UDC 004.71
DOI https://doi.org/10.32782/IT/2024-3-11

Ivan LAKTIONOV
Doctor of Engineering Sciences, Docent, Professor at the Department of Computer Systems Software, Dnipro University of Technology, 19, Dmytra Yavornytskoho Ave., Dnipro, Ukraine, 49005, Laktionov.I.S@nmu.one
ORCID: *0000-0001-7857-6382*
Scopus Author ID: *57194557735*

Oleksandr ZHABKO
Postgraduate Student at the speciality 123 Computer Engineering, Dnipro University of Technology, 19, Dmytra Yavornytskoho Ave., Dnipro, Ukraine, 49005, Zhabko.O.S@nmu.one
ORCID: *0009-0002-7996-9115*

Grygorii DIACHENKO
PhD, Associate Professor at the Department of Electric Drive, Dnipro University of Technology, 19, Dmytra Yavornytskoho Ave., Dnipro, Ukraine, 49005, Diachenko.G@nmu.one
ORCID: *0000-0001-9105-1951*
Scopus Author ID: *57201252081*

To cite this article: Laktionov, I., Zhabko, O., Diachenko, G. (2024). Rezultaty analizu efektyvnosti bezdrotovykh tekhnolohii obminu danymy pid chas pobudovy informatsiinykh system ahromonitorynhu [Results of the analysis of the effectiveness of wireless data exchange technologies when creating information systems for agro-monitoring]. *Computer Science, Software Engineering and Cyber Security*, 3, 108–115, doi: https://doi.org/10.32782/IT/2024-3-11

RESULTS OF THE ANALYSIS OF THE EFFECTIVENESS OF WIRELESS DATA EXCHANGE TECHNOLOGIES WHEN CREATING INFORMATION SYSTEMS FOR AGRO-MONITORING

Relevance. *The reliability of wireless networks is a critical aspect in modern infocommunication systems, especially given their widespread use in a variety of industries, including agriculture, healthcare, transportation, and industry. These networks must provide continuous and reliable communication, which is becoming increasingly important in the context of the growing number of connected devices and increasing requirements for quality of service (QoS). Reliability here includes the ability of a network to continue to function properly during and after failures, as well as ensuring secure data transmission.*

The main aim *is to conduct a comparative analysis of several architectures of neural networks in order to determine the most suitable for modeling the reliability of wireless networks. In the second part of the study, several wireless communication standards will be simulated using the selected algorithm, which will allow for a deeper analysis and draw conclusions about reliability.*

The research object *is the modern wireless communication standards and their effectiveness under various application conditions.* ***The research subject*** *is methods and models of comparison of the performance and characteristics of 5G, Wi-Fi, LTE, and Zigbee for different types of networks and applications.*

Conclusions. *The results emphasize that 5G is the most promising standard for applications requiring high data transfer speeds and low latency. Wi-Fi remains a popular choice for local networks, but its performance decreases over long distances and in environments with significant interference. LTE offers a good balance between coverage area and performance, while Zigbee is the least performant but effective for low-speed and energy-efficient IoT applications. Overall, the research results confirm that the choice of wireless communication standard depends on specific network requirements, including bandwidth needs, coverage area, latency, and energy efficiency.*

Key words: *wireless networks, reliability, neural networks, QoS, data transmission, network performance.*

Іван ЛАКТІОНОВ
доктор технічних наук, доцент, професор кафедри програмного забезпечення комп’ютерних систем, Національний технічний університет «Дніпровська політехніка», пр. Дмитра Яворницького, 19, м. Дніпро, Україна, 49005
ORCID: *0000-0001-7857-6382*
Scopus Author ID: *57194557735*

Олександр ЖАБКО
здобувач вищої освіти за освітньо-науковим рівнем «Доктор філософії» за спеціальністю 123 Комп'ютерна інженерія, Національний технічний університет «Дніпровська політехніка», пр. Дмитра Яворницького, 19, м. Дніпро, Україна, 49005
ORCID: *0009-0002-7996-9115*

