UDC 621.113 DOI: 10.30977/AT.2219-8342.2026.58.0.03

Neuro-fuzzy adaptive control of the power plant of an electric vehicle

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Abstract. Problem. *To date, a number of features of the IVCS for power plants of electric and hybrid vehicles remain insufficiently studied. The applied methods of analysis and synthesis of IVCS do not pay sufficient attention to the multi-criteria nature of the emerging optimization problems. Methods of adapting control to variable external operating conditions are not effective enough. These circumstances do not allow to fully realize the potential of IVCS for power plants of electric and hybrid vehicles.* ***Goal.*** *Substantiation and implementation of a comprehensive methodology for building a highly efficient system of control over technological operations and measurement of information in various types of power units of modern electric vehicles. The developed system allows for the operational synthesis of the optimal control effect and the formation of control influences in real time in accordance with the specified energy and quality efficiency criteria, with mandatory consideration of the dynamic change in external operating conditions and environmental parameters.* ***Methodology****. The methodological basis of this scientific work is a rational and balanced combination of fundamental theoretical provisions and applied experimental research. The work uses a comprehensive systemic approach to the design of an information and measurement control system, which is invariant to the specifics of the design of various power units of electric vehicles. This approach provides the opportunity to quickly and flexibly solve complex tasks of coordination and control of operating modes according to a set of quality, energy and other operational criteria.* ***Results****. During the study, a mathematically based optimal control was obtained, which can be directly used in the development of clear logical rules for choosing a strategy for adaptive vehicle control. In addition, the results provide a reliable scientific justification of the key parameters, operating characteristics and functional relationships of modern systems and individual units of an electric vehicle****. Scientific novelty****. An innovative concept of mathematical modeling and multi-criteria optimization of analytical models of complex physical processes in power plants, which are critically difficult to formalize by classical methods, was formulated and proposed by presenting and approximating them in the form of artificial neural networks.* ***Practical significance****. Further development and practical implementation of the results of this study has broad potential for significant improvement of adaptive control systems for passenger and freight electric trains. The practical use of neural network adaptive criticism methods enables effective overcoming of the chronic lack of a priori information about the key parameters of the real driving cycle and changing external operating conditions, as well as compensating for the low accuracy of traditional deterministic mathematical models.*

Keywords: *electric vehicle, power plant, neural network, strategy.*

Introduction

During the operation of electric vehicles, their energy efficiency and environmental safety are largely determined by the quality of control of the power plant and the degree to which the selected control strategy corresponds to external operating conditions. This circumstance necessitates providing the information-measuring and control system (IMCS) of power plants with adaptive properties, i.e., the ability to

Citation: Bazhynova T., Soloviov M. (2026) Neuro-fuzzy adaptive control of the power plant of an electric vehicle *Automobile Transport*, (58), 23–29.
https://doi.org/10.30977/AT.2219-8342.2026.58.0.03

Received (надійшла) 13.02.2026
Revised (рецензована) 26.03.2026
Accepted (прийнята до друку) 21.04.2026
Published (опублікована) 29.05.2026

select a control strategy for the power plant units that minimizes a chosen quality functional while taking into account external operating conditions under given constraints. To date, a number of features of IMCS for electric and hybrid vehicle power plants remain insufficiently studied. The applied methods of analysis and synthesis of IMCS do not pay sufficient attention to the multi-criteria nature of arising optimization problems. Methods for adapting control to changing external operating conditions are not sufficiently effective. These circumstances do not allow full realization of the potential capabilities of IMCS for electric and hybrid vehicle power plants. This determines the relevance of improving and developing new methods for modeling and optimizing IMCS for controlling power plants of electric and hybrid vehicles based on modern control theory, vector optimization, neural network and neuro-fuzzy adaptive control.

Reference Analysis

The process of training a neural network model and a neurocontroller is considered as an optimal filtering problem using the Kalman filter. The weights of the neural network are represented as a state vector of a dynamic system. The neural network model is trained over 3000 epochs using a dataset consisting of input-output signal pairs from 20 different operating conditions of a hybrid power plant generated by a simulator. The neurocontroller is trained over 1200 epochs.

