantage is that the necessary information can be obtained from any system, regardless of its complexity, using the data for determining the probability density distribution.

Bayesian Probability Theory

Bayesian theory forms the basis for a number of methods that deal with predicting the future state of an object based on known relevant information on the object. It is a way in which, after obtaining new information, indeterminate input data can be quantified by determining the likelihood of their occurrence. The calculations are based on the probability density function (Huynh *et al.*, 2012; Vachtsevanos *et al.*, 2006):

$$f_{X,Y}(x, y) = f_{X/Y}(x/y)f_Y(y) = f_{Y/X}(y/x)f_x(x), \tag{12}$$

where

$f_{X,Y}(x, y)$ ....is common probability density function,

$f_x(x)$ and $f_y(y)$.............are initial probability density functions,

$f_{x/y}(x/y)$ and $f_{y/x}(y/x)$...are conditional probability density functions.

The initial probability density functions $f_x(x)$ and $f_y(y)$ can be calculated using relationships:

$$f_x(x) = \int f_{X/Y}(x, y)dy, \tag{13}$$

$$f_y(y) = \int f_{X/Y}(x, y)dx, \tag{14}$$

where the integrals are defined over the whole area of the probability density function. Then the equations (12), (13) and (14) show:

$$f_{Y/X}(y/x) = \frac{f_{X,Y}(x, y)}{\int f_{X,Y}(x, y)dy}, \tag{15}$$

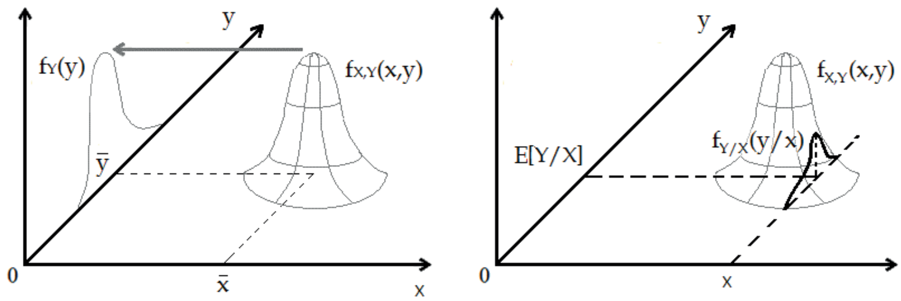
$$f_{X/Y}(x/y) = \frac{f_{X,Y}(x, y)}{\int f_{X/Y}(x, y)dx}. \tag{16}$$

Mean value $E(X)$ and conditional mean value $E(Y/X)$ of the random variable is then given by the relationships (17) and (18):

$$E(X) = \int xf_x(x)dx, \tag{17}$$

$$E(Y/X) = \int yf_{Y/X}(y/x)dy = \frac{\int yf_{X,Y}(x, y)dy}{f_{X,Y}(x, y)dy}. \tag{18}$$

The common probability density function serves as a starting point for the calculation of other important values. For this reason, the calculation gives priority to the calculation of the probability density function, which is given by the available



6: *Representation of initial and conditional probability density functions Huynh et al. (2012) and Vachtsevanos et al. (2006)*

data to which priority attention is given. Fig. 6 shows a procedure for finding the initial and conditional probability density functions, which is shown graphically.

Time to Failure Analysis Using Weibull Distribution

Weibull distribution is a suitable model for tasks where the service life of machine parts is investigated. This distribution is used to model data regardless of whether the failure rate is increasing, decreasing or constant. The Weibull distribution is flexible and adaptable to a wide range of data. Time to failure, cycles to failure, transport distance, mechanical stress or similar related parameters should be recorded for all objects. The Weibull distribution using these measured values is very often used to predict the remaining useful life (RUL) of machine parts. The lifetime probability density distribution can be modelled even if none of the objects has failed.

