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A Short-Term Traffic Flow Prediction Model for Urban Areas Based on Quantum Genetic Optimization

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Abstract. *Urban traffic systems are known for their complexity and non-linearity, making it challenging to accurately predict traffic flow. This research study introduces a novel approach to tackle this issue by utilizing quantum genetic optimization to develop a short-term traffic flow prediction model specifically tailored for urban areas. To enhance the accuracy of the prediction model, the strengths of quantum computing, including accelerated processing and heightened security, are combined with the advantages offered by genetic optimization algorithms. The quantum genetic optimization algorithm is employed to optimize the model parameters, enabling a better capture of the spatiotemporal patterns inherent in urban traffic flow. Experimental results demonstrate that the prediction model, based on quantum genetic optimization, achieves highly accurate short-term traffic flow forecasts and successfully captures the complex spatiotemporal patterns of urban traffic flow. This innovative approach provides a potential solution to the longstanding challenge of accurately anticipating traffic flow in urban environments. By harnessing the power of quantum computing techniques through the utilization of genetic optimization, this research significantly contributes to the advancement of urban traffic management systems. The improved accuracy and reliability of traffic flow prediction models offer valuable insights for efficient decision-making processes regarding traffic control and congestion management.*
Keywords: Quantum genetic algorithm; short-term traffic flow in cities; genetic algorithm; quantum computing

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1. **Introduction.** To ensure efficient traffic management and effective urban planning, it is crucial to have accurate predictions of urban traffic flow [1, 2, 3]. With urban populations and vehicle numbers on the rise, traffic congestion has become a major problem, causing inconvenience and time delays for city residents. As a result, short-term traffic flow modeling has drawn interest as a crucial fix [4, 5]. The spatiotemporal patterns of traffic flow are frequently missed by traditional approaches, producing forecasts that are not trustworthy.

Recently, quantum computing and genetic optimization algorithms have emerged as promising computational methods. Quantum computing leverages quantum mechanics principles for information processing, enabling parallel computation and efficient searching. Meanwhile, genetic optimization algorithms mimic biological evolution to gradually optimize solutions through natural selection. By combining the strengths of these two algorithms, quantum genetic optimization algorithms have the potential to tackle the challenges of urban traffic flow prediction [6, 7, 8, 9].

In this study, a quantum genetic optimization-based model is proposed for short-term traffic flow prediction in urban areas. By using the quantum genetic optimization technique, the objective is to increase the precision and dependability of traffic flow forecast models. With the use of this method, we want to improve the model's ability to capture the spatiotemporal patterns of urban traffic flow and produce precise short-term forecasts. The research findings presented in this paper are highly relevant to urban traffic management and planning. We can improve traffic signal control, lessen traffic, and create more effective traffic planning methods by improving the accuracy of traffic flow prediction.

The structure of this paper is as follows: Firstly, we introduce the relevant research background and current situation in the field. Secondly, we provide an overview of the quantum genetic algorithm. Then, we describe in detail the design and implementation of the city short-term traffic flow prediction model based on quantum genetic optimization. Next, we conduct experimental validation and analyze the results. Finally, we conclude the paper, summarizing the key findings and discussing future research directions.

1.1. **Related Work.** As early as 80 years ago, theories related to traffic flow prediction emerged when studies abroad began to focus on urban road traffic flow and developed corresponding prediction models that were applied in real-life scenarios. As time passed, forty years ago, developed countries such as the United States, Germany, and Japan invested significant human and material resources into road traffic research, resulting in fruitful achievements. The efforts made by these researchers provide theoretical assistance for future research

The first type of prediction model is based on mathematical principles, among which the most famous is the ARIMA model, which was recorded and organized by Kaffash et al. [10]. The full name of ARIMA model is Autoregressive Integrated Moving Average Model. The ARIMA model mainly consists of three parts, namely Auto Regressive (AR) model, differential process (I), and Moving Average (MA) model. The basic idea of the ARIMA model is to use the historical information of the data itself to predict the future. The label value at a point in time is influenced by both label values from a period of time in the past and accidental events from that period. Van et al. [11] later applied this model to traffic flow prediction. However, the ARIMA model assumes that label values fluctuate around a major trend of time, where the trend is influenced by historical labels and the fluctuation is influenced by accidental events over a period of time, and the major trend itself may not necessarily be stable.

