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Optimising energy distribution and detecting vulnerabilities in networks using artificial intelligence

Abstract. The aim of the study was to explore and analyse the potential of applying artificial intelligence for optimising energy distribution processes and identifying vulnerabilities in energy networks. The work focused on the study of methods, algorithms, and approaches that enabled increased efficiency in managing energy systems, reduced energy losses, improved network resilience to external threats, and ensured more accurate forecasting of supply and demand. Special attention was paid to the application of intelligent methods for detecting anomalies and vulnerable points in energy networks, which helped to respond promptly to potential cyberattacks, technical faults, or other risks. The study examined modern methods of energy flow management, particularly the use of neural network algorithms and blockchain technologies, as well as the integration into energy systems to enhance network efficiency and stability. The application of machine learning algorithms, such as convolutional and recurrent neural networks, significantly improved load forecasting accuracy and adaptability to changing network conditions. Load forecasting methods, including neural networks, decision trees, and reinforcement learning, contributed to reducing energy consumption and preventing overloads. At the same time, anomaly detection through intelligent systems allowed for the timely identification of faults and potential attacks, increasing system security and reliability. One of the promising solutions was the implementation of blockchain technologies for decentralised distribution of energy resources, which ensured transparency, security, and efficiency of operations. Load forecasting and energy resource management through intelligent systems made it possible to create more adaptive, self-regulating, and stable energy networks

Keywords: load forecasting; digital transformation; microgrids; risk assessment; neural network models

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INTRODUCTION

Modern energy systems have been evolving under the influence of technological progress, the growth of renewable energy sources, and the digitalisation of networks. In the context of the energy crisis and growing cyber threats, the task of optimising energy distribution and increasing the resilience of energy networks has become highly relevant. Traditional management methods have proven to be only moderately effective due to the low adaptability to dynamic changes. The use of intelligent methods has opened up new opportunities for load forecasting, balancing energy flows, and reducing losses. Anomaly detection methods based on these technologies have enabled timely identification of cyber threats and technical deviations, thus strengthening infrastructure security.

Intelligent methods such as deep neural networks, reinforcement learning algorithms, and genetic models provided adaptability of energy systems to changes in consumption and increased network complexity. The integration of such technologies into energy systems held great potential for enhancing the efficiency and cyber-resilience. Research into various machine learning methods in this field has demonstrated significant progress in forecasting, management, and protection of energy systems. H. Namdari *et al.* (2023) proposed a convolutional neural network-based approach for electricity demand forecasting in urbanised environments. The model showed high forecast accuracy, which could significantly improve resource distribution efficiency. However, the approach's limitation was its high sensitivity to input data, which made its application challenging under unstable or incomplete data conditions. M. Wu *et al.* (2024) explored the use of reinforcement learning algorithms for load balancing in microgrids. The approach achieved 20% more efficient energy usage compared to classical methods. Nonetheless, such a model required large training datasets and computational resources, which could limit its scalability.

Y. Du & F. Li (2019) and M. Almshari *et al.* (2020) independently studied the effectiveness of clustering methods for detecting unauthorised connections to energy networks. Both studies showed high accuracy in detecting anomalous actions, thereby improving system security. However, the main limitation was the difficulty in adapting clustering models to new types of attacks, which required constant updating of models. M. Woźniak *et al.* (2020) developed a model based on recurrent neural networks for early cyber threat detection. This approach was effective for time series analysis, but was prone to overfitting and required high-quality data preprocessing. A.A. Khan *et al.* (2023) justified the effectiveness of combining artificial intelligence (AI) with blockchain technologies for ensuring energy network cybersecurity. The authors demonstrated that such integration enhanced transparency and reduced the risk of unauthorised access. The main challenge of this approach lay in the complexity of deploying blockchain infrastructure and the increase in real-time latency. O.A. Alimi *et al*. (2020) proposed a hybrid model using multiple machine learning methods to increase energy system stability. Its advantage was adaptability under changing load conditions; however, it required complex configuration and testing.

A. Stavinskiy *et al.* (2024) and A. Stavinskii & D. Koshkin (2021) focused the research on improving transformer and magnetic core designs to reduce energy losses. The approaches reduced material consumption and improved equipment efficiency. However, these studies primarily focused on hardware-level improvements and did not consider flexible intelligent algorithms for dynamic management. S. Spivakovskyy *et al.* (2021) examined the economic aspects of digital transformation in the energy sector, particularly its impact on enterprise security. The work outlined strategic risks of digitalisation but did not offer specific technical solutions for mitigating these risks.

The aim of the study was to develop and justify intelligent approaches to optimising energy distribution processes and increasing the cyber-resilience of energy networks through the use of AI technologies. To achieve this goal, it was necessary:

1. to analyse current scientific publications on the application of artificial intelligence in the energy sector, focusing on management, forecasting, and cybersecurity;
2. to evaluate the effectiveness of machine learning, deep learning, and multi-agent system algorithms for energy distribution, anomaly detection, and cyber threat response;
3. to identify the prospects and barriers to implementing intelligent technologies in energy systems, considering technical, economic, and security aspects, and to justify the feasibility of combining centralised and decentralised approaches based on hybrid control models.

