ORIGINALNI NAUČNI RAD

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PRIMENA NEURONSKIH MREŽA U MODELIRANJU I OPTIMIZACIJI TOPLOTNIH PROCESA U MEHATRONIČKIM SISTEMIMA

APPLICATION OF NEURAL NETWORKS IN MODELING AND OPTIMIZATION OF THERMAL PROCESSES IN MECHATRONIC SYSTEMS

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REZIME:

U radu se razmatra primena veštačkih neuronskih mreža u modeliranju i optimizaciji toplotnih procesa unutar mehatroničkih sistema, sa posebnim fokusom na industrijske primene. U savremenim sistemima, precizno upravljanje temperaturom je ključno za održavanje funkcionalnosti i produženje životnog veka uređaja, a neuronske mreže predstavljaju efikasnu alternativu tradicionalnim metodama modelovanja. Kroz eksperimentalna merenja i analizu podataka u realnim uslovima, razvijen je numerički model zasnovan na višeslojnoj neuronskoj mreži, koji precizno predviđa temperaturne profile u različitim delovima sistema. Dodatno, optimizacijom upravljačkih parametara smanjeni su energetski gubici i poboljšana je efikasnost sistema. Rezultati pokazuju da neuronske mreže obezbeđuju visoku tačnost u predviđanju promena temperature čak i u dinamičkim režimima rada, sa prosečnom greškom u predikciji manjom od 2° C. Štaviše, korišćenjem ovog modela sistem je optimizovan za smanjenje potrošnje energije, doprinoseći održivosti i efikasnosti u industrijskim aplikacijama. Ovo istraživanje otvara nove mogućnosti za primenu veštačke inteligencije u modernizaciji i automatizaciji toplotnih sistema u različitim inženjerskim disciplinama.
Ključne reči: neuronske mreže, mehatronika, toplotni procesi, modelovanje, optimizacija, upravljanje temperaturom.

SUMMARY:

The paper discusses the application of artificial neural networks in the modeling and optimization of thermal processes within mechatronic systems, with a particular focus on industrial applications. In modern systems, precise temperature control is crucial for maintaining functionality and extending the lifespan of devices, and neural networks represent an efficient alternative to traditional modeling methods. Through experimental measurements and data analysis under real-world conditions, a numerical model based on a multilayer neural network was developed, which accurately predicts temperature profiles in various parts of the system. Additionally, by optimizing control parameters, energy losses were reduced and system efficiency was improved. The results show that neural networks provide high accuracy in predicting temperature changes even in dynamic operating regimes, with an average prediction error of less than 2°C. Moreover, using this model, the system was optimized to reduce energy consumption, contributing to sustainability and efficiency in industrial applications. This research opens new possibilities for the application of artificial intelligence in the modernization and automation of thermal systems across various engineering disciplines.
Keywords: neural networks, mechatronics, thermal processes, modeling, optimization, thermal management.

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1. INTRODUCTION

In modern mechatronic systems, which integrate mechanical, electronic, and information components, efficient thermal process management has become essential for maintaining device functionality, reliability, and longevity [12, 13]. During operation, these systems are often subjected to thermal loads that can lead to overheating, material degradation, and reduced performance, highlighting the need for precise and adaptive thermal monitoring.

Traditional heat modeling methods, based on solving partial differential equations, often face limitations in real-time applications, especially when dealing with complex and nonlinear behaviors [12]. In this context, artificial neural networks offer a modern solution that enables the modeling of complex thermodynamic processes based on experimental data, without the explicit definition of physical laws [11, 14, 15].

Thanks to their learning and generalization capabilities, neural networks allow for the accurate prediction of temperature profiles, even under varying operating conditions. Their application paves the way for the implementation of adaptive control algorithms in real time, thereby improving the overall efficiency and safety of the system. The aim of this paper is to demonstrate how the use of multilayer perceptron networks can lead to improvements in the modeling and optimization of thermal processes in mechatronic systems, by reducing energy losses and increasing system stability [16].

