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AI-POWERED SMART CITY EVACUATION PLANNING: TRAFFIC CONGESTION PREDICTION USING DEEP BELIEF NETWORKS

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ABSTRACT

This study aims to evaluate the feasibility and efficacy of using Artificial Intelligence (AI) Deep Learning in smart city contexts. A traffic flow prediction model is developed utilizing the Deep Belief Network (DBN) algorithm. The designated road segment and its historical traffic flow data in Tianjin have been gathered and pre-processed. Subsequently, many Restricted Boltzmann Machines (RBMs) are aggregated to construct a Deep Belief Network (DBN), which is trained as a generative model. The performance is ultimately assessed using a simulation exercise. The suggested algorithm model is compared with the Neuro Fuzzy C-Means (FCM) model, Deep Learning Architecture (DLA), and Convolutional Neural Network (CNN) model. The findings indicate that the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) of the suggested algorithm model are 4.42%, 6.21%, and 8.03%, respectively. Its predictive accuracy surpasses that of the other three algorithms considerably. Furthermore, the algorithm can efficiently mitigate the proliferation of congestion in the smart city, facilitating prompt alleviation of traffic bottlenecks. The developed Deep Learning-based traffic flow prediction model demonstrates great precision in forecasting and effective traffic congestion mitigation, offering valuable experimental insights for future smart city development.

Keywords: *Smart cities, Deep Learning, Traffic flow prediction, Artificial Intelligence, Deep Belief Network*

1. INTRODUCTION

The swift advancement of research has led to the use of Artificial Intelligence (AI), Cloud Computing, and Deep Learning throughout diverse sectors of society. The proposal of the smart city concept has garnered significant attention for its development. The acceleration of economic globalization has significantly advanced urbanization in numerous countries, resulting in a yearly increase in the urbanization rate. Nevertheless, it imposes significant strain on world resources and the environment. Urban challenges, including resource scarcity, environmental

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degradation, and transportation congestion, have increasingly intensified, posing significant obstacles to urbanization [1], [2]. Consequently, with the swift advancement of smart cities, the integration of AI technology inside these urban environments has garnered significant interest from scholars in pertinent disciplines.

Smart cities represent the embodiment of contemporary urbanization and the unavoidable outcome of societal advancement. The development of a smart city entails the optimization and enhancement of the urban industrial framework. The complete and transparent perception and processing of information enhance the efficiency of urban management and operations, as well as the quality of urban services. Furthermore, the city's sustainable and leapfrog development is advanced, resulting in a novel paradigm of urban development. The city's automated perception, efficient decision-making, and regulation facilitate citizens' utilization of the smart services and apps provided by the smart city. Transportation is a fundamental element in the creation of smart cities, and the advancement of intelligent transportation systems is a prevailing trend within this domain. Traffic congestion arises not solely from automobiles; other significant factors include rear-end collisions, vehicle malfunction monitoring, information breaches, and various security concerns [4], [5]. The intelligent transportation system is capable of gathering real-time traffic conditions and vehicle-related data in smart cities, while also implementing a comprehensive travel service mechanism that monitors the current location, travel duration, and speed of vehicles in real-time [6]. Deep Learning, as an independent discipline within AI, offers significant advantages for the autonomous assessment and forecasting of traffic flow and dynamic traffic conditions in smart cities. Convolutional Neural Networks (CNN), Deep Belief Networks (DBN), and Back Propagation Neural Networks (BPNN) have attained significant success across multiple domains [7], [8], [9]. Consequently, AI technologies like Deep Learning hold significant value in anticipating traffic flow and alleviating urban congestion in smart cities.

This effort seeks to address the issues of traffic congestion and exhaust pollution in the advancement of smart cities, thereby achieving green and sustainable development. This work innovatively employs the DBN algorithm to develop a traffic flow forecast model, including the safety implications of traffic congestion in smart cities. The algorithm is evaluated against FCM, DLA, and CNN models via simulation. This study serves as a definitive reference for the intelligent enhancement of traffic environments in the subsequent phase of smart city development, and aids in addressing traffic congestion and exhaust pollution within this context.

