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Methodology for Training a Neuro-Fuzzy Control System for a Diesel-Generator Unit Under Variable Operating Conditions

This paper presents a methodology for constructing and training a neuro-fuzzy control system for a diesel-generator unit operating under variable railway conditions. Modern traction power units encounter significant fluctuations in operational factors such as train mass, track profile, and section length, which necessitate adaptive regulation of power output. Traditional control systems are limited in their ability to respond to complex multifactor dynamics, motivating the use of hybrid intelligent systems. The proposed approach integrates Fuzzy C-Means (FCM) clustering to determine the initial structure of the fuzzy rule base and to form Gaussian membership functions based on cluster centers. A hybrid learning strategy is implemented, combining backpropagation and stochastic gradient descent to adjust both the fuzzy and neural components of the model. This enables the system to refine membership parameters, optimize rule interactions, and adapt to nonlinearities in the operational data. The developed neuro-fuzzy model is validated using test samples not included in the training dataset. The results demonstrate high approximation accuracy and strong generalization capability, with prediction errors remaining within acceptable limits. The model effectively reproduces optimal control actions across diverse operating scenarios. The proposed methodology is suitable for integration into traction energy control systems and provides a foundation for future enhancements through expanded datasets, improved optimization algorithms, and full-scale simulation or field testing.

Keywords: *diesel-generator unit, intelligent control, neuro-fuzzy systems, machine learning, autonomous rolling stock.*

Introduction. The increasing complexity of modern railway transport systems places new demands on the efficiency, reliability, and adaptability of traction power units. Diesel-generator installations, which remain a key component of locomotive power systems on non-electrified or partially electrified lines, are required to operate under highly variable conditions that can change drastically over short distances. These variations arise primarily from fluctuations in train mass, differences in track profile, and the length of operational sections, all of which directly influence the traction load and the dynamic behavior of the power unit. Under such circumstances, maintaining stable generator operation, ensuring fuel-efficient performance, and preventing overloads becomes a multifaceted control problem.

Traditional control approaches, often based on fixed-parameter regulators or simplified analytical models, demonstrate limited effectiveness when exposed to the nonlinear and rapidly changing dynamics of real railway operation. They lack the ability to interpret complex interactions between multiple operational factors and cannot provide timely adaptation of control actions. As a result, suboptimal power distribution, increased fuel consumption, and accelerated wear of engine components are commonly observed, especially under demanding operational scenarios.

In contrast, intelligent control systems – particularly those integrating fuzzy logic and neural-network learning – offer significant advantages in handling the nonlinearities and uncertainties inherent in diesel-generator operation. Fuzzy logic enables the incorporation of expert knowledge and heuristic rules, while neural networks provide adaptability through data-driven learning. Combining these approaches within a neuro-fuzzy framework makes it possible to construct controllers capable of real-time adaptation, improved generalization, and robust performance under diverse conditions.

However, developing a high-performance neuro-fuzzy control system is a nontrivial task. It requires the proper definition of the fuzzy knowledge base, the construction of membership functions that accurately represent the operational domain, and effective training of the neural component. Furthermore, due to the heterogeneity of the input parameters – train mass, track gradient and curvature, and section length – additional challenges arise in harmonizing scales, preventing overfitting, and ensuring adequate interpretability.

In this context, the application of Fuzzy C-Means (FCM) clustering provides a systematic approach for deriving the initial fuzzy rule structure directly from operational data. When combined with hybrid optimization techniques – such as backpropagation for consequent parameters and stochastic gradient descent for membership-function tuning. This makes it possible to develop a controller that is both adaptive and data-driven.

Modern diesel-generator units used in railway transport operate under conditions of high variability in operational factors, such as changes in track profile, train mass, and section length. These conditions necessitate dynamic adaptation of control actions to ensure stable operation of the power unit, reduce fuel consumption, and enhance overall efficiency.

Traditional control systems are unable to respond promptly to complex variations in multifactor loads, which limits their adaptability and effectiveness. To address this issue, it is reasonable to employ neuro-fuzzy control systems that combine expert rules with machine-learning capabilities. However, constructing an optimal model of such systems requires determining the structure of the fuzzy knowledge base, designing membership functions, and training the neural component while accounting for operating conditions.

Therefore, the study of methods for constructing and training a neuro-fuzzy control system for a diesel-generator unit based on FCM clustering and combined optimization algorithms is of significant relevance.

