Efficiency of Network Traffic Management and Prediction using SCA

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Abstract
the need for precise prediction systems and effective traffic management has grown as a result of the digital networks' explosive expansion. Applying SCA to prediction and network traffic management systems is the main objective of this paper [1]. Scalable, reusable, and readily maintainable components for anomaly detection, predictive modeling, and real-time traffic analysis can be created and implemented using SCA. The SCA framework improves its capacity to forecast future traffic patterns by utilizing machine learning techniques, which permits proactive resource allocation and congestion alleviation [2].

Keywords
Network Traffic Management, Sin Cosine Algorithm, Predictive Analytics, Recurrent Neural Networks, Deep Learning Techniques.

1. Introduction

The rapid surge in internet traffic, fueled by exponential growth, increased adoption of cloud technology and the Internet of Things (IoT) [1]. Devices and high-bandwidth applications, including video streaming, gaming, and virtual reality, have put considerable pressure on IT networks. In elevated environments with high demand, characterized by substantial volumes of information shared through intricate networks [1], the capability to forecast and oversee infrastructure's traffic patterns cannot be overstated. Effective traffic management is essential to avoid congestion and ensure the quality of service (QoS) and peak network efficiency [1]. Historically, predicting network traffic depended on statistical techniques like linear regression and time series analytics [1].

2. Ai Techniques for Network Traffic Prediction

2.1 Machine Learning Techniques

to estimate network traffic in modern times, machine learning (ML) has become essential [1]. The following are a few popular machine learning methods for traffic prediction: By identifying hyper planes that divide various traffic patterns, SVMs are used to categorize the network traffic and predict the trends [1]. They help with network management, load prediction, and anomaly detection [1]. Forest ensemble learning techniques forecast network traffic by combining several decision trees [1]. By merging results from many trees, they can increase prediction accuracy and are especially useful with big datasets (Chen et al., 2018).

KNN predicts traffic by comparing new data to old records and is used for both classification and regression applications [1]. By identifying comparable historical trends, this method assists in predicting traffic spikes [2]. An effective method for spotting intricate patterns in network traffic data is the use of artificial neural networks, ANNs [1]. In order to predict future traffic demands, multilayer perceptron networks have been employed, utilizing past data [1].

2.2 Deep Learning Techniques

Deep Learning (DL) models, in particular, have demonstrated significant efficiency in network traffic forecasting because of their ability to handle large-scale, high-dimensional data [1].

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Some of the most used DL techniques include: RNNs represent a particular class of neural networks that excel at processing sequential data, like traffic datasets with time series. Their intrinsic capacity to remember information from antecedent time steps makes them especially well-suited for forecasting future traffic situations based on historical trends. One kind of RNN called an LSTM architecture was created specifically to address the shortcomings of conventional RNNs, especially the vanishing gradient phenomenon. Empirical studies have demonstrated that LSTM models are exceptionally good at forecasting time-series traffic patterns in highly demanding IT systems [1], [2].
CNNs have been used to forecast traffic by interpreting traffic data as a kind of spatial pattern, despite their primary use in image identification applications. Large datasets of network traffic can have their features extracted by it [1].

2.3 Proposed Network Traffic Predictor and Traffic Classification Agent

In this part, we discuss the proposed NTPA and NTCA frameworks [3]. First, let's define and contextualize the agents. The agent contains input, output, and communication tools to observe the environment, generate the output or perform the action, and communicate with other agents already present in the MAS. After operating in a particular setting and analyzing its parameters, an agent may form opinions. The following are important characteristics of an agent:

2.3.1 Situations: Agents use actuators to change their environment and sensors or perceptual skills to interact with it. In the contexts of NTPA and NTCA, it refers to taking incoming data as input and generating prediction [3].

2.3.2 Inferential capability: The capacity for inference, which enables agents to strive toward an objective until it is achieved. Analyzing the available data, such as identifying the traffic class and forecasting network traffic, allows agents to make judgments.

2.3.3 Responsiveness: An agent needs to be able to sense its environment and respond to it as quickly as possible in order to function in real-time for the task execution (prediction and classification in the case of NTPA and NTCA).

