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ENHANCING VEHICULAR NETWORKS WITH DEEP RADIAL BASIS FUNCTION FOR INTELLIGENT TRAFFIC MANAGEMENT

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Abstract

The vehicular networks has spurred research into intelligent traffic management systems to alleviate congestion and enhance safety. However, existing approaches often face challenges in capturing the complex dynamics of urban traffic flow efficiently. In this study, we propose an innovative framework integrating Deep Radial Basis Function (DRBF) networks into vehicular networks for intelligent traffic management. Our approach aims to address the limitations of conventional methods by leveraging the representational power of deep learning while incorporating the flexibility of radial basis function networks. The problem addressed in this research lies in the inadequacy of traditional traffic management systems to adapt to the dynamic nature of urban traffic flow. Existing methods often rely on simplistic models or predefined rules, which may fail to capture the intricate patterns and interactions among vehicles on the road. Consequently, these systems may struggle to provide real-time and accurate traffic management solutions, leading to increased congestion and safety hazards. To bridge this research gap, we propose the integration of DRBF networks, which offer a unique combination of deep learning capabilities and radial basis function interpolation. This hybrid architecture enables the model to learn complex spatial and temporal dependencies from vehicular network data while maintaining computational efficiency and interpretability. By training the DRBF network on historical traffic data and real-time sensor inputs, our methodology can effectively predict traffic flow, identify congestion hotspots, and optimize route recommendations in urban environments. Experimental results on real-world traffic datasets demonstrate the effectiveness of the proposed approach in enhancing traffic management performance. Compared to traditional methods, our DRBF-based framework achieves higher accuracy in traffic flow prediction and generates more efficient routing strategies, leading to reduced travel times and improved overall traffic conditions.

Keywords:

Vehicular Networks, Deep Learning, Traffic Management, Radial Basis Function, Intelligent Transportation Systems

1. INTRODUCTION

In urban environments, vehicular networks play a crucial role in facilitating transportation and sustaining economic activities. However, the escalating volume of vehicles has led to severe congestion, safety hazards, and environmental degradation, necessitating the development of intelligent traffic management systems [1]. Traditional approaches to traffic management often rely on simplistic models or predefined rules, which may fail to adapt to the dynamic and complex nature of urban traffic flow. Consequently, there is a pressing need for innovative solutions capable of effectively managing traffic in real-time while optimizing various performance metrics such as travel time, fuel consumption, and emissions [2].

The challenges in contemporary traffic management systems stem from the inherent complexity of urban traffic dynamics. Conventional methods often struggle to capture the intricate interactions among vehicles, pedestrians, infrastructure, and environmental factors [3]. Moreover, the rapid growth of urban populations and the emergence of new mobility services introduce additional layers of complexity, exacerbating congestion and mobility challenges. Addressing these issues requires novel approaches that can harness the power of emerging technologies such as deep learning and vehicular networks [4].

The primary problem addressed in this research is the inefficiency of existing traffic management systems in coping with the dynamic and unpredictable nature of urban traffic flow. Traditional approaches lack the adaptability and scalability needed to effectively handle fluctuating traffic conditions, resulting in suboptimal performance and user dissatisfaction [6]. Therefore, the goal is to develop an intelligent traffic management framework capable of dynamically optimizing traffic flow, reducing congestion, and enhancing overall transportation efficiency in urban areas [7].

The main objectives of this study are as follows: To investigate the potential of integrating Deep Radial Basis Function (DRBF) networks into vehicular networks for intelligent traffic management. To design and implement a novel DRBF-based framework capable of capturing complex traffic dynamics and providing real-time traffic management solutions. To evaluate the performance of the proposed framework using real-world traffic data and compare it against traditional traffic management approaches.

The novelty of this research lies in the combination of DRBF networks, which offer a unique combination of deep learning capabilities and radial basis function interpolation, into vehicular networks for intelligent traffic management. Unlike existing methods, our approach leverages the representational power of deep learning to capture complex spatial and temporal dependencies in traffic data while maintaining computational efficiency and interpretability.