Weibull distribution is characterized by the parameter (β), the service life parameter (η) and the location parameter (γ). The probability density is given for the three-parameter Weibull distribution by the equation (Weibull, 1951):

$$f(t) = \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} exp\left[-\left(\frac{t-\gamma}{\eta}\right)^{\beta}\right], \beta > 0, \eta > 0, t > \gamma. \quad (19)$$

During application, we often see that the three-parameter Weibull distribution becomes a two-parameter distribution ($\gamma = 0$). The location parameter γ defines the minimum time (random variable) during which a fault may occur.

Using the flexibility of the Weibull distribution, it is possible to model the individual phases of the classic bathtub reliability curve. The first phase of the bathtub curve (early failure phase) can be approximated by the probability density function with the $\beta < 1$ shape parameter, the second phase (constant failure rate period) uses the $\beta = 1$ shape parameter, and the last phase (final period) can be approximated using values of the $\beta > 1$ shape parameter.

The failure occurrence data, expressed as time to failure or level of risk, can be applied to the Weibull distribution by parameter estimation or Bayesian analysis with respect to model parameters as a random variable.

Remaining Useful Life Probability Density Function

The basic principle of this prognostic method is to determine the distribution function of the probability density distribution of the remaining useful life of a component. The component must be removed from service before reaching high probability of failure. Unfortunately, the main problem is that the remaining useful life of the probability density function is actually a condition of probability density function that changes over time. In fact, we must recalculate the probability density function of the remaining useful life at each time t based on new information that was not previously available (Engel *et al.*, 2000).

Then, during the time interval *t*, we must recalculate the following probability density function of the remaining useful life on the basis that the failure has not yet occurred in that interval. This is a modification of the probability density function at any time when the region is equal to one. Over time t, the dispersion of the probability density function of the remaining useful life decreases; that means, the probability density function narrows. This corresponds to the fact that, as time passes, the probability density function approaches the point of failure, thus the time of failure becomes more certain and the predicted time becomes more accurate.

Data Driven Prediction Techniques – Neural Network

Non-linear neural network models are often used where statistical information on device failures and signal waveforms that lead to failures is available. These models are designed to approximate the dependence of the required information (parameter) on its attributes through repeated data discovery. This property allows prediction of the time sequence based on the laws of dynamics of the quantity contained in the data history archive.

Neural network is a system of interconnected units – neurons. Neuron is here, as in the biological area, the basic building unit of the entire network.

The mathematical model of the neuron is based on addition of input values x_1 to x_n, which are evaluated by weights w_1 to w_n. This value is referred to as the so-called internal potential of the neuron σ (weighted sum of input values). If the potential level of the neuron inputs $\sum_{i=1}^{n}(w_i x_i)$ is higher than the threshold θ, the neuron output will change. Mathematically, the model can be expressed as (Lewis *et al.*, 1999):

$$y = \sigma\left(\sum_{i=1}^{n} w_i x_i + \theta\right). \quad (20)$$

The output of the neuron y is determined by the value of its transfer function f(σ), whose argument is the value of the internal potential of the neuron. Only a linearly separated problem can be solved with one neuron. More complex problems can be solved by interconnecting more neurons into one unit. Neural network consists of neurons which are organized into layers. The structure of a neural network is based on neurons from one layer interconnected with all neurons of the higher layer. Neurons in one layer are not interconnected.

The values x_1 to xn are inputs, the values y_1 to y_m are outputs. The transfer function f(σ) is contained in the hidden layer of the neural network. The weights in the hidden layer are v_{jk}, the weights in the output layer are w_{jk}. The hidden layer threshold is θ_{vj} and the output layer threshold is θ_{wi}. The number of neurons in the hidden layer is denoted L. Mathematically, this two-layer neural network can be expressed as (Lewis *et al.*, 1999):