3. The Sine Cosine Algorithm (Sca)

The Sine Cosine Algorithm (SCA) is a met heuristic optimization algorithm that mimics mathematical sine and cosine functions to explore and exploit the search space efficiently. It is particularly effective for solving high-dimensional optimization problems, making it suitable for network traffic optimization tasks. Helps predict bandwidth demand to prevent congestion. Used in dynamic resource allocation to enhance Quality of Service (QoS). Efficiently distributes network traffic among a number of servers or channels. Reduces bottlenecks and enhances data flow. SCA dynamically selects the optimal routing paths based on current traffic conditions. SCA optimizes machine learning models (e.g., neural networks, support vector machines) for accurate traffic forecasting [4]. Helps predict bandwidth demand to prevent congestion. Used in dynamic resource allocation to enhance Quality of Service (QoS) [5]. Efficiently distributes network traffic among a number of servers or channels. Reduces bottlenecks and enhances data flow. SCA dynamically selects the optimal routing paths based on current traffic conditions [4].
It is particularly effective for solving high-dimensional optimization problems, making it suitable for network traffic optimization tasks [2].

A. Pseudo-Code

Initialize Parameters:

a. Setmax node capacity (max_capacity):

1. Set up network environment

- Define num_nodes (number of network nodes)
- Generate a random traffic matrix (traffic_matrix)

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2. Initialize PSO parameters

- Initialize particle positions (random routing probabilities)
- Initialize velocities(velocities)
- Set inertia weight (w), cognitive (c1), and social (c2) coefficients

3. Initialize SCA parameters

- Define num_solutions (number of candidate solutions in SCA)
- Generate random initial solutions for SCA
- Set random sine-cosine parameters (r1, r2, r3)

b. Hybrid Optimization Loop (SCA + PSO)

For each iteration (**t = 1**to num_iterations):

Step 1: Evaluate network traffic load

- Compute routing load per node based on current particle positions
- Compute overload penalty for nodes exceeding max_capacity
- Define fitness function (cost) → total congestion + overload penalty

Step 2: Sine cosine algorithm (sca) updates

- Update candidate solutions (X) using sine-cosine equations
- Evaluate new solutions using fitness function
- Replace old solutions if new ones are better

Step 3: Particle swarm optimization (pso) updates

- Update velocities based on p_best (personal best) and g_best (global best)
- Update particle positions
- Ensure values are within valid range (0 to 1 routing probability constraints)
- Update p_bestandg_best

Step 4: Adaptive hybrid mechanism

Every few iterations **(**adaptive tuning rule)**:**

- Use SCA updates for exploration (global search)
- Use PSO updates for exploitation (local refinement)

Step 5: Stopping criteria

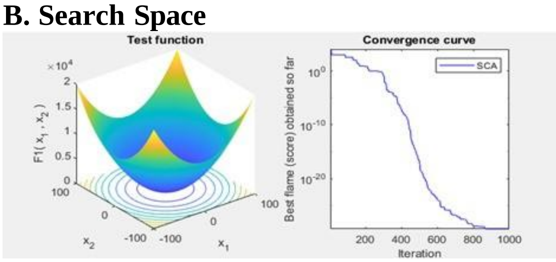
- Stop if max iterations reached or no improvementing_bestcost

c. Output Results

- Display optimized routing table **(**g_best**)**
- Display final optimized traffic load per node

It is particularly effective for solving high dimensional optimization problems; making it suitable for network Helps predict bandwidth demand to prevent congestion.Used in dynamic resource allocation to enhance Quality of Service (QoS). Efficiently distributes network traffic among a number of servers or channels. Reduces bottlenecks and enhances data flow. SCA dynamically selects the optimal routing paths based on current traffic conditions.SCA optimizes machine learning models (e.g., neural networks, support traffic optimization tasks. SCA optimizes machine learning models (e.g., neural networks, support vector machines) for accurate traffic forecasting [4]. Vector machines for accurate traffic forecasting.Helps predict bandwidth demand to prevent congestion.Used in dynamic resource allocation to enhance Quality of Service (QoS) [5].Efficiently distributes network traffic among a number of servers or channels. Reduces bottlenecks and enhances data flow. SCA dynamically selects the optimal routing paths based on current traffic conditions [4].

