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Integrated Neural Network and Wavelet-Based Model for Web Server Load Forecasting

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ABSTRACT This paper presents an integrated model for predicting the load on a web server by combining historical server logs, traffic data, and environmental factors to forecast load variations accurately. Key components include time series analysis for trend and seasonality detection, discrete wavelet transforms for noise reduction and feature extraction and neural networks for predictive modeling. Experimental results demonstrate that the integrated model achieves 15–25% higher forecasting accuracy compared to traditional methods, such as ARIMA. The proposed solution is scalable, adaptable, and provides a foundation for proactive load balancing and resource allocation strategies, ensuring robust server performance even during peak demand. The integrated model accounts for both short-term and long-term load variations, which is crucial for predicting peak loads and planning server resources. Future research may focus on optimizing algorithms and expanding the applications of this model to other systems, including cloud computing and distributed systems. The increasing demand for reliable and efficient web services necessitates accurate load prediction models to ensure optimal server performance and user experience. The modularity of the proposed model makes it scalable and adaptable, providing a foundation for active load balancing and resource allocation strategies to maintain server reliability even during peak load periods. A notable feature of the model is its ability to consider a wide range of variables, making it versatile for various types of data through the combination of classical statistical methods and modern machine learning algorithms. In addition to forecasting web server load, the proposed integrated model can be utilized for user behavior analysis, optimizing energy consumption, monitoring and predicting in data centers.

KEYWORDS web server, load forecasting, time series, web traffic, probability theory.

I. INTRODUCTION

The increasing popularity of online resources and the growing number of users demand high performance and reliability from web servers. One of the primary responsibilities of system administrators is to forecast web server load to prevent overloads, service disruptions, and ensure uninterrupted operation. Traditional methods of monitoring and analyzing server loads often fail to handle unpredictable activity spikes, potentially leading to significant issues in the functionality of web services. In the context of the rapid development of information technologies, the application of innovative forecasting methods has become increasingly pertinent. It is essential to process non-stationary web server load data more accurately.

Load forecasting for web servers is one of the critical tasks in modern information systems. Web servers facilitate access to information and services on the internet, making their stable operation essential for both businesses and users. Fluctuating server loads can result in service outages, decreased performance, and adverse effects on user experience.

II. ANALYSIS OF RECENT RESEARCH AND PUBLICATIONS

In recent years, numerous studies have been conducted on forecasting web server loads. Traditional methods, such as linear regression, AutoRegressive Integrated Moving Average (ARIMA), and other time series models [1], have demonstrated limitations when applied to highly dynamic and unpredictable load variations. Linear models are inherently constrained in their ability to forecast complex, nonlinear processes typical of web server loads.

Although ARIMA models offer greater flexibility, they often fail to achieve sufficient accuracy in scenarios involving unstable trends and seasonal fluctuations. Autocorrelation analysis [2], while useful for identifying recurring patterns or periodicity in signals, is less effective for non-stationary signals due to its poor temporal resolution.

The Fast Fourier Transform (FFT) [3] is another classical method used for analyzing the frequency spectrum of stationary signals. However, its primary drawback lies in the lack of temporal localization. This limitation is partially addressed by the Short-Time Fourier Transform (STFT) [3], which enhances temporal localization by dividing the signal into short segments and applying FFT to each segment. STFT provides simultaneous analysis in both the time and frequency domains. Nevertheless, STFT suffers from a fixed window size, resulting in a trade-off between time and frequency resolution: narrow windows offer high temporal resolution at the expense of frequency resolution, and vice versa.

An alternative approach for modeling systems whose states change over time under the influence of randomness is the application of Markov processes [4]. This approach is particularly suitable for predicting server states, as it enables the estimation of transition probabilities between states, such as from high-load to low-load conditions.

However, Markov models are often limited by a fixed number of states and predefined transitions, which may not capture all influencing factors on server performance. Additionally, such models may fail to account for long-term dependencies, which are crucial for accurate web server load forecasting.