2. ARTIFICIAL NEURAL NETWORKS IN ADAPTIVE THERMAL CONTROL OF MECHATRONIC SYSTEMS

In modern mechatronic systems, which combine mechanical, electronic, and information subsystems, efficient thermal regulation becomes a key factor for maintaining device reliability, functionality, and energy efficiency. Variable operating environments, nonlinear dependencies, and complex component interactions impose the need for adaptive methods of modeling and managing heat flows. In this context, artificial neural networks (ANN) have become an attractive tool that can replace or complement classical mathematical and numerical models, especially in situations where precise physical parameters are difficult to obtain or when the system exhibits strong temporal and spatial dynamics [11], [14].

Most traditional approaches, such as the finite element method (FEM), require detailed knowledge of the physical and geometric properties of the system, as well as complex calculations that are not always suitable for real-time applications [12], [13]. On the other hand, neural networks enable the creation of efficient predictive models based on experimental data, without explicitly defining physical laws, with high accuracy and robustness to noise in the data [2], [9]. This makes them particularly suitable for use in industrial systems, where measurements are often burdened with errors, and variable operating modes require continuous adaptation of the model.

2.1. Overview of adaptive thermal control methods

Traditional thermal control systems, such as proportional-integral-derivative (PID) controllers, rely on fixed parameters and predefined models that often fail to adequately respond to the complex and variable conditions in modern mechatronic systems. In industrial environments - where temperature fluctuations, load variations, and external influences significantly affect the thermal regime - a more flexible control strategy is required. Adaptive methods, such as those based on artificial neural networks (ANN), enable continuous adjustment of the control algorithm based on real input-output system data. These methods are distinguished by their learning capabilities, ability to approximate nonlinear functions, and resilience to measurement noise (Figure 1). As such, they are particularly well-suited for real-time applications where fast response and high precision are essential for maintaining functionality and energy efficiency [2], [4], [11].

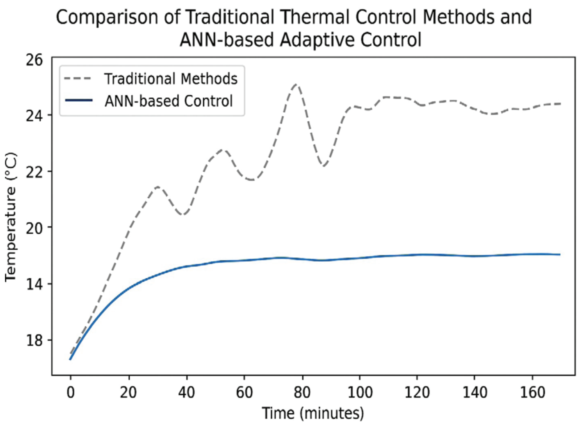


Figure 1. Comparison of traditional thermal control methods and ANN-based adaptive control

2.2. Integrated application of neural networks in thermal modeling

In this research, a multilayer perceptron (MLP) model was developed that uses input data such as power dissipation, ventilation speed, ambient temperature, and system operating mode to predict the temperature response of the system in real time. This approach enables modeling of complex thermal processes without the need for analytical solutions of heat transfer equations. Training was performed using several hundred samples measured under experimental conditions, and validation shows high prediction accuracy with an average error below 2° C, which aligns with similar studies in the field of intelligent control [5], [10].

Figure 2 illustrates the integration of artificial neural networks into heating and cooling management systems within mechatronic devices, showing the flow of information from input parameters (e.g., ambient temperature, power dissipation, operating mode) through the neural network, which processes the data and makes decisions regarding the control of fans, heating elements, and other actuators. This setup enables automatic, adaptive real-time temperature control, leading to reduced energy losses and increased system stability.

