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Development of a Method for Evaluating the Technical Condition of a Car's Hybrid Powertrain

Oleksiy Bazhinov [1], Juraj Gerlici [2], Oleksandr Kravchenko [3], Yevhen Haiek [4], Tetiana Bazhynova [5], Ruslan Zaverukha [6] and Kateryna Kravchenko [2,*]

[1] Department of Technical Operation and Service of Automobiles Named M. Govorushchenko, Kharkiv National Automobile and Highway University, Yaroslava Mudrogo 25, 61002 Kharkiv, Ukraine; alexey.bazhinov@ukr.net
[2] Department of Transport and Handling Machines, University of Zilina, Univerzitna 1, 010 26 Zilina, Slovakia; juraj.gerlici@fstroj.uniza.sk
[3] The Department of Automobile and Transport Technologies, Zhytomyr Polytechnic State University, Chudnivska 103, 10005 Zhytomyr, Ukraine; avtoap@ukr.net
[4] Department of Optimization of Technological Systems Named after T. Yevsiukov, Kharkiv Petro Vasylenko National Technical University of Agriculture, Alchevsky 44, 61002 Kharkiv, Ukraine; gaekevgen@ukr.net
[5] Department of Tractors and Automobiles, Kharkiv Petro Vasylenko National Technical University of Agriculture, Yaroslava Mudrogo 25, 61002 Kharkiv, Ukraine; bazhynova28@ukr.net
[6] Department of Automobiles, Ternopil Ivan Puluj National Technical University, Ruska 56, 46001 Ternopil, Ukraine; Ruslan.zaveruha@email.ua
* Correspondence: kateryna.kravchenko@fstroj.uniza.sk; Tel.: +421-944-100-382

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Abstract: The article presents the results of a study performed and substantiated based on the principles of a new method of diagnostics of technical conditions of a hybrid powertrain regardless of the structural diagram and design features of a hybrid vehicle. The presented new technology of the diagnostics of hybrid powertrains allows an objective complex assessment of their technical condition by diagnostic parameters in contrast to existing diagnostic methods. In the proposed method, a mechanism for the general standardization of diagnostic parameters has been developed as well as for determining the numerical values of the parameters of the powertrain. The control subset was used to control the learning error. As a result of debugging the system, the scatter of experimental and calculated points has decreased, which confirms the quality of debugging the tested fuzzy model. As a result of training the artificial neural network, the standard deviation of the error in the control sample was $0.012{\cdot}P_k$. A symmetry method of diagnostics of the technical state of a hybrid propulsion system was developed based on the concept of a neural network together with a neuro-fuzzy control with an adaptive criteria based on the method of training a neural network with reinforcement. The components of the vector functional include the criteria for control accuracy, the use of traction battery energy, and the degree of toxicity of exhaust gases. It is proposed to use the principle of symmetry of the guaranteed result and the linear inversion of the vector criterion into a supercriterion to determine the technical state of a hybrid powertrain on a set of Pareto-optimal controls under unequal conditions of optimality.

Keywords: vehicle; hybrid powertrain; traction battery; neural network model; fuzzy model

1. Introduction

Features of power units of hybrid and electric vehicles allow for the conclusion that that powertrains as a control object are characterized by a change in a structure, significant nonlinearity of their main elements, and parametric uncertainty [1–4]. The efficiency of using the power unit is determined by the characteristics of its automatic control system, which solves the following tasks: identifying the current state of power unit systems and units; predicting the traction speed mode of movement; selection of the optimal operating mode of the power unit, depending on its technical condition and the mode of vehicle movement; an optimal distribution of power flows between the units of the power unit at a given traction speed mode; the management of braking energy recovery, recharging and energy consumption of the storage device; stabilization of the specified operating modes of individual units of the power unit; providing a driver interface, simulating control of the base car [1,2,5].

Along with the operational properties, it is important to prevent the consequences of a car fire [5] and the risks associated with it [6,7]. A possible application of various fire retardant technologies, such as the use of neutral gases and liquids, the introduction of temperature control systems as well as the emergency shutdown of the traction battery, and others [8]. Moreover, the problems of environmental safety of the use of cars with certain qualities [9], the recycling of the battery elements [10,11] and the greening of technological processes [12], are relevant and have paramount importance in hybrid vehicle operations. Global trends in the development of vehicles force improvements to the infrastructure of power supply to settlements, together with preserving the ecology [13] based on the use alternative energy sources [14]. Many properties of a car depend on the type and properties of the fuel [15]. Products of the fuel combustion have a negative impact on humans and the environment [16]. A hybrid power unit (HPU) together with electronic control units and other components form a complex system that requires special approaches to determining the technical conditions and the repairs.

