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COMPARATIVE ANALYSIS OF ENERGY CONSUMPTION PREDICTION ALGORITHMS IN TELECOMMUNICATION INFRASTRUCTURE

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Аннотация. Данная статья представляет сравнительный анализ современных алгоритмов машинного и глубокого обучения, предназначенных для прогнозирования энергопотребления в телекоммуникационной инфраструктуре, включая базовые станции мобильной связи, центры обработки данных и сети радиодоступа. В исследовании оцениваются точность, временные затраты и применимость в реальных условиях эксплуатации таких алгоритмов, как LSTM, GRU, Transformer, Gradient Boosting и Random Forest. Результаты анализа показывают, что гибридные архитектуры — в частности, комбинации Cond-LSTM и Transformer-LSTM — позволяют снизить среднеквадратическую ошибку (RMSE) на 30–42% по сравнению с традиционными методами. В качестве научной новизны исследования предложены комплексный сравнительный анализ алгоритмов на основе реальных сетевых данных и практические способы повышения энергоэффективности. [1, 2]
Abstract. This article provides a comparative analysis of modern machine learning and deep learning algorithms designed to predict energy consumption in telecommunications infrastructure, including mobile base stations, data centers, and radio access networks. The study examines the accuracy, timing, and production applicability of algorithms such as LSTM, GRU, Transformer, Gradient Boosting, and Random Forest. The analysis results show that hybrid architectures - specifically combinations of Cond-LSTM and Transformer-LSTM - can reduce the RMSE by 30-42% compared to traditional methods. As a scientific novelty of the research, a comprehensive comparative analysis of algorithms based on real network data and practical ways to increase energy efficiency are proposed.

Introduction.

The information and communication technology (ICT) sector currently accounts for approximately 10% of global electricity consumption [1]. Telecommunications infrastructure-ase stations, backbone networks, and data centers-is the primary source of consumption. Especially with the widespread implementation of 5G networks, energy consumption is showing a further trend of growth: 5G base stations consume three times more electricity than 4G stations [2].

For mobile operators, energy costs account for approximately 25% of operating expenses, and about 90% of them are spent on electricity [3]. In this case, predicting and managing energy consumption is important not only from an economic but also from an environmental perspective. According to the GSMA, 62 major operators have committed to drastically reducing carbon emissions by 2030 in accordance with science-based targets [4].

Artificial intelligence and machine learning methods are opening up new opportunities in optimizing network operations. In particular, prediction systems built on recurrent neural networks such as LSTM have been proven to achieve energy savings of 8-21% by monitoring power consumption at base stations in real time [5]. At the same time, scientific debates continue to determine which algorithm is most effective under which conditions.

The aim of this study is to identify the main algorithms for predicting energy consumption in telecommunications infrastructure, their effectiveness, and limitations through a systematic analysis of published scientific articles.

The position of the problem.

Energy consumption forecasting in telecommunications infrastructure involves several interrelated issues:

The first problem is the complex temporal structure of the data. Energy consumption includes short-term (hourly), medium-term (daily and weekly), and long-term (seasonal) fluctuations. It is difficult for traditional statistical methods to reflect these multi-level time dependencies in a single model [6].

The second problem is heterogeneous data sources. In modern 5G networks, energy consumption depends on many parameters, such as hardware characteristics (antenna configuration, processor load), traffic intensity, meteorological conditions, and user location. Effective processing of this multidimensional data requires large computational resources [7].

The third problem is the requirement for real-time forecasting. Energy-saving strategies, such as switching base stations to sleep mode or turning off frequency bands, require decision-making within milliseconds. Therefore, the prediction model must be not only accurate but also computationally efficient [8].

The above problems raise the following key research question: which machine learning or deep learning algorithm can predict energy consumption in various segments of telecommunications infrastructure (base stations, data centers, backbone networks) with the highest accuracy and computational efficiency.

Analysis of research methods and algorithms

Analysis of the literature shows that the following types of data are important for successful forecasting systems: hourly traffic load of the base station, base station identifier, meteorological indicators (temperature, humidity), time parameters (day, week, period of the year). In particular, a study based on real network data obtained within the ITU 5G Base Station Energy Consumption Modeling Challenge showed that using the base station identifier as an input parameter played a key role in solving the "one-to-many" problem [9].

The data processing stage usually includes: restoring lost values using interpolation methods, extracting seasonal and trend components (STL decomposition), min-max or Z-score normalization, and creating features with a sliding window.

The most commonly used algorithms in the literature can be characterized as follows:

LSTM (Long Short-Term Memory): An extended type of recurrent neural network that stores long-term connections through input, output, and forgetting valves. There are studies showing that when predicting the traffic profile at base stations, the RMSE ranges from 3.2 to 5.8% [5, 10].

GRU (Gated Recurrent Unit): A simplified version of the LSTM that operates through update and recovery covers. Although the computational costs are 15-20% lower, the accuracy indicators are close to LSTM: RMSE 3.8-6.1% [11].

Transformer architecture: Allows parallel computation via a self-attention mechanism. When used in a hybrid form with LSTM, an RMSE of 0.7 and an MAE of 0.5 were achieved in the 7-day prediction task [12]. It is the most effective method for long-term forecasting in data centers.

Gradient Boosting (XGBoost, LightGBM): An ensemble of weak predictors that are added one after another. It was noted that a Nash efficiency of 99.1% was achieved when forecasting the fuel consumption of telecommunications operators' diesel generators [13]. Strong for short-term (1-6 hours) prediction.