Analysis of recent research and problem statement. Recent scientific developments demonstrate a growing interest in neuro-fuzzy systems and hybrid intelligent controllers for enhancing the adaptability and efficiency of energy and transport systems. ANFIS-based models have been effectively applied to railway power infrastructures, including prediction of reactive power at traction stations and load control under variable operating conditions [1]. In diesel-engine applications, optimisation-enhanced fuzzy PID controllers combined with UKF-based estimation improve speed stability and disturbance rejection [2]. Advanced neuro-fuzzy network architectures, such as fuzzy recurrent stochastic configuration networks, provide high-accuracy modelling with online adaptation for nonlinear industrial processes [3, 4].

A significant body of research focuses on integrating ANFIS controllers into power-system frequency regulation. Their effectiveness has been demonstrated in both classical LFC tasks and renewable-integrated microgrids, particularly when combined with stabilising devices such as STATCOMs [5 – 9]. In hybrid energy systems, ANFIS-based controllers are used for PV maximum power point tracking [10], power-quality enhancement in PV–battery–diesel supply systems [11], and energy-management strategies in AC and islanded microgrids [12, 13]. In wind-energy systems, hybrid ANFIS-PI controllers considerably improve the dynamic performance of DFIG-based turbines [14].

Another direction of research addresses the construction of fuzzy rule bases and membership functions using clustering-based methods. Techniques employing C-means or fuzzy C-means (FCM) clustering help reveal natural structures in experimental data and reduce dependence on expert-defined rules. Such approaches have demonstrated effectiveness in aerospace systems, robotics, and nonlinear industrial control [15, 16, 17].

In the railway domain, intelligent traction-control and decision-support systems increasingly incorporate fuzzy logic and machine-learning techniques to interpret locomotive operating modes and support driver decisions [18, 19]. Furthermore, studies on energy-recovery zones in DC traction emphasise the significant influence of train mass and track profile on power flow, highlighting the need for adaptive, data-driven control strategies [20]. Despite these advancements, most existing works address global traction-system behaviour rather than the localised control of diesel-generator units under rapidly changing operating conditions.

Several important challenges remain unresolved. Current neuro-fuzzy solutions rarely consider the combined influence of train mass, track profile, and section length when forming control actions for diesel-generator units. Many ANFIS-based systems still rely on static membership functions or heuristic tuning methods that limit adaptability. Furthermore, only a few studies incorporate FCM-based derivation of the fuzzy rule structure together with hybrid backpropagation–SGD training of both antecedent and consequent parameters, although such integration is critical for modelling complex nonlinearities in railway operations [8, 9, 15].

Thus, an important scientific gap persists: the need to develop a unified methodology for constructing and training a neuro-fuzzy control system for diesel-generator units that integrates FCM-based structure identification, normalisation of heterogeneous input parameters, and combined optimisation of neuro-fuzzy parameters. Addressing this gap is essential for improving adaptability, fuel efficiency, and dynamic stability of traction power systems operating under variable real-world railway conditions.

The purpose and tasks of the study. The purpose of this study is to develop a methodology for constructing and training a neuro-fuzzy control system for a diesel-generator unit that accounts for train mass, track profile, and section length.

The primary task is to determine the structure of the fuzzy system using FCM clustering, to design membership functions based on the cluster centers, and to implement a hybrid-training algorithm for the neural component that combines backpropagation with stochastic gradient descent.

Within the scope of the study, a universal rule base adapted to variable operating conditions is to be developed and its effectiveness evaluated at the simulation stage.

Materials and methods of research. The development of the neuro-fuzzy control system for the diesel-generator unit began with the construction of a representative training dataset, in which each element was characterized by a triplet of input parameters: train mass M, track profile P, and section length L. For every combination, the corresponding value of the optimal power-change coefficient K_{opt} was recorded.

The input variables were normalized to the interval [0, 1] in accordance with the relation

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}, \tag{1}$$

which ensured uniform scaling of the parameters and contributed to the stable performance of the clustering algorithm.

At the first stage, the structure of the fuzzy system was determined using FCM clustering. This algorithm minimizes the functional

$$J = \sum_{i=1}^{N} \sum_{j=1}^{C} \mu_{ij}^{m} \left\| X_i - V_j \right\|^2, \tag{2}$$

where N is the number of training samples;
C is the number of clusters;
V_j is the center of the j-th cluster;
μ_{ij} is the degree of membership of the i-th sample to the j-th cluster;
m is the fuzzification coefficient.