Until now, the process of diagnosing a hybrid powertrain remains unexplored. The applied methods of analysis and synthesis of the control system do not pay enough attention to the multicriterion of the arising optimization problems of diagnostics. These circumstances do not allow for fully disclosing the potential of hybrid vehicles [1,2,5,17].

2. Analysis of the Literature Data and the Problem Statement

The HPU operation relates to deterioration of the effective performance of the traction battery (TB), the internal combustion engine (ICE) and the electric motor [18]. This is caused by the wear of parts, reduced capacity of the TB, a lack of necessary maintenance, and other interrelated reasons.

According to work [19], which is focused on the distribution of failures and malfunctions of the HPU, the largest numbers of them are associated with the internal combustion engine. The difficulty of identifying the malfunction of this unit is due to the fact that it is difficult to check the operation of the internal combustion engine as its start and control is carried out by the electronic control unit (ECU) and only in the power consumption mode.

There is also a connection between the failure of the internal combustion engine and the electronic components of the HPU systems. Failures of a high-voltage traction battery during the operation caused by its normal wear and tear make up to 2.5% of the total number of faults [19]. The main reason of the occurrence of the TB failures is the operation of a car with a faulty internal combustion engine, which leads to an unacceptable level of the high-voltage TB and the destruction of its elements [20,21].

The technical condition of the HPU is influenced by the climatic conditions of the operation. When the air temperature decreases, a cold internal combustion engine demands a longer time as well as the need itself for increasing the optimal operational temperature, even in the case that the TB is fully charged. These factors reduce the efficiency of a hybrid vehicle and the fuel consumption increases by 15–30% [22,23]. In addition, at low air temperatures, the number of ICE control system failures increases up to 23% of the total number of faults [24,25].

An analysis of the TB performance at low air temperatures shows that its capacity can decrease by 15–25% at a discharge current of 0.5–1.0 A and the self-discharge decreases at the environment temperature less than 10 °C from 3% to 1% per a day [26,27]. The operation of the TB at low air temperatures causes a decrease in the TB capacity $E \approx 0.7 \cdot E$ [28,29]. This fact is explained by the slowing down of the ongoing chemical reactions of the TB due to the cooling of its elements. In addition, when the internal combustion engine is heated for a longer time, the TB is fully charged for a longer time.

During the operation of the TB, an imbalance of the elements, in terms of capacity, internal resistance, and other parameters, appears and reduces the efficiency of the battery as a whole [30]. The car reacts to the reduction of the TB quality by increasing the fuel consumption, an incorrect indication, and, generally, by decreasing the power.

The hybrid vehicle technical state can vary depending on the mileage and how the distribution of the flow of failures of the HPU systems increases the tendency. Based on statistical data, the largest number of HPU failures are associated with the internal combustion engine and its systems; other failures are most often the result of malfunctions [31]. The methods of adaptation for the control strategy of the hybrid powertrain to the traction speed mode of the vehicle movement are used based on the concept of neural network and neural fuzzy control with an adaptive criterion and a model of the control object, using the implementation of methods of training a neural network with reinforcement [32,33].

3. The Aim and Tasks of the Study

The aim of the work is to increase the operational efficiency of functional systems of a hybrid vehicle by diagnosing the technical state based on the concept of a neural network and a neuro-fuzzy control with the adaptive criticism based on the method of training a neural network with reinforcement.

To achieve the aim, the following tasks were set:

- To scientifically substantiate a new symmetry method for diagnosing the technical state of the HPU on the basis of the system analysis of the task of increasing the environmental cleanliness and efficiency of the vehicle;
- To develop the theoretical foundations of the structural and a parametric identification of a mathematical model of the HPU unit technical state.

4. Theoretical Foundations for Diagnosing the Hybrid Powertrain

The energy consumption (fuel, electricity) of a hybrid vehicle is determined by the load-speed mode. These energy costs cause a deterioration of the technical condition of the hybrid powertrain under given operating conditions. The efficiency of the powertrain of a hybrid vehicle should be assessed by the criterion of the technical condition using a neural network model that is invariant to different powertrains.