2. RELATED WORK

Because of its powerful ability to make accurate predictions, deep learning has found applications in a wide variety of scientific fields. Using modifications to Convolutional Neural Networks (CNN), Chen et al. (2018) developed a multi-scale robust segmentation approach that makes use of Atrous Spatial Pyramid Pooling (ASPP). Additionally, they established a Deep Learning technique for semantic image segmentation in the context of image analysis. ASPP was able to identify the input convolutional feature layers by using a variety of sampling rates and effective fields of vision. This allowed for the collection of objects and visual context at a wide range of scales, which ultimately led to an improvement in placement performance through the utilization of qualitative and quantitative methods [10]. A distributed dynamic power allocation technique that makes use of reinforcement learning was proposed by Nasir et al. (2019). This strategy makes it possible to allocate power in real time that is almost optimal, and it is based on delayed channel state information (CSI). Given the current circumstances, in which the system model is imperfect and the CSI delay cannot be eliminated, this technique is very suitable for the situation that we are currently facing [11]. Sultana et al. (2019) evaluated and developed a Software Defined Network (SDN)-based Network Intrusion Detection System (NIDS) that makes use of Deep Learning to address network security concerns. Additionally, they highlighted the tools that were utilized in the process of developing NIDS models within the framework of SDN [12]. The authors Wang et al. (2020) presented a unique light automated modulation classification (Light AMC) that makes use of deep learning approaches. A scale factor was implemented for each neuron in the CNN, and compressed sensing was used to enhance the sparsity of the scale factor. A scale factor was implemented for each neuron. The Light AMC technique that has been presented has the potential to accelerate computing, considerably reduce the complexity of the model, and minimize the amount of performance deterioration that occurs through simulation [13].

Various fields are developing towards intelligence in the process of building smart cities.

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Ma et al. (2017) proposed a model based on CNN, which learns traffic volume as an image, and predicts the large-scale, network-wide traffic speed with high precision. The average accuracy of this model was increased by 42.91% within an acceptable execution time, and it was suitable for large-scale transportation networks through reasonable training of the model [14]. Chand et al. (2018) analyzed the importance of traffic-related data to passengers according to the accurate and applicable traffic data, combined the Deep Learning and the Internet of Things (IoT) with Intelligent Transportation System (ITS), and further discussed the cluster control system, location recognition, and resource privacy in ITS, providing more convenience for people's travel [15]. Chen et al. (2019) used the complexity of Deep Learning and the wide coverage of smart cities applications to extract useful knowledge in urban traffic, helping citizens better understand the surrounding environment and notifying authorities provide better and more effective public services [16]. Wu et al. (2020) proposed a distributed Deep Learning-Driven Task Offloading (DDTO) algorithm, to generate the near-optimal uninstall decision in mobile devices, edge cloud servers, and central cloud servers in the transportation field, which can effectively generate the near-optimal offloading decisions in edge and cloud computing environments [17].

To sum up, although there are many studies on the role of Deep Learning in smart city scenarios, they mainly predict traffic flow to achieve intelligent traffic in the field of transportation, while the dredging effect after congestion has not been clearly introduced. Therefore, DBN in Deep Learning is adopted to traffic flow prediction in smart cities, and its prediction accuracy and path induction performance are analyzed, which is of great significance to the construction of smart cities.

3. APPROACHES AND EXPERIMENTAL SIMULATION

Due to factors such as increasing population, scarcity of resources, and degradation of the urban environment, the intelligent building and implementation of smart cities have emerged as a trend in urbanization development. The growing need for urban residents' incomes is another factor, as is the pressing necessity to provide smart urban public services and the backing of smart industries for a thriving urban economy.

3.1 Technology for Smart Cities

When individuals make reference to "smart cities," they are referring to urban regions that make use of the Internet of Things (IoT) and cloud computing in order to endow their physical objects with intelligence [18]. The goal and current trend in urbanization expansion is intelligent management, which establishes coordination among the many systems of the city and provides urban dwellers with a living environment that is both convenient and of high quality [19]. Figure 1 illustrates the social and environmental aspects that smart cities contribute to. These aspects are shown in the figure.

The concept of a "smart city" has evolved as a preferred form of city planning and development as a response to the effects of increasing urban populations, dwindling resources, and deteriorating cityscapes. The increasing demand for the earnings of urban people is another aspect, since it necessitates the provision of intelligent urban public services and the immediate support of intelligent businesses, both of which are vital to the healthy growth of an urban economy [20]. According to the intelligence perspective, the four scenarios of artificial intelligence in smart cities are smart medical care, smart transportation, smart housing, and smart parks. However, it is important to note that the resources and development level of each city are different [21]. AI has been implemented in specific sectors of the smart city that is now being built, but the benefits of this technology are not being fully leveraged. As a consequence of this, the attention of this study is directed at intelligent zing traffic in the framework of smart city construction.