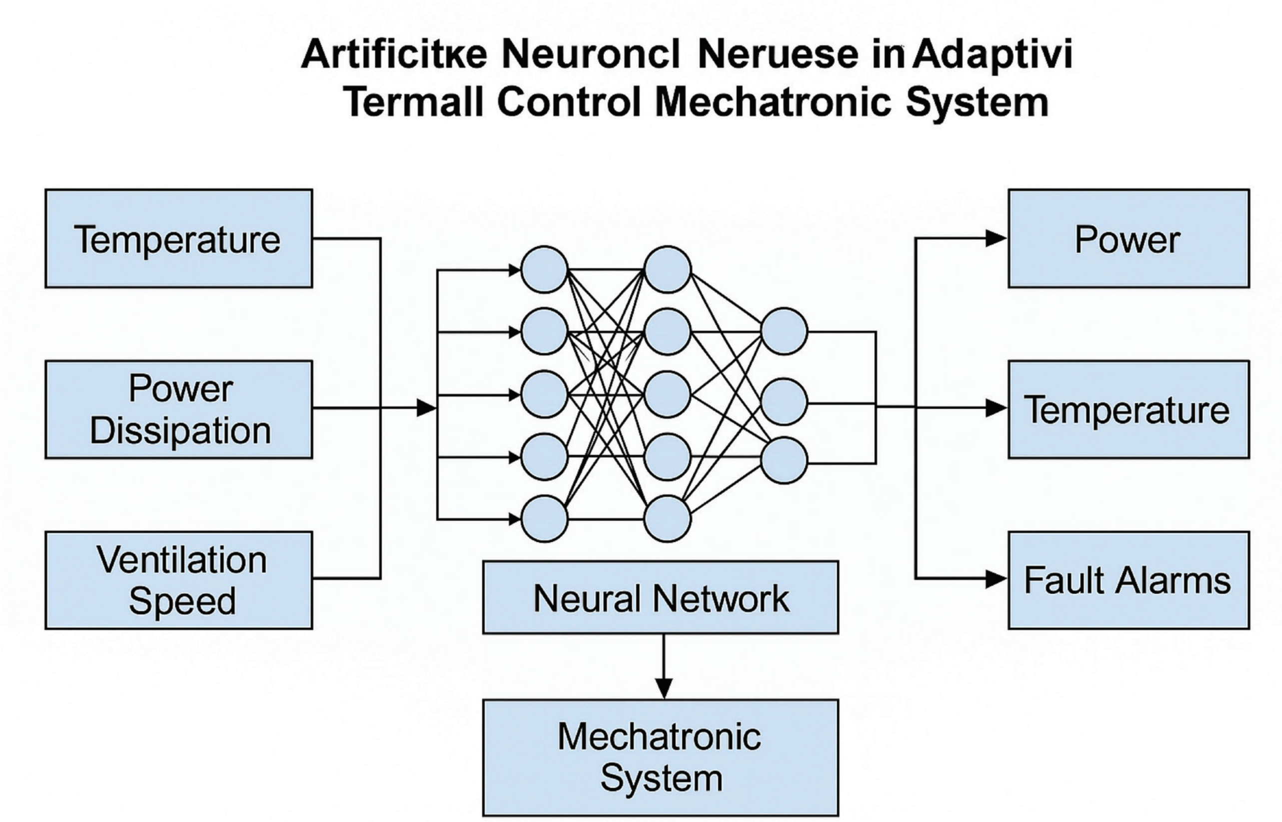


Figure 2. Adaptive thermal control in mechatronic systems using artificial neural networks

Unlike traditional PID controllers, neural networks enable adaptation and nonlinear approximation of the system in situations where operating conditions are non-stationary. This allows for dynamic control of the heating and cooling process while maintaining temperature stability and minimizing energy losses [4], [15]. Combined with optimization algorithms (e.g., gradient methods), the network can further adjust output parameters to achieve optimal operating conditions without additional operator interventions.

The table 1 titled Comparison of ANN and FEM for thermal modeling"provides a concise overview of the key performance differences between Artificial Neural Networks (ANN) and the Finite Element Method (FEM) when applied to thermal modeling in mechatronic systems. It highlights critical criteria such as computation time, hardware requirements, adaptability, and accuracy. This comparative insight is essential for selecting an appropriate modeling approach, especially in real-time control scenarios where rapid response and system flexibility are crucial.