According to the results of testing the neural control method [11], the neurocontroller provides a 17% reduction in fuel consumption and reduces the variation range of the traction battery state of charge by 35%, while also minimizing emissions of toxic substances. To improve the operational characteristics of the power plant, an optimization objective function of the neurocontroller parameters is used in its current form. A disadvantage of this method is the lack of adaptation of the control strategy to changes in driving modes.

These works [9, 12, 13] are devoted to the use of a fuzzy control system for improving fuel efficiency and environmental safety of hybrid vehicles with a parallel powertrain configuration. The effectiveness of the proposed control system was tested by simulating vehicle motion under various operating conditions. When tuning the fuzzy controller to reduce nitrogen oxide emissions, said emissions decrease by 10% while fuel consumption decreases by 25%.

A drawback of this approach to power plant control is the inability to consider more than one optimality criterion when tuning the fuzzy controller, as well as the lack of adaptation to external operating conditions. The method for synthesizing a fuzzy control system for a hybrid vehicle with a parallel configuration ensures efficient redistribution of torque between the internal combustion engine and the traction electric drive based on the analysis of driver input, battery state of charge, and motor rotor speed.

The operation of the fuzzy controller is based on three principles: the state of charge of the traction battery should not be low; driver control inputs from the accelerator and brake pedals are always satisfied, except when they contradict the first principle; optimization of the overall efficiency of the main components of the hybrid power plant, provided it does not contradict the first two principles.

The optimal battery state of charge is determined by the minimum internal resistance. If the battery is discharged below this value, an active charging mode is activated by taking part of the power from the internal combustion engine. If the battery is charged above the optimal value, it is used in the electric drive to generate traction.

These control principles of the hybrid power plant are implemented as a rule base of fuzzy inference in the fuzzy controller, which is the main element of the control system.

Purpose and Tasks

The purpose of this work is to improve the efficiency of vehicle operation by implementing a methodology for the operation of an intelligent information and control system for various electric vehicle power plants, which enables rapid synthesis of control actions based on energy and quality criteria while considering external conditions.

To achieve this goal, it is necessary to scientifically substantiate the development of a methodology for the operation of an intelligent information control system that is invariant to different electric vehicle power plants and allows prompt control of operating modes according to quality, energy, and other criteria.

Adaptive control of an electric vehicle power plant

In cases where preliminary training of a neurocontroller for an adaptive automatic control system of the EV power plant using a reference model is difficult, a neuro-fuzzy network can be used to calculate the utilization coefficient of the electric drive. In this case, initialization of the neuro-fuzzy controller $\varepsilon=F_{GSU.KR}(x_{FC})$, with input vector $x_{FC}=[\omega, \theta_{TAB}, M_{GSU.zd}]^T$, involves the use of a priori expert knowledge of a qualitative nature about the power plant control process, formalized as fuzzy production rules.

Subsequent adaptation of power plant control strategies to the current driving cycle is carried out by training the neuro-fuzzy controller similarly to previous approaches. The controller $F_{GSU.KR}$ may have the structure proposed by L. Wang and J. Mendel. Functionally, the Wang–Mendel network is a special case of the Takagi–Sugeno–Kang fuzzy inference model, where conclusions are represented as zero-order polynomials and the algebraic product operator is used as an aggregator.

On the other hand, the Wang–Mendel network can also be considered as a Mamdani fuzzy inference system with singleton membership functions for the rule base conclusion terms, using centroid defuzzification and algebraic product for conjunction during aggregation.

It has been proven that, with proper parameter selection, the fuzzy inference system with this structure is capable of approximating any nonlinear multivariable function with arbitrary accuracy.

The inference system involves introducing linguistic variables w^L, θ^L_{TAB}, $M^L_{GSU.zd}$, corresponding to the neuro-fuzzy controller $F_{GSU.FC}$. The input linguistic variables form this vector

$$x^L_{FC}=\left[\omega^L,\theta^L_{TAB},M^L_{GNU.zd}\right]^T=\left\{x^L_{FC.i}\right\} \quad (1)$$

$$i=\overline{1,3}$$

These variables are defined on basic term sets $\{T_{ji}\}$, $j=\overline{1,N_{T.i}}$, where $N_{T.i}$ is the amount of terms in term sets corresponding to the i-th linguistic variable.