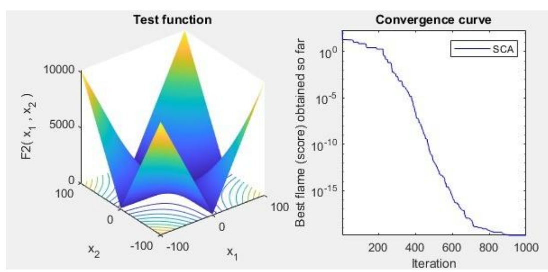
B. Search Space



Function 1:

The search space and the conversion curve for the function 1.

Function 2:



The search space and the conversion curve for the function 2.

Function 3:

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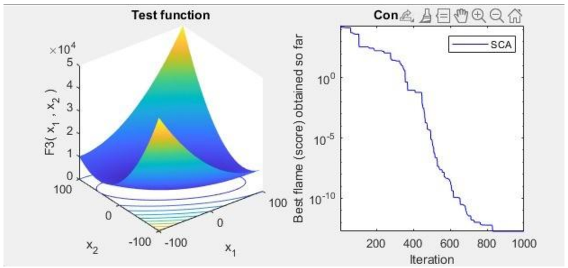
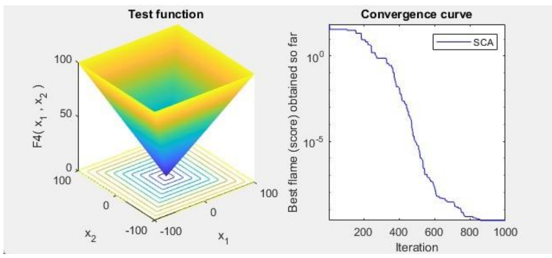


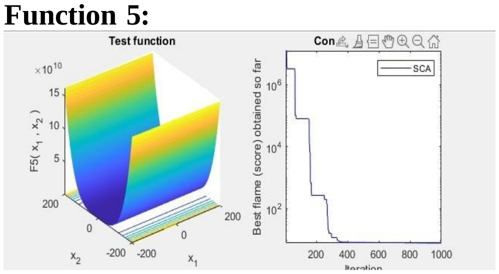
The search space and the conversion curve for the function 3.

Function 4:



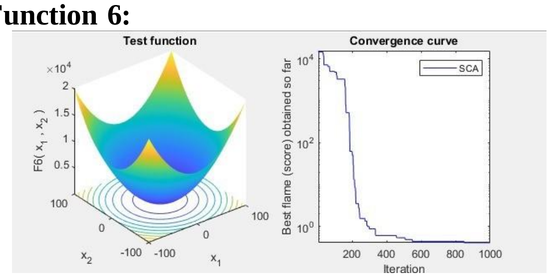
The search space and the conversion curve for the function 4.

Function 5:



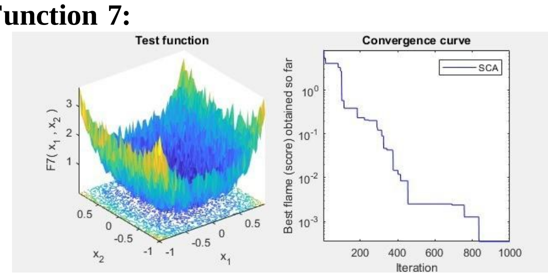
The search space and the conversion curve for the function 5.

Function 6:



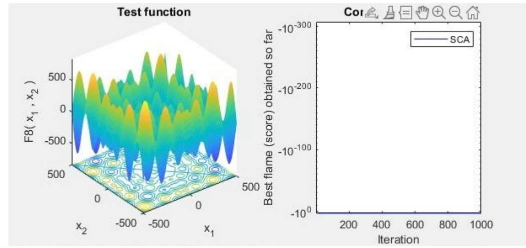
The search space and the conversion curve for the function 6.

Function 7:



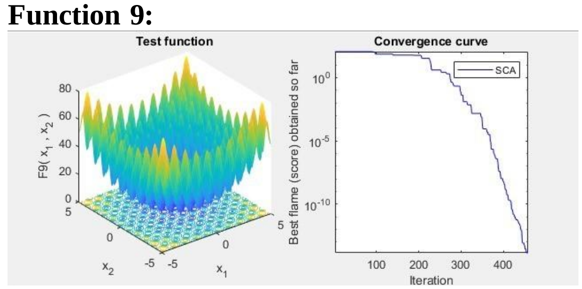
The search space and the conversion curve for the function 7.