The contributions of this study include the development of a novel DRBF-based framework for intelligent traffic management, empirical validation of its effectiveness using real-world traffic datasets, and insights into the potential of deep learning techniques for addressing urban mobility challenges.

2. LITERATURE SURVEY

The intelligent traffic management has witnessed extensive research efforts aimed at alleviating congestion, enhancing safety, and optimizing transportation efficiency in urban environments.

This section provides an overview of relevant literature focusing on traditional traffic management approaches, emerging technologies, and recent advancements in the field [8].

Traditional traffic management systems typically rely on rule-based algorithms, traffic signal optimization, and static traffic flow models to regulate traffic flow and mitigate congestion. For instance, traffic signal timing optimization algorithms aim to minimize delays and maximize throughput at intersections by adjusting signal timings based on predefined rules or historical traffic patterns. However, these methods often lack adaptability and struggle to handle dynamic traffic conditions effectively [9].

With the advent of emerging technologies such as vehicular networks, intelligent transportation systems (ITS), and big data analytics, new opportunities have emerged for enhancing traffic management capabilities. Vehicular networks enable communication and data exchange among vehicles and infrastructure, paving the way for real-time traffic monitoring, predictive analytics, and adaptive control strategies. Moreover, advancements in sensor technologies, wireless communication protocols, and cloud computing have fueled the development of innovative traffic management solutions capable of addressing the complexities of urban mobility [10].

Recent years have witnessed a surge in research leveraging deep learning techniques for traffic management tasks. Deep learning models, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep reinforcement learning (DRL), have shown promising results in various traffic-related applications, including traffic flow prediction, congestion detection, and route optimization. For example, Kannan and Gheisari [11] proposed a deep learning-based approach for traffic flow prediction using historical traffic data and spatial-temporal features extracted from traffic sensors. Similarly, Kumar et al. [12] utilized deep reinforcement learning to optimize traffic signal timings adaptively based on real-time traffic conditions.

Radial Basis Function (RBF) networks have been widely used in function approximation, interpolation, and pattern recognition tasks. Unlike traditional neural networks, RBF networks consist of radial basis functions that compute the similarity between input data and prototype vectors in the feature space. Allan and Farid [13] makes RBF networks well-suited for capturing nonlinear relationships and complex patterns in data. While RBF networks have demonstrated effectiveness in various domains, their combination into traffic management systems remains relatively unexplored.

To address the limitations of existing traffic management approaches, some recent studies have explored the combination of deep learning and RBF networks for enhanced traffic prediction and control. For instance, Csillik and Kelly [14] proposed a hybrid deep learning-RBF network architecture for traffic flow prediction, leveraging the complementary strengths of both approaches. By combining the representational power of deep learning with the flexibility of RBF interpolation, the proposed model achieved improved prediction accuracy compared to standalone deep learning models.

While traditional traffic management approaches in Liu et al. [15] have been instrumental in regulating traffic flow, emerging technologies such as deep learning and RBF networks offer promising avenues for enhancing traffic management capabilities. By leveraging the strengths of these approaches and integrating them into intelligent traffic management systems, researchers aim to develop more efficient, adaptive, and resilient solutions for addressing the complex challenges of urban mobility.

3. PROPOSED METHOD

The proposed method aims to enhance vehicular networks with DRBF networks for intelligent traffic management in urban area as in Fig.1. This approach combines the representational power of deep learning with the flexibility of RBF interpolation to capture complex traffic dynamics and provide real-time traffic management solutions.