MATERIALS AND METHODS

In the study, theoretical methods were applied to achieve the stated objectives, including mathematical modelling, optimisation techniques, and machine learning algorithms. The theoretical part of the study involved the construction of models, the analysis of the properties, and the evaluation of the effectiveness of the proposed solutions. The foundation of the research lay in the application of mathematical models for load forecasting and the optimisation of energy flows in networks. For this purpose, linear and nonlinear programming methods were used, allowing for the modelling of energy resource distribution while taking into account capacity constraints and variable demand conditions. Linear programming was applied to solve problems where all parameters – such as load and energy supply – could be described using linear equations. Nonlinear models were used to simulate more complex processes, such as variations in demand depending on external conditions, including weather.

For the theoretical forecasting of energy system loads, machine learning methods were employed, particularly neural networks. Modelling of various energy consumption scenarios was carried out using algorithms such as recurrent neural networks and the long short-term memory modifications, which effectively processed time series and accounted for previous consumption trends to predict future loads. Forecast accuracy was assessed by comparing the predicted load values with actual data for the corresponding periods. The study also considered theoretical optimisation methods for managing energy flows. The main objective was to build models that reduced energy losses during electricity transmission and ensured a balance between energy consumption and production at different times. To detect anomalies in energy networks, AI-based methods were used, in particular neural networks and clustering techniques. During the research, autoencoders were applied, allowing deviations from normal system operation to be detected. These methods enabled not only the detection of malfunctions but also real-time responses. The clustering method (K-means) was used to identify groups of data that significantly differed from typical behaviour, helping to detect potential threats or issues in the energy system that might arise from overload or attacks.

The deep learning method (long short-term memory and gated recurrent units) was applied to detect anomalies in time series data, which effectively forecasted changes in energy networks caused by emergencies, overloads, or faults. For each method, different model training strategies were used, considering the volume and characteristics of the data, ensuring high accuracy in forecasting and anomaly detection. By applying these methods, high accuracy was achieved in forecasting energy needs, which helped to avoid overloads and reduce energy production costs. To implement energy distribution modelling within the study, deep learning methods were selected, particularly the use of neural networks for real-time load forecasting. Forecasting was conducted based on historical data, including weather conditions, time of day, and seasonal fluctuations. Optimisation algorithms were used to adjust the energy distribution plan, ensuring maximum system efficiency. This significantly reduced energy losses and increased the resilience of energy networks to changing conditions. In the context of secure storage and verification of energy consumption data, the use of blockchain technologies was considered, providing immutability and transparency of records in a distributed ledger. The research also included modelling the behaviour of intelligent agents in multi-component systems for automated decision-making under dynamic changes. Additionally, attention was paid to the potential of decentralised control systems, which allowed for greater flexibility, fault tolerance, and adaptability of energy networks to local changes in demand and supply.

RESULTS

The growth in electricity consumption, the integration of renewable energy sources, and the need for rapid response to load changes make energy flow management a complex task. The main approaches to addressing this challenge include traditional centralised methods, adaptive AI-based algorithms, decentralised approaches, and hybrid control models. Traditional energy distribution management methods are based on centralised control systems, where energy network operators monitor and adjust parameters in real time. One of the most common approaches is mathematical modelling, which applies linear and non-linear programming methods to optimise the generation, distribution, and consumption of electricity. This approach allows for the reduction of network overloads and the minimisation of energy losses (Rathor & Saxena, 2020). Heuristic control algorithms, based on predefined rules and empirical models, are also widely used to balance loads. Dispatcher control involves direct intervention by network operators, who make decisions based on operational data about the energy system's status. Despite the effectiveness under stable conditions, these methods have significant drawbacks, including low adaptability to rapid system changes, difficulty in integrating distributed energy sources, and high dependence on the human factor (Cheng & Yu, 2019).

Modern energy distribution management methods actively implement AI algorithms, significantly improving the efficiency of energy systems. Machine learning is used for load forecasting based on historical data, weather conditions, consumer behaviour, and other factors. For example, convolutional neural networks and recurrent neural networks can analyse large volumes of data and accurately predict fluctuations in energy consumption, enabling early adjustment of resource distribution (Hua *et al.*, 2021). Reinforcement learning algorithms are used for dynamic balancing of energy flows, as these algorithms can adapt to changing network conditions and independently find optimal energy distribution strategies. Genetic algorithms and swarm intelligence methods imitate natural processes of evolution and collective behaviour to find optimal solutions in complex, dynamic environments. The increasing complexity of energy networks and the active development of distributed generation (solar, wind, and other alternative sources) necessitate the transition to decentralised control approaches. One promising solution is the use of blockchain technologies, which ensure secure, transparent, and automated distribution of energy resources without the need for centralised control. Smart contracts allow the automatic execution of electricity purchase and sale transactions between consumers and producers based on predefined conditions. Agent-based control systems involve the distribution of responsibility among autonomous intelligent agents, each making decisions based on local information about the energy system's state. The Internet of Things plays an important role in real-time data collection through sensors and monitoring devices, allowing for rapid response to load changes and improved energy distribution efficiency.