Each of the values (terms) of each linguistic variable is represented by a fuzzy variable in the form of a Gaussian membership function with center c_T and variance 6_T

$$\mu_{T_{ji}}\left(x^L_{FC.i},\sigma_{T_{ji}},c_{T_{ji}}\right)=\exp\left[\frac{-\left(x_{FC.i}-c_{T_{ji}}\right)^2}{2\sigma^2_{T_{ji}}}\right] \quad (2)$$

where $x_{FC.i}$ represents carriers of the corresponding fuzzy sets:

$$x_{FC.i}\in\left[0,w_{\max}\right],\ x_{FC.2}\in\left[0,1\right],$$

$$x_{FC.3}\in\left[M_{GSU.\min},M_{GSU.\max}\right].$$

A rule base of fuzzy productions is formed to formalize a priori expert knowledge about the nature behind the control process for EV power plants, where conditions are expressed as fuzzy linguistic statements and conclusions as crisp values d_m, where m is the number of a rule, $m=\overline{1,N_p}$:P$_m$, $x^L_{FC.2}=T_{j_m1}$ і $x^L_{FC.2}=T_{j_m2}$ і $x^L_{FC.2}=T_{j_m3}$. Therefore

$$\varepsilon=d_m \quad (3)$$

where: $j_m\in\{1,2,...N_{T.i}\}$ is the term number of i-th linguistic variable involved in m-th rule.

The structure of the Wang–Mendel neuro-fuzzy network for determining the electric drive utilization coefficient is shown in Fig. 1.

The calculation of the utilization coefficient at step k is described by the corresponding expression based on the Wang–Mendel fuzzy inference algorithm

$$\varepsilon(k)=\frac{1}{\sum_m\left(\prod_i\mu_{T_{j_mi}}\left(x_{FC.i}(k)\right)\right)}\cdot$$
$$\cdot\sum_m d_m\cdot\left(\prod_i\mu_{T_{j_mi}}\left(x_{FC.i}(k)\right)\right) \quad (4)$$

In this structure, only the first and second layers are parametric. The first layer parameters (σ_{Tji} and c_{Tji}) of the membership functions of the terms of the input linguistic variables are adjustable, while the third layer contains weights d_m, interpreted as centers of output membership functions for fuzzy production rules.

The goal of training the neuro-fuzzy controller is to generate power plant control actions that minimize the quadratic value of the control quality functional.

$$E_{FC}=\frac{1}{2}*\hat{J}^2_{SV_\mu}\to\min \quad (5)$$

During training, parameter adjustment of the Wang-Mendel network is performed according to expressions

$$d_m(k+1)=d_m(k)-\lambda_{FC.d}\cdot\frac{\partial E_{FC}}{\partial\varepsilon}\cdot\frac{\partial\varepsilon}{\partial d_m}\Bigg|_{\substack{d_m=d_m(k)\\ \varepsilon=\varepsilon(k)}} \quad (6)$$

