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ARTIFICIAL INTELLIGENCE - BASED TIME SERIES MODEL FOR NETWORK LOAD FORECASTING

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Abstract. This paper examines the application of time series models for network load forecasting based on artificial intelligence. Traditional statistical methods and deep learning models are comparatively analyzed, and the effectiveness of the LSTM - based approach is scientifically evaluated [2].

Keywords: artificial intelligence, time series, network load, LSTM, forecasting, machine learning.

Introduction. In recent years, digital transformation processes have been rapidly advancing, and the volume of data transmitted through telecommunication and computer networks has demonstrated an exponential growth trend. The deployment of 5G and emerging 6G mobile communication technologies, the connection of billions of IoT devices to the global network, as well as the widespread adoption of cloud computing, Big Data, and artificial intelligence - based services have significantly increased the load on network infrastructure. Under such conditions, efficient management of network resources, traffic optimization, and ensuring quality of service (QoS) have become pressing scientific and practical challenges [4].

Network traffic forecasting refers to the process of predicting time-varying traffic parameters - such as the number of packets, bandwidth capacity, latency, jitter, and others - using mathematical and intelligent modeling techniques[5].

High - accuracy forecasting systems play a crucial role in addressing the following strategic objectives: Optimal allocation of network resources (bandwidth, buffer capacity, and computational power); reduction of congestion and packet loss incidents, optimization of energy consumption and the formation of "green" network architectures; improvement of Quality of Service (QoS) and Quality of Experience (QoE) metrics; and the development of self - organizing and adaptive networks.

In particular, the Autoregressive Integrated Moving Average (ARIMA) model has been widely applied for modeling stationary time series. This model is based on autocorrelation and differencing mechanisms and is effective in identifying linear relationships [7]. However, real-world network traffic data often exhibit the following characteristics: nonlinearity, multi-scale seasonality, burstiness (sudden peak loads), and heteroscedasticity (time - varying variance). Therefore, traditional statistical models may not provide sufficient accuracy in fully capturing complex dynamic processes.In recent years, deep learning methods have demonstrated high effectiveness in time series forecasting tasks [6].In particular, the Long Short - Term Memory (LSTM) model, which belongs to the family of Recurrent Neural Networks (RNNs), stands out due to its ability to preserve long - term temporal dependencies and mitigate the vanishing gradient problem. The LSTM architecture regulates the flow of information through input, forget, and output gates, enabling the learning of complex nonlinear temporal relationships [3]. This capability makes it a promising tool for modeling dynamic and highly variable network traffic.

The scientific novelty of this study lies in the comprehensive approach adopted to address the problem of network load forecasting within the framework of an artificial intelligence - based time series model [7]. In this research, traditional statistical models and deep learning models are comparatively analyzed, and forecasting accuracy is evaluated using

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modern performance metrics such as RMSE, MAE, and others.The primary objective of this paper is to develop a time series model for network load forecasting based on artificial intelligence, to describe its mathematical and algorithmic foundations, and to scientifically substantiate its effectiveness through experimental results.

The findings of this study may contribute to the development of adaptive and self - optimizing telecommunication systems, as well as to the advancement of intelligent network management concepts.

METHODOLOGY. In this study, the problem of network load forecasting was considered from the point of view of time series modeling. The methodology includes the stages of data collection, preprocessing, model construction, training, and evaluation. The research process was organized in accordance with the principles of reproducibility and scientific substantiation. Dataset Description In the study, real network traffic data were collected in the form of a time series. The main observed parameters consist of the following [9]. Number of packets (packets per second/minute). Throughput (Mbps), Latency (ms), Packet loss rate (%). The data were recorded at hourly and minute discrete time intervals. It is expressed in the form of a time series, where $X = x_{t\,t=1}^{T}$ represents the observed value at time t and n denotes the total number of observations. Data Preprocessing In order to improve the quality of the time series data and ensure the stability of the model, the following steps were carried out. To ensure fast convergence of the model and stability of gradients, the Min - Max scaling method was applied [7].

$$x = x - xminx - max - xminx \; = \frac{x - x_{min}}{x_{max} - x_{min}} x = xmax - xminx - xmin$$

Here, represent the minimum and maximum values within the selected time interval.