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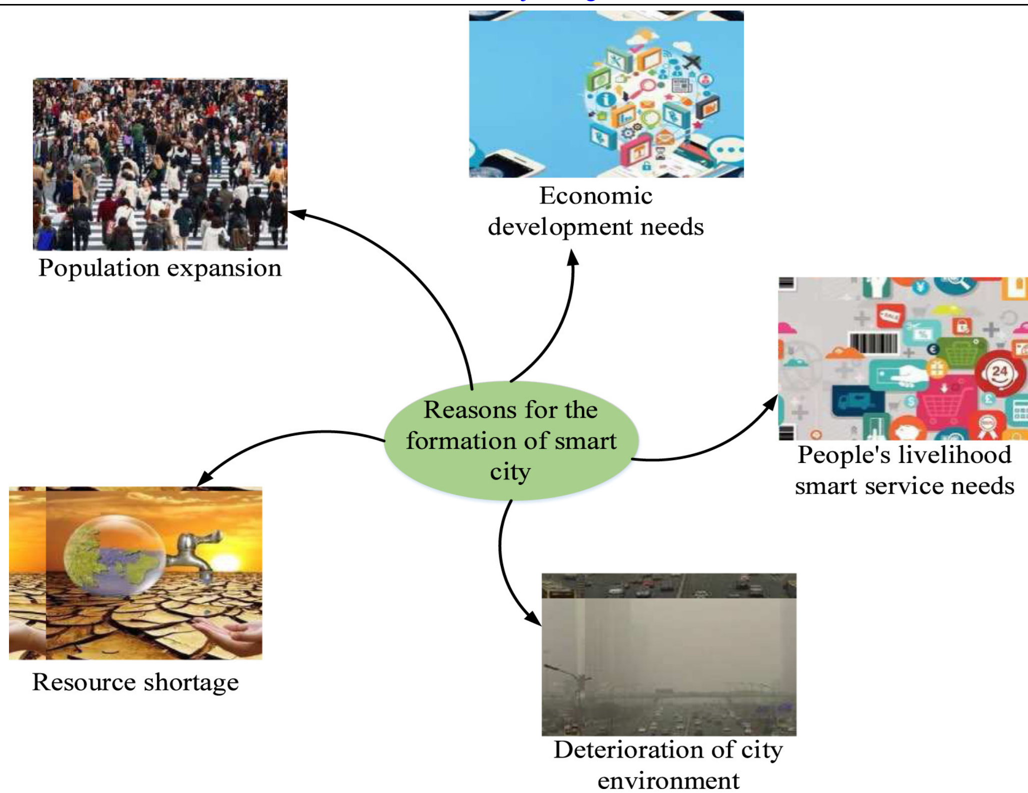

Figure 1: Smart cities' impact on society and the environment.

3.2 Problems with smart city traffic

In addition to the fact that traffic congestion is a phenomenon that occurs everywhere, the unexpected accumulation of traffic on urban roadways is distinguished by a number of characteristics that are exclusive to it. First, the characteristics of traffic congestion as well as the components that are related to judgment are discussed. The purpose of this article is to provide a theoretical foundation for future research on the development of strategies for traffic management. It does this by analyzing the law of congestion propagation under various situations using traffic fluctuation theory and by discussing the response plan process that smart cities traffic management departments go through in the event of sudden congestion.

When doing a study of traffic congestion, the judgment elements that comprise the traffic flow attribute values that are quantifiable include driving speed, road traffic volume, traffic density, and travel duration. These are some of the measurable traffic flow attribute values. [22], [23] Congestion is characterized primarily by its time and place, as well as its type and level of detection. These are the fundamental features of congestion. Fig. 2 provides a visual representation of the components and qualities that comprise the judgment of traffic congestion.