Function 8:



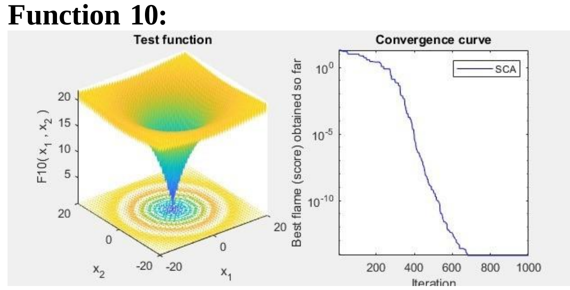
The search space and the conversion curve for the function 8.

Function 9:



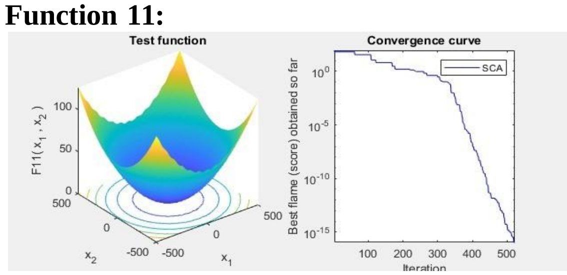
The search space and the conversion curve for the function 9.

Function 10:



The search space and the conversion curve for the function 10.

Function 11:



The search space and the conversion curve for the function 11.

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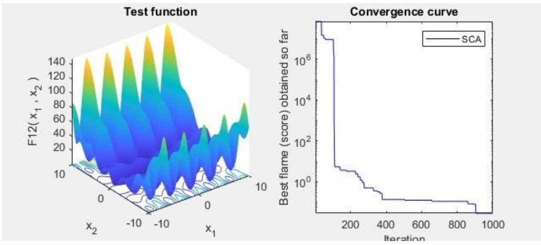
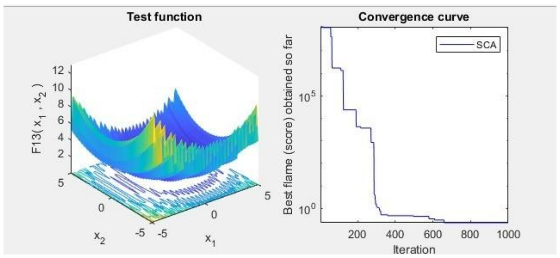
Function 12:



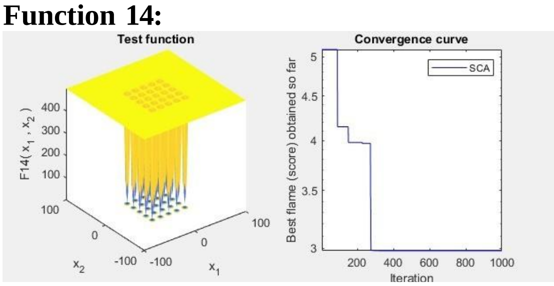
The search space and the conversion curve for the function 12.

Function 13:



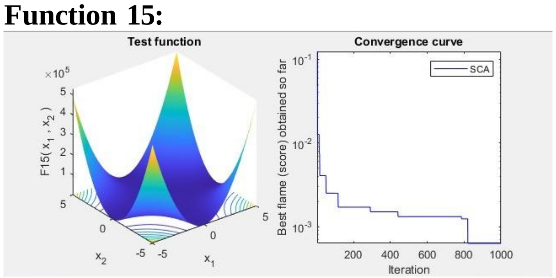
The search space and the conversion curve for the function 13.

Function 14:



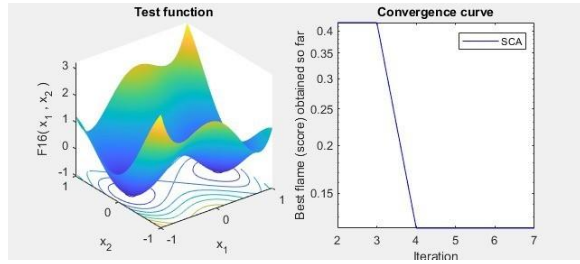
The search space and the conversion curve for the function 14.