At the same time, studies [5, 6] demonstrate that wavelet analysis allows the decomposition of time series into multiple frequency components, enabling the detection of localized features. This capability is particularly advantageous for forecasting irregular and unstable web server loads, as it accommodates both short-term and long-term variations.

However, wavelet analysis is not without limitations [7]. Its application requires careful parameter tuning and the selection of an appropriate wavelet function, which can be challenging for specific tasks.

Furthermore, wavelet analysis tends to be computationally intensive, making it less practical for real-time applications without efficient optimization [8]. In addition to this, depending on data quality, analysis may either enhance or degrade forecasting performance due to noise sensitivity [6].

Despite these challenges, wavelet-based methods have been successfully applied in various domains [8, 9], often outperforming traditional statistical techniques in complex time series forecasting.

Neural networks have also gained significant traction [10] in time series forecasting due to their ability to learn from large datasets and capture complex nonlinear dependencies. In the context of web server load prediction, neural networks [11] excel at modeling intricate relationships among input parameters. Recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) models [12], are commonly employed for time series analysis due to their capacity to retain long-term dependencies in data. However, LSTMs alone may be limited in effectively capturing localized patterns within time series data [12].

Hybrid models that integrate Convolutional Neural Networks (CNNs) and LSTMs offer enhanced capabilities for load forecasting. CNNs extract local features from time series data, while LSTMs process long-term dependencies. This combined approach has shown superior accuracy in time series prediction compared to traditional methods, as demonstrated in several studies [11, 13].

Nevertheless, neural networks face challenges, including the need for extensive hyperparameter tuning, which can increase the risk of overfitting. Additionally, a substantial amount of training data is required to achieve robust performance, and the models' sensitivity to noise may impact forecast accuracy.

Time series forecasting is one of the most complex tasks due to its inherent nonlinearity, stochasticity, and intricate temporal dependencies [14]. Hybrid approaches that integrate wavelet transformation with neural networks provide significant advantages for analyzing diverse time series data.

The combination of wavelet analysis with neural networks enables efficient time series processing and enhances forecasting accuracy through adaptive analysis and the computational power of neural networks.

III. RESEARCH OBJECTIVE

The objective of this study is to develop and implement an integrated model that enhances the efficiency of web server load forecasting.

IV. RESEARCH METHODOLOGY

An integrated model can combine the strengths of various systems while addressing their limitations. Although such a model may appear overly complex, adopting a modular approach – where each system component is responsible for specific aspects of data collection, analysis, and forecasting – allows for flexible customization to meet specific requirements.

Rather than attempting to implement a comprehensive integration of all components simultaneously, the model can be divided into distinct modules, such as data collection, preprocessing, forecasting, and optimization. This modular design facilitates the adaptation of individual system components to specific needs and simplifies overall system management.

Additionally, leveraging cloud services for data processing and storage can reduce infrastructure costs and streamline configuration processes.

The proposed integrated model offers improved forecasting accuracy through the use of wavelet transformation and neural networks, flexibility and adaptability via real-time data stream analysis and dynamic programming, automated resource management for efficient server resource allocation, and simplified implementation through a modular design. This modular approach mitigates the challenges associated with system complexity and reduces development costs.

The proposed model integrates wavelet transformation and neural networks to enhance forecasting quality. Wavelet transformation is employed for preprocessing time series data, enabling the decomposition of load patterns into short-term and long-term components. Wavelets effectively identify key trends, reduce noise, and separate data into different temporal scales.

Unlike traditional methods like Fourier transforms, which only provide frequency-domain analysis, wavelets preserve both time and frequency information, making them particularly well-suited for analyzing non-stationary web traffic data.

In this model, wavelet transformation enables feature extraction by capturing load patterns at multiple time scales, noise reduction by filtering out irregular fluctuations, and multi-resolution analysis by distinguishing between short-term spikes and long-term trends in server load.

A neural network, such as LSTMs, is then utilized to analyze these decomposed components and predict future load values based on wavelet-processed data. LSTMs are well-suited for capturing long-term temporal dependencies, making them ideal for analyzing dynamic load patterns over time.