As a result of emergency-induced congestion in urban road traffic, vehicles on the road segment will move at a slower pace, with longer delays and greater costs. Before beginning to investigate the process that underlies the development of congestion, it is essential to verify the conditions that are listed below. Having determined the time and location of the emergency, the traffic manager has also determined the severity of the situation and made an estimate on how long it will continue [24]. It is required to divide the road segment that contains the emergency event into two sections when conducting a comparative analysis. One of these parts must be located immediately upstream of the incident, and the other must be located immediately downstream. Due to the fact that it is able to accommodate variations in traffic flow density as wave propagation, the wave model is suitable for the aim of studying the evolution of traffic congestion [25], [26]. Researchers focused their attention on the theory of traffic fluctuations in order to gain an understanding of how unanticipated traffic bottlenecks arose as a response to crises.

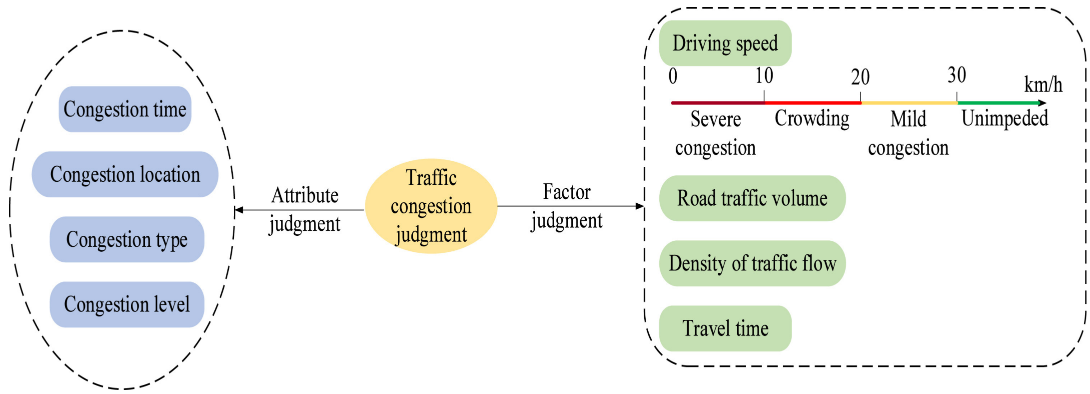

Figure 2: Qualities and components of traffic congestion judgments.