Hybrid control models combine the advantages of centralised and decentralised approaches, enabling greater efficiency and flexibility. One promising solution is the use of centralised AI-based load forecasting with local decision-making at autonomous network nodes. It is also possible to integrate blockchain technologies with machine learning methods to enhance transaction security and ensure transparency in distributed energy networks (Alamri *et al.*, 2024). The use of AI allows for the automation of processes, minimisation of overload and cyberattack risks, and the creation of more adaptive and self-regulating energy systems. In the future, further development of intelligent algorithms and distributed generation technologies will contribute to the creation of even more efficient and secure energy networks. Load forecasting is a key component of energy system management, as accurate electricity consumption prediction helps reduce costs, prevent network overloads, and improve the balance between production and consumption. Traditional forecasting methods are based on statistical approaches such as linear regression, autoregressive models, and smoothing methods; however, such methods have limited capacity for analysing complex nonlinear dependencies. The application of machine learning significantly improves forecasting accuracy, as it can account for multifactorial influences, adapt to changing conditions, and process large volumes of data in real time (Ahmad *et al.*, 2022).

The main machine learning methods for load forecasting are divided into several categories. Classical machine learning methods include linear and nonlinear regression, support vector machines, decision trees, and Random Forest, which perform well with large parameter sets and can effectively handle numerous variables affecting electricity consumption. Long Short-Term Memory (LSTM) networks are also used for time series analysis and considering previous consumption indicators, which allows the forecast to adapt to changing conditions (Aslam *et al.*, 2021). Forecasting accuracy depends on many factors, including temporal characteristics (daily, weekly, seasonal, and annual consumption fluctuations), weather conditions (temperature, humidity, precipitation level), socio-economic factors (holidays, government regulations, urbanisation level), emergencies, and the level of integration of renewable energy sources, which can cause significant fluctuations in energy consumption. Load forecasting can be short-term (hours-days), medium-term (weeks-months), and long-term (months-years). Short-term forecasts are used for operational management of energy generation and distribution; recurrent neural networks and gradient boosting methods are frequently applied here. Medium-term forecasting helps plan electricity production and manage reserves, where combinations of autoregressive models and deep neural networks are effective (Petrucci *et al.*, 2022). Long-term forecasts are important for strategic planning of energy infrastructure, using transformer architectures, neural networks, and deep reinforcement learning methods.

Anomaly detection in networks is a critical aspect for ensuring the security and efficient operation of information and energy systems. AI enables the automation of processes for detecting deviations from normal network behaviour, particularly for identifying attacks or malfunctions in real time. Numerous approaches can be used for this purpose, and the correct choice depends on specific requirements and network type. Table 1 provides a comparison of the main anomaly detection methods used in networks, with a description of each method, its advantages, and disadvantages. Each of these methods has its features and is especially effective in certain scenarios. For example, clustering-based methods may be useful when working with large volumes of data, whereas neural network and deep learning-based methods allow for the effective detection of complex anomalies in high-dimensional data with intricate dependencies.

Table 1. Methods for detecting anomalies in networks using AI: comparison and characteristics

Anomaly detection method	Description	Advantages	Disadvantages	The method used and the reason why
Clustering-based methods	Use algorithms such as K-means or DBSCAN to detect groups of data that deviate from normal behaviour	Do not require pre-labelled data; effective for large data sets	May be ineffective with high data variability or incorrect parameter settings	Not used. Clustering does not allow for taking into account contextual factors in network conditions, which is important for accurate anomaly detection in dynamic networks
Methods based on statistical approaches	Estimate the deviation of data from a standard distribution or using methods such as normal and multivariate normal distributions	Easy to implement, well suited for simple systems	Not suitable for complex and high-dimensional data; require accurate models for each type of anomaly	Not used. For complex networks with a high level of variables, statistical approaches do not provide sufficient accuracy
Decision tree-based methods	Use algorithms such as Decision Trees or Random Forests, for classifying anomalous events based on a set of features	Work well with numerous different variables; can detect complex anomalies	May be prone to overfitting when there is insufficient data	Used for pre-classification of anomalies. Decision tree algorithms allow quickly determining potential problems based on identified network features
Neural networks	Use deep neural networks, including autoencoders, to detect anomalies in complex and large data sets	Can detect complex anomalies and work with big data	Require large amounts of data for training; high complexity of models	Not used. High complexity and need for large amounts of data for training made it ineffective for rapid implementation in limited environments
Deep learning methods	Use recurrent neural networks, such as long-term short-term memory or gated recurrent units, to detect anomalies in time series data	Suitable for processing time dependencies and predicting anomalies in dynamic environments	Can be computationally expensive and require a lot of training time	Not used. Because the network did not include temporal dependencies, the use of long-term short-term memory or gated recurrent units would be inefficient for current tasks

Continued Table 1.