Function 15:



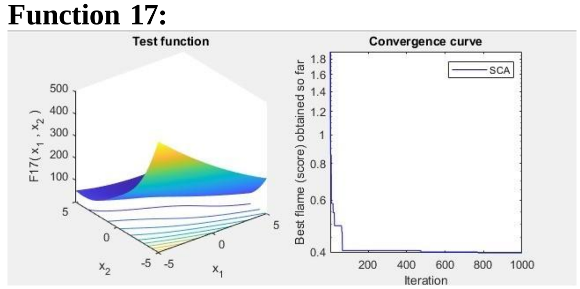
The search space and the conversion curve for the function 15.

Function 16:



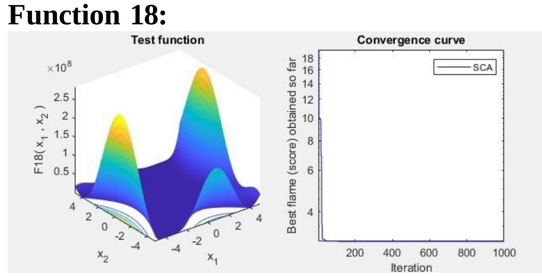
The search space and the conversion curve for the function 16.

Function 17:



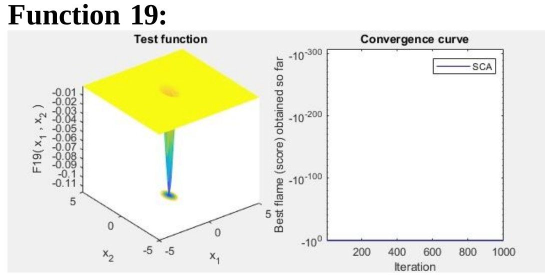
The search space and the conversion curve for the function 17.

Function 18:



The search space and the conversion curve for the function 18.

Function 19:



The search space and the conversion curve for the function 19.

Function 20:

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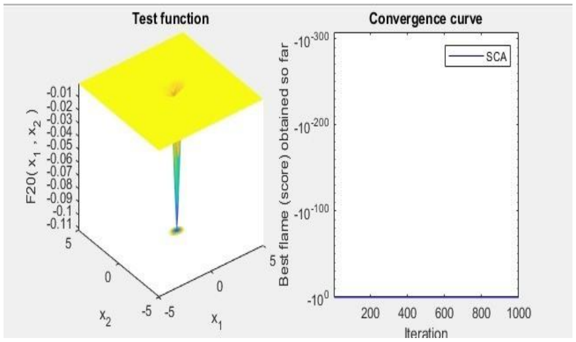
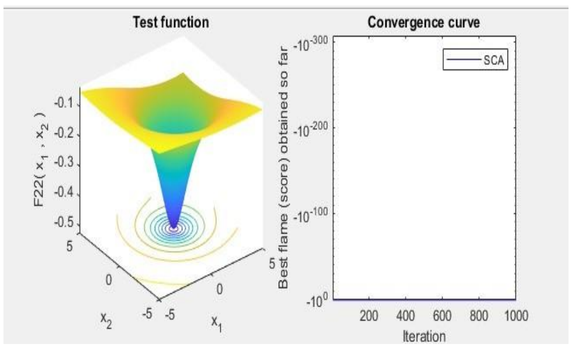


The search space and the conversion curve for the function 20.

Function 21:

The search space and the conversion curve for the function 21.

Function 22:

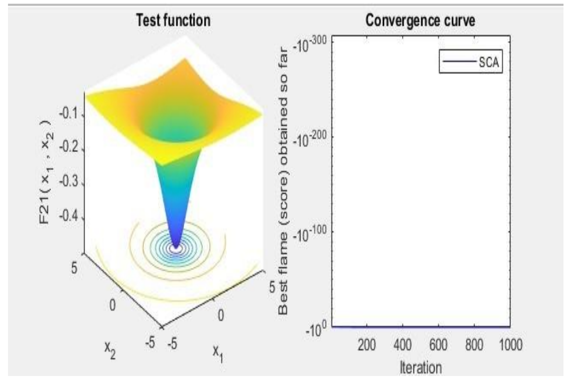


The search space and the conversion curve for the function 23.