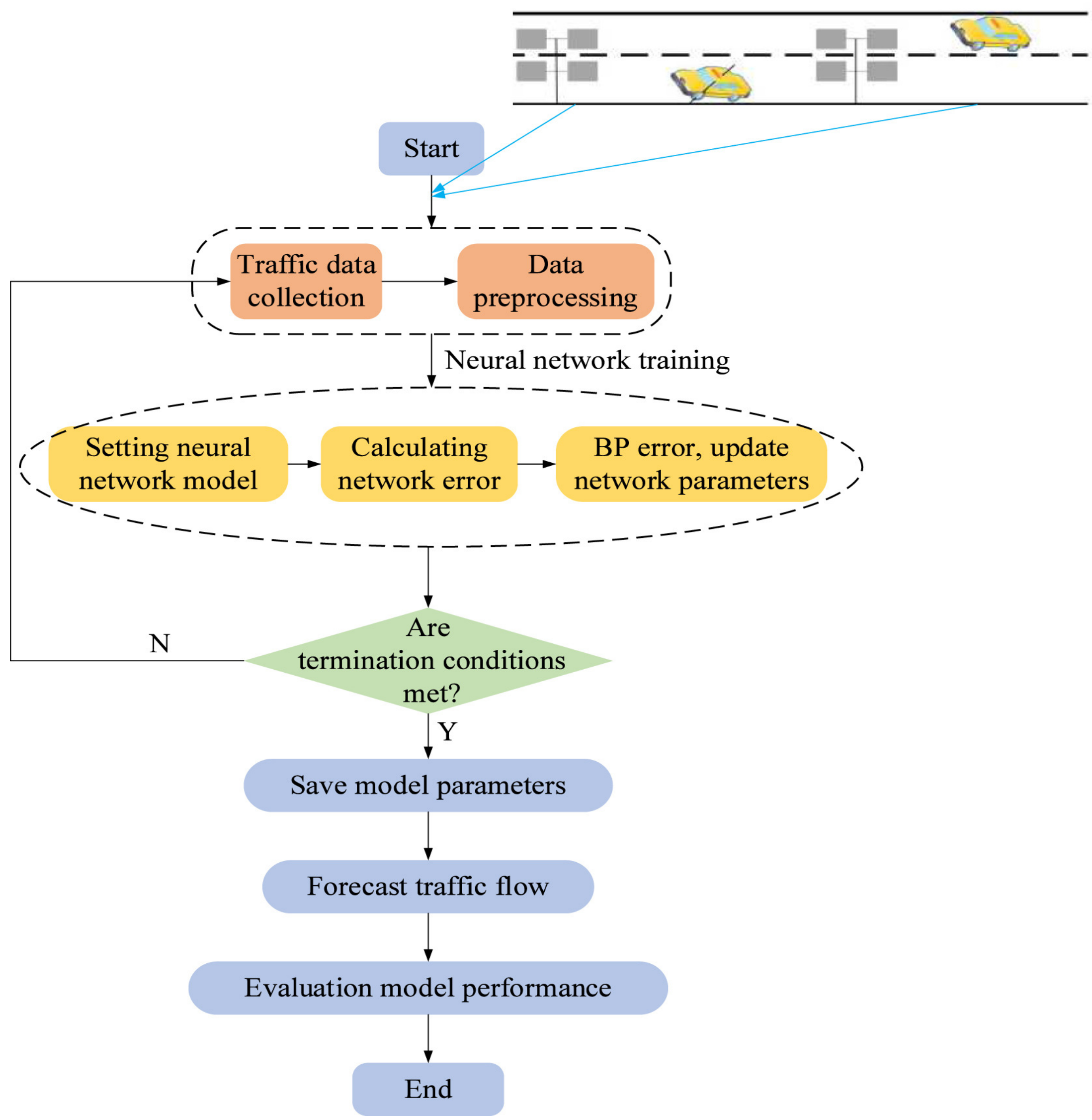

Figure 3: shows the smart city traffic flow forecast model.

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3.3 A model for predicting smart city traffic flows

The whole process of traffic flow prediction is organic, beginning with the gathering of raw data and continuing through data pre-processing, issue prediction, prediction index determination, model creation, training, and testing. We begin by outlining the primary procedures for gathering traffic data in order to provide a real-time picture of the road network's traffic flow status. The second phase is processing the data, which involves correcting, denoising, and normalizing any anomalous data that has been identified. At last, in light of the traffic flow volume estimate, it uses Deep Learning algorithms to assess its regularly utilized indicators. Figure 3 displays the Deep Learning-based traffic flow forecast model.

4. RESULTS AND DISCUSSION

In this study, we simulate a smart city traffic flow prediction model that uses Deep Learning. We then evaluate its forecast accuracy and the effect of its route guiding to that of existing model techniques.

A comparison is made between the FCM, DLA, and CNN models and the suggested traffic flow prediction model that is based on Deep Learning in Figures 4, 5, and 6. The performance of the developed algorithm, as well as the FCM, DLA, and CNN models, is evaluated with regard to the amount of time it takes to execute and the amount of memory it uses in Figure 7 and 8.

Figures 4, 5, and 6 show that the root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) of various algorithms change with the number of iterations of the proposed traffic flow prediction model algorithm. The RMSE, MAE, and MAPE of the proposed algorithm are 4.42%, 6.21%, and 8.03%, respectively. On the other hand, the errors of the additional three models are significantly higher than those of the proposed algorithm model. Because of this, the suggested method for traffic flow prediction model, which is based on Deep Learning, has the ability to significantly reduce the amount of error that occurs while predicting traffic flow in smart cities and produces accurate prediction results.