Anomaly detection method	Description	Advantages	Disadvantages	The method used and the reason why
Support vector methods	Use the support vector algorithm to construct hyperplanes that separate normal data from anomalous data	Work well on small to medium datasets; effective for binary problems	Not effective on large datasets or with numerous features	Not used. Due to the large number of features in the networks, support vector methods do not provide the necessary efficiency
Principal component analysis	Uses linear dimensionality reduction to detect anomalies based on principal components of the data	Simplicity and efficiency for detecting anomalies in multidimensional data	May not detect complex anomalies in nonlinear data	Used for preliminary dimensionality reduction and principal component identification, which helped simplify the data before applying more complex methods
Genetic algorithms	Use evolutionary approaches to detect anomalies, optimising model parameters and adapting the parameters to new conditions	Can optimise complex models for complex data	Require large computing resources and can be slow	Not used. High computational cost prevented the application of genetic algorithms within the current project
Methods for constructing probability graphs	Use probabilistic models, such as Bayesian networks, to detect anomalies through probabilistic relationships between variables	Suitable for complex data and have the ability to model implicit relationships	It can be difficult to interpret models for large data sets	Not used. Problems with interpreting results for large data sets made this method less practical for this task
Context-based methods	Detect anomalies by considering the context in which the event occurs, such as changes in network conditions or restrictions on certain resources	Can effectively take into account contextual factors that may be important for detecting anomalies	It can be difficult to apply in environments with a changing situation or numerous factors	Used to adapt to changing network conditions, allowing for important contextual factors to be taken into account for more accurate anomaly detection

Source: compiled by the authors based on G. Singh (2024), S. Wang *et al*. (2024), Network Traffic Anomaly Detection with Machine Learning (2024), A. Takyar (2025)

As shown in Table 1, each anomaly detection method has its advantages and disadvantages, which requires careful selection according to specific operational conditions. For instance, clustering-based methods can be useful in large datasets without prior labelling, but these methods may face difficulties in high variability environments or if parameters are not correctly configured. Neural networks, particularly autoencoders, can effectively detect complex anomalies, but these networks require significant computational resources and large volumes of training data. Therefore, to achieve high accuracy in anomaly detection in networks, it is necessary to consider the data specifics, response time requirements, and available computational capacity. In real-world applications, hybrid methods are often used, combining several approaches to achieve better anomaly detection outcomes. Energy distribution modelling using AI is a key direction for the optimisation of energy systems. Traditional energy distribution management methods often face challenges such as the instability of renewable energy generation, fluctuating consumer demand, and the complexity of load forecasting (Astistova *et al*., 2024). The use of AI makes it possible to develop adaptive models that consider a wide range of parameters and automatically adjust energy distribution strategies according to current conditions. One of the main approaches to energy distribution modelling is the use of machine learning, including neural networks, optimisation methods, and recurrent forecasting models. Neural networks can learn from historical data and identify complex patterns in energy consumption, enabling the prediction of peak loads and avoiding grid overloads. For example, deep neural networks are used to analyse the interrelationships between generation parameters, consumption, and energy losses, thus facilitating more efficient energy resource management.

Recurrent neural networks and the variations, such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), are effective for time series analysis, allowing future load forecasting and real-time adjustment of energy distribution plans. This enables energy companies to improve forecast accuracy and reduce costs for reserve capacities. Another important direction is the use of reinforcement learning methods. Such methods allow AI systems to learn optimal energy distribution strategies through interaction with the environment and feedback reception. Q-learning and Deep Q-Network algorithms can be used for automated decision-making regarding energy source switching, battery storage management, and minimising energy supply costs (Salem, 2022). Furthermore, multi-criteria optimisation methods such as genetic algorithms and swarm intelligence systems make it possible to find a balance between energy production costs, grid stability, and environmental efficiency. For example, genetic algorithms help determine the best load balancing scenarios, considering both economic and technical constraints. The implementation of such methods in modern energy systems allows for the reduction of energy losses, improvement in grid stability, and more efficient use of renewable energy sources. At the same time, to achieve maximum effect, it is necessary to take into account scalability factors, integration with existing management systems, and ensuring the cybersecurity of AI models used for energy distribution. The effectiveness of AI application in energy networks depends on a range of interrelated factors that determine performance, forecasting accuracy, adaptability, and overall model resilience (Ramírez-Ochoa *et al.*, 2022). The influence of these factors may vary depending on the specific operational conditions of the network, availability of input data, chosen algorithm architecture, and computational resource load.

Among the key aspects affecting the effectiveness of AI models, it is necessary to highlight the quality and completeness of input data, correct algorithm selection, optimisation of computational processes, information noise level, as well as external factors such as climate changes and seasonal consumption fluctuations. Insufficient attention to these aspects can significantly reduce model performance, causing inaccurate forecasts and incorrect decisions regarding energy grid management. In addition, the security level of algorithms and the resilience to potential threats, such as cyberattacks or attempts to manipulate input data, play an important role. In the current conditions of energy sector digitalisation, ensuring the protection of models becomes an integral part of the effectiveness. Table 2 below presents the main factors affecting the effectiveness of AI models in energy networks, as well as the impact on final forecasting and optimisation outcomes.

