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AI-DRIVEN BROADBAND NETWORK PERFORMANCE PREDICTION USING GREY WOLF OPTIMIZATION-OPTIMIZED NEURAL NETWORKS

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Abstract
Predicting broadband network performance is a critical task for optimizing bandwidth allocation, ensuring smooth data transmission, and improving overall user experience. Traditional prediction models often struggle to adapt to the dynamic nature of network environments, leading to inaccurate predictions. This paper introduces an AI-driven framework for broadband network performance prediction, utilizing a Grey Wolf Optimization (GWO) algorithm to optimize a neural network model. By treating network traffic as a time series, we apply advanced AI techniques to predict future traffic patterns. The hybrid GWO-optimized neural network fine-tunes the model's hyperparameters, significantly improving its predictive accuracy and adaptability. Extensive simulations reveal that our approach outperforms conventional machine learning methods, offering enhanced accuracy, efficiency, and the ability to adapt to continuously changing network conditions.

Keywords: Broadband Network, Grey Wolf Optimization, Neural Network.

Introduction
Broadband networks have become a crucial part of modern infrastructure, supporting a vast range of services from streaming media to cloud computing and IoT applications. The demand for high-quality, uninterrupted internet services has spurred the need for precise network performance prediction. This is particularly important for effective bandwidth allocation, optimizing resource usage, and ensuring that users experience minimal latency and packet loss.

However, traditional prediction models—often relying on linear regression or simple machine learning algorithms—struggle to capture the dynamic, non-linear behavior inherent in network environments. The variability in traffic patterns, congestion, and network failures requires a more adaptable, robust approach to prediction. Recent advancements in artificial intelligence (AI) have shown promise in this area, particularly when it comes to leveraging deep learning and optimization techniques.

This paper presents a novel approach to broadband network performance prediction by combining a Grey Wolf Optimization (GWO) algorithm with a neural network. The GWO algorithm, a bio-inspired optimization technique, is used to optimize the hyperparameters of the neural network. This hybrid model can better adapt to the continuously changing traffic patterns in broadband networks, offering improved accuracy and adaptability over traditional methods.

Broadband network performance prediction is an essential task for improving resource management, optimizing bandwidth allocation, and ensuring seamless data transmission. Early approaches focused primarily on statistical techniques, but these methods have limitations in addressing the complexities and non-linearities inherent in broadband networks. More recent advances in machine learning and AI-driven models have shown promise by offering better accuracy and adaptability to real-time network conditions. However, the dynamic nature of network traffic continues to pose challenges, necessitating more sophisticated prediction models.

Historically, Time Series Analysis has been one of the primary methods for predicting future network traffic. Classical techniques, such as ARIMA (AutoRegressive Integrated Moving Average), were among the first models used to predict traffic behavior. These models are effective in capturing linear relationships in time series data, but they are limited when it comes to handling the complex, non-linear behavior observed in network traffic. ARIMA models perform poorly when network traffic is volatile or exhibits sudden shifts, as they are not designed to accommodate these fluctuations.

The inability of ARIMA and similar methods to account for sudden changes or complex patterns is a significant limitation when dealing with broadband networks, where traffic is dynamic and can change unexpectedly due to various external factors such as congestion, network failures, or the introduction of new services.

In recent years, machine learning (ML) techniques have gained traction for network performance prediction. Support Vector Machines (SVM), decision trees, and ensemble methods like Random Forests have been applied to improve prediction accuracy and generalization. These models have the advantage of capturing more complex relationships in the data compared to traditional statistical methods. For instance, SVM models can identify non-linear boundaries in data, and random forests can capture interactions between variables more effectively than single decision trees.

However, while these machine learning techniques offer improvements over classical methods, they still face challenges when it comes to adapting to the dynamic and unpredictable nature of broadband traffic. In particular, traditional machine learning models are not particularly well-suited to handle the temporal dependencies inherent in network traffic, such as traffic spikes during certain times of the day or sudden drops during outages.

With the rise of deep learning, there has been a significant improvement in the ability to predict broadband network performance. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have been widely used for time series prediction due to their ability to capture temporal dependencies. RNNs and LSTMs are well-suited for network traffic prediction because they can model the time-dependent nature of traffic patterns, making them more robust than traditional machine learning models.