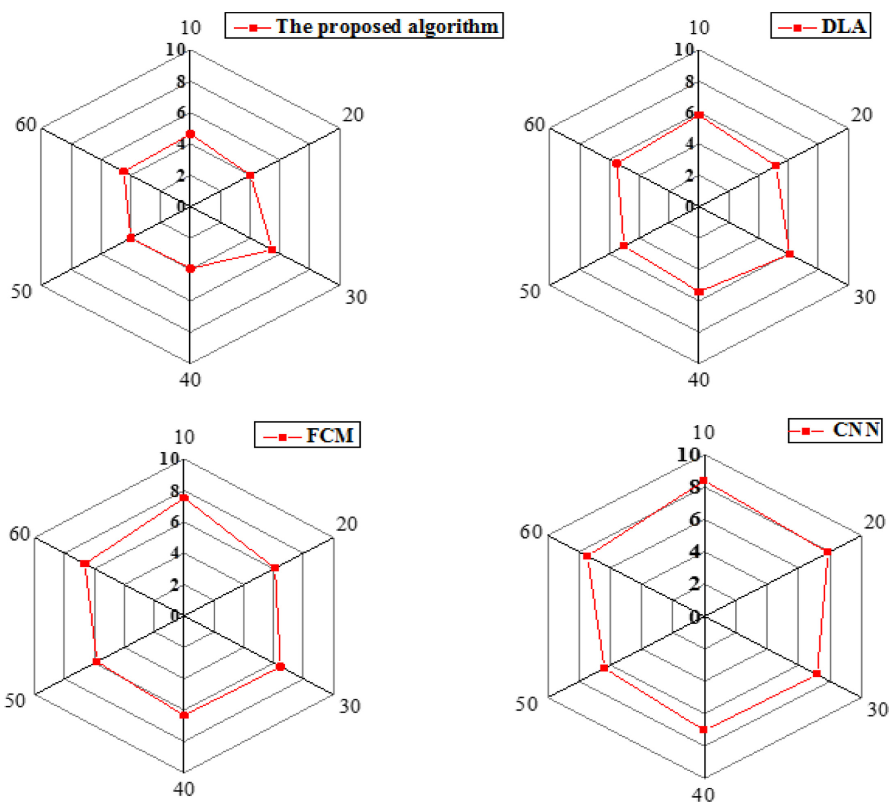

Figure 4: The variations in RMSE (%) for each algorithm as the number of iterations increases.

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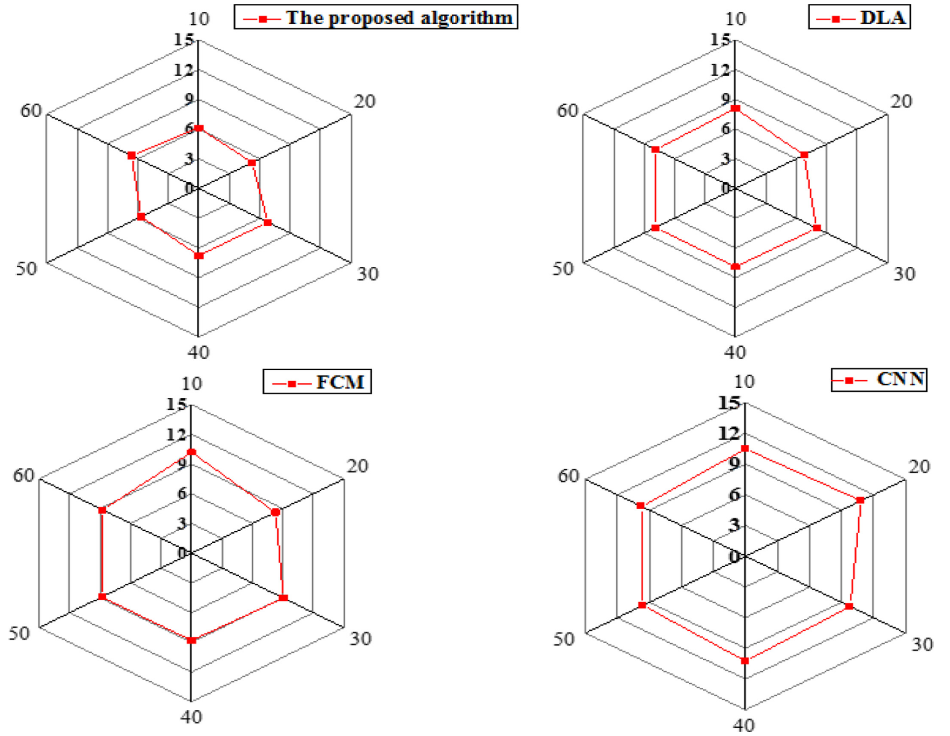

Figure 5: The MAE (in percentage terms) of each algorithm changes as the iteration count increases.