The membership degrees were updated according to the formula

$$\mu_{ij}^{m} = \left(\sum_{k=1}^{C} \left(\frac{\|X_i - V_j\|}{\|X_i - V_k\|} \right)^{\frac{2}{m-1}} \right)^{-1}, \tag{3}$$

whereas the cluster centers were computed using

$$V_j = \frac{\sum_{i=1}^{N} \mu_{ij}^{m} X_i}{\sum_{i=1}^{N} \mu_{ij}^{m}}. \tag{4}$$

The clustering results determined both the number of rules in the fuzzy system and the shapes of the membership functions of the input variables. Within the (*M*, *P*, *L*) space, a set of clusters was obtained that forms regions of stable dynamics for the diesel-generator unit.

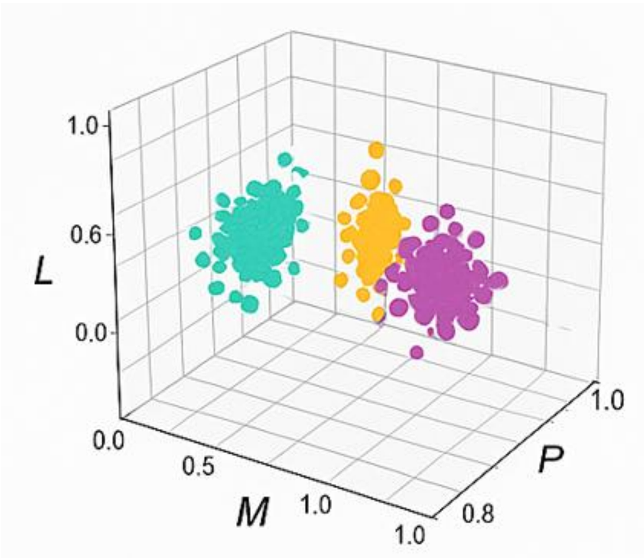

Fig. 1. **Spatial distribution of clusters in the (M, P, L) coordinates**

Based on the center $V_j = (M_j, P_j, L_j)$ of each cluster, membership functions for the fuzzy variables were constructed. Gaussian membership functions of the form were used for the input parameters

$$\mu(x, c, \sigma) = \left[-\frac{(x-c)^2}{2\sigma^2} \right], \tag{5}$$

where *c* is the center of the function, determined by the coordinate of the corresponding cluster;
σ is the width, approximated by the root mean square deviation of the set of points with the highest membership degrees.

For each rule of the ANFIS system, a fuzzy antecedent of the form

$$R_j : if \quad M \in A_j, P \in B_j, L \in C_j, \quad then \quad K_{opt} = f_j(M, P, L) \tag{6}$$

was constructed.

At the initial stage, the functions f_j were assumed to be linear

$$f_j(M, P, L) = a_j M + b_j P + c_j L + d_j, \tag{7}$$

where the coefficients a_j, b_j, and c_j were subject to subsequent training.

The constructed membership functions provided a smooth representation of the data distribution, ensuring a gradual and stable response of the system to changes in operating conditions.

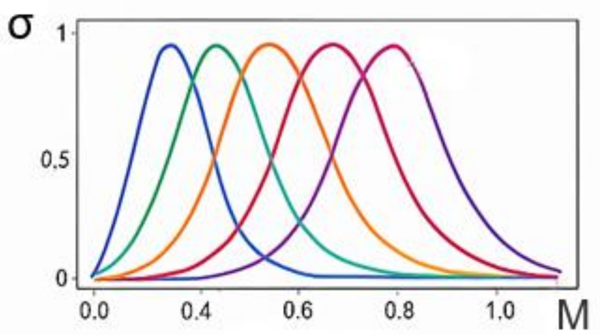

Fig. 2. **Gaussian membership functions for the variable "train mass"**

The figure 2 illustrates the set of membership functions for the input variable *train mass* used in the neuro-fuzzy control system of the diesel-generator unit. Each curve corresponds to a fuzzy term describing a specific interval of mass values (e.g., *very low*, *low*, *medium*, *elevated*, *high*, *very high*).

The values along the horizontal axis are presented in the interval from 0 to 1, which corresponds to the minimum and maximum possible mass values in the input dataset. Such normalization is necessary to ensure the correct operation of both neural and fuzzy learning procedures.

The membership degree σ represents how strongly the current mass value corresponds to a particular fuzzy term. A value of $\sigma=1$ indicates full membership, whereas $\sigma=0$ denotes no membership.

The curves overlap so that, for any specific mass value, two or more membership functions are activated simultaneously. This provides smooth transitions between operating modes, eliminates abrupt changes in control actions, and enhances the adaptive power-adjustment capabilities of the diesel-generator unit.