Григорій ДЯЧЕНКО
кандидат технічних наук, доцент кафедри електропривода, Національний технічний університет «Дніпровська політехніка», пр. Дмитра Яворницького, 19, м. Дніпро, Україна, 49005
ORCID: *0000-0001-9105-1951*
Scopus Author ID: *57201252081*

Бібліографічний опис статті: Лактіонов, І., Жабко, О., Дяченко, Г. (2024). Результати аналізу ефективності бездротових технологій обміну даними під час побудови інформаційних систем агромоніторингу. *Computer Science, Software Engineering and Cyber Security*, 3, 108–115, doi: https://doi.org/10.32782/IT/2024-3-11

РЕЗУЛЬТАТИ АНАЛІЗУ ЕФЕКТИВНОСТІ БЕЗДРОТОВИХ ТЕХНОЛОГІЙ ОБМІНУ ДАНИМИ ПІД ЧАС ПОБУДОВИ ІНФОРМАЦІЙНИХ СИСТЕМ АГРОМОНІТОРИНГУ

Актуальність. *Надійність бездротових мереж є критично важливим аспектом у сучасних інфокомунікаційних системах, особливо з огляду на їх широке застосування в різноманітних галузях, включаючи сільське господарство, охорону здоров'я, транспорт та промисловість. Ці мережі мають забезпечувати безперервний і надійний зв'язок, що стає дедалі важливішим в умовах зростання числа підключених пристроїв та підвищення вимог до якості обслуговування (QoS). Надійність включає здатність мережі продовжувати функціонувати належним чином під час і після збоїв, а також забезпечення безпечної передачі даних.*

Метою роботи *є проведення порівняльного аналізу кількох архітектур нейронних мереж задля визначення найбільш придатної для моделювання бездротових мереж щодо оцінки їх надійності. Також у статті проведено дослідження методами моделювання кількох стандартів бездротового зв'язку за допомогою обраного алгоритму, що дозволило провести глибший аналіз і зробити висновки щодо надійності.*

Об'єктом дослідження *є сучасні стандарти бездротового зв'язку та їх ефективність у різних умовах застосування.* ***Предметом дослідження*** *є методи і моделі порівняння продуктивності та характеристик 5G, Wi-Fi, LTE та Zigbee для різних типів мереж і застосувань.*

Висновки: *результати моделювання підкреслюють, що 5G є найбільш перспективним стандартом для додатків, що вимагають високої швидкості передачі даних і низької затримки. Wi-Fi залишається популярним вибором для локальних мереж, але його продуктивність знижується на великих відстанях і в умовах великої кількості перешкод. LTE пропонує хорошу збалансованість між зоною покриття та продуктивністю, а Zigbee є найменш продуктивним, проте ефективним для низькошвидкісних і енергоефективних додатків IoT. Загалом, результати дослідження підтверджують, що вибір стандарту бездротового зв'язку залежить від конкретних вимог до мережі, включаючи потреби в пропускній здатності, зоні покриття, затримці та енергоефективності.*

Ключові слова: *бездротові мережі, надійність, нейронні мережі, QoS, передача даних, продуктивність мережі.*

The relevance of the scientific and applied research task. Reliability of wireless networks is a critically important aspect of modern infocommunication systems, especially considering their widespread use across various sectors, including healthcare, transportation, and industry. These networks must provide continuous and reliable connectivity, which becomes increasingly important as the number of connected devices grows and the demands for quality of service (QoS) increase. Reliability here includes the network's ability to continue functioning properly during and after failures, as well as ensuring the secure transmission of data (Sharma et al., 2023).

Various methods and algorithms are used to analyze and improve the reliability of wireless networks, with neural networks playing a significant role. Specifically, in studies of the reliability of neural networks used in critical systems, it has been found that even the best models can be prone to errors during deployment. In such cases, methods like SelfChecker and DeepInfer are employed to assess model reliability based on the analysis of the model's internal layers or conditions on input data, thereby enhancing the accuracy of reliability predictions (Pinconschi et al., 2024).