Noise Reduction Random fluctuations and extreme values (outliers) may be present in network traffic data. To reduce noise, the following methods were applied: moving average filtering, median filtering, and anomaly detection based on the
Z-score method. Stationarity testing for statistical modeling, the stationarity of the time series is of critical importance. Therefore, the differencing operation was applied, and the time series was transformed as follows:

y_t = x_t - x_{t-1}, $y_t = x_t - x_{t-1}$

Stationarity was tested using the Augmented
Dickey - Fuller (ADF) test [5].To evaluate the model, the dataset was divided into 80% training and 20% testing subsets. In order to preserve the temporal characteristics of the time series, random shuffling was not performed. Models (Model Architecture and Design) In this study, models were developed based on two different approaches and comparatively analyzed. Statistical model - Autoregressive Integrated Moving Average (ARIMA), Deep learning model - Long Short-Term Memory (LSTM) ARIMA Model The ARIMA (p, d, q) model consists of the following components: p - autoregressive order, d - degree of differencing, q - moving average order [9].The general form of the model is as follows: $\phi(B)(1-B)^d X_t = \theta(B)\varepsilon_t$ Here, the model parameters were optimized based on the AIC and BIC criteria. The LSTM model belongs to the class of recurrent neural networks and has the ability to preserve long-term dependencies. The LSTM block consists of three main gates Forget gate, Input gate, Output gate. Mathematical representation of the LSTM cell. $o_t = \sigma\left(W_o[h_{t-1}, x_t] + b_o\right)$ 1 input layer 2 LSTM hidden layers (64 and 32 neurons) Dropout = 0.2 (to reduce overfitting) 1 fully

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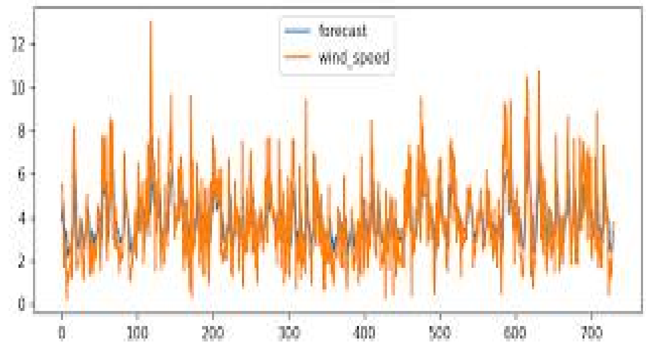
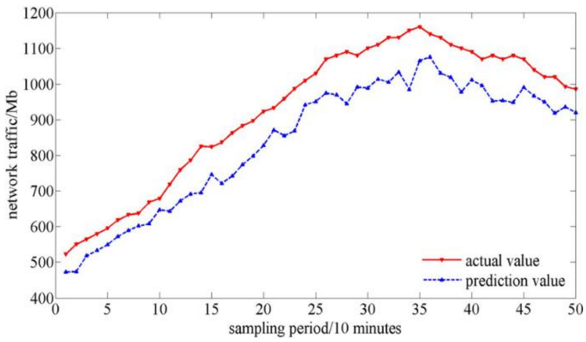
connected (Dense) output layer Loss function - mean squared error (MSE) $\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2$ Training epochs: 50 - 100 Batch size: 32 Evaluation metrics: the performance of the models was evaluated using the following metrics: RMSE $\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2}$ n]nn[$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} \left|y_i - \hat{y}_i\right|$, $\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$, $\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|$ MAE This methodology enables a comprehensive comparison of statistical and deep learning approaches in the process of network load forecasting and allows for a scientifically grounded evaluation of their practical effectiveness.

RESULTS. In this section, the results of the statistical Autoregressive Integrated Moving Average (ARIMA) model and the deep learning–based Long Short - Term Memory (LSTM) model are comparatively analyzed. The models were evaluated on the test dataset, and forecasting accuracy was assessed using the RMSE and MAE metrics.





