КОМП'ЮТЕРНІ НАУКИ

UDC 004.89
DOI https://doi.org/10.32782/2521-6643-2025-1-69.5

Aloshyn S. P., Candidate of Technical Sciences, Associate Professor, Associate Professor at the Department of Computer and Information Technologies and Systems
National University "Yuri Kondratyuk Poltava Polytechnic"
ORCID: 0009-0002-4239-4194

INTELLIGENT VEHICLE CONDITION ANALYZER BASED ON PARAMETER DYNAMICS TRENDS

The article considers the problem of timely assessment of a vehicle's technical condition based on the analysis of informative wear indicators, enabling the prevention of critical failures without the need to visit a service center. Traditional approaches to technical diagnostics, which rely on mileage or scheduled maintenance intervals, are often insufficiently effective, as they do not reflect the actual condition of vehicle components and assemblies. Therefore, an intelligent approach based on an ensemble of artificial neural networks is proposed, allowing the determination of the wear degree of major vehicle systems by analyzing the dynamics of their operational parameters.

The purpose of this research is to develop a model that enables automated classification of a vehicle's technical condition based on a set of indicators signaling potential faults. To achieve this, a representative training dataset was formed using statistical data on typical wear symptoms (such as reduced acceleration dynamics, unstable engine starting, increased fuel consumption, engine knocking, etc.), enabling the timely detection of early failure signs and determination of optimal moments for maintenance. The developed model is based on the Kolmogorov–Arnold theorem and implemented as a pattern recognition task using supervised learning methods.

Experimental results confirm the high accuracy and practical applicability of the model. The proposed neural network architecture can be adapted to different classes of vehicles. Practical application of such an analyzer reduces maintenance costs, enhances operational safety, and ensures prompt response to emerging technical issues. The developed solution can be integrated into existing hardware and software systems for vehicle condition monitoring, providing convenience, accessibility, and reliability of the diagnostic process. The results of the study promote the broader adoption of artificial intelligence technologies in the field of vehicle technical diagnostics.

Key words: *vehicle condition monitoring, intelligent diagnostics, neural networks, technical wear indicators, artificial intelligence, pattern recognition, Kolmogorov–Arnold theorem, supervised learning, input features.*

Альошин С. П. Інтелектуальний аналізатор стану автомобіля за тенденціями динаміки його параметрів

У роботі розглядається проблема своєчасної оцінки технічного стану автомобіля на основі аналізу інформативних ознак зносу, що дозволяє попередити критичні відмови без необхідності звернення до сервісного центру. Традиційні підходи до технічної діагностики, що ґрунтуються на пробігу або регламентних інтервалах, є недостатньо ефективними, оскільки не враховують реальний стан вузлів і агрегатів. У зв'язку з цим запропоновано інтелектуальний підхід на основі ансамблю штучних нейронних мереж, що дозволяє визначати ступінь зносу основних систем автомобіля за динамікою параметрів його роботи.

Метою дослідження є розробка моделі, яка забезпечує автоматизовану класифікацію технічного стану транспортного засобу на основі сукупності ознак, що сигналізують про потенційні несправності. Для цього сформовано репрезентативну навчальну вибірку з використанням статистичних даних про типові симптоми зносу (зниження динаміки розгону, нестабільний запуск двигуна, зростання витрати пального, поява детонації тощо), що дозволяє своєчасно виявляти ознаки потенційних несправностей і визначати оптимальні моменти для технічного обслуговування. Розроблена модель базується на теоремі Колмогорова–Арнольда і реалізована як задача розпізнавання образів із використанням методів навчання з учителем.

Експериментальні результати підтверджують високу точність та практичну застосовність моделі. Запропоновану нейромережеву архітектуру можна адаптувати під різні класи транспортних засобів. Практичне застосування такого аналізатора дозволяє знизити витрати на обслуговування, підвищити безпеку експлуатації та своєчасно реагувати на технічні проблеми. Розроблене рішення може бути інтегроване в існуючі програмно-апаратні системи моніторингу стану автомобіля, забезпечуючи зручність, доступність та надійність діагностичного процесу. Резуль-

тати дослідження сприяють ширшому впровадженню технологій штучного інтелекту у сфері технічної діагностики автотранспорту.