Aim and objectives of the article. The main aim of the article is to analyze and synthesize approaches to enhancing the reliability of wireless networks by leveraging the latest advancements in neural network technologies, ensuring stable and secure operations in critical communication systems. To achieve the set aim, the following objectives need to be met:

– conduct a critical analysis and logical generalization of existing approaches to improving the reliability of wireless infocommunication networks;

– identify and examine the most effective architectural solutions and algorithms for enhancing network reliability, with a focus on neural networks;

– develop and evaluate structural models and algorithms for assessing the reliability of wireless networks using selected neural network architectures;

– provide recommendations for future research directions to advance the reliability of wireless communication systems, particularly in critical applications.

Comparative analysis of neural networks. For the comparative analysis, four main neural network architectures were selected: Multilayer Perceptron (MLP), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Transformers. These models were chosen based on their popularity in solving various tasks related to prediction and classification, as well as their potential suitability for analyzing the reliability of wireless networks (Muñoz-Zavala et al., 2024).

The main criteria for selection were:

– performance: the model's ability to provide high accuracy in complex conditions, which is important for reliability;

– noise resistance: the model's ability to maintain effectiveness in the presence of noise in the input data;

– computational complexity: an evaluation of resource requirements for running the models, especially in the context of real-time processing.

Architectures description:

– MLP (Multilayer Perceptron): a classic model with full connectivity between layers, capable of solving a wide range of tasks;

– CNN (Convolutional Neural Network): used for processing data with spatial dependencies, particularly effective for image analysis;

– RNN (Recurrent Neural Network): specializes in processing sequential data, such as text or time series;

– transformers: a modern architecture that has shown high efficiency in tasks where processing long sequences and complex contexts is important.

For comparing the selected neural networks, the following metrics were used:

– accuracy: the overall proportion of correct predictions, allowing the evaluation of the model's effectiveness;

Detail Compact Column

sort_id	date_d_m_y	time	sensor_id	sensor_ty...
1	5.02.2016	13:01:06	310	B
3	5.02.2016	13:01:16	306	B
6	5.02.2016	13:02:40	368	B
12	5.02.2016	13:03:32	367	B
20	5.02.2016	13:04:13	365	B
23	5.02.2016	13:04:45	302	B
31	5.02.2016	13:06:49	306	B
38	5.02.2016	13:09:06	367	B
45	5.02.2016	13:09:51	365	B
48	5.02.2016	13:10:20	302	B
56	5.02.2016	13:12:22	306	B
61	5.02.2016	13:13:38	368	B

Fig. 1. Dataset for further analysis (retrieved from kaggle.com/datasets/halimedogan/wireless-sensor-network-data/data)

– recall: reflects the model's ability to identify all actual positive cases;

– F1-score: the harmonic mean between accuracy and recall, allowing the assessment of balance between them.

To obtain quantitative and qualitative evaluations presented in Table 1, a series of experiments was conducted on synthetic and real data. Initially, datasets were collected and prepared that reflected various aspects of wireless networks, including traffic data, signal level, latency, and errors. Synthetic data were generated by simulating different scenarios of wireless networks, allowing for controlled parameters and the introduction of targeted noise (Zhu et al., 2023). Real data were obtained from existing datasets containing information on real operational conditions and potential failures.

The models were trained on training datasets with subsequent validation on test datasets that included cases with varying levels of noise. To increase the accuracy and stability of the results, the k-fold cross-validation method was used. Each model underwent several cycles of training and testing with different data distributions, reducing the impact of random factors (Wang et al., 2023).

Various public datasets collected from reputable sources were used for modeling and analyzing neural networks in the context of wireless network reliability research. The training and testing datasets were selected considering the specifics of the network scenarios under study, ensuring high modeling quality and relevance of the obtained results. In particular, the following sources were used to train the models:

1. Wireless Network Traffic Data (UCI Machine Learning Repository) is a dataset containing information about traffic in wireless networks. This dataset allows for modeling various aspects of network operation, including signal level analysis, latency, and errors. Using this dataset provided the opportunity to test the models under real wireless network operating conditions.