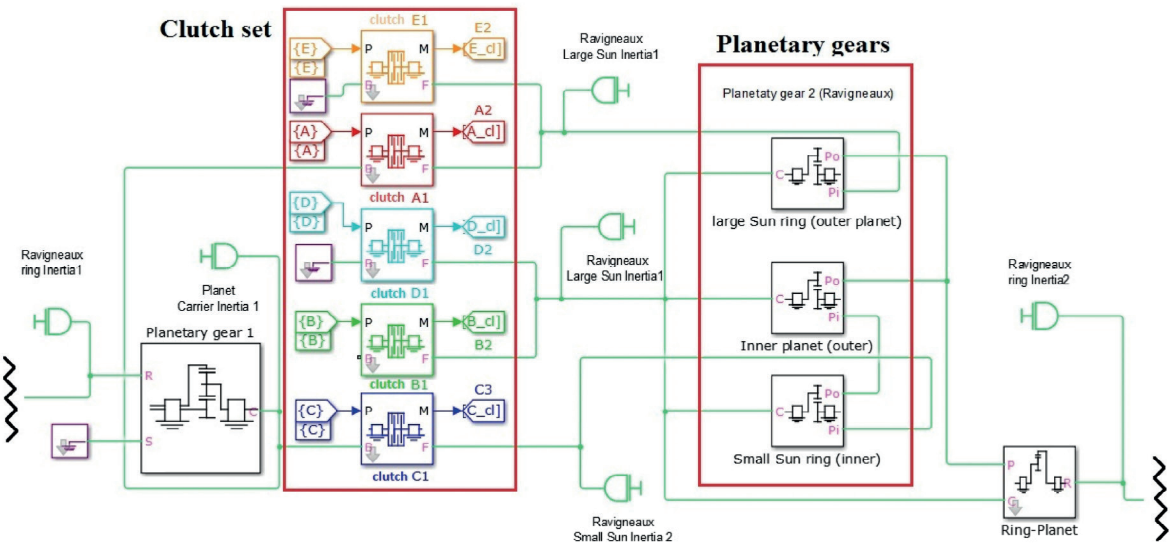
$$y_i = \sum_{j=1}^{L} w_{ij}\sigma\left(\sum_{k=1}^{n} v_{jk} x_k + \theta_{vj}\right) + \theta_{wi} i = 1, 2, \ldots, m. \quad (21)$$

In order for a neural network to be able to provide relevant outputs, its use is conditional on the implementation of the network teaching phase. At this stage, the network is "taught" how to respond to certain inputs, which are the basis for generating corresponding outputs in the working phase. There are several ways to define the weight settings of individual neurons in the network teaching phase (teaching with a teacher, without a teacher, with a partial-teacher) (Lewis *et al.*, 1999).

RESULTS AND DISCUSSION

One way to detect an emerging failure or abnormal behaviour of a particular group of a motor vehicle in time, as shown in Fig. 3, is the use of simulation for the given group of the motor vehicle. The created computational model for the selected machine group must be able to simulate the operation of the group that is in a trouble-free state based on the input data from the vehicle network. The second part of this fault detection method consists in comparing the output data from the model with the real data obtained from the vehicle network. This method of fault detection corresponds to the proactive maintenance system described in chapter Telemetry Monitoring (Fig. 2).

The Iveco automatic transmission was selected for the experiment and subsequent comparison with the fault detection model. For this particular case, a virtual automatic transmission model was created in Matlab & Simulink software. The input data (gear engaged and gearbox input shaft speed) are recorded from the vehicle network using a datalogger and entered in an appropriate format as input information for the virtual model operation. It is not a real-time fault detection, however, with a suitable system of automatic downloading of stored data and its subsequent transfer to a virtual model, this method is very suitable for detecting non-standard states, or early



7: *Part of the virtual model – automatic transmission elements* detection of incipient failure and prevention of major damage to the aggregate.

The structure of the model corresponds to the physical design of the ZF 6HP260 gearbox, where the torque is transmitted through the planetary gear set in the required gear ratio. The change of the gear ratio or gear shifting is ensured by a system of five clutches, which in a corresponding combination brake individual elements of the planetary gears and ensure the appropriate gear ratio. A part of the virtual model with the above elements is shown in Fig. 7.