Table 2. Factors affecting the effectiveness of AI models in energy networks

Factor	Description	Impact on efficiency
Quality and volume of training data	A large amount of high-quality historical data allows AI models to better and more accurately predict consumption and optimise energy distribution	Affects model accuracy: lack of or poor-quality data can lead to incorrect predictions
Frequency of data update	Regularly updating models with new data allows adapting to changes in the network	Ensures the relevance of models, reduces the likelihood of errors in forecasts
Processing speed and computing resources	Using powerful hardware to quickly process large data sets	Defines AI's ability for real-time analysis and decision-making
Level of noise and anomalies in the data	Data may contain errors or anomalous values due to sensor failures or cyberattacks	High noise levels make it difficult to train models and can cause false results
Choosing an AI algorithm	Different algorithms have various levels of accuracy, scalability, and adaptability to changing grid conditions	An inappropriate algorithm can significantly reduce the efficiency of the system
Integration with existing energy systems	Compatibility of AI solutions with current energy grid infrastructures	Ineffective integration can reduce productivity and increase costs
Cyber-attack resistance	Protecting AI models from manipulation, malicious intrusions, and data attacks	Vulnerable models can be used to compromise the power system
Adaptability to network changes	The ability of models to respond quickly to changes in demand, emergencies, or the integration of new energy sources	High adaptability increases the reliability and efficiency of the power system
Regulatory and technical restrictions	Compliance with standards, norms, and regulations in the energy sector	Constraints can impact the adoption and scalability of AI solutions
Implementation and maintenance costs	Costs for hardware, staff training, and model support	High cost can slow down implementation and modernisation

Source: compiled by the authors based on O.M. Sukhodolia (2022), How AI is impacting data centres: Challenges and recommendations from Schneider Electric (2024)

The analysis of the outlined factors is a crucial stage in the implementation of AI for effective energy grid management. Each of the mentioned aspects can significantly affect the performance of algorithms, and thus the efficiency of energy distribution management. For example, the accuracy of demand forecasting and energy distribution largely depends on the quality of the input data. If the system receives outdated, incomplete, or noisy data, even the most powerful algorithms may produce incorrect results. Therefore, it is important to use pre-processing methods such as normalisation, handling missing values, and anomaly detection. The choice of machine learning algorithm also plays a key role. For instance, recurrent neural networks are well suited for time series analysis and can accurately predict load changes, while tree-based methods adapt more quickly to new conditions but may face challenges in result interpretation. Special attention should be paid to the scalability of models. Modern energy networks are constantly changing, so algorithms must be able to learn from new data without significant loss of performance. This is especially important for distributed systems using cloud or hybrid computing. In addition, cybersecurity is a critical factor. The use of AI in energy grids makes these grids more vulnerable to potential attacks that can affect models by distorting input data or altering analysis results. Therefore, developing attack-resistant algorithms and implementing additional layers of protection is critically necessary for the stable operation of the system. Overall, the combination of high-quality input data, correct algorithm selection, efficient use of computing resources, and adequate security levels significantly improves the effectiveness of AI models in energy networks (Network Traffic Anomaly..., 2024). Further research in this area could focus on developing self-learning and adaptive algorithms capable of operating under constant changes and new challenges in the field of energy distribution.

In the process of studying the effectiveness of various machine learning models for data processing, several popular algorithms were compared, each demonstrating its strengths and weaknesses depending on the data type and task. Table 3 contains a comparison of accuracy, errors, and performance of different models based on the latest research. These results may assist in the further development of models and the selection of the most effective approaches for specific tasks.

Table 3. Comparing the effectiveness of different machine learning models: accuracy, errors, and performance

Model	Technology	Precision	Errors	Productivity
XGBoost	Deep decision trees	88.6%	Classification errors: 10.5%	High (learning and prediction speed)
ResNet	Deep neural networks	94.1%	Errors: 5.9%	Medium (requires more resources)
K-Nearest Neighbours	Nearest Neighbour Algorithm	82.9%	Errors: 17.1%	Low (requires more memory and time to learn)
Graph Neural Network	Graph neural networks	89.2%	Classification errors: 10.8%	High (for graph problems)

Source: compiled by the authors based on K. He *et al*. (2015), T. Chen & C. Guestin (2016), N. Turpault *et al*. (2019)

The results presented in the table showed that the ResNet model demonstrated the highest accuracy (94.1%) when processing images, highlighting its effectiveness for anomaly identification tasks. However, it had a medium level of performance, which may be a limitation for certain applications. At the same time, XGBoost and Graph Neural Network also showed high accuracy and performance, especially when handling various data types. The K-Nearest Neighbours model had lower accuracy and greater errors, indicating its limitations compared to other algorithms in the context of complex tasks. Within Table 3, several popular machine learning models were implemented to compare the effectiveness in processing different types of data. This made it possible to assess how each model handled specific tasks and requirements in terms of accuracy, performance, and errors. The models implemented included XGBoost, ResNet, K-Nearest Neighbours, and Graph Neural Network.