2. CICIDS 2017 Dataset (Canadian Institute for Cybersecurity) is a dataset for anomaly detection in networks, containing detailed information about various types of network traffic, including both normal traffic and traffic related to attacks. This dataset was used to evaluate the models' ability to detect anomalies in complex conditions.

3. IEEE Dataport Wireless Network Data is a platform providing access to datasets collected in real wireless networks. Choosing data from this platform ensured modeling and testing of neural networks under real conditions with varying levels of noise and other factors affecting network reliability.

The training data underwent preprocessing to ensure the correctness of the modeling:

1. Data Collection and Preprocessing: real data were collected from public sources such as UCI, CIC, and IEEE Dataport. The data were cleaned of potential artifacts and anomalies that could negatively impact the modeling results.

2. Statistical Characteristics Analysis: for each dataset, an assessment of the main statistical characteristics, such as mean, variance, median, and range, was conducted. This allowed for the evaluation of possible correlations between parameters and ensured high-quality model training.

3. Creation of Synthetic Data: to model various scenarios of wireless network operation, synthetic data were generated, including variations in noise levels and other network characteristics. This provided the opportunity to test the models in different conditions and evaluate their noise resistance.

The data preparation approach ensured high accuracy, stability, and realism of the modeling results, as confirmed in the presented results table (Table 1).

Based on the conducted analysis, transformers were chosen as the most suitable architecture for further research on the reliability of wireless networks. They demonstrated the highest results across all key metrics, indicating their ability to

Table 1

Comparison of neural network architectures by basic metrics

Neural Network Architecture	Accuracy	Recall	F1-Score	Noise Resistance	Computational Complexity
MLP (Multilayer Perceptron)	85%	82%	83%	Medium	Low
CNN (Convolutional Neural Network)	88%	85%	86.5%	High	High
RNN (Recurrent Neural Network)	84%	80%	82%	Medium	Medium
Transformer	92%	89%	90.5%	High	High
MLP (Multilayer Perceptron)	85%	82%	83%	Medium	Low

effectively handle the tasks presented in this study (Rafique et al., 2024).

The algorithm for using transformers in this research consists of several key stages as shown in Fig. 2.

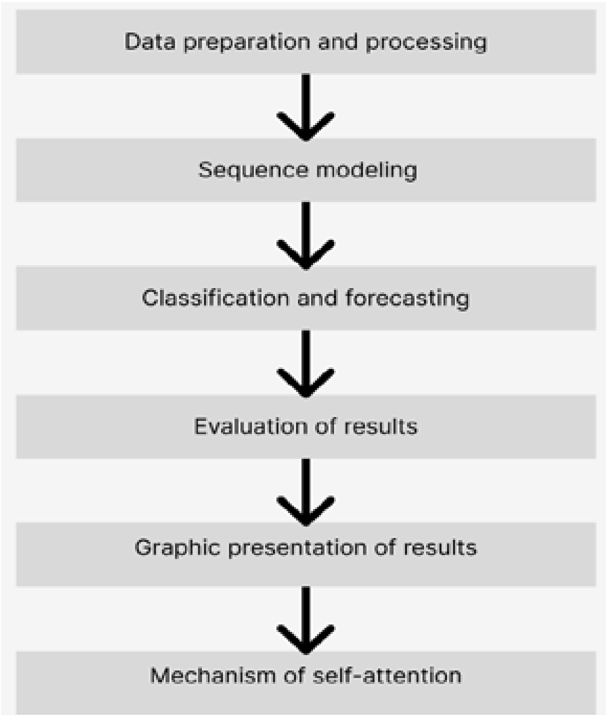

Fig. 2. The algorithm for using transformers

Thus, transformers will be used for time series analysis and reliability prediction of wireless networks, enabling the early detection of potential issues and the prevention of network failures.