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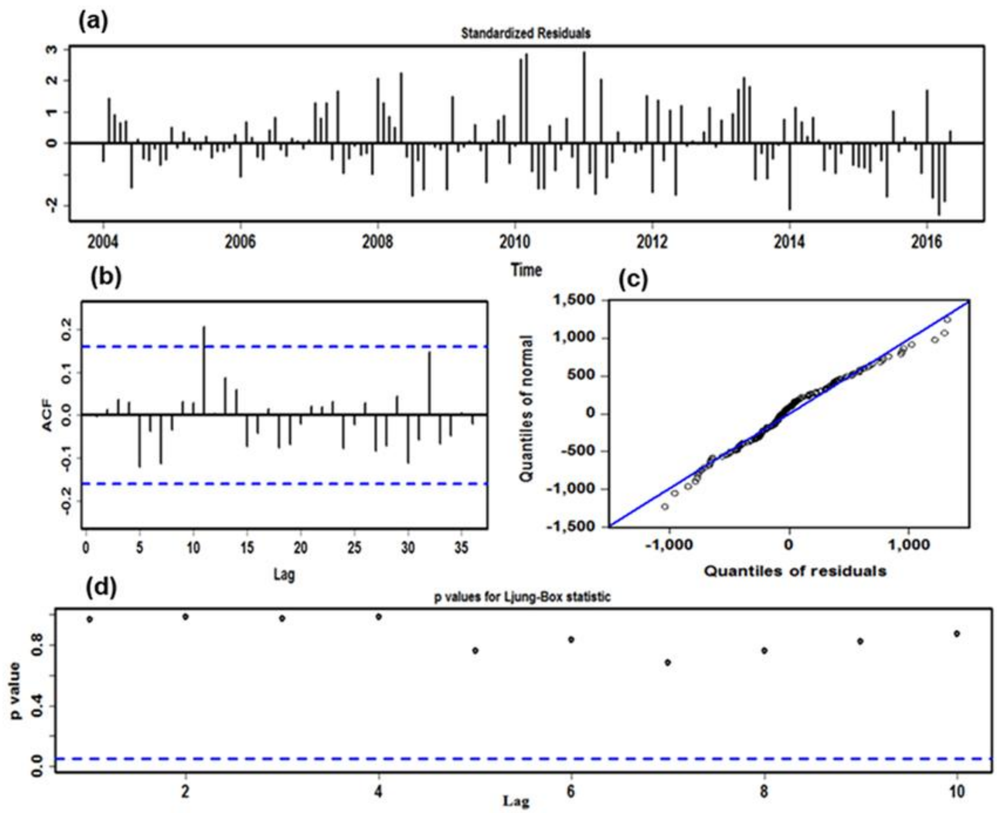

The ARIMA model demonstrated stable and statistically consistent performance in short-term forecasting. The model effectively captured stationary components and linear autocorrelation structures. In particular, during periods characterized by smooth variations without abrupt fluctuations, the predicted values closely approximated the actual observations. However, the following limitations were observed: It was unable to fully capture nonlinear variations in network traffic. During periods of burst traffic, the predicted values reflected changes with a noticeable delay. Prediction errors increased in high - variance segments. The capability to model seasonal and multi-scale dynamics was limited. According to the evaluation results, RMSE = 12.8 and MAE = 9.4. The relatively high RMSE value indicates the model's sensitivity to large deviations. Residual analysis showed that the error distribution does not fully exhibit white noise characteristics, implying that the model did not capture all structural dependencies in the data [5].