Ключові слова: *діагностика технічного стану, інтелектуальна діагностика, нейронні мережі, індикатори технічного зносу, штучний інтелект, розпізнавання образів, теорема Колмогорова–Арнольда, навчання з учителем, вхідні ознаки.*

Formulation of the problem. The average mileage of a modern vehicle before reaching critical wear of its main components typically ranges from 200,000 to 300,000 km [1]. However, this indicator may vary significantly depending on the engine quality and operating conditions. Therefore, assessing the technical condition of an engine should rely not solely on the odometer readings, but rather on informative features of potential failures and statistical data from a representative precedent database of vehicles in the same class, enabling timely detection and prevention of possible malfunctions.

It is well known that the earlier the signs of potential failures are identified, the easier, cheaper, and faster the issue can be resolved. As practice shows [1,2], even minor engine damage often leads to a cascade of further faults, which can ultimately result in complete vehicle failure. Thus, it is crucial for a vehicle owner to determine the optimal moment for maintenance or repair based on reliable statistical indicators while minimizing the risks of Type I and Type II errors [3].

Analysis of recent research and publications. A comprehensive study on the vehicle maintenance was conducted by V. D. Myhal [3], in which the structure and key functions of intelligent transportation systems were also examined.

Gong C.A. et al. [4] performed an in-depth analysis of artificial intelligence algorithms – specifically supervised learning, unsupervised learning, and reinforcement learning – in the context of vehicle failure prediction. Their work emphasizes the identification of appropriate artificial intelligence architectures for various types of vehicle system faults and highlights the strengths of each learning paradigm in addressing diagnostic and predictive challenges.

Studies dedicated to vehicle condition diagnostics explore the implementation of neural network approaches, particularly deep neural networks (DNNs), convolutional neural networks (CNNs), recurrent neural networks (RNNs), and ensemble models. These works underline a paradigm shift from reactive to predictive maintenance, especially through the integration of neural methods with conventional diagnostic techniques.

Nikitin D.M. and Rybitskyi O.M. [5] discuss the use of automaton models for processing and analyzing vehicle diagnostic data.

The purpose of the article is to enable qualified and timely assessment of a vehicle's technical condition without requiring a visit to a service center or consultation with specialists. This can save time and financial resources by utilizing intelligent analysis of retrospective precedent data for vehicles of the corresponding class.

Given the capabilities of modern technical data analysis software and the availability of sufficient statistical data in databases, the stated problem is addressed through the synthesis of an ensemble of neural network models. These models are trained on a representative sample of examples and serve as an independent tool for recognizing the degree of wear and determining the optimal timing for preventive maintenance [6].

The main goal of this study is to develop an effective neural network model for identifying the technical condition of a vehicle and determining the optimal maintenance schedule while minimizing the risk of Type I and Type II errors [6].

Presenting main material. Mathematical Problem Statement and Solution Algorithm.

The task is to establish an analytical relationship (*F*) between the informative features of potential failures (*X*) and the degree of wear (technical condition) of the vehicle's main systems. This task can be interpreted as mapping the feature space to the space of condition classes [6]:

$$F{:}X \to Y_{\text{opt}},\, X \subset \mathfrak{R}^{m},\, Y \subset \mathfrak{R}, \tag{1}$$

where X is the vector of the vehicle input condition features;

S is the vehicle's technical condition (class).

The analytical form of function F is derived based on the Kolmogorov–Arnold representation theorem, which allows expressing a multivariable function as a superposition of univariate functions. This can be transformed into a neural network format according to the Hecht-Nielsen formula [6]:

$$y(x) = \alpha \sum_{i=1}^{M} v_i \left(w_{i1}x_1 + w_{i2}x_2 + \ldots + w_{in}x_n + u_i \right), \tag{2}$$

where$M$ is training sample size;

α, v are neural network parameters:

n is number of neurons:

$w_{i1}, w_{i2}, \ldots, w_{in}$ are weight coefficients.

The task of identifying the weight coefficients is reduced to training the neural network (or an ensemble of models with various architectures and complexities) on a representative dataset. The goal is to achieve the required recognition accuracy within acceptable errors on both training and test sets. This can be formally described as:

$$\max A(S, X) \quad at\ \delta \le \delta_0 \tag{3}$$

where $A(S, X)$ – decision rule for recognizing class S in feature space X;
S – set of technical condition levels to be recognized;
X – set of input features;
δ – training and testing error rate;
δ_0 – maximum allowable error.