Comparative modeling of wireless infocommunication standards. For this study, four wireless communication standards were selected: Wi-Fi, LTE, 5G, and Zigbee. These standards were chosen based on their relevance in modern wireless networks and their widespread application in various fields (Naidu et al., 2019).

– Wi-Fi: a standard for local area networks (LAN) that provides high data transmission speeds over relatively short distances. It is used in many consumer and industrial applications;

– LTE: a mobile communication standard that offers high bandwidth and serves as the foundation for modern cellular networks. It provides broad coverage and supports high mobility;

– 5G: a mobile communication standard that promises to significantly increase data transmission speeds, reduce latency, and improve connection reliability. 5G also supports a massive number of IoT connections (Alsabah et al., 2021);

– Zigbee: a standard designed for low-speed wireless networks with low power consumption, often used in IoT, smart homes, and industrial automation.

The standards were selected considering various aspects of their use and technological capabilities, allowing for a comprehensive study of reliability (Shilpa et al., 2022).

The modeling was conducted using the NS-3 simulation environment, a standard for network modeling. The main tools were Python for scripting and TensorFlow for integrating the transformer neural network, which was chosen in the previous stage of the study.

The study used real datasets on network traffic obtained from various sources, such as public databases like Kaggle and IEEE DataPort. The main simulation parameters included setting up network topology, configuring communication channels, and parameters for interference and network load (Shuaib et al., 2006).

Experiment stages:

1. Network topology creation: separate network scenarios were configured for each wireless communication standard (Wi-Fi, LTE, 5G, Zigbee). Network topologies reflecting real-world usage conditions were created:

– Wi-Fi: a local network with multiple access points (APs) and client devices, modeling an environment similar to an office or home;

– LTE and 5G: mobile communication scenarios with base stations and moving subscribers. These models reflect typical conditions of operator networks with varying numbers of users and traffic;

– Zigbee: a network consisting of sensor nodes, with low bandwidth and low power consumption, ideally suited for smart homes or IoT systems.

2. Communication channel configuration: the communication channel parameters were configured, such as frequency range, channel width, transmitter power, and interference level. Characteristic parameters corresponding to the specifications of each standard were used.

3. Traffic and load modeling: according to typical usage scenarios, characteristic types of traffic were modeled for each standard:

– Wi-Fi: high-speed internet traffic, streaming video, file transfer;

– LTE and 5G: high levels of mobile traffic with an emphasis on latency and bandwidth;

– Zigbee: low-speed sensor data traffic, simulating smart lighting systems or temperature sensors.

4. Neural network integration: a transformer neural network implemented on TensorFlow was used for analyzing and predicting network behavior. Its integration into NS-3 enabled predictions based on real data, significantly improving the

accuracy of the modeling and allowing for the consideration of nonlinear dependencies in network processes.

5. Results evaluation: the key performance parameters, such as average latency, bandwidth, packet loss rate, and power consumption, were assessed for each standard. These results were visualized as graphs, allowing for a comparison of the efficiency of different standards under various conditions (Raza et al., 2017).

Simulation results and parameter comparison are shown in Fig. 3 and Table 2.

Key evaluation parameters:

1. Average data transfer speed (Mbps):

– measurement: the average bandwidth was measured for each standard based on the transmission of large amounts of data under various conditions. Network load was simulated, including different types of traffic (e.g., streaming video, large files, sensor data for IoT);

– Wi-Fi: measured under moderate load and at distances up to 30 meters;

– LTE: measured in a mobile environment with multiple subscribers over a large coverage area;

– 5G: measured in densely urbanized areas with high-speed requirements;

– Zigbee: measured under low transmission power conditions, typical for IoT sensor networks.