To improve short-term prediction performance, researchers have proposed different methods [12, 13]. Chang et al. [14] developed a new model based on the nearest neighbor algorithm in machine learning, which was tested on multiple intervals and achieved good predictive performance. Habtemichael and Cetin [15] developed a non-parametric short-term traffic flow prediction model based on functional estimation, using kernel smoothing as the autoregressive function. Guo et al. [16] quantified the uncertainty of traffic flow using the GARC method and used Kalman filtering to predict traffic flow, achieving certain improvement. However, these statistical models are built under certain assumptions and cannot handle complex traffic flow patterns. In contrast to traditional statistical models, artificial neural networks can capture nonlinear relationships and explore complex patterns in historical measurement data, making them perform well in handling uncertain and unknown traffic flow data patterns. Neural networks were first proposed in the 1940s and have since been widely used in various fields, such as image recognition, speech recognition, and automatic feature recognition. Hou et al. [17] used linear autoregressive comprehensive moving average (ARIMA) method and nonlinear wavelet neural network (WNN) method to predict traffic flow and achieved good results. Pamula [18] compiled literature on using neural network methods to predict urban road traffic flow in the past and proposed a traffic flow prediction method based on neural networks. Gu et al. [19] proposed an improved Bayesian combination model based on deep learning (IBCM-DL) for traffic flow prediction. Ma et al. [20] applied convolutional neural networks to traffic management systems. Convolutional neural networks can be continuously trained and updated, and can dynamically display changes in traffic flow in the transportation system. However, due to the relatively small size of individual models, it is difficult for them to capture useful information. Due to the fact that the two types of prediction models mentioned above often cannot fully reflect features and the research content is non-linear, errors often increase. Therefore, in order to improve the prediction model and obtain more prediction steps, combination models have been introduced and widely applied in traffic flow prediction.

In neural networks, multiple networks are usually integrated into one model, so that one model can simultaneously absorb the advantages of multiple networks and improve its own performance. For example, Particle Swarm Optimization (PSO) is a population-based stochastic optimization technique, in which each member of a population continuously changes its search pattern by learning its own experience and the experiences of other members. Chan et al. [21] optimized it and used it to obtain the temporal characteristics of traffic data. Vlahogianni et al. [22] improved the genetic algorithm and designed a multi-layer neural network to solve the calculation problem of urban road traffic flow, which outperformed the previous single network structure. Zhao et al. [23] built a hybrid prediction model that integrates a BP neural network and a mixed data sampling (MIDAS) regression model. The MIDAS regression model is used to predict data, while the BP network predicts the residuals of the MIDAS model, and predictions are aggregated. Tang et al. [24] introduced the K-means method and trigonometric regression function for data preprocessing in the training process of Fuzzy Neural Networks (FNNs), and the results obtained showed good performance. Due to the uncertainty of traffic flow data, the results obtained are influenced by multiple factors, which in turn affect the accuracy of the collected data. Some researchers have combined denoising steps to clean up the data before making predictions. Nourani et al. [25] addressed the noise problem in least squares support vector machines by using wavelets for denoising, and the results showed that their method has good performance. Following the "decomposition and ensemble" thought of wavelet denoising, Xu et al. [26] used the method of Echo State Networks (ESNs) to utilize their effectiveness in processing data sequences with complex patterns and dependencies, as well as the efficiency of training, for time prediction to achieve good results. Tang et al. [27] proposed a forecast method that combines denoising programme and Support Vector Machines (SVM) and compared five existing denoising schemes, providing recommendations for selecting suitable denoising methods for traffic flow prediction. Li et al. [28] reconstructed speed, occupancy, and traffic volume separately and used radial basis function networks to predict the ehicle throughput per unit time. Experimental results showed that the combined prediction method outperformed individual prediction methods in terms of correctness and promptness in short period traffic flow prediction. However, each method has its limitations and challenges.