The technical condition of the powertrain of a hybrid vehicle depends on the load-speed mode, and on the other hand, the energy consumption (fuel, electricity) is also determined by the load-speed mode. At a constant speed of movement, the relationship between a change in the technical state of the power unit and energy costs depends on the torque of the driving wheels.

This dependence allows for the assessment of the technical condition of the power unit, in terms of energy costs, during the operating hybrid vehicles under the specific operating conditions. This regularity is used as the basis for assessing the technical conditions of the power unit of a hybrid vehicle based on the total energy consumption [18,22]:

$$P_k = A \cdot \left[B \cdot V_c \cdot \omega^2 \cdot t_i + 9.1 \cdot 10^{-4} \cdot U \cdot I \cdot (0.85 + 0.05 \cdot T_e) \right] \cdot V_c, \quad (1)$$

where $A = 0.35 \cdot Q_{min} \cdot V_{max}$—constant coefficient of the hybrid power plant, which reflects the energy consumption for transport work; $B = 12.8 \cdot 10^{-6} \cdot g_e \cdot E \cdot X_c$—constant coefficient of the hybrid power plant, which reflects the design features of the internal combustion engine; g_e—specific fuel consumption, g·kWh^{-1}; ω—engine crankshaft rotation speed, rpm; U—traction battery voltage, V; I—traction battery current, A; T_e—environment temperature, °C; X_c—number of ICE cylinders; E—fuel injector capacity, ml·min^{-1}; t_i—injection time of the fuel injector, s; Q_{min}—minimum fuel consumption per 100 km of mileage, l; V_{max}, V_c—respectively, the highest speed and speed at the time of diagnosis, km·h^{-1}.

The formulation (1) is called the supercriterion, because it includes all factors, which are used the method.

The identification of the nonlinear dependence $P_k = f\ (I, U, S, V_c)$ from the experimental data by traditional methods turns out to be a difficult task and it is associated with the significant difficulty of collecting the sufficient data as well as computational difficulties [17].

At the same time, there are methods that make it possible to successfully identify dependencies of the complex functions based on the experimental studies with the limited data. Among such approaches, one can single out the use of fuzzy inference systems [30]. The advantages of the latter include the possibility of formalizing and using primary information about the phenomena of the study. However, there are currently no substantiated recommendations of applicability of a particular method. The study of the capabilities of fuzzy systems, artificial neural networks, and hybrid neural networks was conducted to select the most substantiated approach to approximating the required dependence.

Among the various systems of fuzzy inference, the Mamdani system was used, as it is the most transparent from the point of view of the formulation of the rules of fuzzy products. The fuzzification of the parameters, I, U, S, and V_c, is performed by specifying their term sets I—{L, LM, M, MB, B}, U—{L, M, B}, S—{L, M, B}, V_c—{L, M, B}, where the terms are assigned with the following values: L—"small", LM—"less than average", M—"average", MB—"more than average", B—"large". The output variable of the system is K—{L, LM, M, MB, B}.

Terms can be represented by fuzzy sets that use the membership function:

$$\mu(u) = \exp\left(-\frac{(u-b)^2}{2c^2}\right), \tag{2}$$

where u—the normalized value of the corresponding variable; b—the maximum coordinate; c—the concentration factor.

The choice of the Gaussian function relates with the dependence of the internal combustion engine and the traction battery. The advantage of this membership function is that only two parameters are needed for its task: b and c. The method of two stage identification of the nonlinear Rothstein dependence [30] was used to synthesize a fuzzy identification system for the dependence $P_k = f\ (I, U, S, V_c)$. According to this method, firstly, the base of fuzzy rules of the form "if something" (structural identification) is formed, then, a parametric identification of the dependence is performed by finding such weights of rules and parameters of membership functions of fuzzy terms that minimize deviations of the results of fuzzy modelling from the experimental data.

The base of fuzzy rules is composed on the basis of weakly formalized empirical knowledge about the operation of internal combustion engines at various degrees of technical condition. Table 1 shows the resulting database containing 127 rules.

Since only the fuzzy conjunction (an "AND" operation) is used in all fuzzy rules as a logical connection for a subcondition, the min-conjunction operation is chosen as the aggregation method. When determining the result of the logical conjunction of fuzzy statements, the expression is used:

$$T(A \cap B) = \min\{T(A), T(B)\}, \tag{3}$$

where $T(\bullet)$—the degree of truth of the corresponding expression.