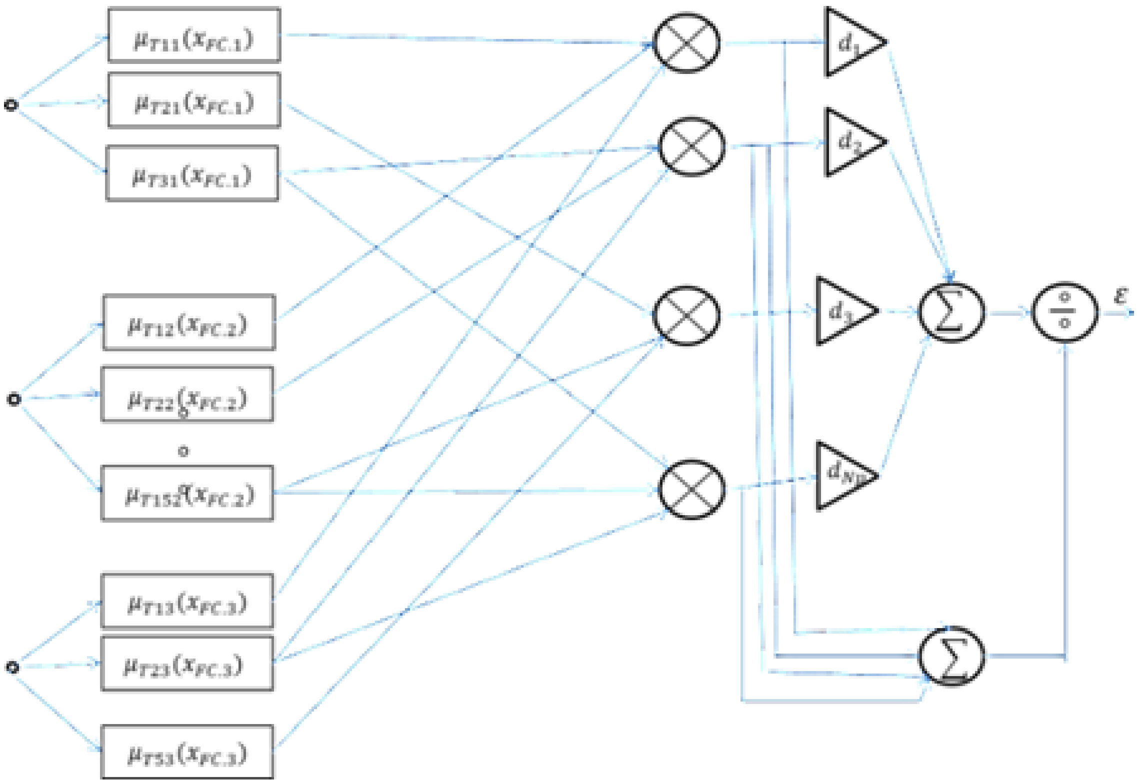

Fig. 1. The structure of the Wang–Mendel neuro-fuzzy network

$$C_{T_{jm^i}}(k+1)=C_{T_{jm^i}}(k)-\lambda_{FC.c}\cdot\frac{\partial E_{FC}}{\partial\varepsilon}\cdot\frac{\partial\varepsilon}{\partial C_{T_{ji}}}\Bigg|_{\substack{C_{T_{ji}}=C_{T_{ji}}(k)\\ \varepsilon=\varepsilon(k)}} \quad (7)$$

$$\sigma_{T_{jm^i}}(k+1)=\sigma_{T_{jm^i}}(k)-\lambda_{FC.\sigma}\cdot\frac{\partial E_{FC}}{\partial\varepsilon}\cdot\frac{\partial\varepsilon}{\partial \sigma_{T_{ji}}}\Bigg|_{\substack{\sigma_{T_{ji}}=\sigma_{T_{ji}}(k)\\ \varepsilon=\varepsilon(k)}} \quad (8)$$

where

$$\frac{\partial E_{FC}}{\partial\varepsilon}=\left\{W_{41}^{T}\cdot\left(W_{42}^{T}\cdot\left\{W_{51}^{T}\cdot W_{52}^{T}\cdot\hat{J}_{SV_{\mu}} * \right.\right.\right. \quad (9)$$
$$\left.\left.\left. *\left(1-N_{51}^{2}\right)\right\}_{1.2}\right)*\left(1-N_{41}^{2}\right)\right\}_{1}$$

$$\frac{\partial\varepsilon}{\partial d_m}=\frac{\exp\left[\sum_i\frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^2_{T_{jm^i}}}\right]}{\sum_m\exp\left[\sum_i\frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^2_{T_{jm^i}}}\right]} \quad (10)$$

$$\frac{\partial\varepsilon}{\partial d_m}=\sum\nolimits_m d_m\cdot\frac{\partial}{\partial d_m}\left(\frac{\prod_i\mu_{T_{jm^i}}}{\sum_m\prod_i\mu_{T_{jm^i}}}\right) \quad (11)$$

$$\frac{\partial}{\partial\sigma_{T_{ji}}}\left(\frac{\prod_i\mu_{T_{jm^i}}}{\sum_m\prod_i\mu_{T_{jm^i}}}\right)=$$
$$=\left(\sum\nolimits_m\exp\left[\sum\nolimits_i\frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^2_{T_{jm^i}}}\right]\right)^{-2}\cdot$$
$$\cdot\exp\left[\sum\nolimits_i\frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^2_{T_{jm^i}}}\right]\times$$
$$\mathrm{x}\left(\frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^2_{T_{jm^i}}}\cdot\right. \quad (12)$$
$$\cdot\sum\nolimits_m\exp\left[\sum\nolimits_i\frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^2_{T_{jm^i}}}\right]-$$
$$-\sum\nolimits_m\exp\left[\sum\nolimits_i\frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^2_{T_{jm^i}}}\right]\cdot$$
$$\left.\cdot\frac{x_{FC.i}-C_{T_{jm^i}}}{2\sigma^2_{T_{jm^i}}}\right)$$