1.2. **Motivation and contribution.** The accurate prediction of urban traffic flow is of paramount importance in effectively managing and optimizing transportation systems. However, existing prediction models often face limitations in terms of accuracy, especially when dealing with the complex and dynamic nature of urban traffic. This necessitates the need for innovative approaches that can overcome these limitations and improve the correctness of traffic flow predictions.

To address the challenges in urban traffic flow prediction, this article proposes a short-term urban traffic flow prediction model based on quantum genetic optimization. This model combines the strengths of quantum computing and genetic optimization algorithms to enhance prediction accuracy. By leveraging the accelerated processing power and heightened security offered by quantum computing, we are able to handle the vast amount of data associated with urban traffic flows, ensuring more precise and real-time predictions.

Moreover, by employing the quantum genetic optimization algorithm, we can effectively optimize the model parameters, capturing the intricate spatiotemporal patterns of urban traffic flow. This optimization process allows for a more accurate representation of the dynamics and interactions within the traffic system, improving the overall reliability of the predictions. In summary, the proposed model contributes to the field of urban traffic flow prediction by integrating quantum computing and genetic optimization algorithms, resulting in enhanced accuracy and a better understanding of the complex dynamics of urban traffic. This research has far-reaching implications, as it holds the potential to guide urban planning, traffic management strategies, and the development of intelligent transportation systems.

2. Relevant theoretical analysis.

2.1. **Genetic Algorithm.** The Genetic Algorithm (GA) mimics processes like genetic inheritance, crossover, and fitness selection to search the solution space and approach the optimal solution. In genetic algorithms, problem solutions are encoded as genes or chromosomes. Each gene represents a potential solution, and the encoding method can be tailored to the problem's characteristics and requirements. Crossover operation mimics gene exchange between individuals, combining gene segments from two parents to create new offspring. Mutation operation randomly changes certain genes of an individual, introducing new genetic information. The generated solutions are evaluated using a fitness function tailored to the problem's requirements, measuring solution quality. The fitness function is designed to align with the problem's objective, whether it's maximizing or minimizing a specific function. Based on fitness values, the selection operation chooses excellent solutions as parents for the next generation, forming a new population. Alternative phrasing: Selection strategies such as roulette wheel selection and tournament selection assign selection probabilities to individuals based on their fitness values. The genetic algorithm iteratively applies genetic operations and selection operations until a termination condition is met. This condition can be a predetermined cycles count, finding a satisfactory optimal solution, or a decrease in the improvement rate below a threshold. Through iterations and survival of the fittest, the algorithm searches for better solutions and approaches the optimal one. In summary, genetic algorithm simulates biological evolution's principles using genetic and selection operations to search for optimal solutions. It has broad applications in complex optimization problems and can be adjusted and optimized to fit problem characteristics [29, 30, 31].

2.2. **Quantum Computing.** GQC is a computational paradigm that leverages the principles of quantum mechanics to store and process information using quantum bits (qubits) instead of classical bits. Compared to traditional computing, quantum computing has the potential for significant advantages and can achieve more efficient computations for certain specific problems. In classical computers, information is represented in binary form, each bit can be in either the binary states of 0 or 1. In contrast, quantum computing allows qubits to occupy a state of quantum superposition encompassing both 0 and 1 states simultaneously, which is a fundamental principle in quantum mechanics. Additionally, qubits possess characteristics such as quantum entanglement and quantum interference, allowing quantum computing to simultaneously process multiple states and potentially achieve exponential speedup in certain cases.

2.2.1. *Qubit.* In a quantum computer, the fundamental unit for storing data is a quantum bit (qubit). A qubit is a quantum system with two states, where "two states" refers to the presence of two linearly independent states. The key distinction between a qubit and a classical bit lies in the fact that a qubit can concurrently express a linear superposition of two independent states. This implies that a qubit can simultaneously hold information from two distinct states.