The max-disjunction method is used to accumulate rule inferences. When determining the result of a logical disjunction ("OR" operation) of fuzzy statements A and B, the expression is used:

$$T(A \cup B) = \max\{T(A), T(B)\}. \tag{4}$$

The formulation (5) is considered to determine the degree of truthfulness of the negation of a fuzzy statement ("NOT"):

$$T(\overline{A}) = 1 - T(A). \tag{5}$$

The parametric identification of the model is performed based on the experimental data obtained in the study of the hybrid power unit of the car.

Table 1. The fuzzy products rule base.

I	ω	L			LM			M			MB			B		
	U \ T_e	L	M	B	L	M	B	L	M	B	L	M	B	L	M	B
B	B	B	B	B	B	B	B	MB	B	B	MB	MB	B	M	MB	B
	M	B	B	B	MB	B	B	MB	B	B	MB	MB	B	M	MB	B
	L	B	B	B	MB	B	B	MB	MB	B	MB	MB	B	M	MB	MB
MB	B	MB	B	B	MB	MB	B	MB	MB	B	M	MB	MB	M	MB	MB
	M	MB	MB	B	M	MB	B	M	MB	MB	M	MB	MB	M	M	MB
	L	MB	MB	B	M	MB	MB	M	M	MB	M	M	MB	LM	M	MB
M	B	M	MB	MB	M	M	MB	M	M	MB	M	M	MB	LM	M	M
	M	M	MB	MB	M	M	MB	M	M	MB	M	M	MB	LM	LM	M
	L	M	M	MB	M	M	MB	M	M	MB	LM	M	M	LM	LM	M
LM	B	LM	M	MB	LM	M	M	LM	M	M	LM	LM	M	LM	LM	LM
	M	LM	M	M	LM	LM	M	LM	LM	M	LM	LM	M	L	LM	LM
	L	LM	LM	M	LM	LM	M	LM	LM	M	L	LM	LM	L	L	LM
L	B	LM	LM	M	L	LM	M	L	LM	LM	L	L	LM	L	L	L
	M	L	LM	M	L	LM	M	L	L	LM	L	L	LM	L	L	L
	L	L	LM	M	L	LM	LM	L	L	LM	L	L	L	L	L	L

After preliminary processing of the experimental results, a matrix was formed from the obtained data. Each of the 313 rows contains the results of a separate measurement of the parameters I, U, ω, T_e, and P_k corresponding to the moment of motion at the speed of 0.3 V_{max}. The data set was divided into training and control samples by 2:1.

Normalized values $\overline{I}$, $\overline{U}$, $\overline{\omega}$, $\overline{T}_e$ from the training sample were used as input variables of the fuzzy model. The normalization was aimed at bringing the values of the input variables into the interval [0, 1]; it was performed according to the expression:

$$\overline{x}_i = \frac{x_i - \min\{x\}}{\max\{x\} - \min\{x\}},\ i = \overline{1, N}, \tag{6}$$

where $\overline{x}$—the normalized parameter value; x—the measured parameter value; min $\{x\}$, max $\{x\}$—the minimum and maximum values of the corresponding set of parameter values.

The denormalization operation was applied to the normalized value of the technical state coefficient of the HPU obtained at the output of the fuzzy system:

$$P_{k\,\mathrm{mod}} = \overline{P}_{k\,\mathrm{mod}}[\max\{P_k\} - \min\{P_k\}] + \min\{P_k\}, \tag{7}$$

where $P_{k\,\mathrm{mod}}$—the denormalized value of the coefficient of the technical condition of the HPU.

The correspondence of the actual P_k and model $P_{k\,\mathrm{mod}}$ values of the technical condition coefficient of the HPU on the training and control samples is shown in Figure 1.