The Fig. 8 shows an example of a comparison of the output shaft speed values of the automatic transmission from the model (Chart 2) and the actual measured shaft speed values of the Iveco automatic transmission (Chart 3). The output shaft speed of the automatic transmission shows a 10-minute driving period of the Iveco motor vehicle.

Numerical values are evaluated using the Pearson correlation coefficient. The compared sets A and B represent the values of the output shaft speed of the automatic transmission measured on the vehicle (real data – Chart 3) and the values of the same parameter processed by the model (Chart 2). The covariance cov is calculated from the variables X and Y. To get the Pearson correlation coefficient ρ, the covariance is divided by the square root of variance of sets X and Y by (Stigler, 1989):

$$\rho_{X,Y} = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y}, \qquad (22)$$

where

$$\mu_X = \mathrm{E}(X),\ \sigma_X^2 = \mathrm{E}(X^2) - \mathrm{E}^2(X), \qquad (23)$$

$$\mu_Y = \mathrm{E}(Y),\ \sigma_Y^2 = \mathrm{E}(Y^2) - \mathrm{E}^2(Y), \qquad (24)$$

than

$$\rho_{X,Y} = \frac{E(XY) - E(X)E(Y)}{\sqrt{E(X^2) - [E(X)]^2}\sqrt{E(Y^2) - [E(Y)]^2}},\ \rho_{X,Y} \in \langle -1,1 \rangle, \qquad (25)$$