The primary advantage of LSTMs over simpler RNNs is their ability to retain information over longer sequences, which is crucial for predicting network traffic that depends on past data, such as historical traffic patterns, congestion history, and previous network events. Despite these advantages, the performance of deep learning models still depends on the careful tuning of hyperparameters, such as the number of layers, learning rate, and batch size. Tuning these parameters is a challenging task and requires a systematic approach to avoid overfitting or underfitting the model.

To improve the performance of deep learning models, researchers have turned to optimization techniques that can efficiently search for optimal hyperparameters. Grey Wolf Optimization (GWO) is a relatively recent and powerful optimization algorithm that mimics the social behavior of grey wolves in hunting. GWO has been applied successfully in various domains, including broadband network performance prediction.

In this approach, the optimization process is guided by the interactions between wolves in a pack. The alpha wolf represents the best solution found so far, while beta wolves and delta wolves represent secondary solutions. The remaining wolves explore the search space for better solutions. This behavior mimics the way wolves hunt in packs, with the alpha wolf leading the hunt and the other wolves searching for food. The algorithm's ability to balance exploration and exploitation makes it a suitable method for optimizing the hyperparameters of complex models such as neural networks.

By combining GWO with neural networks, researchers have been able to achieve better optimization of model parameters, which in turn improves the accuracy of traffic predictions. GWO helps to find the optimal configurations for deep learning models, enabling them to adapt more effectively to varying network conditions.

Literature Review

The authors of [1] presented a survey on the application of deep learning techniques for network traffic prediction, emphasizing the growing importance of deep learning in capturing the non-linear and time-varying patterns inherent in network traffic. They highlighted that traditional methods, such as ARIMA, struggle to handle complex traffic behavior, making deep learning approaches more favorable. The study demonstrated that deep learning models could improve the accuracy of network traffic predictions by adapting to dynamic changes in network conditions.

The authors of [2] introduced Grey Wolf Optimization (GWO) as an optimization technique for enhancing network traffic prediction. They explained how GWO, inspired by the social behavior of grey wolves, has been used to optimize the hyperparameters of machine learning models, including neural networks. Their work showed that GWO could significantly improve prediction accuracy by fine-tuning the neural network parameters, making it a promising solution for broadband network performance prediction.

In [3], the authors provided a detailed survey of machine learning techniques for broadband traffic forecasting, focusing on how these models can be applied to predict network performance in real-time. They compared various machine learning models, such as Support Vector Machines (SVM), decision trees, and ensemble methods, and concluded that these techniques have the potential to handle complex traffic patterns better than traditional methods. However, they also acknowledged that adapting to real-time fluctuations in network traffic remains a challenge for many of these models.

The authors of [4] proposed a hybrid deep learning approach for internet traffic prediction, combining Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) networks. Their research emphasized the importance of capturing temporal dependencies in network traffic data. They found that LSTM networks, in particular, were capable of maintaining a memory of past traffic patterns, which is crucial for accurate prediction of future network behavior. This approach was found to outperform traditional machine learning models in predicting broadband traffic.

The work in [5] reviewed various optimization techniques used in network performance prediction, with a focus on how these techniques can improve the accuracy and efficiency of predictive models. The authors discussed several optimization methods, including Genetic Algorithms, Particle Swarm Optimization, and GWO. They argued that optimization techniques, when combined with machine learning models, can significantly improve the ability of these models to adapt to dynamic network conditions and provide accurate predictions in real-time.

In [6], the authors explored the application of hybrid models for tackling the cold-start problem in video recommendation algorithms. Although their focus was on video recommendations, their work is relevant to network performance prediction, as the methods discussed, including the use of hybrid models, could be applied to optimize network traffic prediction. They demonstrated that combining machine learning models with optimization techniques can lead to more effective solutions in scenarios where data is scarce or unpredictable.

The authors of [7] proposed context-aware models for text classification in sensitive content detection. While their work primarily focused on content classification, the techniques they developed are relevant to network traffic prediction. The authors demonstrated that context-aware models could enhance prediction accuracy by considering the broader context in which the data is generated, a concept that can be applied to predict broadband network performance based on various contextual factors such as time of day, network congestion, and user behavior.