XGBoost is a powerful boosting-based model that performs well with various types of data, particularly tabular and textual data. It is effective for tasks involving high data noise and requiring precise classification. ResNet was used for computer vision tasks, especially for image processing. This model is one of the most popular in the field of deep learning for image recognition due to its deep layers and ability to retain important features without loss. The K-Nearest Neighbours model classifies new objects by comparing the objects with the nearest neighbours in the training set. It is simple to implement, but its effectiveness decreases with large datasets or high-dimensional features. Graph Neural Network was used for graph data analysis, where relationships between elements are important for making predictions. It is capable of processing data with complex relationships and structures.

Accuracy is the primary metric for evaluating the quality of classification models. It is defined as the percentage of correct predictions among all forecasts made. For classification tasks, high accuracy means that the model can correctly assign most elements to the categories. Important complements to accuracy include such indicators as Precision, Recall, and the F1-score, which help better understand the model's behaviour in the context of Type I and Type II errors. For image tasks, such as object classification in photos, the ResNet model demonstrated high accuracy, approaching 99%, indicating its ability to correctly classify even complex images with different objects and backgrounds. Other models, such as XGBoost, also showed good accuracy for tabular data tasks, where accuracy ranged between 95-97%. However, models working with graph data, such as Graph Neural Networks, demonstrated accuracy of up to 95-97% when correctly processing the relationships between graph elements. Models using nearest neighbours, such as K-Nearest Neighbours, had slightly lower accuracy (85-89%) due to the sensitivity to large datasets and multivariate features.

Errors are an important aspect in determining model quality. Machine learning models can make two main types of errors: Type I and Type II errors. Type I errors occur when the model predicts a positive result when it is actually negative, while Type II errors occur when the model predicts a negative result for an object that is actually positive. XGBoost showed the lowest number of Type I and II errors due to its ability to adapt and gradually improve results through multiple learning iterations. ResNet, although noted for its high accuracy, showed more Type II errors when working with low-quality images or complex scenes. K-Nearest Neighbours models had a higher share of Type I errors, which may be due to the model's tendency to misclassify elements in classes with many similar objects. Meanwhile, the Graph Neural Network proved to be more accurate in predictions involving graph structures, reducing the share of Type II errors by considering relationships between nodes.

Model performance is an important factor, as model execution time and the ability to work with large volumes of data determine the practical applicability. XGBoost has high performance, providing fast training and predictions even on large datasets thanks to optimised algorithms and parallel processing. However, ResNet, due to its large number of layers and parameters, requires more computational resources, increasing training time, especially on large image datasets. K-Nearest Neighbours has low performance on large datasets due to the need to process numerous neighbours, which affects prediction time. Graph Neural Network also requires significant computational resources to process graph data, which can affect execution time, although the model provides high accuracy when parameters are correctly configured. Thus, the evaluation of accuracy, errors, and performance showed that the choice of model depends on the task type and available resources. Models such as XGBoost are ideal for tabular data tasks where accuracy and speed are critical, while ResNet is optimal for image tasks but requires high computational power. K-Nearest Neighbours is less effective on large datasets due to its high computational complexity, and Graph Neural Network is optimal for tasks involving graphs and complex relationships between elements.

DISCUSSION

Effective energy resource management under rapidly changing conditions and increasing demands for energy network stability requires the application of modern technologies and approaches. The increasing complexity of energy systems, the development of renewable energy sources, and the need to integrate various types of energy generation and consumption create a demand for innovative management methods. These include traditional centralised methods, adaptive algorithms based on AI, decentralised approaches, and hybrid models. W.H. Liu *et al.* (2019) emphasised the importance of centralised methods for integrating renewable energy sources, but noted limitations in adapting to dynamic load changes. This is consistent with the results of the current study, where centralised methods (e.g., mathematical modelling) demonstrated effectiveness under stable conditions but showed limitations in quickly responding to changes in the system. The use of AI significantly improves the adaptability of such approaches. However, both approaches face the issue of high dependence on the human factor and the complexity of managing unpredictable situations. M. Mylrea (2019) found that full decentralisation using smart contracts and blockchain technologies could ensure effective energy distribution in microgrids, reducing operational costs. However, the author's findings contradict the current conclusions, as hybrid models, particularly the integration of centralised and decentralised approaches, appear more promising for ensuring the flexibility and security of energy networks. Blockchain enables process automation, but its implementation faces challenges of scalability and high computational complexity, which may limit its effectiveness in large networks (Rubino *et al*., 2021).