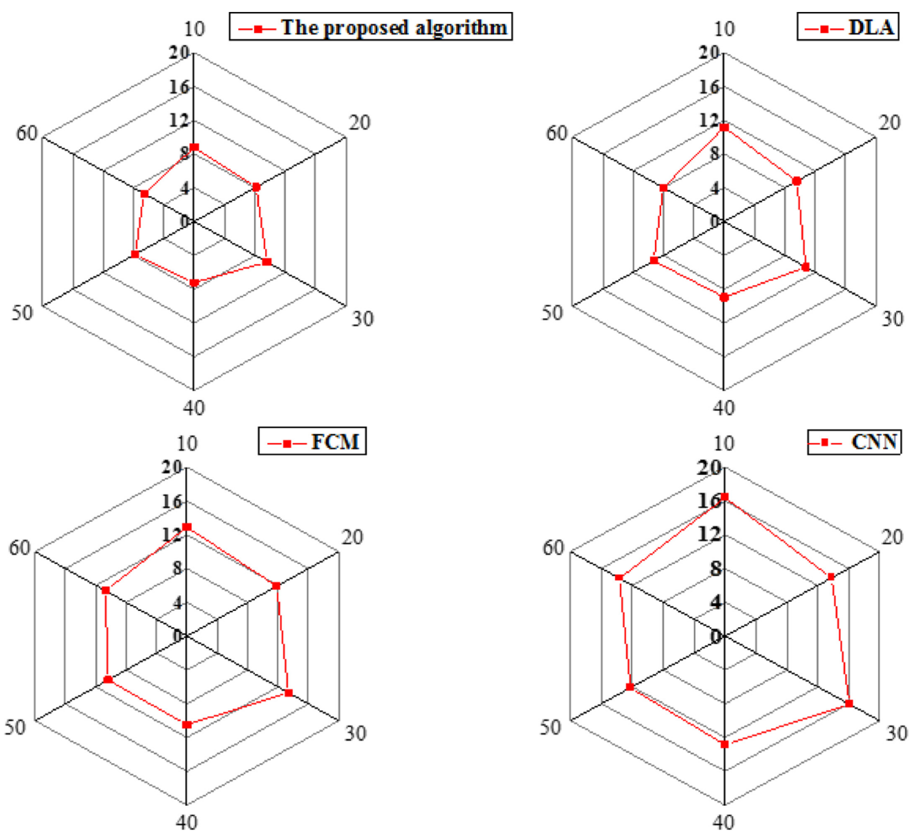

Figure 6: The variations in MAPE (%) for each method as the number of iterations increases.

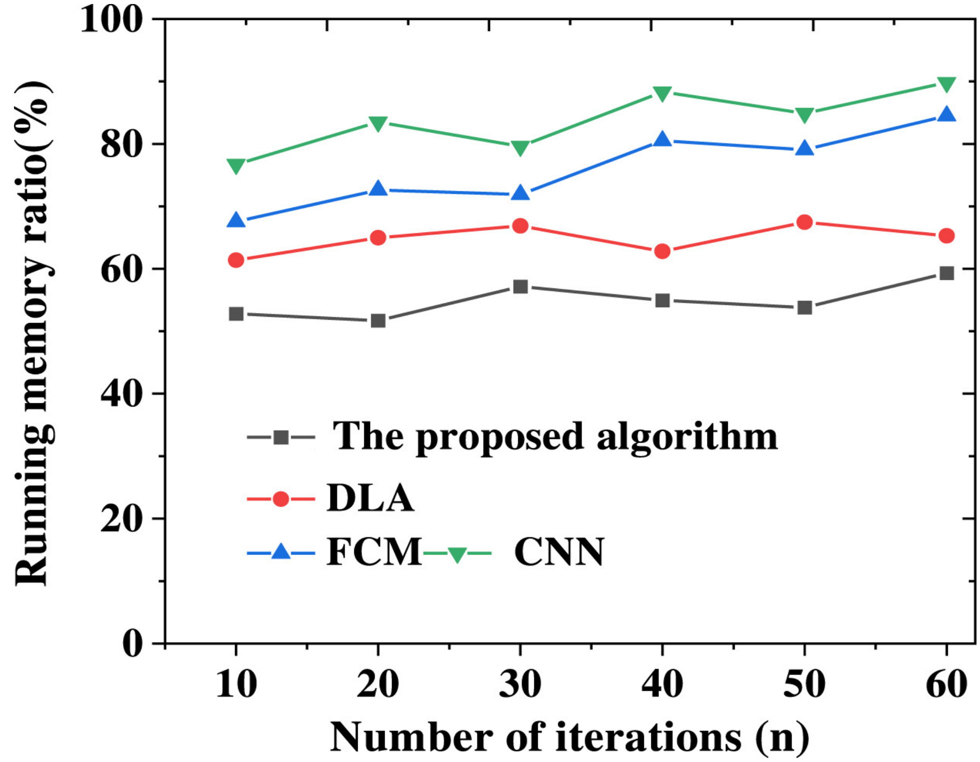

Figure 7: The memory consumption ratio curve for various methods as the iteration count increases.