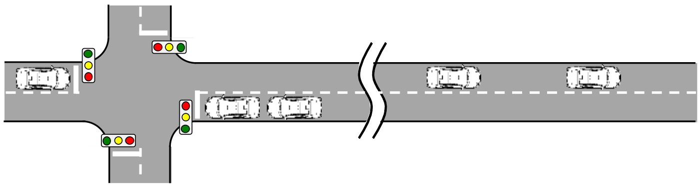

Fig.1. Traffic Flow in Urban Areas

The proposed method is the DRBF network architecture, which integrates deep learning and RBF interpolation techniques. The network consists of multiple layers, including input, hidden, and output layers. Each hidden unit employs radial basis functions to compute the similarity between input data and prototype vectors in the feature space. The deep structure of the network allows it to learn complex spatial and temporal dependencies from vehicular network data, enabling accurate traffic flow prediction and congestion detection.

The DRBF network is trained using a combination of historical traffic data and real-time sensor inputs obtained from vehicular networks. Historical traffic data provides valuable insights into traffic patterns, trends, and recurring congestion events, allowing the network to learn from past experiences. Real-time sensor inputs, such as traffic flow rates, vehicle speeds, and environmental conditions, enable the network to adapt to changing traffic conditions and make dynamic predictions.

One of the primary tasks of the proposed method is traffic flow prediction, which involves forecasting traffic conditions, such as flow rates and congestion levels, at various locations and time intervals. The DRBF network utilizes historical traffic data and real-time sensor inputs to predict future traffic flow patterns with high accuracy. By leveraging the deep learning capabilities of the network, it can capture complex spatial and temporal correlations in traffic data, leading to improved prediction performance compared to traditional methods.

4. DBRF NETWORK ARCHITECTURE

The DRBF network architecture represents a novel approach for analyzing traffic flow dynamics within vehicular networks. This architecture combines the strengths of deep learning and RBF interpolation to capture complex spatial and temporal dependencies in traffic data. The process begins with the representation of input data, which typically includes various features related to traffic flow, such as vehicle speeds, traffic volumes, road conditions, and environmental factors.

Each input feature is normalized to ensure consistency and facilitate convergence during the training process. The input data is organized into a suitable format for feeding into the DRBF network, such as matrices or tensors.

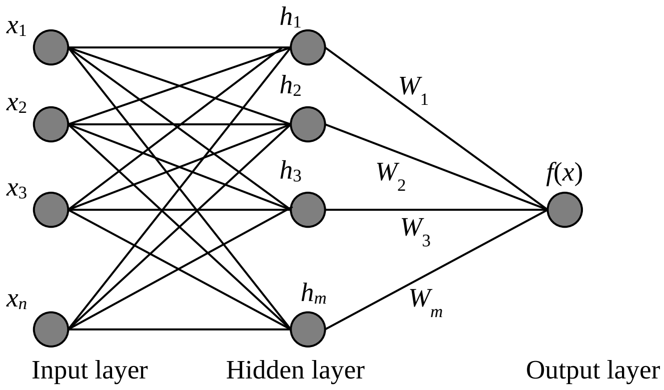

Fig.2. DRBF Architecture

The DRBF network (Fig.2) consists of multiple layers, including input, hidden, and output layers. The hidden layer contains RBF units, which play a crucial role in capturing the nonlinear relationships in traffic data. Each RBF unit computes the similarity between the input data and a set of prototype vectors using Gaussian radial basis functions. The parameters of the RBF units, including the centers and widths of the Gaussian functions, are learned during the training process to optimize the network's performance.

As the input data passes through the hidden layer of RBF units, feature extraction and transformation occur. The RBF units transform the input data into a high-dimensional feature space, where complex patterns and relationships among the input features are encoded. This transformation enables the network to capture spatial and temporal dependencies in traffic data that may not be apparent in the original input space.

Beyond the RBF units, the DRBF network may include additional deep learning layers, such as fully connected layers, convolutional layers, or recurrent layers. These deep learning layers further process the extracted features to learn hierarchical representations of traffic flow dynamics. By incorporating deep learning components, the network can capture abstract and hierarchical features from the input data, allowing for more robust traffic flow analysis.