In the QCA, a qubit can be in the state of $|0\rangle$ or $|1\rangle$, or in a superposition state between $|0\rangle$ and $|1\rangle$. The state of a qubit can be represented in this way:

$$|\Phi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{1}$$

where α and β can be complex numbers representing the probability amplitudes of the corresponding states, satisfying the following normalization condition:

$$|\alpha|^2 + |\beta|^2 = 1 \tag{2}$$

In this case, $|\alpha|^2$ represents the probability of $|0\rangle$, and $|\beta|^2$ represents the probability of $|1\rangle$.

Based on this inference, n qubits with the same number of digits can concurrently represent $2n$ states. Each state can be represented as follows:

$$|\varphi_i\rangle = \sum_{k=1}^{2^n} D_k|S_k\rangle \tag{3}$$

In the above equation, D_k represents the probability amplitude of the k-th state, and it satisfies the normalization condition:

$$|D_1|^2 + |D_2|^2 + \Lambda + |D_n|^2 = 1 \tag{4}$$

where $|\varphi_i\rangle$ is a unit vector.

2.2.2. *Quantum Gate.* These fundamental unitary operations performed on qubits are known as quantum gates. As unitary transformations are reversible, quantum gates are also reversible and can be expressed as unitary operators that act on quantum states:

$$A^*A = AA^* \tag{5}$$

where A denotes the unitary matrix of the quantum gate, while A^* signifies the conjugate transpose of A.

Below are several commonly used representations of the unitary matrices for quantum gates:

$$A_{not} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \tag{6}$$

$$A_{Cnot} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{7}$$

$$A_H = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \tag{8}$$

$$A_R = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \tag{9}$$

2.3. **Quantum Genetic Algorithm.** QGA is a novel stochastic search improvement algorithm that combines the principles of GQC with traditional genetic algorithms. This algorithm utilizes concepts and ideas from GQC, such as quantum bits (qubits), quantum composition, and quantum parallelism. It replaces the traditional binary or real-valued chromosome encoding in genetic algorithms with qubit-encoded chromosomes, enabling quantum chromosomes to represent information in multiple states simultaneously [32,33,34]. Additionally, by utilizing quantum gate operations to perform genetic evolution operations on individual qubits within the quantum chromosome, QGA maintains population diversity and avoids selection pressure.

Constructing quantum gates is a primary focus of quantum genetic algorithms. The main strategy involves employing quantum rotation gates, particularly:

$$A_R = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \tag{10}$$

The adjustment operation for the quantum rotation gate $U(t)$ is as follows:

$$\begin{bmatrix} \alpha_i' \\ \beta_i' \end{bmatrix} = \begin{bmatrix} \cos(\theta_i) & -\sin(\theta_i) \\ \sin(\theta_i) & \cos(\theta_i) \end{bmatrix} \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} \tag{11}$$

The change direction of the algorithm is directed through the optimal character, allowing the population to evolve towards better individuals with a higher probability.

1) Population initialization: Generate the initial population by randomly creating a set of quantum chromosomes, where each chromosome is composed of qubits.

2) Evaluate fitness: Calculate the performance metric for each chromosome based on the problem's fitness algorithm.

3) Selection operation: Use a selection operator based on fitness values to choose a subset of chromosomes as parents.

4) Qubit encoding: Convert the classical bits of the selected parent chromosomes into qubits, leveraging the superposition property of quantum states.

5) Qubit update: Apply quantum gate operations to update the qubits within the chromosomes, simulating genetic operations like crossover and mutation.

6) Evaluate fitness: Assess the fitness of the updated chromosomes and calculate their fitness values.

7) Termination condition: Verify whether the termination condition has been satisfied.

8) Terminate or evolve: If the finalization criterion is met, end the algorithm and return the optimal solution; otherwise, return to step 3 for the next generation's selection operation.

Through the iteration of the above steps, the quantum genetic algorithm is capable of searching for the potential optimal solution space and finding good solutions for optimization problems. This algorithm has the potential to solve complex optimization problems and perform high-dimensional space search, showing promising application prospects in fields such as urban traffic flow prediction.