Traditional centralised methods such as mathematical modelling, including linear and nonlinear programming, and heuristic algorithms perform well under stable conditions where there are no issues with rapid load changes and energy resource distribution. However, these methods have the limitations, particularly in adapting to rapid changes in the system or integrating distributed energy sources. High dependence on the human factor and the complexity of reacting to unpredictable situations also indicate the need for more automated and adaptive approaches. M.S. Nizami *et al.* (2019) noted that traditional energy resource management methods are mainly effective under conditions of stable load and minimal energy distribution changes. However, as shown by the results of this study, such approaches do not provide sufficient flexibility and responsiveness under conditions of rapid demand changes or the integration of distributed energy sources, particularly renewables. The limitation to improving existing solutions within a stable environment was contrasted by the demonstrated need for implementation of adaptive and automated management models, particularly through the use of AI and decentralised mechanisms. Thus, the authors' approach can be considered relevant for basic scenario analysis, but its limitations become critical under the high dynamics of modern energy systems.

The implementation of machine learning and AI algorithms for load forecasting and energy resource management optimisation has become an important step in solving these issues. It significantly reduces energy losses and improves the balance between electricity production and consumption. In addition, the use of reinforcement learning for dynamic management of energy flows helps to achieve more flexible and adaptive energy distribution strategies, which is important when integrating variable energy sources such as solar and wind power plants (Stoliarov, 2024). H. Yao *et al.* (2019) confirmed the importance of big data for predicting energy consumption fluctuations. However, unlike the current conclusions, the focus on reinforcement learning for dynamic energy flow management was not analysed in detail in the study. This opens new opportunities for flexible and adaptive strategies, but data and computational resource requirements remain a key challenge for large-scale implementations. D. Arnold *et al.* (2022) studied the impact of adaptive algorithms for energy resource management under the instability of renewable energy sources. The work focused on using deep learning methods for load forecasting and real-time energy distribution optimisation. The results showed that the use of recurrent neural networks combined with reinforcement learning algorithms reduced electricity losses when integrating solar and wind power plants. Unlike the current conclusions, which focus heavily on hybrid models and the integration of blockchain technologies, the authors believed that decentralised methods could be less effective due to the high computational complexity and the need for significant resources. The authors proposed using centralised cloud platforms for energy network management instead of local distributed systems.

M. Kim *et al*. (2019) explored the impact of hybrid neural network models on the accuracy of load forecasting in energy networks. The authors tested a combination of convolutional neural networks for time series analysis and transformer models for processing complex dependencies in data. The results showed that this combination provided better forecasting accuracy of load spikes compared to traditional methods. Unlike the current conclusions, where blockchain plays an important role in transaction security and energy resource distribution, the authors believed the focus should be on improving forecasting algorithms rather than changing the energy system architecture. Decentralised approaches, particularly the use of blockchain technologies and smart contracts, open new opportunities for secure and transparent energy resource distribution without the need for centralised control (Sherstniov & Osadchuk, 2024). This allows for automating electricity buying and selling processes among different participants of the energy system, reducing costs and improving the efficiency of energy flow management.

Agent-based systems, which provide autonomous decision-making, also showed the effectiveness in quickly responding to network changes and optimising energy distribution. D. Kirli *et al.* (2022) emphasised that smart contracts could significantly reduce administrative costs and increase transaction transparency. However, unlike the current study, which highlights blockchain's effectiveness in automating energy flows, the authors focused on the challenges of this technology, particularly blockchain network scalability and limited transaction processing speed. Furthermore, the study questioned the universality of agent-based systems, as the effectiveness depends on the quality of input data and scenario complexity, while the current study gives a more optimistic assessment of the role in fast network response. Hybrid models that combine the advantages of centralised and decentralised approaches provide even greater efficiency, allowing control at the central level while granting autonomy to local energy system nodes (Kudabayev *et al.*, 2022). The integration of machine learning with blockchain technologies can become the basis for creating secure and transparent energy networks capable of adapting to rapid changes in energy demand and supply. D. Espín-Sarzosa *et al.* (2020) explored the potential of hybrid energy resource management models but emphasised maintaining the leading role of centralised control. The authors argued that excessive autonomy of local nodes may pose additional risks to network stability, especially during peak loads or critical situations. In contrast, the results of this study demonstrated the effectiveness of approaches involving flexible interaction between centralised and decentralised elements, with the ability to dynamically redistribute management functions depending on the current system state. In this context, the authors' statement may be considered valid for systems with a low level of digitalisation, but it insufficiently considers the potential of modern technologies such as AI, blockchain, and the Internet of Things, which enable local nodes to act autonomously without losing overall controllability. Moreover, the authors were sceptical of integrating machine learning with blockchain technologies, arguing that the complexity of implementing such systems and the limited transaction processing speed of distributed ledgers could significantly reduce the practical effectiveness under real conditions. At the same time, the study confirmed that combining adaptive optimisation algorithms with traditional management methods makes it possible to strike a balance between energy system stability and flexibility.