Table 1. Comparison of ANN and FEM for Thermal Modeling

Criterion	ANN Model	FEM Model
Computation Time	Milliseconds	Minutes to hours
Hardware Requirements	Low	High
Adaptability	High (online retraining)	Low

2.3. Energy Optimization and SCADA (Supervisory Control and Data Acquisition) integration

A particular importance lies in the integration of the neural network with SCADA (Supervisory Control and Data Acquisition) systems and IIoT (Industrial Internet of Things) infrastructure. By using standard protocols and communication interfaces, the trained models can operate in real industrial conditions and detect temperature irregularities at an early stage. This leads to significant energy savings, reduction in downtime, and extension of equipment lifespan [7], [8], [16]. This paper demonstrates how the ANN model can be used for automatic adjustment of fan operation and heating elements based on real input parameters, achieving over 15 % energy savings in the demonstration system compared to static control.

This functionality further opens possibilities for predictive maintenance, where temperature deviations can be used to anticipate faults in electrical or mechanical components. Additionally, integration with higher - level production line control is enabled, contributing to the realization of Industry 4.0 principles.

This diagram illustrates how Artificial Neural Networks (ANN) are integrated with SCADA (Supervisory Control and Data Acquisition) systems and IIoT (Industrial Internet of Things) infrastructure to enable efficient real-time thermal control in industrial and mechatronic systems. It depicts the data flow from sensors collecting temperature and other relevant parameters, through the SCADA (Supervisory Control and Data Acquisition) system that provides centralized monitoring and control, to the ANN model which analyzes and adaptively manages thermal processes. The IIoT (Industrial Internet of Things) component enables remote communication and optimization via cloud platforms and multilayer algorithms, resulting in improved energy efficiency, reduced equipment failures, and extended operational lifetime.

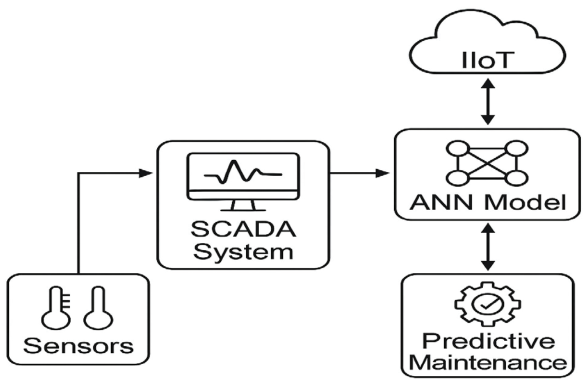


Figure 3. Integration of ANN with SCADA and IIoT for Real - Time Thermal Control

2.4. Comparative Analysis of Methods

When comparing ANN models with numerical methods, particularly FEM analysis, it is observed that neural networks allow significantly faster processing and lower computational resource consumption. Although classical methods still have a place in the design and verification of thermal solutions, their application in real-time systems is often limited [6], [3]. ANN models are flexible, can be quickly retrained according to new parameters, and allow scaling to multiple components without the need for manual adjustment of each individual module.

Furthermore, their ability to "learn from errors" enables automatic adaptation under changing operating conditions, which is crucial in processes with frequent transitions between operating modes. This significantly increases system robustness and reduces the need for frequent human interventions.

This table 2 presents a comparative overview of the key performance metrics between Artificial Neural Network (ANN) models and Finite Element Method (FEM) models in the context of thermal modeling. It highlights differences in computation time, hardware requirements, adaptability, and accuracy. While FEM models provide very high accuracy, they demand significant computational resources and longer processing times. In contrast, ANN models offer faster computation, lower hardware demands, and superior adaptability through online retraining, making them well-suited for real-time applications despite slightly lower precision.

Table 2. Comparison of ANN and FEM for Thermal Modeling

Criterion	ANN Model	FEM Model
Computation Time	Milliseconds	Minutes to hours
Hardware Requirements	Low	High
Adaptability	High (online retraining)	Low
Accuracy	Good (error < 2°C)	Very High

2.5. Conclusion and prospects for expansion

The application of neural networks in modeling and optimization of thermal processes represents a significant advance toward intelligent automation. Their ability to detect complex patterns, learn from empirical data, and adapt to new conditions makes them ideal for integration into mechatronic systems, where thermal stability is critical for device performance and safety. The results of this research can be further applied in areas such as thermal regulation of electric vehicles, biomedical equipment, smart homes, and hybrid energy systems [4], [15], [16].