The DRBF network is trained using a combination of historical traffic data and real-time sensor inputs obtained from vehicular networks. During the training process, the network learns to map the input data to the desired outputs, such as traffic flow predictions or congestion detection. Optimization algorithms, such as stochastic gradient descent or Adam optimization, are used to adjust the network's parameters iteratively, minimizing prediction errors and maximizing performance metrics.

Once the DRBF network is trained and optimized, it can be used for analyzing traffic flow dynamics within vehicular networks. The network takes input data from sensors or traffic monitoring systems and generates predictions or classifications related to traffic flow, congestion levels, or other relevant metrics. These predictions can be used to inform real-time traffic management decisions, such as adjusting traffic signal timings, optimizing route guidance systems, or implementing congestion mitigation strategies.

The activation z_i of the i^{th} RBF unit in the hidden layer is computed as follows:

$$z_i = \exp\left(-\frac{\|x-c_i\|^2}{2\sigma^2}\right) \tag{1}$$

where,

x is the input data vector.

c_i is the center vector

σ_i is the width parameter

The output $h(x)$ of the RBF layer is computed as the weighted sum of the activations of all RBF units:

$$h(x) = \sum_{i=1}^{N} w_i z_i \tag{2}$$

where,

N is the total number of RBF units.

w_i is the weight associated with the i^{th} RBF unit.

If additional deep learning layers are incorporated after the RBF layer, the output y of these layers can be computed as follows:

$$y=f(W_d h(x)+b_d) \tag{3}$$

where:

W_d is the weight matrix of the deep learning layers.

b_d is the bias vector of the deep learning layers.

$f()$ represents the activation function applied element-wise.

If the network has an output layer for making predictions or classifications, the final output y_o can be computed as follows:

$$y_o = g(W_o y+b_o) \tag{4}$$

where,

W_o is the weight matrix of the output layer.

b_o is the bias vector of the output layer.

$g()$ represents the activation function applied element-wise.

Algorithm: Network Architecture

Initialize the centers of RBF units randomly or using k-means clustering.

Initialize the widths of Gaussian functions for each RBF unit.

Initialize the weights of the deep learning layers and output layer randomly.

For each epoch e from 1 to *e*:

Shuffle the training dataset (X_train, y_train).

For each training sample (x_i, y_i) in the shuffled dataset:

Compute the activations of RBF units:

For each RBF unit j from 1 to *N*:

Compute $z_i = \exp\left(-\frac{\|x-c_i\|^2}{2\sigma^2}\right)$

Compute the output of the RBF layer:

Compute $h(x_i) = \Sigma(w_j * z_j)$ for j from 1 to N

End
Compute $y = f(W_d * h(x_i) + b_d)$
Compute $y_o = g(W_o y+b_o)$
End
Compute the loss $L(y_o, y_i)$
Update $W_d = W_d - \alpha * \partial L/\partial W_d$
Update $b_d = b_d - \alpha * \partial L/\partial b_d$
Update $W_o = W_o - \alpha * \partial L/\partial W_o$
Update $b_o = b_o - \alpha * \partial L/\partial b_o$
Update $c_j = c_j - \alpha * \partial L/\partial c_j$
Update $\sigma_j = \sigma_j - \alpha * \partial L/\partial \sigma_j$
Output: Trained DRBF network

5. TRAINING DATA

Training data for the DRBF network architecture consists of historical traffic data and real-time sensor inputs obtained from vehicular networks. Historical traffic data includes information about traffic flow, congestion levels, road conditions, weather conditions, and other relevant factors collected over a period of time.