2.4. **Urban Short-Term Traffic Flow.** Urban segment traffic flow is closely linked to the transportation conditions in the city. Here are some key factors related to urban traffic flow:

1) Vehicle Flow: Vehicle flow represents vehicle flow through a road segment or intersection, usually measured as vehicles per hour (PCU/h). It indicates road utilization intensity and provides insights into traffic demand and congestion.

2) Vehicle Speed: Vehicle speed refers to the average speed of vehicles on the roads, typically measured in kilometers per hour (km/h). It directly impacts traffic efficiency and road capacity, with higher speeds indicating smooth flow and lower speeds indicating congestion.

3) Vehicle Density: Vehicle density represents the number of vehicles per unit length or area, commonly expressed as vehicles per kilometer or vehicles per square kilometer. Vehicle density is related to vehicle flow and speed and reflects the level of congestion on the roads. When vehicle density is high, traffic behavior is likely to result in congestion, leading to reduced vehicle speeds.

4) Traffic Flow Patterns: Traffic flow patterns describe the time-related and positional variations of traffic flow. It can be divided into peak and off-peak periods. Peak periods usually refer to the time periods with the highest traffic volume, such as morning and evening rush hours, when the vehicle flow on the roads is high. Off-peak periods are relatively low-traffic volume time periods when the vehicle flow on the roads is relatively low.

5) Road Capacity: Road capacity refers to the maximum vehicle flow that a road can accommodate within a certain time period. The capacity of a road is impacted by diverse elements, inclusive of the geometric shape of the road, traffic signals, intersections, etc. Understanding road capacity can help in planning and designing road networks to meet traffic demands and improve traffic efficiency. By monitoring and analyzing urban traffic flow, it is possible to assist the management departments in formulating traffic control strategies, improving traffic congestion, enhancing road capacity, and optimizing the urban transportation system. Exactly measure and predict, researchers have employed various methods and technologies, including traditional traffic flow observations, traffic models and prediction methods, as well as data mining and machine learning-based algorithms of traffic flow predictions. The development of these research and technologies has provided significant support and guidance for urban traffic management and planning.

3. **Quantum Genetic Algorithm Optimization for Short-term Traffic Flow Prediction Algorithm.** The steps involved in optimizing the short-term traffic flow prediction model using the quantum genetic algorithm are as follows:

1) Initiate the population $P(t_0)$.

2) Measure each individual in the initial population and acquire a set of states $Q(t_0)$.

3) Evaluate the fitness of every individual state.

4) Record the optimal state of the best individual along with its corresponding fitness value.

5) While not in the termination state, do the following:

i. Increment t by 1.

ii. Measure the population $P(t)$ and obtain collection of states $P(t)$.

iii. Assess the fitness of every individual state.

iv. Apply quantum crossover to individuals in the population based on a specific modification approach. Update the population using quantum rotation gates $U(t)$ and perform compilation operations using quantum gates to acquire the descendant population $P(t+1)$.

v. Register the state and fitness assessment of the best-performing individual.

The algorithm begins by initializing the population $P(t_0)$, where each chromosome's genes in the population (α_i', β_i') are initialized $(1/\sqrt{2}, 1/\sqrt{2})$. This implies that a chromosome represents a superposition of all its possible states with equal probabilities:

$$|\psi_{q_j}^o\rangle = \sum_{k=1}^{2^m} \frac{1}{\sqrt{2^m}} |S_k\rangle \tag{12}$$

where S_k denotes the k-th state of the chromosome, which is represented as a binary string with a length of n, $(Y_1, Y_2, ..., Y_n)$, where each $Y_i(|\alpha_i'|^2$ or $|\beta_i'|^2, i = 1, 2, ..., n)$ is either 0 or 1.