These functions have Gaussian or near-Gaussian shapes, allowing the system to respond gently to changes in mass and improving the learning performance of the ANFIS-type structure.

Membership functions determine how the system perceives train mass not as a strict numerical value, but as a linguistic variable. This enables adaptive adjustment of generator power depending on the train weight, supports the formation of rules such as "if the mass is high, increase traction," and allows mass information to be integrated with other parameters such as track profile and railway-section length.

The construction of membership functions for the input parameters, including train mass, is a fundamental stage in the development of the fuzzy control system, as it is at this level that numerical values are transformed into linguistic terms subsequently used in the inference mechanism. The membership functions shown in the figure represent the distribution of possible states of the *train mass* variable within the normalized range and determine the degree to which each value belongs to a corresponding fuzzy set. This ensures smooth system response to load variations and enables the consideration of intermediate, imprecisely defined operating conditions.

However, an individual membership function represents only a single parameter and does not capture the combined influence of multiple operational factors on the resulting control action. To construct a complete rule base, it is necessary to extend the analysis space and integrate several input variables within a unified model. For this reason, the next step involved forming a multidimensional representation in which the optimal control coefficient depends simultaneously on the track profile and the train mass.

The three-dimensional plot illustrates the outcome of integrating the membership functions into the inference structure and demonstrates how variations in two key operational parameters affect the optimal control value. In this way, the system transitions from a one-dimensional fuzzy description of a single variable to a generalized decision surface, which serves as the foundation for an adaptive and robust neuro-fuzzy control system for the diesel-generator unit.

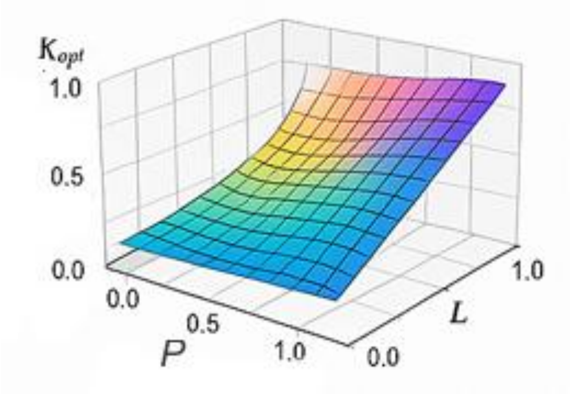

Fig. 3. **The dependence of the optimal control coefficient on track profile and railway section length**

The figure 3 presents a three-dimensional graphical representation of the dependence of the optimal control coefficient K_{opt} on two key operational parameters – track profile and railway section length. The surface shown in the plot is the result of interpolating the discrete rule base of the neuro-fuzzy system, which makes it possible to transform individual input values into a continuous functional relationship.

The P axis represents the transition from downhill to uphill conditions. During downhill operation, the diesel-generator unit requires a reduction in power output, which is reflected in lower values of K_{opt}. Conversely, during uphill operation, the demand for higher traction effort increases, leading to higher values of the control coefficient. The L axis corresponds to the railway section length, whose influence is integrative: as the length of the segment increases, the controller must compensate for cumulative effects associated with motion resistance and thermal variations in the system.

The surface demonstrates a smooth increase in the control coefficient, from lower values on descents to higher values on ascents and its further growth with increasing section length. This behavior reflects the physical logic of the traction process: the greater the inertial and external forces acting on the rolling stock, the more intensive the energy supply required from the diesel-generator unit.

The resulting surface is a key element in the formation of membership functions and the logical structure of the neuro-fuzzy knowledge base. It provides the ability to implement adaptive control in intermediate operating modes where the conditions are not strictly discrete. Thus, the figure illustrates the generalized relationship governing the variation of the optimal control action depending on the combination of track profile and route length, forming the foundation for designing an intelligent control system for traction power units.

After constructing the fuzzy component, the training of the neural part was carried out using the backpropagation method. The objective of the training process was to minimize the global error

$$E = \frac{1}{2}\sum_{i=1}^{N}\left(K_{opt,i} - \hat{K}_{opt,i}\right)^2, \tag{8}$$

where $\hat{K}_{opt,i}$ is the system response for the *i*-th sample.