Upon training completion, the network is capable of implementing an optimal pattern recognition algorithm according to hypothesis testing theory, accepting a feature vector of the examined object as input.

The input feature set X and the class alphabet S implement recognition rule [6]:

$$\omega_g \in \Omega_k \text{, if } L(\omega, \{\omega_g\}) = \sup{}_i L(\omega, \{\omega_i\}) \tag{4}$$

$$L(\omega, \{\omega_g\}) \to \omega_g \in \Omega_k,$$

where
$L(\omega, \{\omega_g\})$ – classification rule assigning an object with features X to a class in S;
S – set of classes (vehicle condition states).

According to the Kolmogorov–Arnold theorem and the network training algorithm, there exists a set of parameters H, n, α, ν_i, u_i such that the function F can be approximated by (2) over the entire domain with established small error. This allows the relationship between features and condition classes to be implemented using a three-layer neural network [6, 7].

Training Sample Formation

The informative features indicating the degree of vehicle wear are represented as a vector comprising the following characteristics [1,2]:

- reduced acceleration dynamics (by 25% compared to nominal),
- low oil pressure (indicated on the dashboard),
- increased engine oil consumption,
- unstable engine start and fluctuating RPM,
- low compression of the fuel-air mixture,
- uneven idling,
- increased fuel consumption,
- increased engine knock during operation,
- engine overheating.

Vehicle condition is classified into two example classes:
0 – acceptable condition,
1 – critical condition.

The feature values may be quantitative or nominal (symbolic). A fragment of the training sample is shown in Fig. 1.

1 Var1	2 Var2	3 Var3	4 Var4	5 Var5	6 Var6	7 Var7	8 Var8	9 Var9	10 Var10
1	0	1	1	1	0	1	0	0	1
0	0	0	1	1	0	1	0	0	0
0	0	0	0	0	1	0	0	0	0
0	0	0	0	0	0	0	1	1	0
1	0	0	1	1	0	0	0	0	0
1	1	0	1	1	1	1	1	0	1
0	1	0	1	1	1	1	1	1	1

Fig. 1. Fragment of the training sample for the neural network

Network Architecture Configuration and Training

Initial settings for training modes, architectures, and learning methods are selected based on the chosen data analysis software. Weight coefficient optimization is performed via combination search using the backpropagation algorithm with various modifications [6–7]:

$$w_{hq}^{(n)}(t) = w_q(t-1) + \Delta w_{hq}^{(n)}(t), \tag{5}$$

$$w_q(t-1) = w_q(t) + \alpha \cdot \frac{\partial E(k)}{\partial w_q(t)}$$

where w – set of weight coefficients at layer n;
n – layer number;
q – neuron number in the n-th layer;
h – input number of the neuron in the n-th layer.

The synthesis of an ensemble of models with varying complexity and architecture, trained on a representative sample, made it possible to achieve satisfactory modeling accuracy. Training graphs for models with various architectures and weight adjustment methods are presented in Fig.2.

Experimental studies demonstrated stable convergence of the training process to minimum error values for each vehicle condition class. The achieved levels of performance and accuracy are acceptable for practical implementation, validating the modeling results and justifying their application in real vehicle condition diagnostics.