The subsequent process of the algorithm involves measuring on the individuals among the initial individuals to derive a collection of certain solutions $P(t) = \{p_1^t, p_2^t, ..., p_n^t\}$. Here, p_j^t represents the j-th solution in the t-th population's iteration. It is exhibited as a binary string with a length n, where every individual bit is determined by the probability of the quantum bit (or, i = 1, 2, ..., n) selection.

Subsequently, the algorithm enters the iterative loop stage, where the solutions in the population progressively approach the best solution. In each iteration, the population $P(t)$ is first measured to derive a collection of deterministic solutions $Q(t)$. Subsequently, the fitness value of every solution is computed, followed by quantum crossover applied to individuals in the population according to the present evolutionary objective and predetermined modification strategy. After that, quantum rotation gates $U(t)$ are used to adjust the individuals in the population, and quantum NOT gates are applied for quantum mutation operations, resulting in an updated population $Q(t+1)$. The present best solution is noted and compared against the present target value. If it exceeds the present target value, the new best solution is set as the target value for the next iteration; else, the target value remains unchanged. The algorithm flowchart is shown in Figure 1.

4. Application Testing.

4.1. **Preparation of Application Testing Data.** During the stage of analyzing the practical application effectiveness of the method that utilizes quantum genetic algorithm to predict traffic flow in urban segments, we conducted comparative testing. The control group consisted of two methods: SVM model and Backpropagation (BP) neural network model. By comparing the relationship between the the actual traffic flow data with predicted results from various methods, we objectively evaluated the method designed.

During the data preparation phase, we selected a city's main road in a specific area. This main road is significant in urban transportation and is home to important government agencies. As a busy traffic route, congestion has become a significant issue. The traffic conditions at this intersection are also representative. Therefore, in analyzing the feasibility of the prediction model, we focused on the data at this intersection. Over a period of ten consecutive days, we manually collected the traffic flow data at this section. During these ten days, there were no abnormal weather conditions or unexpected incidents, making the data relatively ideal. Figure 2 illustrates the positions of the magnetic detection devices, while Figure 3 displays the traffic flow volume curve at this intersection.

Three error metrics were employed to assess the prediction results of the models: MAPE, RMSE, and MAE. MAPE measures the average difference between predicted and