The partial derivatives of the error function with respect to the parameters of the membership functions were computed according to

$$\frac{\partial E}{\partial c_j} = \sum_{i=1}^{N}\left(\hat{K}_{opt,i} - K_{opt,i}\right)\frac{\partial \hat{K}_{opt,i}}{\partial c_j}; \tag{9}$$

$$\frac{\partial E}{\partial \sigma_j} = \sum_{i=1}^{N}\left(\hat{K}_{opt,i} - K_{opt,i}\right)\frac{\partial \hat{K}_{opt,i}}{\partial \sigma_j}. \tag{10}$$

The coefficients of the linear functions a_j, b_j, c_j were updated using the stochastic gradient descent rule

$$\theta^{(t+1)} = \theta^{(t)} - \eta\frac{\partial E}{\partial \theta}, \tag{11}$$

where η is the learning rate.

The combination of FCM-based structural initialization with neural-network training enabled the development of a hybrid model capable of both generalizing the data and improving control accuracy.

The figure presents the structural model of a neural network designed for the automated determination of fuzzy membership function parameters used in the neuro-fuzzy control system of a diesel-generator unit. The depicted architecture represents a multilayer perceptron with differentiable parameters, which ensures adaptive adjustment of the shape and position of membership functions for each input factor, namely: train mass M, track profile P, and railway section length L. This enables the modelling of complex nonlinear relationships between operating conditions and the optimal control actions of the diesel-generator unit.

The first layer of the neural network consists of three inputs, each corresponding to a physical variable. At this stage, the data are provided in a normalized form, which eliminates scale differences between parameters and ensures stable learning. Each input is connected to all neurons of the hidden layer, forming a fully connected structure and enabling the network to process combinations of input factors comprehensively. In this way, the model incorporates the mutual influence of operating parameters, which is critically important for simulating the behavior of traction power systems.

The hidden layer functions as a spatial transformer of the input data, forming a multidimensional representation in which clustering and subsequent identification of fuzzy sets are performed with higher accuracy. The neurons of this layer use nonlinear activation functions, which allow the model to approximate the nonlinear characteristics of diesel-generator operation. Special attention is given to the part of the architecture enclosed in a dashed frame, which represents the subsystem responsible for adjusting membership-function parameters during training. This indicates a modular structure of the network in which the parameters of membership functions constitute a trainable subsystem separate from the main mechanism of generating control actions.

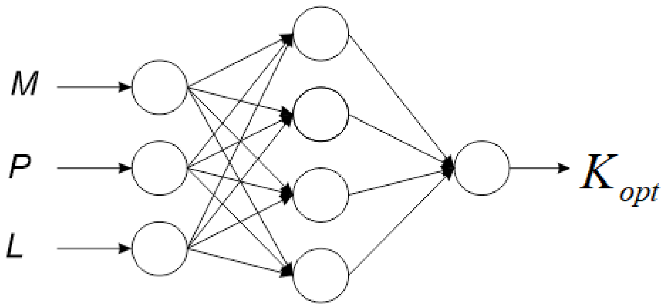

Fig. 4. **Simplified neural network architecture**

The architecture provides the system with the capability to automatically determine the parameters of fuzzy sets without relying on expert assessments. This aspect is particularly important in the context of controlling diesel-generator units of autonomous rolling stock, where decision-making must account for a wide range of operational states, including variations in train mass, track profile characteristics and segment duration. The neural component enables the formation of a generalized model describing the influence of these parameters and supports learning based on real or synthetic data obtained during simulation or actual operation.

Thus, the presented scheme reflects the adaptation mechanism of the neuro-fuzzy system, in which each parameter of a membership function is the result of an iterative optimisation process. This ensures significantly higher accuracy in forming the rule base and allows the system to efficiently determine optimal control actions for the diesel-generator unit under changing external conditions. Owing to such an architecture, full integration of artificial intelligence methods is achieved in the development of adaptive controllers for transport energy systems.

The training process of the neuro-fuzzy control system involves a staged procedure aimed at ensuring the accurate adaptation of its parameters to a wide spectrum of operating conditions of the diesel-generator unit. At the initial stage, a representative dataset is formed, incorporating input variables such as the train mass, track profile characteristics, and section length, together with corresponding optimal control actions derived from simulation models or empirical measurements. Prior to training, all input variables undergo normalization, which minimizes scale-related distortions and improves the convergence of the learning algorithms.

The system employs a hybrid learning mechanism that combines gradient-based optimization with elements of error backpropagation. Within this framework, the neural component is responsible for adjusting the parameters of membership functions (centers, widths, and slopes) while the fuzzy component ensures the logical consistency of the rule base. During each training iteration, the model evaluates the discrepancy between predicted and target control actions, computes a gradient vector, and updates differentiable parameters to minimize the loss function. This iterative refinement allows the system to capture nonlinear dependencies and interactions among the operational factors.