$$\frac{\partial\varepsilon}{\partial d_m}=\sum\nolimits_m d_m\cdot\frac{\partial}{\partial\sigma_{T_{jm^i}}}\left(\frac{\prod_i\mu_{T_{jm^i}}}{\sum_m\prod_i\mu_{T_{jm^i}}}\right)$$

$$\frac{\partial}{\partial \sigma_{T_{ji}}}\left(\frac{\prod_i \mu_{T_{jm^i}}}{\sum_m \prod_i \mu_{T_{jm^i}}}\right)=$$
$$=\left(\sum_m \exp\left[\sum_i \frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^2_{T_{jm^i}}}\right]\right)^{-2}\cdot$$
$$\cdot\exp\left[\sum_i \frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^2_{T_{jm^i}}}\right]\times$$
$$\times\left(\frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^3_{T_{jm^i}}}\cdot\right. \tag{13}$$
$$\cdot\sum_m \exp\left[\sum_i \frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^2_{T_{jm^i}}}\right]-$$
$$-\sum_m \exp\left[\sum_i \frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^2_{T_{jm^i}}}\right]\cdot$$
$$\left.\cdot\frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^3_{T_{jm^i}}}\right)$$

- if the j-th term of a linguistic variable is used in the m-th rule;

$$\frac{\partial}{\partial C_{T_{ji}}}\left(\frac{\prod_i \mu_{T_{jm^i}}}{\sum_m \prod_i \mu_{T_{jm^i}}}\right)=$$
$$=\left(\exp\left[\sum_i \frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^2_{T_{jm^i}}}\right]\cdot\right.$$
$$\cdot\sum_m \exp\left[\sum_i \frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^2_{T_{jm^i}}}\right]\cdot \tag{14}$$
$$\left.\cdot\frac{x_{FC.i}-C_{T_{jm^i}}}{2\sigma^2_{T_{jm^i}}}\right)\cdot$$
$$\cdot\frac{1}{\left(\sum_m \exp\left[\sum_i \frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^2_{T_{jm^i}}}\right]\right)^2}$$

- if the j-th term of a linguistic variable is not used in the m-th rule;

$\lambda_{FC.d}$, $\lambda_{FC.c}$, $\lambda_{FC.\sigma}$ – learning speed coefficients for the neuro-fuzzy controller;

$$\frac{\partial}{\partial \sigma_{T_{ji}}}\left(\frac{\prod_i \mu_{T_{jm^i}}}{\sum_m \prod_i \mu_{T_{jm^i}}}\right)=$$
$$=\left(\exp\left[\sum_i \frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^2_{T_{jm^i}}}\right]\cdot\right.$$
$$\cdot\sum_m \exp\left[\sum_i \frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^2_{T_{jm^i}}}\right]\cdot \tag{15}$$
$$\left.\cdot\frac{x_{FC.i}-C_{T_{jm^i}}}{2\sigma^3_{T_{jm^i}}}\right)\cdot$$
$$\cdot\frac{1}{\left(\sum_m \exp\left[\sum_i \frac{-\left(x_{FC.i}-C_{T_{jm^i}}\right)^2}{2\sigma^2_{T_{jm^i}}}\right]\right)^2}$$

m' – the number of a fuzzy production rule in which the j-th term of i-th linguistic variable is used;

«*» – indicates element-wise vector multiplication.

To ensure linear ordering of the elements in the term sets of the fuzzy inference system, appropriate constraints must be imposed on the parameters, which prevent the adaptation algorithm from making, for example, the fuzzy set “low” larger than the fuzzy set “high.”

The presented expressions make it possible to adapt the control strategy of the EV power plant to the current driving cycle based on the concept of reinforcement learning for the neuro-fuzzy controller.