4. Result

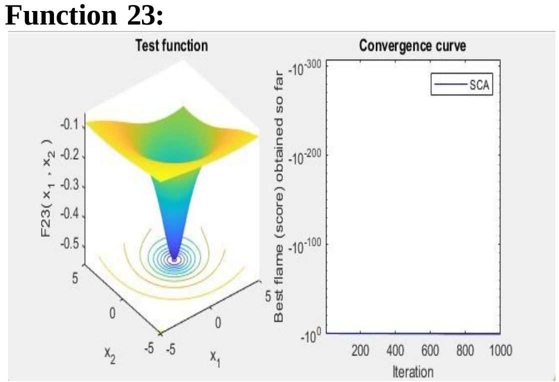
The Original value denotes the true solution, and the Hybrid value is the outcome generated by the Particle Swarm Optimizer that executing the algorithm to determine an optimal solution.

According to the resultant search space and convergence curve of the 23 given function there are different hybrid values and original values are obtained by applying the sin cosine algorithm (SCA). Among the 23 functions, function1 (F1) has original value zero (0) where it shows that, efficient value at that end. Whereas, it has hybrid value of 8.5265.



The search space and the conversion curve for the function 22.

Function 23:



To check the efficiency and performance of the different network traffic control panel, it has been clear that it totally calculated through using sin cosine algorithm (SCA). The point where the values are zero means they have the accurate performance at that end.

The function 14 (F14) has the original value 2.9821 and the hybrid value 1. So that at F14 it has optimal value. All the functions are performed using the sin cosine algorithm to get the optimal values. The best optimal values show that, particular functions are efficient or not. In the given data F14 and F9 has the optimal solution and show the best efficiency level in the network traffic management and prediction using sin cosine algorithm (SCA). The search values of different functions from F1 to F14 are shown in table as given below.

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Function	Original Value	Hybrid Value
Function 1	2.022e-26	1.5666e-29
Function 2	1.8384e-18	7.9477e-20
Function 3	3.0294e-08	6.888e-13
Function 4	3.0185e-10	2.3613e-08
Function 5	7.148	7.3884
Function 6	0.24206	0.33777
Function 7	0.00070305	0.00072636
Function 8	-2362.9423	0.00072636
Function 9	0	8.5265e-14
Function 10	9.1167e-12	3.9968e-15
Function 11	1.87e-06	3.0798e-09
Function 12	0.044372	0.093301
Function 13	0.4042	0.27891
Function 14	2.9821	1
Function 15	0.00072958	0.0012985
Function 16	-1.0316	-1.0316
Function 17	0.40467	0.39822
Function 18	3	3
Function 19	-3.8548	-3.8533
Function 20	-3.0003	-2.256
Function 21	-6.73	-3.7182
Function 22	-4.8536	-5.602
Function 23	-8.5668	-3.6801

5. Conclusion

Predictive analytics and advanced network traffic management are now essential due to the exponential growth of digital networks. Congestion and inefficiency result from antiquated traffic management strategies' inability to regulate the volume and complexity of modern networks. This study demonstrates how traffic prediction and optimization could be revolutionized by artificial intelligence (AI), namely through Machine Learning (ML) and Deep Learning. Support Vector Machines (SVM), Decision Trees, K-Nearest Neighbors (KNN), and Neural Networks (ANNs, RNNs, LSTMs, and CNNs) are just a few of the methods that AI-based traffic prediction models can use to precisely examine network patterns. Furthermore, by dynamically improving network pathways and resource allocation, the Sine Cosine Algorithm (SCA) in conjunction with Particle Swarm Optimization (PSO) improves traffic routing efficiency. AI-driven techniques can provide real-time responsiveness, adaptive learning, and effective traffic categorization, as demonstrated by the proposed Network Traffic Predictor and Traffic Categorization Agent (NTPA & NTCA). AI-based approaches can greatly improve network performance, congestion, and quality of service (QoS). To improve network traffic management systems even more, future studies can examine hybrid AI models, real-time adaptive algorithms, and edge computing integration. In the digital age, the development of AI and ML technologies will be essential to creating network infrastructures that are more intelligent, resilient, and self-optimizing.

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Fluorescence Spectra 3 1.4 Criteria for Optimization 4 1.5 Multicriteria Optimization 4," Encycl. Anal. Chem., pp. 9678–9689, 2000, [Online]. Available: https://pdfs.semanticscholar.org/5c5c/908bb00a54439dcee50ec1ada6b735694a94.pdf

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