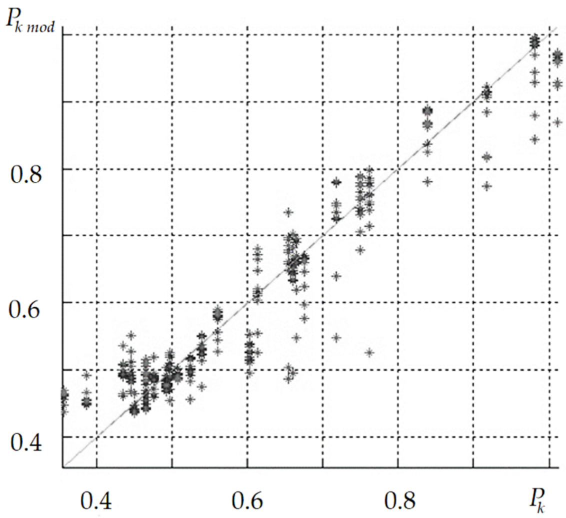

Figure 1. Testing the Mamdani fuzzy model for training.

To assess the quality of the synthesized fuzzy model, one can use the mathematical expectation M_{Pk} and the standard deviation σ_{Pk} of the discrepancy between the actual and simulated values of the HPU technical state coefficient. For the convenience of comparing the results obtained from other models, their relative values $M_{Pk\%}$ and $\sigma_{Pk\%}$ were also calculated:

$$M_{P_k\,\%} = \frac{M_{P_k}}{\max\{P_k\} - \min\{P_k\}} \cdot 100\%, \tag{8}$$

$$\sigma_{P_k\,\%} = \frac{\sigma_{P_k}}{\max\{P_k\} - \min\{P_k\}} \cdot 100\%, \tag{9}$$

The values of these quantities are given in Table 2 and indicate the insufficient quality of the created fuzzy model and the need for its modification.

Table 2. The value of the mathematical expectation and the standard deviation of the error for various methods of approximation of the dependence.

Methods		Training Subset				Control Subset			
		M_{Pk}	$M_{Pk\%}$, %	σ_{Pk}	$\sigma_{Pk\%}$,%	M_{Pk}	$M_{Pk\%}$, %	σ_{Pk}	$\sigma_{Pk\%}$,%
Model Mamdani	Before settings	0.937	1.43	0.209	13.2	0.89	2.42	0.714	32.75
	After settings	0.76	0.27	0.65	7.26	0.482	0.74	0.63	8.78
Neural network		0.03	0.004	0.42	4.05	0.463	0.71	0.50	5.41

The setting of the system serves to find such parameters of the membership functions and such weighting coefficients of the rules that minimize the deviations between the experimental values of the coefficient of the HPU technical state $\{P_k\}$ and the values $\{P_{k\,\mathrm{mod}}\}$ obtained using the fuzzy model in the training sample [25]. A large number of rules and the nonobviousness of the relationships between the parameters gives a reason to suppose that using the standard optimization functions is better than the "manual" setting of the system.

In this case, the training of the fuzzy model was carried out using the fmincon function of the Optimization Toolbox package, which is designed to solve optimization problems using the nonlinear programming method, and it works based on the least-squares method. With an increase in the number of iterations (in this case, 10 iterations were performed), the mean square of the modelling error for the normalized values of the technical condition coefficient of the HPU is:

$$D = \frac{1}{n} \cdot \sum_{i=1}^{n} \left(\overline{P}_{k\,\mathrm{mod}} - \overline{P}_k \right)^2, \tag{10}$$

where n—the number of points in the control sample.

As a result of setting the system, the spread of points (P_k, $P_{k\,\mathrm{mod}}$) decreased, which is reflected in Figure 2 and indicates the successful completion of the setting. The values of M_{Pk} and σ_{Pk} characterizing the discrepancy between the experimental data and the results of fuzzy modelling of the training and control samples also have decreased significantly.

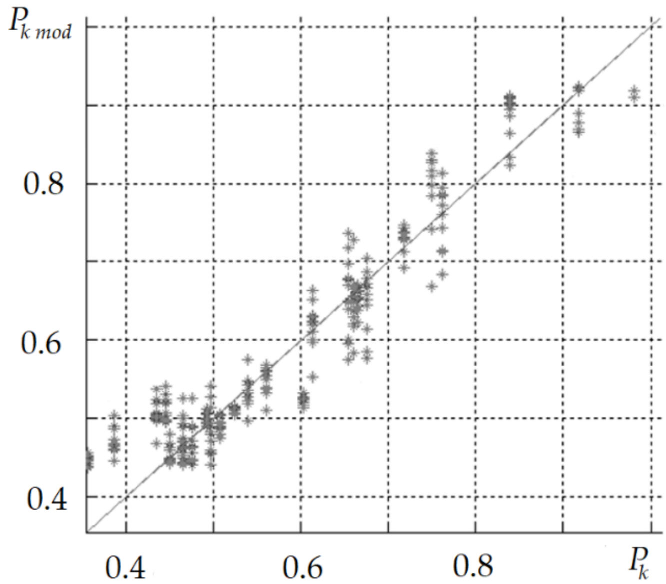

Figure 2. Setup of the Mamdani fuzzy model after setting.