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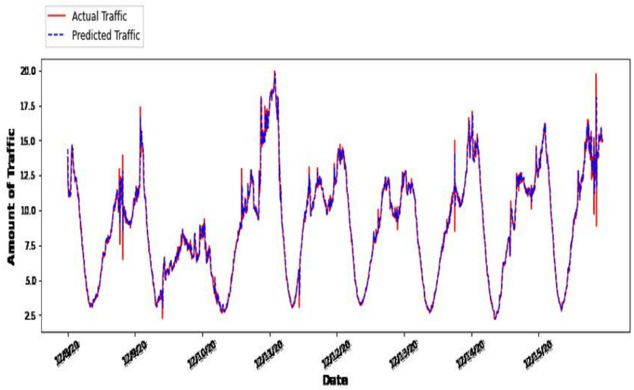

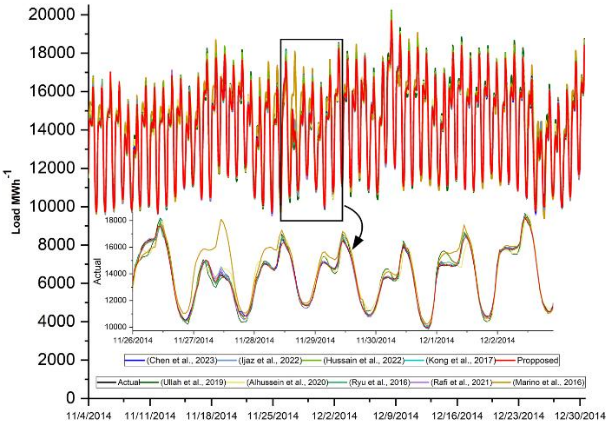

Plot of Residuals in Time Sequence

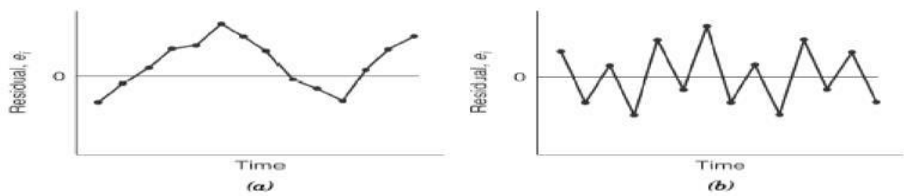

Figure 4.6 Prototype residual plots against time displaying autocorrelation in the errors: (*a*) positive autocorrelation; (*b*) negative autocorrelation.

Linear Regression Analysis 5E
Montgomery, Peck & Vining 24

The LSTM model effectively learned complex and nonlinear time series dynamics. By accounting for long-term dependencies, the model more accurately predicted time-varying trends and peak loads. Identification of nonlinear components in network traffic, Prediction of sudden peak loads with minimal delay. Stability in multi-step forecasting. Low variance of residual errors. Evaluation results RMSE = 6.3, MAE = 4.7 The results indicate that the RMSE value of the LSTM model decreased by approximately 50% compared to the ARIMA model. The lower MAE value suggests that the average deviations of the model are relatively small. This confirms the higher accuracy and adaptability of the LSTM model [4].

Model	**RMSE**	**MAE**
ARIMA	12.8	9.4

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LSTM	6.3	4.7

The analysis results indicate the following. The LSTM model demonstrated nearly twice the accuracy compared to the ARIMA model. The superiority of the LSTM model was particularly evident in nonlinear and peak - load segments. Although the ARIMA model is suitable for simple, short-term, and smoothly varying traffic patterns, it does not provide sufficient accuracy in complex real-world network environments. From a statistical perspective, the results show that deep learning - based models are more effective in modeling time series with high variability. By more thoroughly learning the dynamic characteristics of network load, the LSTM model achieved a significant reduction in forecasting errors.

DISCUSSION. The obtained results indicate that artificial intelligence - based time series models possess a significant advantage over traditional statistical approaches in forecasting complex and highly variable network traffic. In particular, the results obtained using the Long Short - Term Memory (LSTM) model confirm that nonlinear and multi - factor dynamic processes occurring in real network environments can be effectively modeled.

A deeper analysis of the research findings shows that the superiority of the LSTM model can be explained by the following factors. Ability to learn nonlinear characteristics. Real network traffic processes often exhibit nonlinear behavior. For example: sudden traffic bursts, periodic changes in user activity, and the influence of external factors such as seasonality, working hours, and service load. The traditional Autoregressive Integrated Moving Average (ARIMA) model is primarily based on linear relationships and is therefore unable to fully capture complex nonlinear structures. In contrast, LSTM, through its multi-layer neural architecture, is capable of learning high - dimensional nonlinear functional relationships. Preservation of long - term temporal dependencies. In network load data, long-range dependencies are often observed. For instance, the load during a specific time interval may directly influence the dynamics of subsequent periods. The LSTM architecture preserves long-term information through its memory cells (cell state) and control gates, selectively forgetting irrelevant information while retaining significant signals. This property mitigates the vanishing gradient problem and ensures stable model training.