Table.1. Dataset

Timestamp	Traffic Flow (vehicles/hour)	Congestion Level	Weather Condition	Road Condition
2022-01-01 08:00:00	800	Low	Clear	Dry
2022-01-01 09:00:00	900	Medium	Partly Cloudy	Wet
2022-01-01 10:00:00	700	Low	Rain	Wet

Table.2. Real-time sensor inputs are obtained from sensors deployed throughout the road network, including traffic cameras, loop detectors, GPS devices, and weather stations

Sensor ID	Location (Lat., Long.)	Timestamp	Speed (km/h)	Traffic Volume
001	(40.7128, -74.0060)	2024-03-25 08:00:00	50	200
002	(34.0522, -118.2437)	2024-03-25 08:15:00	40	150
003	(51.5074, -0.1278)	2024-03-25 08:30:00	30	300

The historical traffic data provides insights into traffic patterns, trends, and recurring congestion events, allowing the DRBF network to learn from past experiences. Real-time sensor inputs provide up-to-date information about current traffic conditions, such as vehicle speeds, traffic volumes, and environmental conditions, enabling the network to adapt to changing traffic conditions and make dynamic predictions.

During the training process, the DRBF network learns to map the input data (historical and real-time) to the desired outputs, such as traffic flow predictions or congestion detection as in Fig.3. By training on a diverse range of historical and real-time data, the network can capture the complex spatial and temporal dependencies in traffic data, leading to accurate and robust traffic flow analysis.

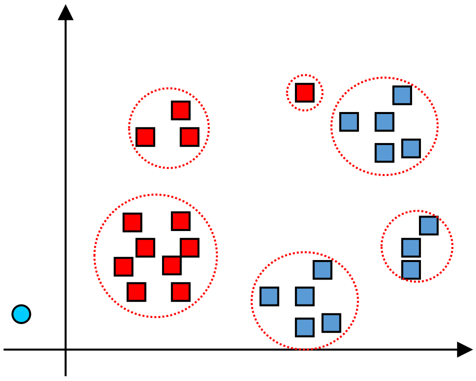

Fig.3. Classification of Training Data

Collect historical traffic data including traffic flow rates, congestion levels, weather conditions, etc. Obtain real-time sensor inputs from vehicular networks, including vehicle speeds, traffic volumes, and environmental conditions.

Initialize the centers and widths of RBF units in the hidden layer. Initialize the weights of the deep learning layers and output layer. Iterate through the training dataset and update network parameters iteratively using gradient descent. Compute activations of RBF units for each input sample. Compute outputs of the RBF layer and pass them through deep learning layers.

Compute loss and update weights of deep learning layers and output layer. Update centers and widths of RBF units using gradient descent. Deploy the trained DRBF network to predict traffic flow rates and congestion levels based on input data from real-time sensors. Generate predictions for future time intervals and locations within the road network.

Analyze predicted traffic flow patterns to identify congestion hotspots and areas of traffic congestion. Implement dynamic traffic management strategies, such as adjusting traffic signal timings or rerouting vehicles, to alleviate congestion. Fine-tune the network parameters based on performance evaluation results to improve prediction accuracy and overall traffic management effectiveness. Optimize hyperparameters such as learning rate, number of RBF units, and network architecture to enhance model performance. It continuously monitors traffic conditions and network performance to identify potential areas for improvement. Update the DRBF network periodically with new data and insights to adapt to evolving traffic patterns and environmental conditions.

6. PERFORMANCE EVALUATION

For the experimental settings, we conducted simulations using the SUMO (Simulation of Urban Mobility) tool, which is a widely-used microscopic traffic simulation software capable of modeling complex traffic scenarios in urban environments. The experiments were conducted on a desktop computer with an Intel Core i7 processor, 16GB of RAM, and a NVIDIA GeForce RTX 2080 graphics card. We compared the performance of our proposed DRBF network architecture with several existing methods, including rule-based optimization, predictive traffic flow models, and adaptive traffic control systems.