5. Results of the Experimental Studies of a Power Hybrid Unit

During road tests on the car (Figure 3), the following findings were determined:

- The mode of driving on the electric traction with uniform movement and the charged battery for determining the speed of the vehicle at which the internal combustion engine is turned on, the power of the electric motor when the internal combustion engine is turned on, the power of energy recirculation through the generator. These parameters are necessary to find out the power limit of the internal combustion engine, which is irrational with uniform movement;
- The electric traction mode on a steep ascent. It is necessary to determine the maximum power of the electric motor at which the internal combustion engine is turned on regardless of the speed of movement. This parameter is also required to determine the limits of using the internal combustion engine;
- The mutual operation of the electric motor and the internal combustion engine with the uniform movement. The determination of the synergistic effect of electric powertrains as a percentage depending on the speed of movement and the energy reserve in the battery. The power of the electric motor, the speed of rotation of the crankshaft of the internal combustion engine, the fuel consumption, the speed of movement, the regeneration of the generator's energy are measured;
- The amount of power used for charging the battery and how it affects the specific fuel consumption;
- The mutual operation of the electric motor and the internal combustion engine with acceleration corresponding to the European urban cycle (up to 1 m·s^{-2}). The determination of the percentage influence of the internal combustion engine and the electric motor on the power indicators of the power unit;

- The mutual operation of the electric motor and the internal combustion engine at maximal acceleration.

Figure 3. A measuring complex in the car.

The internal combustion engine power and vehicle acceleration are measured.

Typical examples of processed measurements of energy flow distributions for various driving modes are shown in Figures 4 and 5.

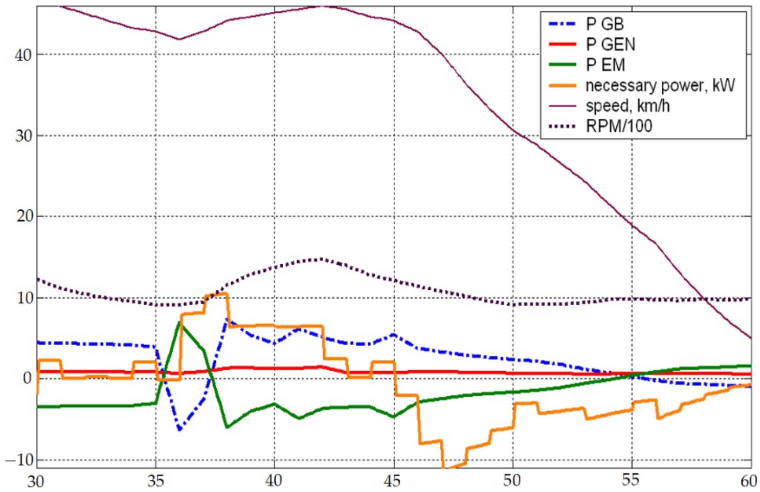

Figure 4. The distribution of energy flows from 30 to 60 s of the movement: P GB—battery power, kW; P GEN—generator power, kW; P EM—electric motor power, kW; necessary power—power required for movement or power returned during recuperation, kW; speed, km·h^{-1}; RPM/100—turnover crankshaft of the ICE/100.