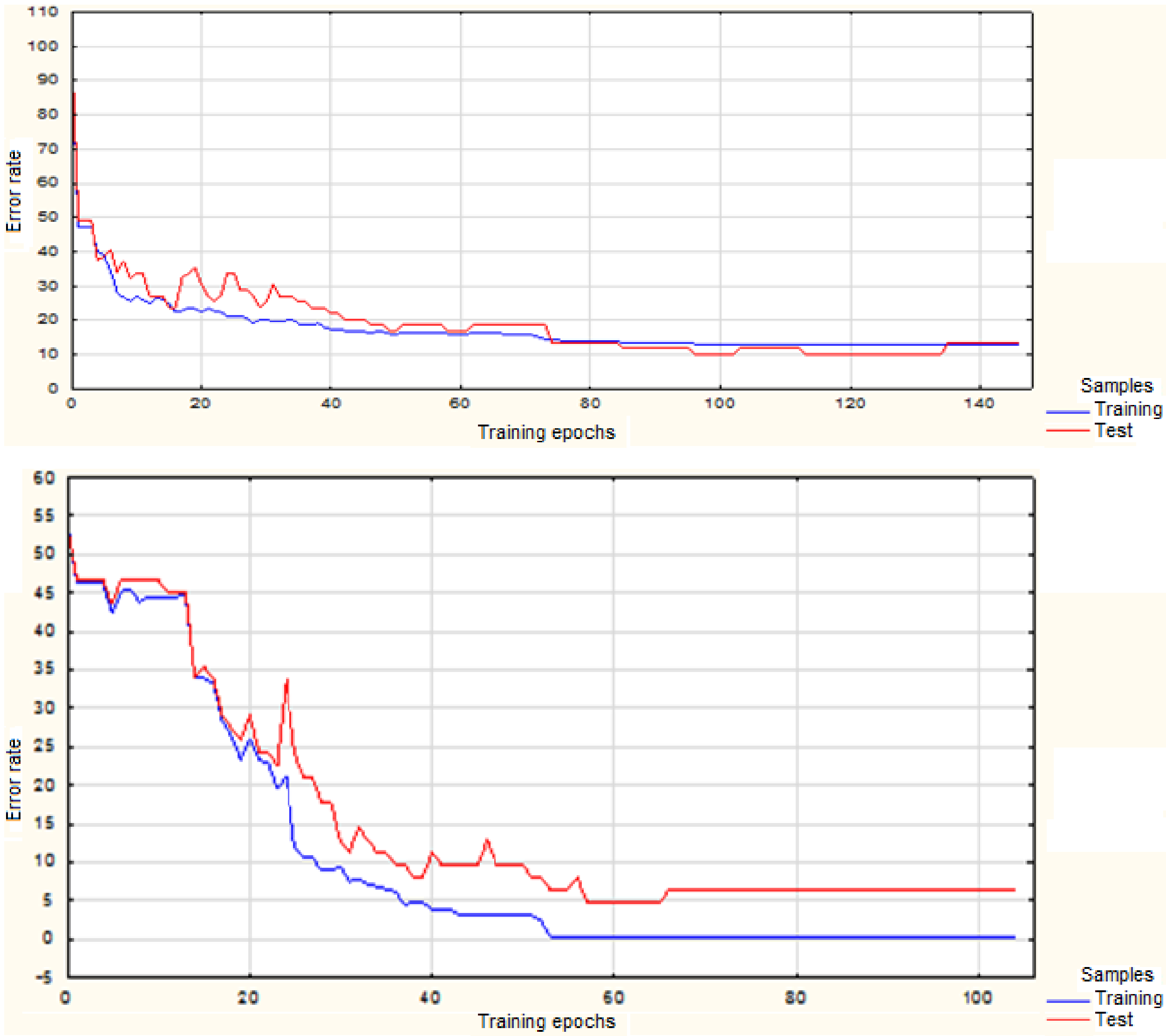

Fig. 2. Training curves of neural network models with different weight update methods, architectures, and complexity levels

Modeling confirmed the stable convergence of the iterative training process to minimum error on both training and test datasets. The performance of the synthesized models is sufficient for practical use. The task was implemented using a standard data analysis software package.

Conclusions. For the timely identification of a vehicle's technical condition, it is essential to establish a functional correlation between the state of the vehicle and its relevant input indicators. This objective was accomplished through the use of supervised learning techniques within neural networks, framed as a pattern recognition problem.

The outcomes of the study hold substantial practical value, as they contribute to the development of high-performance models for evaluating the technical state of a vehicle and supporting well-informed, prompt maintenance decisions. These decisions are made with due consideration of safety, operational reliability, diagnostic efficiency, and economic feasibility.

Functionally, the developed neural network models can be integrated as standalone components within existing technical data analysis systems.

The proposed diagnostic methodology, implemented via conventional data analysis platforms, enhances the applicability of artificial intelligence technologies in the automotive sector, broadens user accessibility, and offers a resource-efficient approach for monitoring vehicle health.

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