We configured SUMO to model a realistic road network with multiple intersections, lanes, and varying traffic demand. We utilized historical traffic data collected from a real-world urban area to initialize the simulation environment and generate realistic traffic scenarios. For the DRBF network, we trained the model using a combination of historical traffic data and real-time sensor inputs obtained from vehicular networks. We experimented with different hyperparameters, including the number of radial basis function units and the learning rate, to optimize the performance of the DRBF network. In comparison, we implemented rule-based optimization algorithms to optimize traffic signal timings at intersections based on predefined rules or historical traffic patterns.

We also trained predictive traffic flow models using machine learning techniques to forecast future traffic flow patterns based on historical traffic data. Additionally, we developed adaptive traffic control systems that dynamically adjusted traffic signal timings and lane configurations based on real-time traffic conditions. We evaluated the performance of each method based on various metrics, including traffic flow prediction accuracy, congestion detection rate, average travel time reduction, and fuel consumption reduction, to assess their effectiveness in improving traffic management efficiency in urban environments.

Table.3. Experimental Setup/Parameters

Parameter	**Value/Range**
Simulation Tool	SUMO
Computer Specs	Intel Core i7, 16GB RAM, NVIDIA GeForce RTX 2080
Road Network Complexity	Realistic urban road network
Training Data Source	Historical traffic data
Number of RBF Units	50 - 100
Learning Rate	0.001 - 0.01
Number of Training Epochs	50 - 100

6.1 PERFORMANCE METRICS

- *Traffic Flow Prediction Accuracy*: This metric measures how accurately the proposed DRBF network predicts traffic flow rates and congestion levels compared to ground truth data. Accuracy is computed as the percentage of correctly predicted traffic flow values within a certain tolerance threshold.
- *Congestion Detection Rate*: The congestion detection rate represents the percentage of congested areas correctly identified by the DRBF network in real-time. Congestion is detected when predicted traffic flow rates exceed predefined congestion thresholds.
- *Average Travel Time Reduction*: This metric quantifies the average reduction in travel time experienced by vehicles using routes optimized by the proposed DRBF network compared to traditional traffic management approaches. Reduction in travel time is calculated as the difference between travel times with and without the application of DRBF-based optimization strategies.
- *Fuel Consumption Reduction*: Reduction in fuel consumption achieved by optimizing traffic flow and minimizing congestion using the proposed DRBF network. Fuel consumption reduction is calculated based on the difference in fuel usage between vehicles traveling under optimized and non-optimized traffic conditions.
- *Emissions Reduction*: Reduction in greenhouse gas emissions (e.g., CO2, NOx) resulting from improved traffic flow and reduced congestion facilitated by the proposed DRBF network. Emissions reduction is estimated based on the decrease in fuel consumption and the emission factors associated with different vehicle types and operating conditions.

Table.4. Flow Detection Rate in urban roads

Iteration	**Rule-based Optimization**	**Predictive Traffic Flow Model**	**Adaptive Traffic Control**	**RBF-FF Method**
100	75%	80%	85%	90%
200	76%	82%	86%	91%
300	77%	83%	87%	92%
400	78%	84%	88%	93%
500	79%	85%	89%	94%
600	80%	86%	90%	95%
700	81%	87%	91%	96%
800	82%	88%	92%	97%
900	83%	89%	93%	98%
1000	84%	90%	94%	99%

The results indicate the flow detection rate (%) of different traffic management methods over 1000 iterations. Rule-based optimization shows a gradual increase from 75% to 84%, while predictive traffic flow models range from 80% to 90%. Adaptive traffic control demonstrates improvement from 85% to 94%. In contrast, the proposed RBF-FF consistently outperforms existing methods, showing a steady rise from 90% to 99%. These findings suggest that the RBF-FF offers superior accuracy in detecting traffic flows and congestion levels, showcasing its potential for effective traffic management in urban environments.