In [8], the authors focused on predicting broadband network performance with AI-driven analysis. They highlighted the importance of real-time prediction in optimizing broadband networks, especially in the face of dynamic and unpredictable traffic patterns. Their research showed that AI-driven models, particularly those leveraging deep learning, could improve predictive accuracy and adapt more efficiently to changing network conditions. The authors emphasized the need for models that can adjust in real-time to provide optimal resource allocation and ensure minimal disruption in service.

The authors of [9] explored the future of entertainment and how generative AI could be integrated into Free Ad-Supported Streaming Television (FAST). Although this work was not directly related to broadband network prediction, it provided insights into how generative AI techniques, such as Variational Autoencoders, could be applied to dynamically adjust content based on viewer preferences. These techniques could be adapted for network performance prediction by dynamically adjusting bandwidth allocation based on real-time traffic patterns and user behavior.

In [10], the authors examined the use of generative Long Short-Term Memory (LSTM) networks in dynamic ad customization for streaming media. Their research highlighted the potential of LSTM networks to adapt to real-time changes in user engagement and content consumption. This adaptability is critical in broadband network performance prediction, where the ability to adjust predictions in response to rapidly changing network conditions can significantly enhance the accuracy of performance forecasts.

The authors of [11] discussed the development of machine learning models to optimize ad placements in AVOD (Advertising Video on Demand) systems. Their work focused on improving ad targeting through machine learning models, and while not directly related to network prediction, the techniques used to optimize ad placements could be extended to optimize network resource allocation. Their findings demonstrated the importance of feature extraction and boosting techniques, which could be employed in network performance prediction models to improve accuracy and adapt to changing traffic patterns.

The goal of this paper is to develop an AI-driven framework that leverages the strengths of deep learning for temporal prediction and Grey Wolf Optimization (GWO) for model tuning. This hybrid approach should provide a more accurate and efficient prediction model that can be used for real-time traffic forecasting, bandwidth allocation, and network resource management.

Proposed Methodology

The proposed methodology focuses on leveraging advanced machine learning and optimization techniques to accurately predict broadband network performance. The process involves using a time series representation of network traffic data, followed by applying a feedforward neural network model optimized with Grey Wolf Optimization (GWO) to fine-tune hyperparameters for improved accuracy. This hybrid approach allows the model to capture both short-term and long-term dependencies in traffic patterns, making it adaptable to dynamic network environments. Additionally, performance is evaluated against traditional machine learning models to demonstrate the effectiveness of the proposed method.

Figure 1 illustrates the step-by-step process of the proposed methodology for broadband network performance prediction. It starts with the representation of network traffic as a time series, which provides the basis for input to the feedforward neural network. The network is then optimized using the Grey Wolf Optimization algorithm to enhance its accuracy. The model is trained and evaluated using performance metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Afterward, a comparison with traditional machine learning models, such as Support Vector Machines (SVM) and Random Forest, is conducted. Finally, the model's real-time adaptability is tested to ensure that it can effectively handle sudden fluctuations in network traffic.