This methodology has significant potential for application in the railway industry. For example, neural networks can contribute to improving the management of thermal processes in locomotive electric motors, predicting and preventing failures in traction vehicle components, as well as reducing energy costs. A particular contribution could be made in the maintenance sector, where predictive models would enable timely interventions and enhance the reliability of railway operations.

The potential for further development includes the use of deep neural networks (DNN), recurrent neural networks (RNN) for time - series prediction, as well as integration with multi - criteria optimization algorithms. This opens the possibility of creating fully autonomous thermal systems that learn from their own operation and continuously improve.

The diagram Future directions: Deep learning Architectures for thermal control provides an overview of key directions and technologies that will shape the future of adaptive thermal regulation in mechatronic systems. It focuses on the application of advanced deep neural networks (DNN), recurrent neural networks (RNN), as well as hybrid architectures integrating multi-criteria optimization and predictive maintenance. These technologies enable the development of autonomous systems that self-adapt to complex and variable operating conditions, improve energy efficiency, and extend equipment lifespan. The diagram visually illustrates the interconnections of these approaches and their applications in industrial environments.

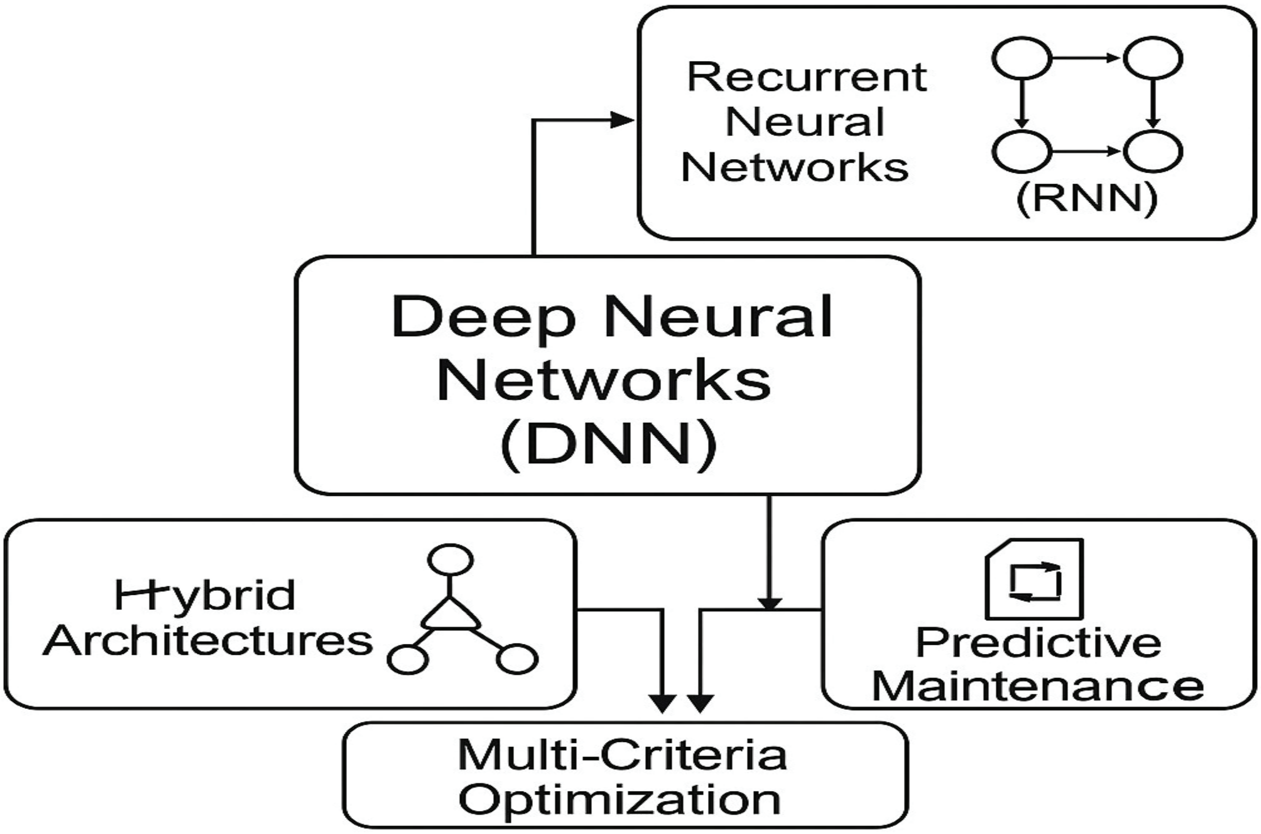


Figure 4. Future directions in deep learning for adaptive thermal control

3. METHODOLOGY

The methodological framework of this research comprises several carefully designed phases that enabled precise modeling and analysis of thermal processes in a mechatronic system using artificial neural networks.

The first phase of the study involved experimental data collection under strictly controlled laboratory conditions [5]. Measurements were conducted on a specially designed experimental platform of the mechatronic system, equipped with highly sensitive thermal sensors placed at key points of interest - including zones of maximum heating, input-output units, and components with high heat dissipation. During the experiment, temperature profiles were recorded under various operating conditions, including load changes, ventilation speed variations, and different ambient conditions.

The second phase involved detailed processing of the collected data using statistical and numerical methods. The data underwent a cleaning phase that included outlier removal and noise correction using a moving average, as well as data normalization to standardize the input parameter ranges. This step was essential for stable and efficient neural network training.