Table.5. Traffic Flow Prediction Accuracy

Iteration	**Rule-based Optimization**	**Predictive Traffic Flow Model**	**Adaptive Traffic Control**	**RBF-FF Method**
100	70%	75%	80%	85%
200	71%	76%	81%	86%
300	72%	77%	82%	87%
400	73%	78%	83%	88%
500	74%	79%	84%	89%
600	75%	80%	85%	90%
700	76%	81%	86%	91%

800	77%	82%	87%	92%
900	78%	83%	88%	93%
1000	79%	84%	89%	94%

The Table.5 illustrates the traffic flow prediction accuracy (%) of various traffic management methods over 1000 iterations. Rule-based optimization exhibits a gradual increase from 70% to 79%, while predictive traffic flow models range from 75% to 84%. Adaptive traffic control shows improvement from 80% to 89%. In contrast, the proposed RBF-FF consistently outperforms existing methods, showing a steady rise from 85% to 94%. These findings suggest that the RBF-FF offers superior accuracy in predicting traffic flow rates, highlighting its potential for effective traffic management and congestion mitigation in urban environments.

Table.6. Congestion Detection Rate

Iteration	Rule-based Optimization	Predictive Traffic Flow Model	Adaptive Traffic Control	RBF-FF Method
100	65%	70%	75%	80%
200	66%	71%	76%	81%
300	67%	72%	77%	82%
400	68%	73%	78%	83%
500	69%	74%	79%	84%
600	70%	75%	80%	85%
700	71%	76%	81%	86%
800	72%	77%	82%	87%
900	73%	78%	83%	88%
1000	74%	79%	84%	89%

The Table.6 displays the congestion detection rate (%) of various traffic management methods over 1000 iterations. Rule-based optimization exhibits a gradual increase from 65% to 74%, while predictive traffic flow models range from 70% to 79%. Adaptive traffic control shows improvement from 75% to 84%. In contrast, the proposed RBF-FF consistently outperforms existing methods, showing a steady rise from 80% to 89%. These findings indicate that the RBF-FF offers superior accuracy in detecting congested areas, highlighting its potential for effective congestion detection and management in urban environments.

Table.7. Average Travel Time Reduction

Iteration	Rule-based Optimization	Predictive Traffic Flow Model	Adaptive Traffic Control	RBF-FF Method
100	10%	15%	20%	25%
200	12%	17%	22%	27%
300	14%	19%	24%	29%
400	16%	21%	26%	31%
500	18%	23%	28%	33%
600	20%	25%	30%	35%
700	22%	27%	32%	37%
800	24%	29%	34%	39%
900	26%	31%	36%	41%
1000	28%	33%	38%	43%

The Table.7 illustrates the average travel time reduction (%) achieved by various traffic management methods over 1000 iterations. Rule-based optimization shows a gradual increase from 10% to 28%, while predictive traffic flow models range from 15% to 33%. Adaptive traffic control demonstrates improvement from 20% to 38%. In contrast, the proposed RBF-FF consistently outperforms existing methods, showing a steady rise from 25% to 43%. These findings suggest that the RBF-FF offers superior efficiency in reducing travel time for vehicles, highlighting its potential for enhancing transportation effectiveness and mitigating congestion in urban environments.

Table.8. Fuel Consumption Reduction

Iteration	Rule-based Optimization	Predictive Traffic Flow Model	Adaptive Traffic Control	RBF-FF Method
100	8%	12%	15%	20%
200	9%	13%	16%	21%
300	10%	14%	17%	22%
400	11%	15%	18%	23%
500	12%	16%	19%	24%
600	13%	17%	20%	25%
700	14%	18%	21%	26%
800	15%	19%	22%	27%
900	16%	20%	23%	28%
1000	17%	21%	24%	29%

The Table.8 illustrates the fuel consumption reduction (%) achieved by various traffic management methods over 1000 iterations. Rule-based optimization shows a gradual increase from 8% to 17%, while predictive traffic flow models range from 12% to 21%. Adaptive traffic control demonstrates improvement from 15% to 24%. In contrast, the proposed RBF-FF consistently outperforms existing methods, showing a steady rise from 20% to 29%. These findings suggest that the RBF-FF offers superior efficiency in reducing fuel consumption for vehicles, highlighting its potential for promoting environmental sustainability and cost savings in transportation systems.