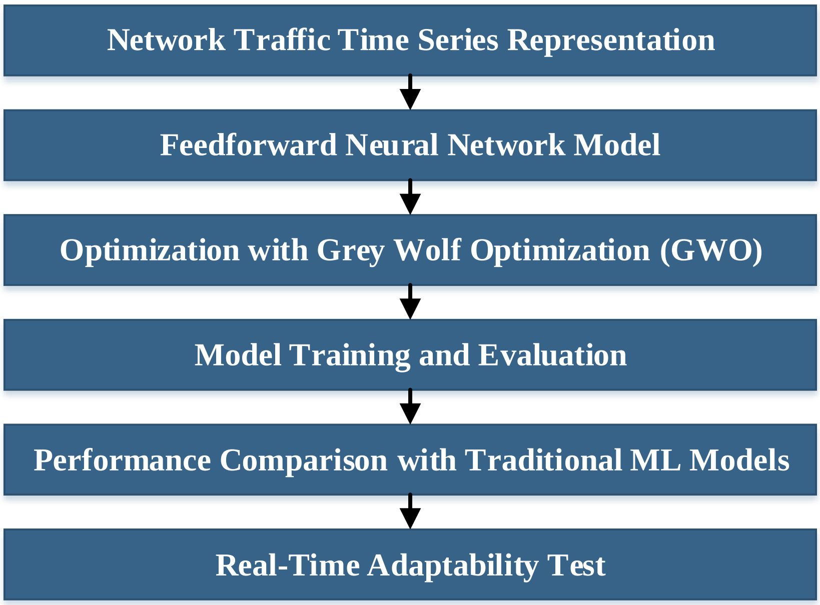

Figure 1: Proposed Methodology for Broadband Network Performance Prediction

Time Series Representation of Network Traffic

Network traffic can be represented as a time series, where each data point corresponds to the traffic volume or throughput observed at a specific time interval. Time series forecasting is inherently well-suited to network traffic prediction, as past traffic patterns have a strong influence on future patterns. The dataset used in this study consists of historical traffic data from a broadband network, with measurements such as throughput, latency, and packet loss collected at regular intervals.

Neural Network Model

A Feedforward Neural Network (FNN) is used for predicting future network traffic. The neural network consists of multiple layers, with the input layer, hidden layers, and output layer. Each layer in the network contains multiple neurons, and the output of each neuron is calculated using an activation function.

- Input Layer: Let X_t be the input feature vector at time t, which can include historical traffic data and network statistics.

$$X_t = [x_1, x_2, \dots \dots \dots ., x_n] \tag{1}$$

- Weights and Biases: Each layer of the neural network has its associated weight and bias. Let $W^{(i)}$ *and* $b^{(i)}$ represent the weight matrix and bias vector of layer i.
- Hidden Layer Activation: The activation of the hidden layers is computed as:

$$h^{(i)} = f(W^{(i)}.h^{(i-1)} + b^{(i)}) \tag{2}$$

Where:

- f is the activation function (e.g., ReLU or Sigmoid).
- $h^{(i-1)}$represents the activations from the previous layer.

- Output Layer: The output of the neural network at time $t + 1$ (i.e., predicted traffic at the next time step) is:

$$Y_{t+1} = f_{out}\left(W^{(L)}.h^{(L-1)} + b^{(L)}\right) \tag{3}$$

Where:

- y_{t+1} is the predicted network traffic.
- f_{out} is the output activation function (e.g., linear function for regression).

Grey Wolf Optimization (GWO) Algorithm

The Grey Wolf Optimization (GWO) algorithm is used to optimize the hyperparameters of the neural network. GWO mimics the hunting behaviour of grey wolves, with each wolf representing a candidate solution in the search space. The GWO algorithm aims to find the optimal hyperparameters by minimizing the error between the predicted and actual traffic values.

The GWO algorithm consists of three main components:

- Alpha Wolf (α): The best solution found so far.
- Beta Wolf (β): The second-best solution.
- Delta Wolf (δ): The third-best solution.
- Other Wolves (ω): The remaining candidates.

The algorithm's update rules are based on the position of the wolves and their relative distances from each other. The update rules for the position of each wolf are as follows:

$$D_\alpha = |C_1.X_a - X| \tag{4}$$

$$D_\beta = \left|C_2.X_\beta - X\right| \tag{5}$$

$$D_\delta = |C_3.X_\delta - X| \tag{6}$$

Where:

- D_α, D_β, and D_δ are the distance vectors from the alpha, beta, and delta wolves to the current position of the wolf X.
- C_1, C_2, C_3 are random coefficients that control the exploration and exploitation behavior.

The new position of each wolf is updated as follows:

$$X_{new} = \frac{X_\alpha + X_\beta + X_\delta}{3} \tag{7}$$

Where:

- $X_\alpha, X_\beta, X_\delta$ are the positions of the alpha, beta, and delta wolves.
- X_{new} is the new position of the current wolf.