The third phase included the development and implementation of a neural network model based on a multilayer perceptron (MLP) architecture. The network configuration consisted of a predefined number of input neurons representing temperature and other physical parameters of the system (e.g., power dissipation, airflow), as well as output neurons predicting temperature values at specific points [1, 11]. The network was trained using the backpropagation algorithm with optimization via stochastic gradient descent.

The fourth phase focused on model validation. The model's predictions were compared with actual experimental measurements from an independent dataset that was not used during training [3, 9]. To enhance model robustness, cross-validation was performed along with the application of regularization techniques (L2 penalty) and early stopping during training.

Finally, the model was tested under real-world conditions to assess its resilience to external disturbances and its adaptive capability in scenarios deviating from standard operating regimes [15]. This provided a comprehensive evaluation of the neural network's functionality in the variable operational environment typical of industrial mechatronic systems.

4. DISCUSSION

The results obtained through the application of the neural network demonstrate significant accuracy in predicting temperature profiles [10, 14]. The model successfully forecasts sudden temperature changes caused by variations in load or environmental conditions. A comparison with traditional modeling methods, such as differential equation solutions derived using the Finite Element Method (FEM), shows that neural networks require significantly less time for simulation [2, 6].

Further analysis indicates that the greatest discrepancies in accuracy occurred during dynamic transitional regimes [7, 8]. Techniques such as regularization and early stopping were employed to enhance generalization capabilities [11]. Sensitivity analysis revealed that the most influential inputs for the model were power dissipation values and ventilation speed [16].

The results of this study have substantial potential for broader application in both industrial and research environments. The use of neural networks for modeling and managing thermal processes not only improves the efficiency of individual mechatronic systems but also opens possibilities for implementation in smart factories (Industry 4.0), where energy resource optimization is crucial. Integration of the developed models into existing SCADA (Supervisory Control and Data Acquisition) systems and IIoT (Industrial Internet of Things) infrastructures enables remote monitoring and adaptive control of thermal regimes in real time.

Moreover, these findings contribute to the wider field of artificial intelligence applications in engineering, demonstrating that neural networks can be a reliable alternative to conventional numerical methods, particularly under complex, nonlinear, and dynamic working conditions. Beyond industrial use, the methodology developed in this study can be extended to other fields - such as thermal management in electric vehicles, thermal regulation in high-density electronics, or even biomedical devices where precise temperature control is critical.