Conclusions

For the tractive performance determined by the specified functions of vehicle speed variation and external operating conditions, the optimal control strategy of the electric vehicle power plant can be obtained using the dynamic programming method. However, this approach does not provide a practical way to construct an automatic control system due to the need for a priori information, reference and disturbance inputs, and high computational complexity of the algorithm. The obtained optimal control can be used to develop logical rules for selecting control strategies and for scientific justification of system and unit parameters for the EV power plant.

The use of adaptive control of the EV power plant with a neural network adaptive critic allows overcoming the lack of a priori information about the parameters of the driving cycle and external operating conditions, as well as the low mathematical model accuracy. This approach provides adaptation of the EV power plant control strategy, ensuring asymptotic convergence $J_{SV} \to J^*_{SV}$ and $u \to u^*$ as $t \to \infty$, based on the concept of reinforcement learning.

To accelerate the adaptation of the control strategy, it is advisable to carry out preliminary offline training of the neurocontroller and the neural network model using a reference control model. As a reference model, control based on logical rules for strategy selection or an optimal strategy obtained by the dynamic programming method for a given driving cycle can be used.

If preliminary training of the neurocontroller of the adaptive automatic control system of the EV power plant using a reference model is impossible, the calculation of the electric power plant utilization coefficient can be implemented based on a neuro-fuzzy controller that realizes the Wang–Mendel algorithm for fuzzy inference conclusions.

Conflict of interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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Нейро-нечітке адаптивне управління силовою установкою електромобіля

Анотація. Проблема*. На сьогоднішній день низка особливостей Інтегрованої системи керування двигуном (ІСУД) для силових установок електричних та гібридних транспортних засобів залишається недостатньо вивченою. Застосовані методи аналізу та синтезу ІСУД не приділяють достатньої уваги багатокритеріальній природі нових задач оптимізації. Методи адаптації керування до змінних зовнішніх умов експлуатації є недостатньо ефективними. Ці обставини не дозволяють повною мірою реалізувати потенціал ІСУД для силових установок електричних та гібридних транспортних засобів.* ***Мета.*** *Обґрунтування та впровадження комплексної методології для побудови високоефективної системи контролю над технологічними операціями та виміром інформації у різних типах силових агрегатів сучасних електромобілів. Розроблена система дозволяє здійснювати оперативний синтез оптимального ефекту керування та формування керуючих впливів у режимі реального часу відповідно до визначених енергетичних та якісних критеріїв ефективності, з обов'язковим урахуванням динамічної зміни зовнішніх умов експлуатації та параметрів навколишнього середовища.* ***Методологія.*** *Методологічною основою даної наукової роботи є раціональне та збалансоване поєднання фундаментальних теоретичних положень і прикладних експериментальних досліджень. У роботі застосовано комплексний системний підхід до проектування інформаційно-вимірювальної системи керування, яка є інваріантною до специфіки конструктивного виконання різних силових установок електромобілів. Такий підхід забезпечує можливість оперативно й гнучко вирішувати складні завдання координації та керування робочими режимами за сукупністю якісних, енергетичних та інших експлуатаційних критеріїв.* ***Результати.*** *У ході дослідження отримано математично обґрунтоване оптимальне керування, яке може бути безпосередньо використане при розробці чітких логічних правил для вибору стратегії адаптивного керування транспортним засобом. Крім того, результати забезпечують надійне наукове обґрунтування ключових параметрів, робочих характеристик і функціональних зв'язків сучасних систем та окремих агрегатів електромобіля.* ***Наукова новизна.*** *Сформульовано та запропоновано інноваційну концепцію математичного моделювання та багатокритеріальної оптимізації аналітичних моделей складних фізичних процесів у силових установках, які критично складно формалізуються класичними методами, шляхом їх представлення та апроксимації у вигляді штучних нейронних мереж.* ***Практична значимість.*** *Подальший розвиток і практичне впровадження результатів цього дослідження має широкий потенціал для суттєвого вдосконалення систем адаптивного управління пасажирських та вантажних електропоїздів. Практичне використання методів нейромережевої адаптивної критики дає змогу ефективно подолати хронічну нестачу апріорної інформації про ключові параметри реального їздового циклу та мінливі зовнішні умови експлуатації, а також компенсувати низьку точність традиційних детермінованих математичних моделей.*

Ключові слова: *електромобіль, силова установка, нейро-мережа, стратегія.*

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