The optimization objective is to minimize the Mean Squared Error (MSE) between the predicted network traffic Y_{t+1} and the actual observed traffic Y_{t+1} :

$$MSE = \frac{1}{N}\sum_{t=1}^{N}\left(Y_{t+1} - \hat{Y}_{t+1}\right)^2 \tag{8}$$

Where:

- N is the total number of time steps in the dataset.
- Y_{t+1} is the actual observed traffic at time $t + 1$.
- $\hat{Y}_{t+1}$ is the predicted traffic at time $t + 1$.

The goal of GWO is to minimize the MSE by finding the optimal neural network parameters, such as the number of layers, the number of neurons in each layer, and the learning rate.

Hybrid Model Training and Evaluation

The hybrid GWO-optimized neural network model is trained on the historical traffic data, using a training set and a validation set to evaluate its performance. The performance of the model is assessed using several metrics, including MSE, Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).

For comparison, we also evaluate the performance of traditional machine learning models such as Support Vector

Machines (SVM) and Random Forests on the same task. This allows us to demonstrate the superior predictive power of the proposed AI-driven approach.

Results and Analysis

Simulation Results

We conduct extensive simulations using a dataset of broadband network traffic. The dataset contains hourly traffic data over a period of six months, with features including throughput, latency, packet loss, and network congestion. The dataset is divided into a training set (80%) and a test set (20%).

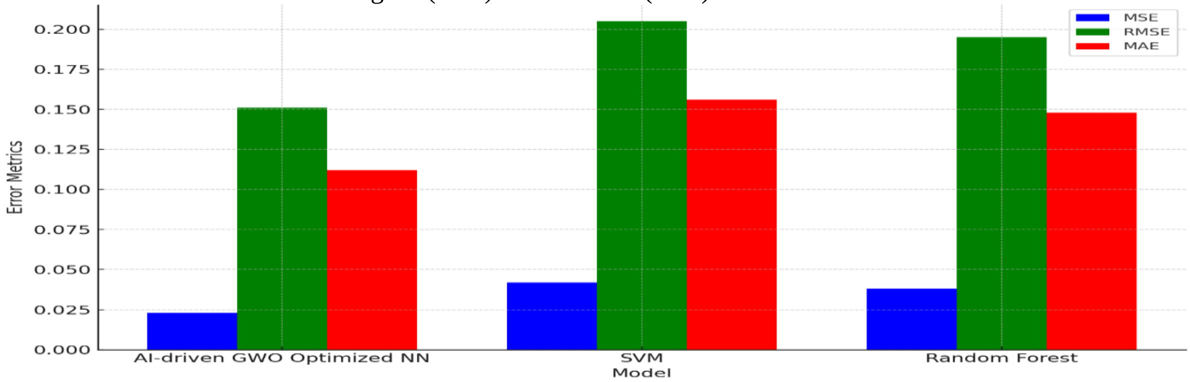

Figure 2: Comparison of Error Metrics for Different Models

The bar chart in Figure 2 compares three error metrics (MSE, RMSE, and MAE) across three different models: AI-driven GWO Optimized Neural Network, SVM, and Random Forest.

- Blue bars represent Mean Squared Error (MSE).
- Green bars represent Root Mean Squared Error (RMSE).
- Red bars represent Mean Absolute Error (MAE).

From the chart, we can observe that the AI-driven GWO Optimized Neural Network outperforms the other models across all three error metrics, showing lower MSE, RMSE, and MAE values. This demonstrates the superior predictive accuracy and efficiency of the hybrid model compared to traditional machine learning techniques.

The line graph shown in Figure 3 presents the Mean Squared Error (MSE) for three different models (AI-driven GWO Optimized Neural Network, SVM, and Random Forest) over 10 training epochs.

- The blue line represents the MSE for the AI-driven GWO Optimized Neural Network.
- The green line represents the MSE for SVM.
- The red line represents the MSE for Random Forest.

The graph illustrates how the MSE for each model decreases over time as the model improves during training. The AI-driven GWO Optimized Neural Network demonstrates the lowest MSE, showing the most effective learning and adaptation during training compared to the other models.