Thus, the integrated model combines the strengths of existing systems, providing more accurate forecasting and resource optimization while overcoming their limitations through an adaptive and modular approach to system design:

- integration of wavelets and neural networks enhances

prediction quality by considering both local and global features of time series data;
- wavelet transformation reduces the influence of noise on the data, enabling the neural network to train more effectively on cleaner datasets;
- the model demonstrates improved flexibility and accuracy in forecasting unstable time series, which are characteristic of web server loads.

At the same time, it is important to consider potential limitations when developing such an integrated model:
- the computational complexity increases due to the combined use of wavelet transformation and neural networks;
- careful parameter tuning for both wavelets and the neural network is required to avoid overfitting.

In conclusion, integrating wavelet transformation with neural networks can address the shortcomings of traditional approaches, offering more accurate and adaptive load forecasting for web servers. This integration improves resource management efficiency and ensures stable server performance.

V. RESEARCH IMPLEMENTATION

The study utilized a dataset containing information on web server loads collected over several months. The data included parameters such as the number of requests per time unit and request processing times, which are factors influencing server load.

To ensure more accurate analysis data preprocessing was conducted. This included noise reduction and anomaly detection, where outliers caused by sudden traffic spikes or system failures were identified using a Z-score analysis and machine learning-based anomaly detection. By applying Z-score-based filtering, anomalies are replaced using moving averages, leading to a cleaner dataset for training machine learning models.

Additionally, data normalization was applied to standardize input values, preventing scale differences from biasing model training. Min-max scaling was used to transform the data into the range [0,1], enhancing model convergence and stability.

For time series analysis, Discrete Wavelet Transformation (DWT) was employed, as it effectively decomposes signals into detail levels (Fig. 1). DWT operates with a limited set of scales and shifts, making it well-suited for processing large datasets.

The application of wavelet analysis for data preprocessing and trend extraction enables the identification of both long-term and short-term trends in time series data. This approach effectively reduces noise and prepares the data for subsequent analysis.

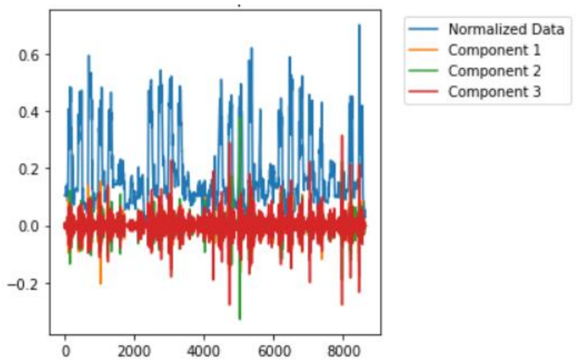

FIG. 1. Wavelet coefficients decomposition.

The selection of an appropriate wavelet function is a critical step in forecasting web server load, as it should align with the specific characteristics of the analyzed data. For example, wavelets suited to sharp transitions are preferable for data with abrupt changes, while smoother wavelets are better for more continuous signals.

The rationale for selecting a wavelet function should consider the following factors:
- high temporal-frequency localization, which facilitates the detection of short-term load peaks and long-term trends;
- robustness to noise, essential for real-world web server data that often exhibit high variability and stochastic components;
- sufficient smoothness, to avoid artifacts during signal reconstruction;
- compact support, which reduces computational requirements and accelerates processing of large datasets.

In the subsequent stage, a neural network module is employed for load forecasting. Neural networks are capable of uncovering complex patterns in load behavior that may be overlooked by traditional analytical methods.

This study presents a method for predicting web server load that integrates wavelet transformation with advanced neural network architectures. One such approach is a hybrid CNN+LSTM neural network. Wavelet transformation is utilized for data preprocessing, allowing for the extraction of primary trends and the mitigation of noise in time series data. The hybrid CNN+LSTM model combines the strengths of both methods: CNNs excel at capturing local patterns, while LSTMs account for long-term dependencies in the data.