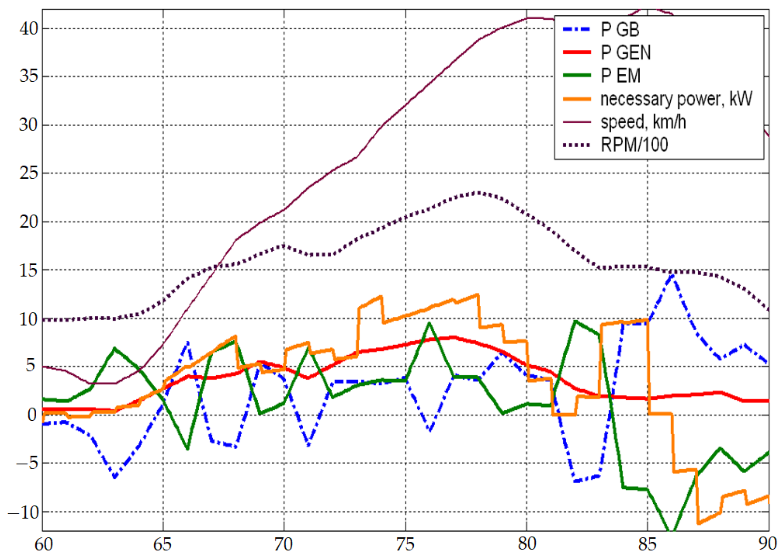

Figure 5. The distribution of energy flows from 60 to 90 s of movement: P GB—battery power, kW; P GEN—generator power, kW; P EM—electric motor power, kW; necessary power—power required for movement or that is returned during recuperation, kW; speed, km·h^{-1}; RPM/100—turnover crankshaft of ICE/100.

The research was carried out on a Prius car and it showed that an average power of 15 kW is taken for urban driving speeds of up to 40 km·h^{-1} with an accumulator battery at an acceleration of up to 1 m·s^{-2}.

The dependence of the actual amount of fuel on the injection time of the injectors at a certain speed of rotation of the crankshaft within 1000–3000 rpm was obtained to determine the experimental dependences of the amount of fuel injected by each injector during a certain period of time. The injection pressure of each injector was the same during the entire study.

The aim of the experimental studies was to determine the amount of fuel symmetrically injected by each injector during a certain period of time. Since the injection pressure of each injector is the same, the dependences on the actual amount of fuel on the injection time of the injectors at a certain crankshaft rotation speed (simulated) have been obtained as the result of the research. The fuel injection volume varied within 6–18% in the study of fuel injectors. In this case, the maximum operating time of the injectors was 40 s. The increase of the crankshaft rotation speed is carried out using a modulator (pulse regulator) and the value was observed on the tachometer of the instrument panel.

During the operation of the traction battery, not all battery modules operate at the same temperature conditions. When the battery was charging, a significant voltage difference was formed in the battery modules. This potential difference of the circuit of battery modules connected in the series tends to self-destruct and, thus, it causes self-discharge of the traction battery. It should be noted, that at the beginning of the charge carried out after a deep discharge, there is a sharper increase in the internal resistance of the traction battery than when it is fully charged.

At the initial stage of charging the traction battery, the charging current must be at least 0.15 C_{nom} of the nominal battery capacity. At the beginning of battery charging, a high difference in the charging voltage of the battery modules occurs. With further battery charging, the voltage difference across the battery modules does not appear to decrease. In this regard, there is an automatic disconnection from the battery charging when the capacity is not more than 0.6–0.7 C_{nom}.

The continued high level of the difference of the charging current of the battery modules is the reason for its high-intensity self-discharge. These reasons cause a failure of the traction battery after operating at 50–60% of its resource. The main reason for the failure of the traction battery is not the maximum depletion of the active mass material, but the abundant accumulation of hardly soluble discharge products. Battery modules fail due to leakage of the housings at high internal pressure under the influence of a high charge current.

Thus, the efficiency of using the energy approach of diagnosing the technical state of a hybrid power unit has been experimentally confirmed. The diagnostic parameters of an internal combustion engine and a traction battery are scientifically substantiated based on a computational experiment and road tests of the hybrid vehicle.

6. Generalization of the Method of Diagnostics of the Hybrid Powertrain

The efficiency of diagnosing the technical condition of a hybrid vehicle significantly depends on the selected control method of the HPU, according to its operating mode and the control of the distribution of energy between the internal combustion engine and the traction battery and depending on the technical condition of the vehicle components. This determines the need to develop new methods for diagnosing the technical state of the HPU on the basis of modern advances in the information technology. The use of the principle of a guaranteed result and a linear inversion of a vector criterion into a supercriterion for determining the technical state of the HPU on the set of the Pareto-optimal controls with unequal optimality criteria is provided. The theoretical foundations of the structural and parametric identification of the mathematical model of the technical state of the HPU is developed. A neural network model for diagnosing the technical state of the HPU is obtained, which determines the dependence on the criterion of the resource indicator on the energy consumption of a car. Vehicle speed, TB voltage and current, fuel injection time by an injector, and internal combustion engine crankshaft rotation speed are energy indicators for diagnosing the technical state of a hydraulic control system.