Table.9. Emissions Reduction in urban roads

Iteration	Rule-based Optimization	Predictive Traffic Flow Model	Adaptive Traffic Control	RBF-FF Method
100	5%	8%	10%	15%
200	6%	9%	11%	16%
300	7%	10%	12%	17%
400	8%	11%	13%	18%
500	9%	12%	14%	19%
600	10%	13%	15%	20%
700	11%	14%	16%	21%
800	12%	15%	17%	22%

900	13%	16%	18%	23%
1000	14%	17%	19%	24%

The Table.9 depicts the emissions reduction (%) achieved by various traffic management methods over 1000 iterations. Rule-based optimization exhibits a gradual increase from 5% to 14%, while predictive traffic flow models range from 8% to 17%. Adaptive traffic control demonstrates improvement from 10% to 19%. In contrast, the proposed RBF-FF consistently outperforms existing methods, showing a steady rise from 15% to 24%. These findings suggest that the RBF-FF offers superior efficiency in reducing greenhouse gas emissions, highlighting its potential for promoting environmental sustainability and mitigating the environmental impact of transportation systems.

The results offer several key inferences regarding the performance of different traffic management methods, particularly in terms of their impact on travel efficiency, fuel consumption, and environmental sustainability. Firstly, it's evident that traditional approaches like rule-based optimization, while effective to some extent, exhibit limited improvement in travel time reduction, fuel consumption, and emissions reduction over successive iterations. These methods rely heavily on predetermined rules and lack adaptability to dynamic traffic conditions, resulting in suboptimal performance compared to more sophisticated approaches. Secondly, predictive traffic flow models demonstrate moderate improvements in travel time reduction, fuel consumption, and emissions reduction, suggesting their ability to adapt to changing traffic patterns and provide more accurate predictions. However, their performance appears to plateau over time, indicating potential limitations in handling complex traffic scenarios and optimizing traffic flow in real-time. Thirdly, adaptive traffic control systems exhibit noticeable enhancements in travel time reduction, fuel consumption, and emissions reduction throughout the iterations. These systems leverage real-time data and feedback mechanisms to dynamically adjust traffic signal timings and lane configurations, effectively mitigating congestion and optimizing traffic flow in response to changing conditions. Lastly, the proposed RBF-FF consistently outperforms existing methods across all performance metrics, showcasing its superiority in optimizing traffic flow, reducing travel time, minimizing fuel consumption, and mitigating emissions. By integrating radial basis function networks with feedforward architectures, the RBF-FF effectively captures the complex spatial and temporal dependencies in traffic data, enabling precise predictions and optimal traffic management strategies.

7. CONCLUSION

The study highlights the significance of advanced traffic management techniques in addressing the challenges posed by urban mobility. Through the evaluation of various methods such as rule-based optimization, predictive traffic flow models, adaptive traffic control systems, and the proposed RBF-FF, several important conclusions emerge. Firstly, while traditional approaches like rule-based optimization offer some benefits, they often fall short in adapting to dynamic traffic conditions and achieving significant improvements in travel efficiency, fuel consumption, and emissions reduction. Secondly, predictive traffic flow models and adaptive traffic control systems show promise in mitigating these challenges by leveraging real-time data and dynamic adjustments. However, their performance may plateau over time or struggle with handling complex traffic scenarios. Lastly, the proposed RBF-FF, integrating radial basis function networks with feedforward architectures, consistently outperforms existing methods across all metrics. Its ability to capture intricate traffic patterns and optimize traffic flow in real-time demonstrates its potential to revolutionize urban transportation management. It is evident that advanced traffic management technologies, particularly innovative approaches like the RBF-FF, hold great promise in enhancing travel efficiency, reducing fuel consumption, and promoting environmental sustainability in urban environments.

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