The hybrid model consists of the following components:
- Input Layer, which accepts normalized time series sequences of web server load data;
- CNN Layers, which detect local features in the time series through convolutional layers;
- LSTM Layers, which process the extracted patterns while considering long-term dependencies;
- Fully Connected Layer, which performs the final data processing and generates the load forecast;
- Dropout Layers, which help prevent overfitting during training.

This integrated approach demonstrates the potential to enhance forecasting accuracy by leveraging wavelet transformation for data preprocessing and the complementary strengths of CNNs and LSTMs in feature extraction and temporal analysis.

Other neural network architectures explored in this study include Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) networks enhanced with an attention mechanism. These two popular types of RNNs are widely employed for time series analysis and effectively address the "vanishing gradient" problem inherent to classical RNNs. GRU represents a simplified version of LSTM, characterized by fewer parameters and a more computationally efficient architecture.

Integrating an attention mechanism into GRU and LSTM models further enhances their capabilities by enabling a focus on the most relevant parts of the input time series, akin to the functionality of transformer-based models. The attention mechanism allows the network to selectively prioritize significant portions of the input sequence without relying solely on the sequential nature of the RNN.

Incorporating attention into GRU or LSTM improves the model's ability to concentrate on the most critical segments of the input time series during output generation. This feature is particularly advantageous in tasks where context from specific positions in the time series holds greater importance than others. The key components of GRU or LSTM models with attention include their standard elements, augmented by an additional attention mechanism that computes a context vector. This vector represents a weighted sum of hidden states across the entire input time series.

The context vector, as shown in Eq. 1, is calculated as a weighted sum of the hidden states of the entire input sequence, using attention weights. It is then combined with the current hidden state (GRU or LSTM) to generate the final output:

$$K = \sum_i \alpha_i h_i , \qquad (1)$$

where h_i – the hidden state of the encoder at the i-th time step, α_i are the attention weights, interpreted as the probability that each element in the sequence contributes to the current output.

This attention mechanism enables the model to focus on the most relevant parts of the time series, enhancing the quality of data processing in tasks involving long time sequences, such as web server load data.

The proposed model architecture comprises the following key components:

- wavelet-transformed data preparation: After wavelet transformation, the number of time steps changes, and the size of the transformed training dataset is used as the new time step parameter;
- GRU (LSTM) layer: This layer processes the wavelet-transformed data, incorporating the feature dimension;
- Attention mechanism: This module generates a context vector that allows the model to concentrate on critical portions of the transformed time series;
- final layer: Predicts outputs based on the combined results from the neural network and the attention mechanism.

By adjusting hyperparameters, such as the type of wavelet function and the level of detail in the wavelet transformation, the model can be fine-tuned to match the specific characteristics of the data. This flexibility ensures optimal preprocessing and feature extraction tailored to the dataset.

This approach integrates the strengths of wavelet transformation, which effectively analyzes the frequency components of time series data, with the capabilities of neural networks to capture temporal dependencies.

The architecture of this integrated model (Fig. 2) illustrates its components for time series processing, including wavelet transformation and options for selecting different neural network configurations. This design enables efficient and accurate predictions of web server load, allowing the identification of peak loads and the prevention of system overloads.

The experimental results demonstrate that the proposed integrated model significantly outperforms traditional forecasting methods. By adjusting model parameters, such as the type of wavelets and the level of decomposition, it is possible to identify optimal configurations that enhance prediction accuracy.

For experimental web server load forecasting, Daubechies wavelets were selected, specifically the Daubechies 4 (db4) wavelet function, as it offered superior performance in the given application.