where

cov ......covariance,

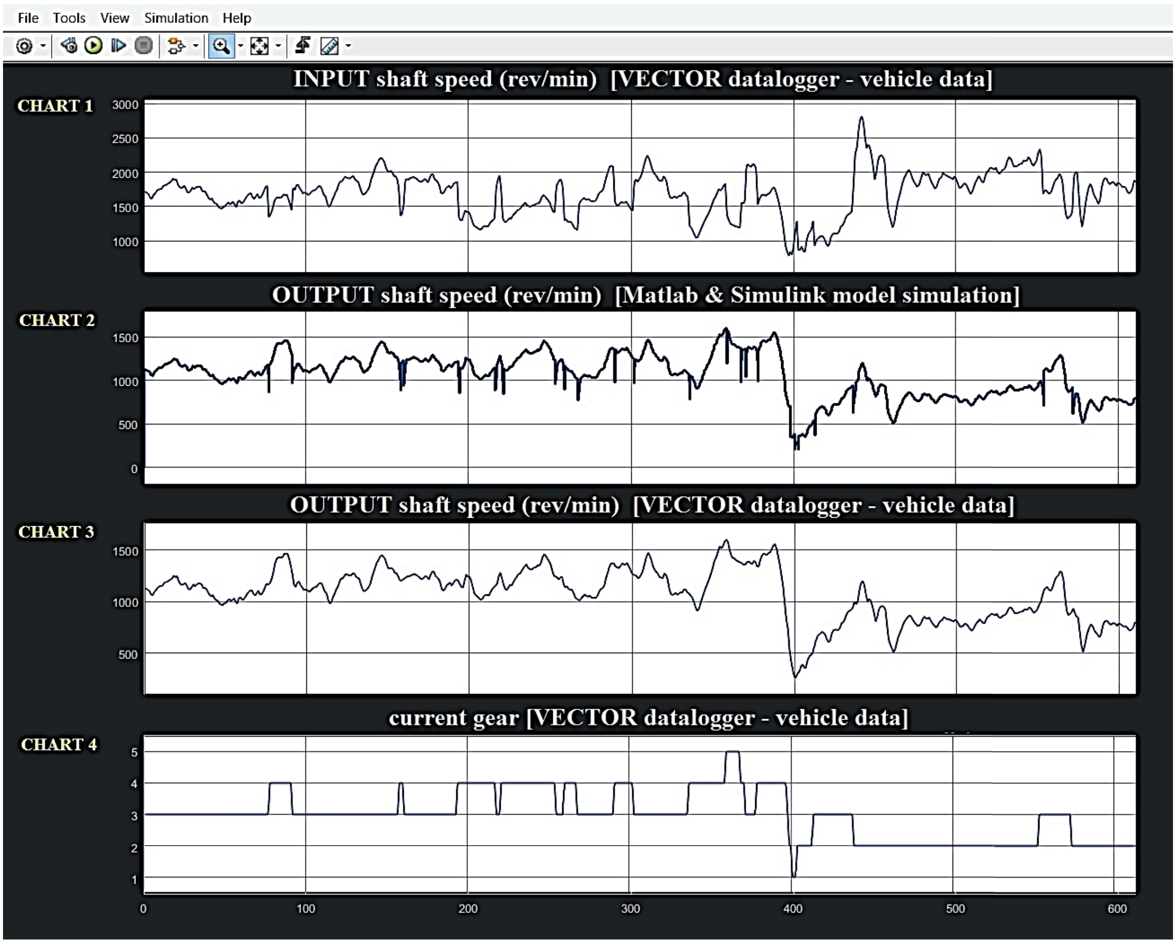
σ_X ....standard deviation of X,

σ_Y ....standard deviation of Y,

μ_X ....mean of X,

μ_Y ....mean of Y,

E...........expectation.



8: *Example of measured data and data processed by the Simulink model*

When comparing the measured data sets with the data processed by the model, the Pearson correlation coefficient ranged from 0.96 to 0.98. The initial measurement included 5 motor vehicles that travelled the same route. An important fact is that at that time, the motor vehicles measured by real data had very few kilometres (short distance) travelled. From this fact it can be assumed that the automatic transmissions of the measured motor vehicles were in very good technical condition. This range of correlation coefficient values may be considered as reference values for assessing the technical condition of the automatic transmission of the given motor vehicle.

A very important part of the fault detection system by comparing the values of the real operating variables with the variables coming out of the model is the whole process automation system. Using the telemetry transmission, as shown in Fig. 2, the motor vehicle can be "under constant technical supervision" without restricting its operation.

CONCLUSION

With increasing demands on the operation of technical equipment, the approaches to their preventive maintenance have necessarily changed. A well-designed and mastered preventive maintenance system is reflected in the increased reliability of the equipment in operation. In the field of motor vehicles, reliability is a very important feature. Therefore, the effort of manufacturers, but also operators, is to eliminate the immobilisation of motor vehicles for technical reasons to a minimum.

Also, advanced armies currently combine different approaches to preventive maintenance to ensure maximum reliability and, most importantly, the combat capability of motorized vehicles. Modern preventive maintenance systems rely on advanced vehicle architecture, regardless of the preferred preventive maintenance system. In general, the operators endeavour is to know the current technical condition of motor vehicles, or the condition in which the motor vehicle (monitored groups) will gradually approach the specified wear limits, when it is necessary to carry out preventive maintenance intervention.

The authors demonstrated on a simple example of an automatic transmission of an Iveco motor vehicle the way of setting limit values for the implementation of preventive maintenance intervention. The system is based on the comparison of modelled data with the operational data of the motor vehicle using the Pearson correlation coefficient. If the structure of the model corresponds to the structure of the monitored group of the motor vehicle, then it is possible to determine the specific part of the group that shows abnormal behaviour (limit wear). A timely preventive intervention can thus avert a failure or total damage to the group. The current possibilities of wireless data transmission extend the possibilities in the field of telemetric monitoring and evaluation of the technical condition of motor vehicles in real time. There is no direct danger when operating the fleet in the civilian sector using 'Fleet Management' and telemetry data. In a military environment, the confidentiality situation is considerably more complex, and there are therefore some limitations to the use of telemetric data transmission for monitoring the technical condition of military motor vehicles. It is mainly about finding the location of these military motor vehicles.

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