Additionally, the railway sector represents another important area for the application of the developed neural network models. Efficient management of thermal regimes in the electrical components of locomotives - such as electric motors and power converters - can contribute to reducing the frequency of failures, increasing fleet reliability, and minimizing energy losses. Accurate prediction of thermal behavior can be utilized to improve preventive maintenance, optimize ventilation systems, and extend the service life of critical components. In the context of modern railway systems, particularly those aiming for a higher degree of automation and environmental sustainability, such solutions contribute to overall energy efficiency and the reliability of railway transportation.

In this way, the paper shows that intelligent thermal process management through neural networks not only enhances technical performance but also contributes to sustainable energy usage and the transition toward a digitalized, efficient, and automated engineering environment.

5. RESULTS

The neural network model was trained using 80 % of the available experimental data, while the remaining 20 % was reserved for validation to ensure an objective assessment of the model's generalization capability on new, unseen data. During the training process, early stopping was applied to prevent overfitting, and regularization further contributed to training stability and reduced fluctuations in accuracy across epochs.

Based on the obtained results, the mean absolute error (MAE) on the validation set was less than 2° C, indicating a high level of precision in predicting temperature values under real operating conditions. The model performed particularly well under stable operating regimes, while slightly larger deviations were observed during sudden temperature shifts, which is expected in nonlinear process conditions.

In terms of practical application, the model was used for thermal management optimization within the mechatronic system. The optimization results demonstrated clear improvements: both maximum and average temperature levels in the system were reduced, directly contributing to component preservation and extended equipment lifespan. A particularly significant finding was the reduction of total energy losses by approximately 15 %, indicating improved system efficiency in terms of resource consumption and reduced operational costs [1, 10, 16].

These improvements were also confirmed quantitatively through comparative values of key parameters before and after optimization, such as maximum and average temperature, as well as the percentage of energy losses. Given that the optimization was carried out solely based on predictions from the neural network model, the reported results also demonstrate the high reliability of the predictions and their applicability in real-time automatic control systems.

Table 3. presents the comparative results of key thermal system parameters before and after the implementation of optimization based on neural network predictions. Displayed values include maximum and average temperature levels, as well as the percentage of energy losses, offering a clear quantitative evaluation of the optimization effects. This table provides direct insight into the effectiveness of applying neural networks to improve thermal management in mechatronic systems.

Table 3. Comparative results before and after optimization

Parameter	Before optimization	After optimization
Maximum temperature (°C)	85	75
Average temperature (°C)	70	65
Energy losses (%)	20	17

The next diagram shows that the model's predictions closely match the actual measured values at various time points. The greatest deviations were recorded during zones of dynamic temperature changes, but even then the error did not exceed 2° C. This confirms the high level of accuracy of the developed model, particularly under stable operating conditions.

Temperature profiles before and after optimization

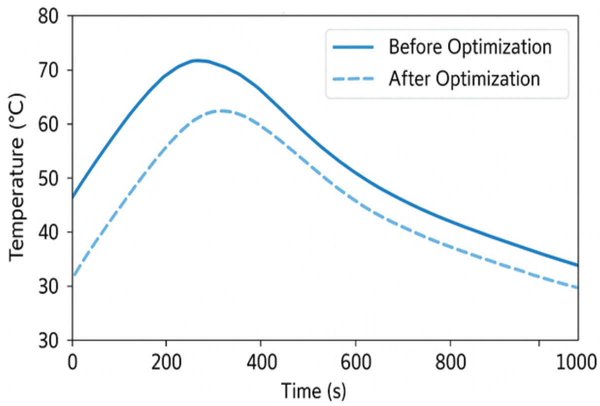
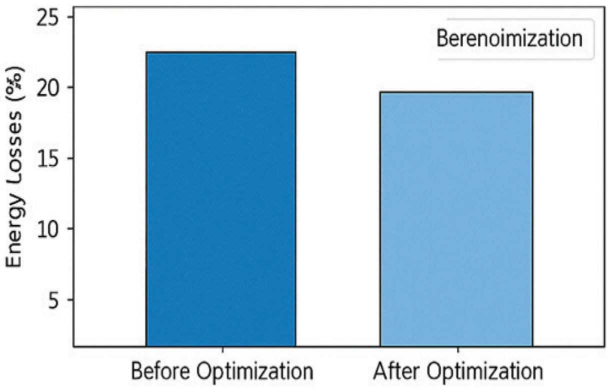