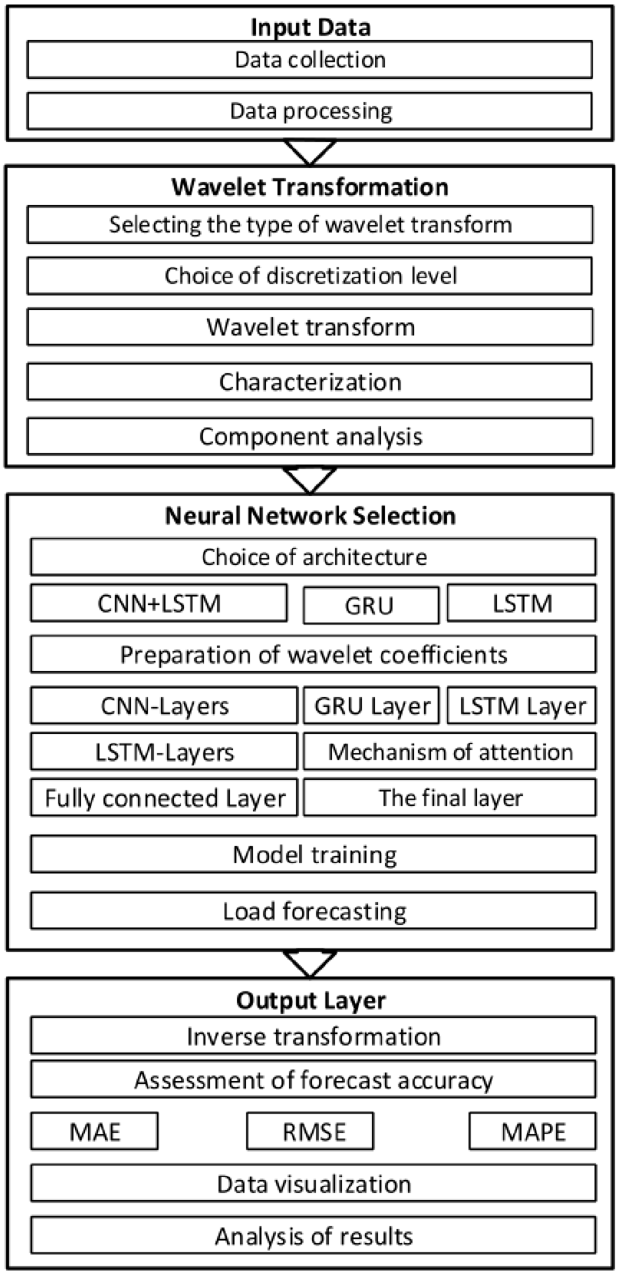

FIG. 2. Architecture of an integral model for processing time series.

TABLE 1. Model errors description.

Model	RMSE	MAE	MAPE
ARIMA	1.0514	0.7990	0.4878
CNN+LSTM	0.0867	0.0606	0.3133
GRU+Attention	0.0620	0.0484	0.2297
LSTM+Attention	0.0602	0.0435	0.2235

Testing on real-world data demonstrated that the integrated model delivers lower forecasting errors and better adaptability to variations in server load.

The models were compared based on three standard error metrics: Root Mean Squared Error (RMSE), which emphasizes larger errors; Mean Absolute Error (MAE), which measures average absolute deviations; and Mean Absolute Percentage Error (MAPE), which expresses error as a percentage for normalized accuracy.

As shown in Table 1, the RMSE of the integrated models was 15–25% lower compared to the ARIMA model, indicating superior predictive accuracy.

The results obtained (Fig. 3) validate the effectiveness of employing wavelet transforms for web server load forecasting. However, certain limitations of the model should be acknowledged. First, the computational complexity of wavelet transforms can be significant, particularly for large datasets, requiring substantial computational resources and time for analysis. Second, the development of an effective model necessitates large volumes of training data, which may be challenging to obtain in certain scenarios.

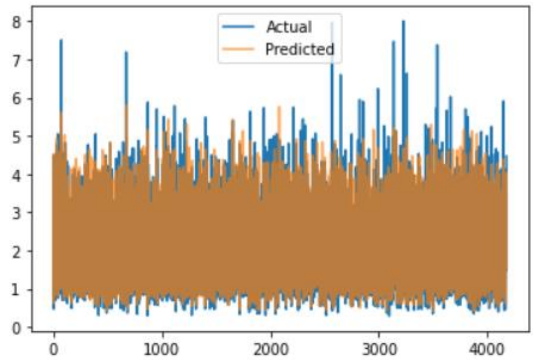

FIG. 3. Actual and predicted data comparison.