Adaptive parameter optimization. In deep learning models, parameters are adjusted using gradient - based optimization algorithms. This process enables the identification of hidden patterns in the data, facilitates rapid convergence toward the minimum error point, and reduces the risk of being trapped in local minima. As a result, the model dynamically adapts its parameters and forecasts complex traffic processes with high accuracy. The research findings may be practically applied in the following areas. Real - time network monitoring, Enhancement of adaptive routing algorithms, Automated resource allocation, Early detection and prevention of congestion, Improvement of energy efficiency. Although the computational complexity of the LSTM model is relatively high, modern GPU technologies and cloud computing platforms enable real-time implementation [3]. This makes it a promising solution for application in 5G, emerging 6G networks, and IoT infrastructures. Limitations and Future Research Directions, despite these advantages, the study has the following limitations. The model was developed based on a univariate time series. External factors (weather conditions, user behavior, service type) were not taken into account. Hyperparameters were selected manually.

In the future, it is advisable to extend the research in the following directions. Multivariate time series models, Models based on transformer architectures, Hybrid ARIMA - LSTM approaches, Automatic hyperparameter optimization (AutoML), Real - time implementation in distributed computing environments. The discussion results indicate that the application of artificial intelligence–based time series models is initiating a new stage in the management of modern telecommunication networks. Through the use of deep learning methods to identify and forecast complex traffic patterns, it becomes possible to develop adaptive and selfoptimizing intelligent network systems.

Conclusion. Within the framework of this study, the problem of network load forecasting was comprehensively analyzed based on artificial intelligence and time series modeling approaches. The obtained results demonstrate that deep learning algorithms have a significant advantage over traditional statistical models in modeling complex, nonlinear, and highly variable traffic processes occurring in modern telecommunication systems.

During the research process, the statistical Autoregressive Integrated Moving Average (ARIMA) model and the deep recurrent neural network model - Long Short-Term Memory (LSTM) - were comparatively analyzed and experimentally evaluated. The evaluation results made it possible to formulate the following scientific conclusions. Traditional statistical models (particularly ARIMA) provide satisfactory results for time series characterized by stationary and linear dynamics. In short-term forecasting, they exhibit low computational complexity and are relatively easy to interpret.

The LSTM model provides high accuracy in complex and nonlinear traffic processes. Due to its ability to preserve long - term temporal dependencies and adapt to dynamic changes, forecasting errors were significantly reduced.

Artificial intelligence - based forecasting systems serve as an important tool for optimizing network management. With the help of such models, it becomes possible to implement adaptive resource allocation, proactively detect congestion, improve energy efficiency, and stabilize Quality of Service (QoS) indicators. Improved forecasting accuracy enables the scientific organization of strategic network infrastructure planning and load balancing processes. The scientific significance of this study lies in the objective comparison of statistical and deep learning approaches to time series modeling using the same dataset. This contributes to determining appropriate model selection criteria for network traffic forecasting. It can be applied in 5G and emerging 6G networks, IoT infrastructures, cloud service data centers, intelligent transportation systems, and industrial networks. In the future, the research is planned to be extended in the following directions. Time series models based on transformer architectures (utilizing self - attention mechanisms to more effectively capture long-range dependencies) [4]. Multivariate time series modeling, incorporating external factors alongside traffic data. Hybrid models (combining ARIMA and LSTM approaches). Development of real - time forecasting systems based on edge-AI technologies. Automated hyperparameter optimization (AutoML). Overall, network load forecasting based on artificial intelligence represents one of the key steps toward the intellectualization of modern telecommunication systems [8]. With the continued advancement of deep learning technologies, the potential for developing self-managing and self - optimizing networks will further expand in the future.

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