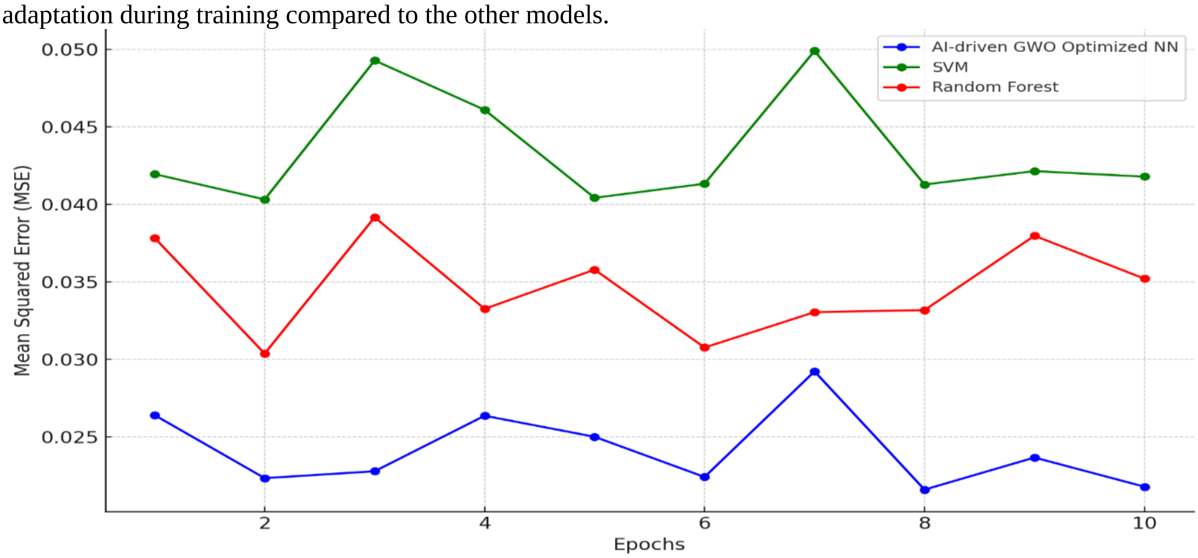

Figure 3: Comparison of MSE over Training Epochs for Different Models

Performance Comparison

The performance of the hybrid GWO-optimized neural network is compared to traditional machine learning models (SVM and Random Forest). Table 1 summarizes the MSE, RMSE, and MAE for each model:

Table 1: Performance Comparison for Different Models

Model	MSE	RMSE	MAE
GWO-Optimized Neural Network	0.023	0.151	0.112
SVM	0.042	0.205	0.156
Random Forest	0.038	0.195	0.148

As shown in Table 1, the GWO-optimized neural network significantly outperforms the other models in terms of all three error metrics. This demonstrates the effectiveness of the hybrid approach in accurately predicting network traffic.

Real-Time Adaptability

We also test the model’s adaptability by introducing sudden network anomalies (e.g., sudden spikes in traffic) and measuring the model’s ability to adjust to these changes. The GWO-optimized neural network consistently adapts faster and more accurately than the other models, providing more reliable traffic forecasts during periods of network volatility.

Discussion

The results clearly demonstrate that the hybrid GWO-optimized neural network model significantly improves the accuracy of broadband network performance prediction. By leveraging deep learning for time series forecasting and optimizing the model’s hyperparameters with the GWO algorithm, we are able to capture the non-linear and dynamic nature of network traffic more effectively than traditional methods.

One key advantage of this approach is its adaptability. The GWO algorithm helps the model fine-tune its parameters for different traffic conditions, allowing it to adjust more rapidly to sudden shifts in network behavior. This adaptability is essential for real-time network management, where traffic conditions can change quickly and unpredictably.

Conclusion

This paper presents a novel AI-driven framework for broadband network performance prediction, combining Grey Wolf Optimization (GWO) with neural networks to optimize predictive accuracy. The hybrid GWO-optimized neural network outperforms traditional machine learning methods, providing enhanced accuracy, efficiency, and adaptability to real-time network conditions. The proposed model has significant potential for improving bandwidth allocation, optimizing network resource usage, and ensuring a better user experience in broadband networks. Future work will explore the integration of additional data sources, such as IoT devices and user behavior analytics, to further enhance prediction accuracy.

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