Future research could focus on real-world implementation by integrating the developed model into server management systems, conducting real-time testing, and evaluating its performance under diverse load scenarios.

Potential directions for future research include optimizing wavelet transform algorithms to reduce computational complexity, analyzing the impact of external factors such as seasonality, time of day, events, and campaigns, and exploring the potential of combining wavelet-based models with other forecasting techniques to achieve even higher accuracy.

VI. CONCLUSION

The proposed integrated model is a robust and flexible tool for handling non-stationary time series, enabling effective web server load forecasting. Compared to other signal processing methods, such as Fourier transforms and autocorrelation analysis, wavelet analysis provides superior time-frequency localization and captures both short-term and long-term variations in the signal. This makes it an indispensable method for forecasting tasks in dynamic and complex environments.

In this study, an integrated model for web server load forecasting was investigated. Wavelet analysis demonstrated its efficacy in extracting key features from server load time series, resulting in high forecasting accuracy.

Compared to traditional methods like ARIMA and standalone neural networks, the integrated model outperformed these approaches in processing non-stationary data and identifying both short- and long-term variations in load patterns. This capability is particularly critical for forecasting peak loads, which can significantly impact web server performance.

The proposed model can be effectively employed by web server administrators to achieve more accurate load predictions, preventing overloads, enhancing server performance, and ensuring uninterrupted web service operations. The high accuracy of the forecasts facilitates resource optimization and reduces infrastructure maintenance costs.

AUTHOR CONTRIBUTIONS

I.T. – conceptualization, methodology; K.R. – software, validation, formal analysis, investigation, visualization.

COMPETING INTERESTS

The authors declare no conflict of interest.

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Інтегрована модель для прогнозування навантаження на вебсервер на основі вейвлетів і нейронної мережі

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АНОТАЦІЯ У статті представлено інтегровану модель для прогнозування навантаження на вебсервер шляхом аналізу зібраних статистичних даних історичних журналів сервера, даних про поточний трафік та фактори навколишнього середовища для точнішого прогнозування коливань навантаження. Ключові компоненти включають аналіз часових рядів для виявлення трендів і сезонності, дискретні вейвлет-перетворення для зменшення шуму й виділення ключових ознак та нейронні мережі для прогнозування навантаженості вебсерверу. Експериментальні результати показують, що інтегрована модель досягає точності прогнозування на 15–25% більшу у порівнянні з традиційними методами, зокрема ARIMA. Інтегрована модель дозволяє враховувати як короткострокові, так і довгострокові зміни у навантаженні, що є важливим для прогнозування пікових навантажень на вебсервер та планування його ресурсів. Подальші дослідження можуть бути спрямовані на оптимізацію алгоритмів та розширення застосувань представленої моделі для інших типів систем, включаючи хмарні обчислення та розподілені системи. Зростання попиту на надійні та ефективні вебсервіси вимагає точніших моделей прогнозування навантаження для забезпечення оптимальної продуктивності вебсервера та взаємодії з користувачем. Запропонована модель за рахунок реалізації модульності є масштабованою, адаптованою і забезпечує основу для активного балансування навантаження та стратегій розподілу ресурсів, забезпечуючи надійну продуктивність сервера навіть під час пікового навантаження. Особливістю моделі є її здатність враховувати широкий спектр змінних, завдяки поєднанню класичних статистичних методів та сучасних алгоритмів машинного навчання. Окрім прогнозування навантаження на вебсервери, модель можна використовувати для аналізу поведінки користувачів, оптимізації енергоспоживання, моніторингу та прогнозування продуктивності.

КЛЮЧОВІ СЛОВА вебсервер, прогнозування навантаження, часові ряди, вебтрафік, теорія ймовірностей.