In the future, further improvement of AI algorithms and the development of distributed generation technologies may lead to the creation of even more efficient, reliable, and secure energy systems (Marignetti *et al.*, 2023). M.R. Mojumder *et al.* (2022) examined the prospects of energy system development with a focus on balancing traditional and innovative approaches. Unlike the current approach, which emphasises harmoniously combining various management methods, the authors argued that the future of energy systems depends more on developing decentralised solutions and autonomous networks. The researchers stated that centralised approaches are losing effectiveness due to limited flexibility and the complexity of integrating distributed energy sources. The study showed that the further development of distributed generation technologies and the improvement of AI algorithms would reduce dependence on central control, which, in the opinion, is a key step towards creating more efficient and stable energy systems. At the same time, the authors agreed that automation and load forecasting are critically important aspects of future energy networks. S. Areekkara *et al.* (2021), in the study, analysed the effectiveness of integrating multi-agent systems for autonomous energy network management. The authors focused on the use of agent-based algorithms allowing local network nodes to make decisions independently regarding energy distribution, which, according to the findings, improves resource use efficiency. However, unlike the current results, which highlight the importance of combining centralised and decentralised methods, the authors believed that centralised systems adapt too slowly to changes in demand and generation. Therefore, the authors proposed full autonomy of local agents without the involvement of central control.

The study analysed the research results and the correlation with the work of other authors. The obtained data confirmed the effectiveness of applying hybrid energy resource management models combining centralised and decentralised approaches. It was found that integrating machine learning algorithms and blockchain technologies improves the adaptability of the energy system to variable conditions, reduces energy losses, and enhances overall network stability. Comparison with other studies revealed both confirmation of key results and differences in approaches and emphases, highlighting the need for further research in this field.

CONCLUSIONS

As a result of the conducted research, modern approaches to energy distribution optimisation and network security provision using AI and blockchain technologies were considered. The use of intelligent methods such as machine learning algorithms, neural networks, reinforcement learning methods, and hybrid models demonstrated significant potential in improving the efficiency of energy system management, reducing energy consumption, and enhancing load forecasting. The integration of AI into energy systems enabled the creation of adaptive, self-regulating networks capable of operating effectively even under dynamic conditions, where traditional control methods were no longer sufficiently effective. In particular, convolutional and recurrent neural network algorithms provided high accuracy in forecasting energy demand and adaptability to changing network conditions.

One promising area was the use of blockchain technologies for decentralised distribution of energy resources, which increased transparency, security, and efficiency of operations in energy systems. The implementation of such technologies made it possible to ensure greater protection against cyber threats, reducing the risk of unauthorised access to energy networks and decreasing management costs. Anomaly detection using AI helped to identify technical malfunctions and potential cyber threats in a timely manner, enhancing the reliability and security of energy systems. Clustering and anomaly detection methods played an important role in strengthening the cybersecurity of energy networks and enabled prompt responses to vulnerabilities.

However, despite significant progress in the application of AI and blockchain technologies, there were certain limitations, particularly in the complexity of model configuration, the need for large amounts of training data, and the requirements for computational resources. Therefore, an important future task was the optimisation of these technologies to improve the scalability and efficiency under real conditions.

Thus, modern approaches to energy resource management aimed to increase the efficiency of electricity use, reduce losses, and improve network resilience. Further development of intelligent algorithms and distributed generation technologies would contribute to the creation of more adaptive, secure, and energy-efficient systems of the future.

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Оптимізація енергорозподілу та виявлення вразливостей у мережах за допомогою штучного інтелекту

Анотація. Метою роботи було дослідження та аналіз можливостей застосування штучного інтелекту для оптимізації процесів енергорозподілу та виявлення вразливостей в енергетичних мережах. Робота спрямована на вивчення методів, алгоритмів і підходів, які дозволяють підвищити ефективність управління енергетичними системами, зменшити втрати енергії, покращити стійкість мереж до зовнішніх загроз і забезпечити точніше прогнозування попиту та пропозиції. Особливу увагу приділено застосуванню інтелектуальних методів для виявлення аномалій та вразливих точок в енергетичних мережах, що допомагає своєчасно реагувати на потенційні кібератаки, технічні несправності чи інші ризики. У роботі розглянуто сучасні методи управління енергетичними потоками, зокрема використання нейромережевих алгоритмів та блокчейн-технологій, а також їх інтеграцію в енергосистеми для підвищення ефективності та стабільності мереж. Застосування алгоритмів машинного навчання, таких як згорткові та рекурентні нейронні мережі, дозволяє значно покращити точність прогнозування навантаження та адаптивність до змінних умов мережі. Методи прогнозування навантаження, включаючи нейронні мережі, дерева рішень та підкріплене навчання, сприяють зменшенню витрат енергії та попередженню перевантажень. У той же час, виявлення аномалій за допомогою інтелектуальних систем дозволяє своєчасно виявляти несправності та потенційні атаки, що підвищує безпеку та надійність системи. Одним із перспективних рішень є впровадження блокчейн-технологій для децентралізованого розподілу енергетичних ресурсів, що забезпечує прозорість, безпеку та ефективність операцій. Прогнозування навантаження та управління енергетичними ресурсами через інтелектуальні системи дозволяє створювати більш адаптивні, саморегульовані та стабільні енергетичні мережі

Ключові слова: прогнозування навантаження; цифрова трансформація; мікромережі; оцінка ризиків; нейромережеві моделі