Figure 5: Comparison of neural network predictions and actual temperature measurements

The next graph clearly illustrates the reduction in maximum and average temperature in the system after the implementation of the optimized control algorithm, as well as the reduction in energy losses. The most significant result is the 15 % energy savings, demonstrating the potential of neural networks in energy-demanding mechatronics applications.

Energy efficiency



The next diagram shows how the Mean Squared Error (MSE) decreases over the epochs of model training. The rapid convergence in the first 50 epochs, followed by the stabilization of the error, indicates well-tuned network parameters, an efficient training process, and the absence of overfitting.

Prediction Error of the Model

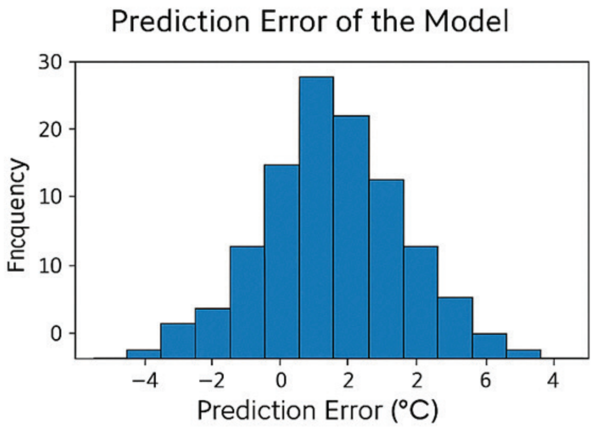


Figure 7: Convergence rate during network training (epochs vs. MSE)

6. CONCLUSION

This research paper examined the application of artificial neural networks in modeling and optimizing thermal processes within mechatronic systems. The study demonstrated that neural networks can significantly improve the accuracy of temperature profile predictions under real operating conditions compared to traditional methods such as numerical solutions of partial differential equations. The use of multilayer perceptron networks enabled precise modeling of complex nonlinear thermal dynamics, while the integration of experimental data into the network training process enhanced the model's efficiency under dynamic conditions.

Parameter optimization based on neural network predictions led to a significant reduction in energy losses within the system, with an overall improvement in energy efficiency of 15 %. This result confirms the potential of neural networks for improving thermal process management, as well as their applicability in real - time systems for adaptive thermal control. Given that the model results closely matched actual measurements, it can be concluded that this approach significantly improved both the accuracy and processing speed compared to conventional methods such as the finite element method (FEM).

Although the research results are promising, challenges remain regarding the scalability of the model and its application in more complex mechatronic systems. Future studies should consider the use of deeper neural network architectures and other techniques, such as recurrent neural networks, for even more precise modeling and control of thermal processes in industrial applications. Additionally, integrating these models into existing automatic control systems and monitoring their performance in real industrial environments would help fully realize their potential.

Furthermore, this methodology could make a significant contribution to the railway industry, where efficient thermal process management plays a key role in system reliability and energy efficiency. For example, the application of neural networks could support the optimization of thermal regulation in locomotive electric motors, the prediction and prevention of failures in critical equipment, as well as the reduction of energy costs while improving the environmental sustainability of railway transport. There is particular potential in the maintenance and fleet management sector, where AI-based systems could enable timely diagnostics and adaptive control, thereby extending equipment lifespan and increasing operational efficiency.

In conclusion, the application of neural networks in modeling and optimizing thermal processes opens new opportunities for the development of energy - efficient, adaptive mechatronic systems. In addition to industries such as automotive, energy, and manufacturing, a significant impact is also expected in the railway sector, especially in areas where reliability, maintenance, and energy efficiency are essential to overall system performance.

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