A significant aspect of the training process is the preservation of interpretability. Although the neural network modifies numerical parameters, the linguistic structure of the fuzzy rules remains intact, ensuring that the resulting control actions can still be interpreted within the framework of expert knowledge. The optimization process continues until the model reaches a stable configuration in which further improvements become marginal. As a result, the trained system is capable of generating adaptive control signals for the diesel-generator unit, providing improved energy efficiency, stable dynamic behavior, and robustness with respect to variations in load and track conditions.

During the training process, the parameters of the membership functions were adapted, which ensured improved fuzzification for intermediate train mass values and complex track profiles. Particular emphasis was placed on adjusting the widths of the Gaussian functions, as variations in σj directly influenced the smoothness of the system's response and the breadth of the fuzzy regions. To prevent overfitting, regularisation coefficients were applied, limiting abrupt parameter shifts and stabilising the learning trajectory.

As a result of the training procedure, a continuous approximation surface was formed, providing a coherent representation of the nonlinear dependence between the input variables and the optimal control coefficient of the diesel-generator unit.

$$\hat{K}_{opt} = F\left(M,P,L\right). \tag{12}$$

The practical implementation (fig. 5) of the developed intelligent neuro-fuzzy control system for the diesel-generator unit required the creation of a hardware complex capable of ensuring stable operation of the algorithms under real operating conditions of autonomous rolling stock. The figure shows an experimental prototype of the hardware module, which integrates tools for data acquisition, signal processing, and the generation of control actions. The structural design of the system is implemented in the form of a protected metal enclosure with anti-vibration mounting, which ensures reliable operation of the equipment in harsh transportation environments, including temperature variations, shock loads, and electromagnetic interference.

Fig. 5. **Practical Implementation of the Intelligent Control System for a Diesel-Generator Unit**

The internal structure of the hardware complex is built according to a modular principle. Each module performs a specific function - from preliminary signal filtering to the implementation of adaptive neuro-fuzzy control algorithms. The photograph on the right shows the layout of the internal bus compartment, which contains a series of standardized functional boards. These include analog-to-digital conversion modules, communication units, logic processing controllers, and a high-speed computational module responsible for executing machine-learning algorithms and fuzzy-logic operations.

The key element of the hardware complex is the computational module, which hosts the software environment supporting neuro-fuzzy logic, optimization methods, and machine learning algorithms. Unlike traditional controllers with fixed parameters, the proposed approach enables dynamic reconfiguration of fuzzy-set parameters without the need for manual intervention. As a result, the system can adapt to variations in train mass, track-profile changes, load conditions, and other operational factors that influence the performance of the diesel-generator unit.

During implementation, special attention was given to ensuring the system's reliability and fault tolerance. Each functional module is equipped with redundant power channels and hardware diagnostic mechanisms that provide autonomous fault detection and enable a safe-mode transition in the event of critical deviations.

The resulting neuro-fuzzy model demonstrated the ability to reproduce the optimal operating modes of the diesel-generator unit under various combinations of operational parameters. The validation of the model was performed by supplying control sets of input values *M*, *P*, and *L* that were not included in the training dataset. The system provided an accurate estimation of the output variable with minimal deviations, which confirms its generalisation capability.

To assess the effectiveness of the model, the prediction error was analysed

$$\varepsilon = K_{opt} - \hat{K}_{opt}, \tag{13}$$

and its average value did not exceed the established threshold of permissible deviations.

The conducted research resulted in the development of an integrated neuro-fuzzy control model for a diesel-generator unit intended for autonomous rolling stock, demonstrating the system's capability to adapt to a wide spectrum of operational conditions. The proposed architecture combines detailed physical modeling of the power plant with intelligent data-driven mechanisms, enabling dynamic adjustment of control actions in response to variations in train mass, track profile, and route length. Through the implementation of machine-learning-based adaptation of membership-function parameters and the formation of a continuous rule surface, the system achieved a high degree of flexibility and robustness, essential for traction applications characterized by significant nonlinearities and rapidly changing load regimes.

Validation using test inputs not included in the training dataset confirmed the generalization ability of the developed model. The predicted optimal control coefficients exhibited deviations that remained within prescribed tolerance limits, indicating the reliability of the neuro-fuzzy structure in reproducing realistic operating modes of the diesel-generator unit. Analysis of prediction accuracy also revealed that the most challenging scenarios correspond to steep or rapidly changing track profiles, where the system must compensate for abrupt transitions between traction and regenerative modes. Nevertheless, even under such conditions, the controller maintained stable performance due to the optimized configuration of Gaussian membership functions and the use of regularization mechanisms during training.