2. Average latency (ms):

– measurement: latency was measured for data packets of various sizes in scenarios simulating real-world technology use. The latency was assessed based on the average time it takes for packets to travel from the source to the receiver;

– Wi-Fi: latency was measured under normal and increased network load;

– LTE: latency was evaluated in a mobile environment with subscriber movement;

– 5G: latency was measured in high-density device environments with stringent latency requirements (e.g., for VR/AR applications);

– Zigbee: latency was considered under low-power consumption conditions and frequent interference.

3. Packet loss (%):

– Measurement: packet loss was measured in each environment to assess the network's resilience to interference and overload. Scenarios with varying traffic intensity and the number of connected devices were used;

– Wi-Fi: stability was analyzed as the number of connected devices and distance increased;

– LTE: packet loss was evaluated in conditions of moving subscribers and high user density;

– 5G: packet loss was evaluated in high-density data transmission environments using different frequency bands;

– Zigbee: losses were analyzed under low bandwidth and energy-saving operating modes.

4. Interference resilience:

– measurement: this parameter was assessed based on simulations of the impact of different types of interference on network performance. Each scenario used models of radio frequency interference, multipath effects, and interference from other devices;

– Wi-Fi: resilience to radio frequency interference in multi-channel environments was considered;

– LTE: the network's ability to operate in overlapping base station coverage areas was analyzed;

– 5G: resilience to interference in new frequency bands, including millimeter waves, was evaluated;

– Zigbee: resilience in environments with significant low-frequency interference was assessed.

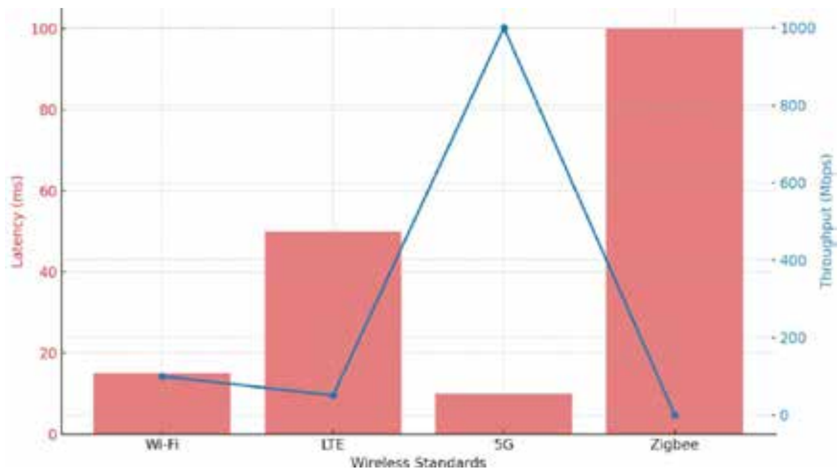

Fig. 3. Comparison of latency and throughput across wireless standards

Table 2

Main simulation parameters

Parameter	Wi-Fi	LTE	5G	Zigbee
Bandwidth	20 MHz	1.4-20 MHz	100 MHz	2.4 GHz
Maximum Speed	Up to 600 Mbps	Up to 300 Mbps	Up to 10 Gbps	Up to 250 kbps
Coverage Area	Up to 100 m	Up to 10 km	Up to 20 km	Up to 100 m
Latency	~1-10 ms	~20-30 ms	~1-2 ms	~30 ms

Table 3

Comparison of standard performance

Standard	Average Data Transfer Speed (Mbps)	Average Latency (ms)	Packet Loss (%)	Interference Resilience
Wi-Fi	150	5	2	Medium
LTE	100	25	1	High
5G	1000	1	0.5	High
Zigbee	0.2	30	5	Low

Simulation results:

– Wi-Fi demonstrated high data transfer speeds over short distances, but its reliability decreased with increasing distance and interference;

– LTE showed stable performance over long distances, but its data transfer speed was lower compared to Wi-Fi and 5G;

– 5G exhibited the highest data transfer speeds and low latency, making it the most promising standard for future applications requiring high reliability (Al-Fuqaha et al, 2015);

– Zigbee was the least performant but its energy efficiency and ease of configuration make it attractive for low-speed IoT applications.