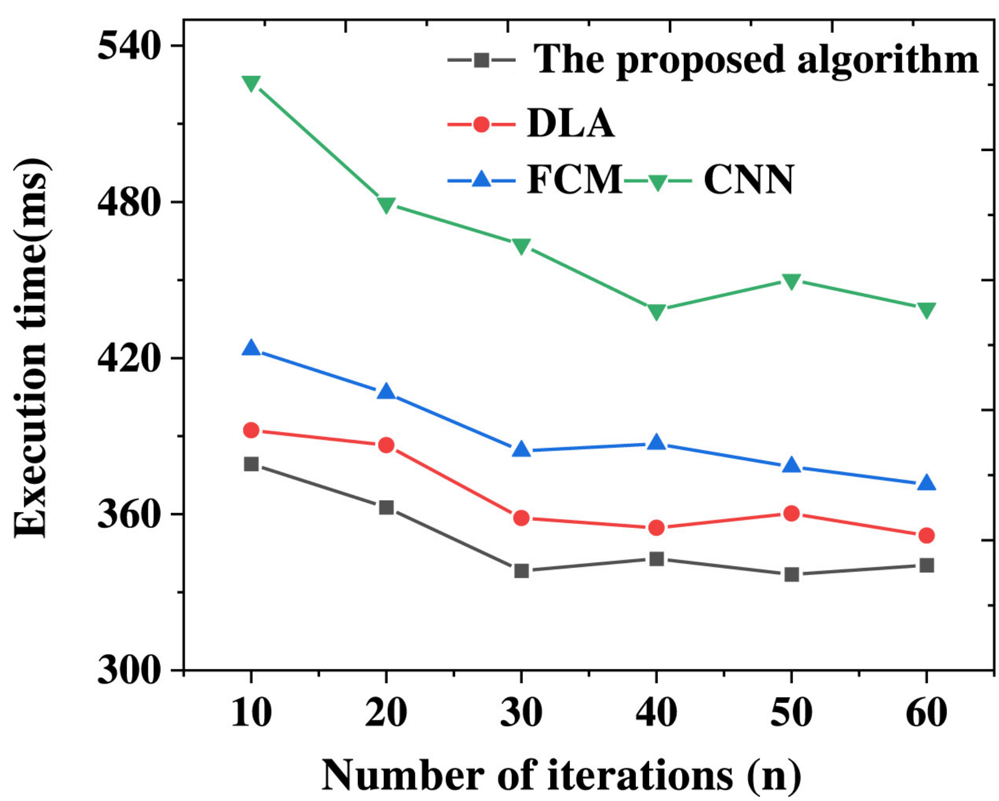

Figure 8: Comparison curve of execution time required for different algorithms as the number of iterations increases.

The memory usage ratio of each algorithm is in the order of the proposed model algorithm<DLA<FCM<CNN. Consequently, in the memory usage analysis, the model constructed in this research has the smallest proportion of memory usage and the highest resource utilization. This is demonstrated in Fig. 7, which shows that the memory usage ratio of each model algorithm remains relatively constant as the number of iterations increases. The memory usage of the proposed model algorithm is approximately 55%, while the memory usage of the FCM, DLA, and CNN models is approximately 70%, 65%, and 85%, respectively.

Figure 8 shows a comparison of the running times of the different algorithms as the number of iterations increases. As the number of iterations decreases, the running times of the algorithms start to stabilize. The suggested model algorithm has a stable time of about 340 ms, while the other model algorithms have times higher than 360 ms. The order of the required times is DLA<FCM<CNN. The model algorithm has the smallest execution time, which means its operation efficiency is high, and the traffic jam is evacuated in the follow-up traffic.

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