Overall, the created model forms a foundation for further enhancement of intelligent traction-power control systems. Prospective research directions include deepening the physical detail of subsystems, integrating more advanced neural-network architectures, and extending the optimization framework to multi-criteria formulations that simultaneously account for fuel economy, emission reduction, and dynamic stability. The obtained results demonstrate that hybrid neuro-fuzzy approaches offer substantial potential for improving the efficiency and adaptability of autonomous rolling-stock energy systems.

Conclusions. This article presents a methodology for constructing and training a neuro-fuzzy control system for a diesel-generator unit that provides adaptive power regulation depending on train mass, track profile, and section length. The proposed approach combines the FCM clustering method for forming the initial structure of the fuzzy system with a hybrid-training algorithm for the neural component based on backpropagation and stochastic gradient descent. This integration made it possible to determine the optimal number of rules, construct membership functions that reflect the patterns present in the input data, and ensure parameter adjustment during the training process.

The results of the study have shown that the use of fuzzy clustering enables proper structuring of the input space, while the combined training approach improves the accuracy of approximating the relationship between operational parameters and the optimal control action. The resulting model demonstrates the ability to generalize training data and reproduce the optimal operating modes of the power unit across a wide range of operating conditions, confirming its suitability for use in control systems of traction power installations.

Promising directions for further research include improving the algorithms for optimizing fuzzy set parameters, expanding the set of input factors through real-time operational data, integrating the model into full-scale MATLAB/Simulink simulation systems, and conducting field experiments to validate the performance of the neuro-fuzzy system under real railway operating conditions.

REFERENCES

1. Al-Hadithi, B. M., & Gómez, J. (2025). Fuzzy control and modeling techniques based on multidimensional membership functions defined by fuzzy clustering algorithms. *Applied Sciences, 15*(8), 4479. https://doi.org/10.3390/app15084479.
2. Chen, T., & Chen, J. C.-Y. (2020). Decentralized fuzzy C-means robust algorithm for continuous systems. *Aircraft Engineering and Aerospace Technology, 92*(2), 222–228.
3. Cheng, Y., Zhang, J., Al Shurafa, M., Liu, D., Zhao, Y., Ding, C., & Niu, J. (2025). An improved multiple adaptive neuro fuzzy inference system based on genetic algorithm for energy management system of island microgrid. *Scientific Reports, 15*, 17988. https://doi.org/10.1038/s41598-025-98665-x.
4. Elborlsy, M. S., Hamad, S. A., El-Sousy, F. F. M., Mostafa, R. M., Keshta, H. E., & Ghalib, M. A. (2025). Neuro-fuzzy controller based adaptive control for enhancing the frequency response of two-area power system. *Heliyon, 11*(4), e42547. https://doi.org/10.1016/j.heliyon.2025.e42547.
5. Ferdaus, M. M., Anavatti, S. G., Garratt, M. A., & Pratama, M. (2019). Development of C-means clustering based adaptive fuzzy controller for a flapping wing micro air vehicle. *Journal of Artificial Intelligence and Soft Computing Research, 9*(2), 99–109. https://doi.org/10.2478/jaiscr-2018-0027.
6. Fekry, H. M., ElDesouky, A. A., Kassem, A. M., & Abdelaziz, A. Y. (2020). Power management strategy based on adaptive neuro fuzzy inference system for AC microgrid. *IEEE Access, 8*, 192087–192100. https://doi.org/10.1109/ACCESS.2020.3032705.
7. Fu, J., Li, J., Li, Y., Dai, X., Sun, J., & Xiao, J. (2025). Research on optimization of diesel engine speed control based on UKF-filtered data and PSO fuzzy PID control. *Processes*, *13*(3), 777. https://doi.org/10.3390/pr13030777.
8. Gorobchenko, O., Holub, H., & Zaika, D. (2024). Theoretical basics of the self-learning system of intelligent locomotive decision support systems. *Archives of Transport, 71*(3), 169–186. https://doi.org/10.61089/aot2024.gaevsp41.
9. Gorobchenko, O., Zaika, D., Maliuk, S., Arkhypov, O., & Nevedrov, O. (2025). Research of theoretical basis of implementation of intelligent control systems for locomotive traction transmission. *Transport Systems and Technologies*, (45), 145-160. https://doi.org/10.32703/2617-9040-2025-45-11.
10. Hussein, H., Aloui, A., & AlShammari, B. (2018). ANFIS-based PI controller for maximum power point tracking in PV systems. *International Journal of Advanced and Applied Sciences, 5*(2), 90–96.
11. Kumar, K., Das, M., & Karn, A. K. (2024). ANFIS robust control application and analysis for load frequency control with nonlinearity. *Journal of Electrical Systems and Information Technology, 11*, 65. https://doi.org/10.1186/s43067-024-00175-9.
12. Mantalas, E.-M., Sagias, V. D., Zacharia, P., & Stergiou, C. I. (2025). Neuro-fuzzy model evaluation for enhanced prediction of mechanical properties in AM specimens. *Applied Sciences*, *15*(1), 7. https://doi.org/10.3390/app15010007.
13. Nasim, F., Khatoon, S., Ibraheem, Urooj, S., Shahid, M., Ali, A., & Nasser, N. (2025). Hybrid ANFIS-PI-based optimization for improved power conversion in DFIG wind turbine. *Sustainability, 17*(6), 2454. https://doi.org/10.3390/su17062454.
14. Oladipo, S., Sun, Y., & Adegoke, S. A. (2025). Application of soft computing techniques to load frequency control system of electric power systems: A brief survey. *Cogent Engineering, 12*(1), 2572297. https://doi.org/10.1080/23311916.2025.2572297.
15. Panoiu, M., Panoiu, C., & Mezinescu, S. (2023). Modelling and prediction of reactive power at railway stations using adaptive neuro fuzzy inference systems. *Applied Sciences*, *13*(1), 212. https://doi.org/10.3390/app13010212.
16. Rahmani, M., Arabi Nowdeh, S., & colleagues. (2018). Frequency control of islanded microgrids based on fuzzy controller equipped with STATCOM. *Journal of Renewable Energy and Environment*.
17. Selvaraju, R. K., & Somaskandan, G. (2017). ACS algorithm tuned ANFIS-based controller for LFC in deregulated environment. *Journal of Applied Research and Technology, 15*(2), 152–166. https://doi.org/10.1016/j.jart.2017.01.010.
18. Sharma, K., Menaka, C., Saraswat, N., & Kulhar, K. S. (2024). Neuro-fuzzy controllers for power quality improvement of grid connected PV-battery-diesel based hybrid supply system. *E3S Web of Conferences, 540*, 10002. https://doi.org/10.1051/e3sconf/202454010002.
19. Shynkarenko, V. I., Sablin, O. I., & Ivanov, O. P. (2016). Constructive modelling for zone of recovery energy distribution of DC traction. *Science and Transport Progress, 5*(65), 125–135. https://doi.org/10.15802/stp2016/84036.
20. Wang, D., & Dang, G. (2024). Fuzzy recurrent stochastic configuration networks for industrial data analytics. *IEEE Transactions on Fuzzy Systems*. Advance online publication. https://doi.org/10.1109/TFUZZ.2024.3511695.