Priority directions for further research. Based on the analysis and formulation of key requirements, the next steps involve addressing three crucial tasks:

1. Investigate methods to enhance 5G network performance in specialized environments, such as urban areas with high interference and remote rural areas, to ensure consistent high-speed data transfer and low latency.

2. Explore advanced technologies and algorithms to extend the effective range of Wi-Fi networks and mitigate performance degradation in environments with significant interference.

3. Develop strategies to optimize LTE networks, focusing on maximizing coverage while maintaining high performance, particularly in transitioning environments between urban and rural settings.

4. Study the potential for combining different wireless communication standards, such as 5G, Wi-Fi, LTE, and Zigbee, to create hybrid networks that can dynamically adapt to varying network requirements and conditions.

Conclusions. The results emphasize that 5G is the most promising standard for applications requiring high data transfer speeds and low latency. Wi-Fi remains a popular choice for local networks, but its performance decreases over long distances and in environments with significant interference. LTE offers a good balance between coverage area and performance, while Zigbee is the least performant but effective for low-speed and energy-efficient IoT applications. Overall, the research results confirm that the choice of wireless communication standard depends on specific network requirements, including bandwidth needs, coverage area, latency, and energy efficiency.

BIBLIOGRAPHY:

1. Sharma P., Khatri S. P., Kumar P. An intelligent healthcare system using IoT in wireless sensor network. *Sensors*. 2023. Vol. 23 (11). P. 1–14. https://doi.org/10.3390/s23115055.

2. Pinconschi E., Gopinath D., Abreu R., Păsăreanu C. S. Evaluating Deep Neural Networks in Deployment: A Comparative Study (Replicability Study). *arXiv preprint arXiv: arXiv:2407.08730v2*. 2024. https://doi.org/10.48550/arXiv.2407.08730

3. Muñoz-Zavala A. E., Macías-Díaz J. E., Alba-Cuéllar D., Guerrero-Díaz-de-León J. A. A Literature Review on Some Trends in Artificial Neural Networks for Modeling and Simulation with Time Series. *Algorithms*. 2024. Vol. 17 (2). P. 1–45. https://doi.org/10.3390/a17020076.

4. Zhu H., Zhang H., Lu W., Li X. Foreformer: An enhanced transformer-based framework for multivariate time series forecasting. *Neural Comp. and App*. 2023. Vol. 35. P. 14467–14480. https://doi.org/10.1007/s00521-023-08091-1.

5. Wang Y.-C., Houng Y.-C., Chen H.-X., Tseng S.-M. Network Anomaly Intrusion Detection Based on Deep Learning Approach. *Sensors*. 2023. Vol. 23 (4), P. 1–21. https://doi.org/10.3390/s23042171.

6. Rafique S. H., Abdallah A., Musa N. S., Murugan T. Machine Learning and Deep Learning Techniques for Internet of Things Network Anomaly Detection–Current Research Trends. *Sensors*. 2024. Vol. 24 (6). P. 1–32. https://doi.org/10.3390/s24061968

7. Naidu G. A., Kumar J. Wireless Protocols: Wi-Fi SON, Bluetooth, ZigBee, Z-Wave, and Wi-Fi. In R. K. Singh & G. Kumar (Eds.), *Proceedings of the 5th International Conference on IT & Multimedia*. 2019. P. 229–239. https://doi.org/10.1007/978-981-13-3765-9_24.

8. Alsabah M., Naser M. A., Mahmmod B. M., Abdulhussain S. H., et al. 6G Wireless Communications Networks: A Comprehensive Survey. *IEEE Access*. 2021. Vol. 99. P. 1–9. https://doi.org/10.1109/ACCESS.2021.3124812.

9. Shilpa B., Radha R., Movva P. Comparative Analysis of Wireless Communication Technologies for IoT Applications. *Artificial Intelligence and Technologies*. 2022. P. 383–394. https://doi.org/10.1007/978-981-16-6448-9_39.