7. Discussion of the Results of Diagnostics of the Hybrid Power Unit

A symmetry method for diagnosing the technical condition of a hybrid power unit based on the concept of neural network control is proposed (Equation (8)). Studies have formed the theoretical basis for diagnosing and scientifically substantiating the basic diagnostic parameters of hybrid vehicles (Equation (1)).

The method for diagnosing the technical condition of a hybrid power unit differs in the fact, that it takes into account the scientific substantiation of the diagnostic parameters. The numerical value of the diagnostic parameters is confirmed by the computational experiments using the developed mathematical models.

Road tests of the vehicle are required to use the developed symmetry method for diagnosing the technical condition of a hybrid powertrain. It is necessary to use an inertial stand with running drums for an accurate assessment of the technical condition of the hybrid powertrain, which provides a vehicle speed at the stand of $0.3 \cdot V_{max}$.

It should be noted, that the need for the use an inertial rig with running drums is a disadvantage of this study.

The methodological foundations of diagnostics of the technical condition of a hybrid power unit can be used to diagnose the power unit of electric vehicles. Additional experimental studies are required to assess the technical condition of the powertrain of an electric vehicle.

8. Conclusions

The symmetry method for diagnosing the technical state of a hybrid powertrain is based on the use of an artificial neural network and a fuzzy inference system to identify the coefficient of the technical state of an internal combustion engine and a traction battery. The use of an artificial neural network provides rational characteristics of the technical state coefficient of a hybrid powertrain based on a three layer direct distribution network. The efficiency of diagnosing the technical condition of a hybrid powertrain has been increased due to the use of intelligent information and a control system. This system is invariant to different powertrains and allows to quickly identify malfunctions, as well as minimize energy or resource consumption under specified operating conditions. The proposed method can be used as a built-in diagnostic system or as an additional function in the motor tester.

9. Patents

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Nomenclature

P_k	Actual values of the technical condition coefficient of the HPU (supercriterion)
P GB	Battery power
c	Concentration factor
B	Constant coefficient of the hybrid power plant, which reflects the design features of the internal combustion engine
A	Constant coefficient of the hybrid power plant, which reflects the energy consumption for transport work
$T(\bullet)$	Degree of truth of the corresponding expression
ECU	Electronic control unit
P EM	Electric motor power
ω	Engine crankshaft rotation speed
T_e	Environment temperature
E	Fuel injector capacity
P GEN	Generator power
HPU	Hybrid powertrain
ICE	Internal combustion engine
t_i	Injection time of the fuel injector
M_{Pk}	Mathematical expectation
b	Maximum coordinate
x	Measured parameter value
$\mu(u)$	Membership function
D	Mean square of the modelling error for the normalized values of the technical condition coefficient of the HPU

min $\{x\}$, max $\{x\}$	Minimum and maximum values of the corresponding set of parameter values, respectively
Q_{min}	Minimum fuel consumption per 100 km of mileage
$P_{k\,\mathrm{mod}}$	Modal P_k values of the technical condition coefficient of the HPU
$\overline{I}$, $\overline{U}$, $\overline{\omega}$, $\overline{T}_e$, $\overline{P}_{k\,\mathrm{mod}}$, $\overline{x}$, $\overline{A}$	Normalized parameter value of I, U, ω, T_e, P_{kmod}, x, A
u	Normalized value of the corresponding variable
X_c	Number of ICE cylinders
n	Number of points in the control sample
C_{nom}	Nominal battery capacity
$M_{Pk\%}$, $\sigma_{Pk\%}$	Relative values of the mathematical expectation and standard deviation
M	Scale "average"
B	Scale "large"
LM	Scale "less than average"
MB	Scale "more than average"
L	Scale "small"
M, L, B	Scales of rules and parameters of membership functions of fuzzy terms (according to the theory of fuzzy sets)
g_e	Specific fuel consumption
σ_{Pk}	Standard deviation
V_{max}, V_c	The highest speed of the car and speed of the car at the time of diagnosis, respectively
TB	Traction battery
I	Traction battery current
U	Traction battery voltage
RPM/100	Turnover crankshaft of ICE/100

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