Conditional LSTM: An extended LSTM architecture with conditional input parameters. It has been proven that 5G reduces the RMSE for macro base stations by 69.6% compared to a standard LSTM and by 42.7% compared to a Transformer [9, 14]. The following table summarizes the main indicators of the main algorithms (based on literature analysis) (Table 1)

Table 1. Comparative indicators of energy prediction algorithms in telecommunications infrastructure

Algorithm	RMSE (%)	MAE (%)	Sliding window	Scope of application
LSTM	3.2–5.8	2.1–4.3	1 - 24 hours	Base station
GRU	3.8–6.1	2.5–4.7	1 - 12 hours	5G RAN
Transformer	2.8–4.5	1.9–3.8	24 - 168 hours	Data center
Gradient Boosting	4.5–7.2	3.1–5.6	1 - 6 hours	Base station
Random Forest	5.1–8.3	3.8–6.2	1 - 24 hours	Data center
Cond-LSTM	1.9–3.4	1.4–2.8	1-72 hours	5G Makro-BS

As seen from the table data, the Cond-LSTM and Transformer-LSTM hybrid models are superior in terms of accuracy. However, these models require significant computational resources and require specific optimization for application in real-time systems.

Conclusion

This study provided a comprehensive analysis of the latest scientific literature on predicting energy consumption in telecommunications infrastructure. The main conclusions are as follows:

First, deep learning methods - especially models based on LSTM, GRU, and Transformer - provide significantly higher predictive accuracy for telecommunications networks compared to traditional statistical methods (ARIMA, linear regression).

Secondly, there is no single "universal" algorithm - the most effective approach varies depending on the field of application: Cond-LSTM or LSTM for base stations, Transformer-LSTM hybrid model for data centers, and Gradient Boosting for short-term tasks.

Thirdly, the inclusion of specific features such as the hardware identifier (BSID) as an input parameter significantly increases prediction accuracy and serves to eliminate the "one-to-many" problem.

As a scientific innovation, this work identifies a research gap regarding the adaptation of algorithms based on the conditions of Uzbekistan's telecommunications networks, specifically local climate and traffic profiles. In future research, we plan to test hybrid models based on real network data from national operators in Uzbekistan.

References

1. ITU-T // Global ICT Development Index 2024, International Telecommunication Union, 2024.
2. N. Piovesan, D. López-Pérez, A. De Domenico, X. Geng and H. Bao // Power Consumption Modeling of 5G Multi-Carrier Base Stations: A Machine Learning Approach, ICC 2023 - IEEE International Conference on Communications, Rome, Italy, 2023, pp. 3633-3638, doi: 10.1109/ICC45041.2023.10278569.
3. GSMA Intelligence // The Mobile Economy 2024, GSMA, London, 2024.
4. GSMA // State of the Industry on Climate Action 2023, GSMA, 2023.
5. N. Diouf, C. V. Anamuro, C. Gueguen, M. Ndong, K. Talla and X. Lagrange // Traffic Load Prediction and Power Consumption Reduction for Multi-Band Networks," 2023 26th International Symposium on Wireless Personal Multimedia Communications (WPMC), Tampa, FL, USA, 2023, pp. 1-6, doi: 10.1109/WPMC59531.2023.10338969.
6. Lassoued N., Boujnah N. // A Comprehensive Review of Energy Efficiency in 5G Networks: Past Strategies, Present Advances, and Future Research Directions. Computers 2026, 15, 50. https://doi.org/10.3390/computers15010050.
7. Lorincz, J., Kukuruzović, A., Blažević, Z. A. // Comprehensive Overview of Network Slicing for Improving the Energy Efficiency of Fifth-Generation Networks. Sensors 2024, 24, 3242. https://doi.org/10.3390/s24103242.
8. Ezzeddine, Z., Khalil, A., Zeddini, B., Ouslimani, H.H. // A Survey on Green Enablers: A Study on the Energy Efficiency of AI-Based 5G Networks. Sensors 2024, 24, 4609. https://doi.org/10.3390/s24144609.
9. Y. Zhang et al., // Modelling the 5G energy consumption using real-world data: Energy fingerprint, arXiv:2406.16929, 2024.
10. Mahjoub, S., Chrifi-Alaoui, L., Marhic, B., Delahoche, L. // Predicting Energy Consumption Using LSTM, Multi-Layer GRU and Drop-GRU Neural Networks. Sensors 2022, 22, 4062. https://doi.org/10.3390/s22114062.
11. Abumohsen, M., Owda, A.Y., Owda, M. // Electrical Load Forecasting Using LSTM, GRU, and RNN Algorithms. Energies 2023, 16, 2283. https://doi.org/10.3390/en16052283.
12. Li J., Zhang B., Ying Y. // 6GN for Future Wireless Networks. 6GN 2023. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, vol 553. Springer, Cham. https://doi.org/10.1007/978-3-031-53401-0_27
13. G. M. Nguegnang, M. Atemkeng, T. Ansah-Narh, R. Rockefeller, J. Mulongo and M. A. Garuti // Predicting Fuel Consumption in Power Generation Plants using Machine Learning and Neural Networks, 2021 International Conference on Electrical, Computer and Energy Technologies (ICECET), Cape Town, South Africa, 2021, pp. 1-5, doi: 10.1109/ICECET52533.2021.9698776.
14. S. Buzzi, C. -L. I, T. E. Klein, H. V. Poor, C. Yang and A. Zappone // A Survey of Energy-Efficient Techniques for 5G Networks and Challenges Ahead, IEEE Journal on Selected Areas in Communications, vol. 34, no. 4, pp. 697-709, April 2016, doi: 10.1109/JSAC.2016.2550338.