10. Shuaib K., Boulmalf M., Sallabi F., Lakas A. Co-existence of ZigBee and Wi-Fi: An Experimental Study. *Wireless Communications and Mobile Computing*. 2006. P. 1–6. https://doi.org/10.1109/WTS.2006.334532.

11. Raza U., Kulkarni P., Sooriyabandara M. Low Power Wide Area Networks: An Overview. *IEEE Communications Surveys & Tutorials*. 2017. Vol. 19, No. 2. P. 855–873. https://doi.org/10.1109/COMST.2017.2652320.

12. Al-Fuqaha A., Guizani M., Mohammadi M., Aledhari M., Ayyash M. Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications. *IEEE Commun. Surveys & Tutorials*. 2015. Vol. 17, No. 4. P. 2347–2376. https://doi.org/10.1109/COMST.2015.2444095.

REFERENCES:

1. Sharma, P., Khatri, S. P., Kumar, P. (2023). An intelligent healthcare system using IoT in wireless sensor network. *Sensors*. Vol. 23 (11). P. 1–14.

2. Pinconschi, E., Gopinath, D., Abreu, R., Păsăreanu, C. S. (2024). Evaluating Deep Neural Networks in Deployment: A Comparative Study (Replicability Study). *arXiv preprint arXiv: arXiv:2407.08730v2*.

3. Muñoz-Zavala, A. E., Macías-Díaz, J. E., Alba-Cuéllar, D., Guerrero-Díaz-de-León, J. A. (2024). A Literature Review on Some Trends in Artificial Neural Networks for Modeling and Simulation with Time Series. *Algorithms*. Vol. 17 (2). P. 1–45.

4. Zhu, H., Zhang, H., Lu, W., Li, X. (2023). Foreformer: An enhanced transformer-based framework for multivariate time series forecasting. *Neural Comp. and App*. Vol. 35. P. 14467–14480. DOI: 10.1007/s00521-023-08091-1

5. Wang, Y.-C., Houng, Y.-C., Chen, H.-X., Tseng, S.-M. (2023). Network Anomaly Intrusion Detection Based on Deep Learning Approach. *Sensors*. Vol. 23(4), 2171.

6. Rafique, S. H., Abdallah, A., Musa, N. S., Murugan, T. (2024). Machine Learning and Deep Learning Techniques for Internet of Things Network Anomaly Detection–Current Research Trends. *Sensors*. Vol. 24 (6). P. 1–32.

7. Naidu, G. A., Kumar, J. (2019). Wireless Protocols: Wi-Fi SON, Bluetooth, ZigBee, Z-Wave, and Wi-Fi. In R. K. Singh & G. Kumar (Eds.), *Proceedings of the 5th International Conference on IT & Multimedia*. P. 229–239.

8. Alsabah, M., Naser, M. A., Mahmmod, B. M., Abdulhussain, S. H., et al. (2021). 6G Wireless Communications Networks: A Comprehensive Survey. *IEEE Access*. Vol. 99. P. 1–9.

9. Shilpa, B., Radha, R., Movva, P. (2022). Comparative Analysis of Wireless Communication Technologies for IoT Applications. *Artificial Intelligence and Technologies*. P. 383–394.

10. Shuaib, K., Boulmalf, M., Sallabi, F., Lakas, A. (2006). Co-existence of ZigBee and Wi-Fi: An Experimental Study. *Wireless Communications and Mobile Computing*. P. 1–6.

11. Raza, U., Kulkarni, P., Sooriyabandara, M. (2017). Low Power Wide Area Networks: An Overview. *IEEE Communications Surveys & Tutorials*. Vol. 19, No. 2. P. 855–873.

12. Al-Fuqaha, A., Guizani, M., Mohammadi, M., Aledhari, M., Ayyash, M. (2015). Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications. *IEEE Commun. Surveys & Tutorials*. Vol. 17 (4). P. 2347–2376.