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Методика навчання нейро-нечіткої системи керування дизель-генераторною установкою в умовах змінних експлуатаційних умов

Анотація. *У статті представлено комплексну методику розроблення інтелектуальної нейро-нечіткої системи керування дизель-генераторною установкою автономного рухомого складу. Дослідження спрямоване на підвищення енергоефективності, динамічної стабільності та адаптивності роботи силового агрегату в умовах значної варіативності експлуатаційних параметрів, зокрема маси поїзда, профілю колії та довжини ділянки руху. Запропоновано підхід, що поєднує кластеризацію даних за методом Fuzzy C-Means для формування базової структури нечіткої системи та використання комбінованого алгоритму машинного навчання, який містить зворотне поширення помилки і стохастичний градієнтний спуск. Це забезпечує автоматизоване налаштування параметрів функцій належності та підвищує точність моделювання нелінійних залежностей. У роботі наведено процес формування розширеної дискретної бази правил та побудови інтерпольованої поверхні керувальних дій, яка узагальнює поведінку системи в усьому робочому діапазоні параметрів. Представлено структурну схему нейро-нечіткого контролера, результати навчання та оцінювання моделі на контрольних даних. Показано, що система здатна коректно відтворювати оптимальні режими роботи дизель-генераторної установки з мінімальними відхиленнями та зберігає високі узагальнюючі властивості. Результати дослідження підтверджують ефективність поєднання методів нечіткої логіки і машинного навчання для реалізації адаптивних регуляторів у транспортних енергетичних системах та створюють підґрунтя для подальших розробок у сфері інтелектуального керування автономним рухомим складом.*

Ключові слова: *дизель-генераторна установка, інтелектуальне керування, нейро-нечіткі системи, машинне навчання, автономний рухомий склад.*

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