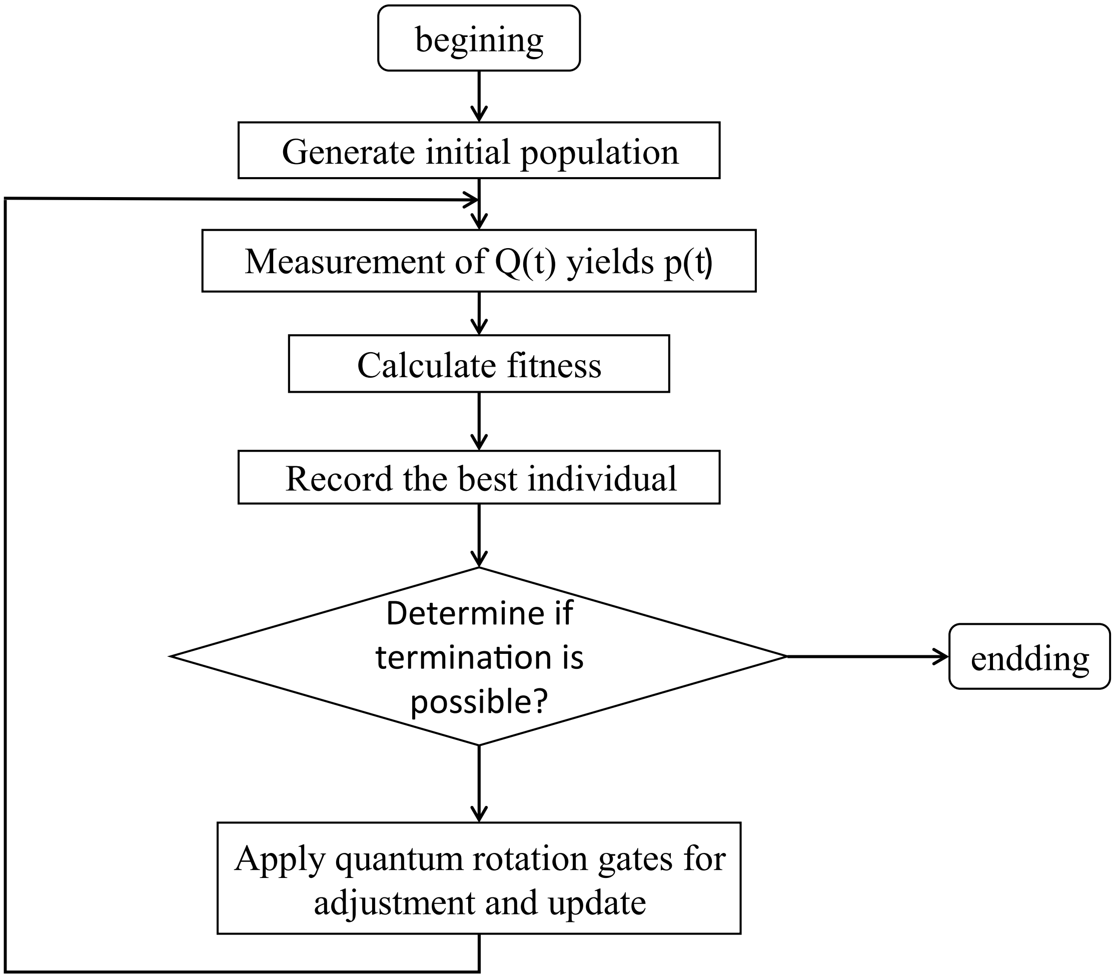

Figure 1. Flowchart of quantum genetic algorithm

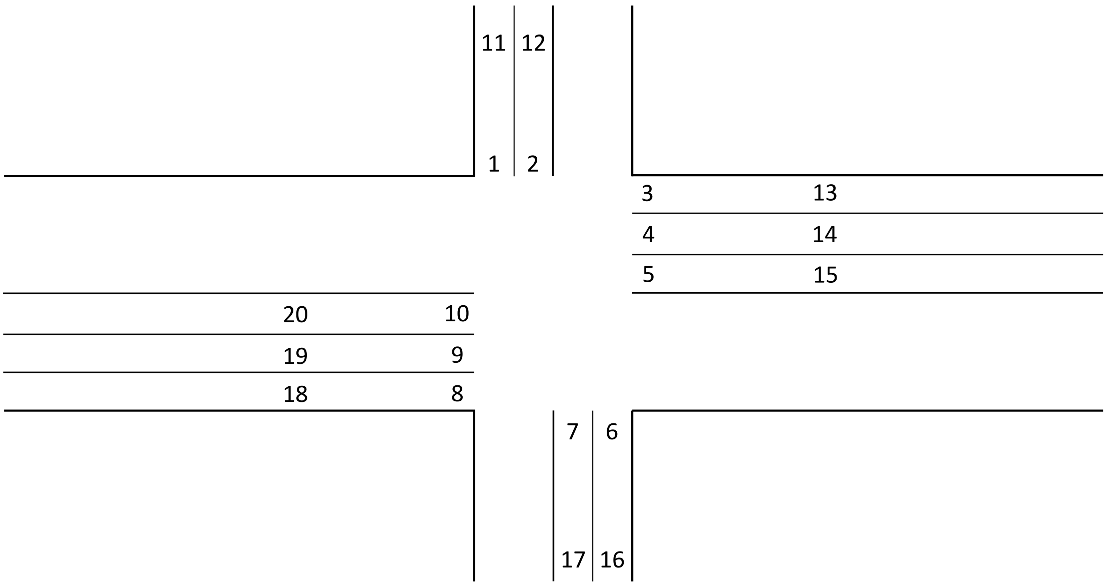

Figure 2. Schematic representation of magnetic detection device locations

actual results, assessing prediction accuracy. RMSE quantifies the discrepancy between actual and predicted values, indicating model robustness. MAE represents the average

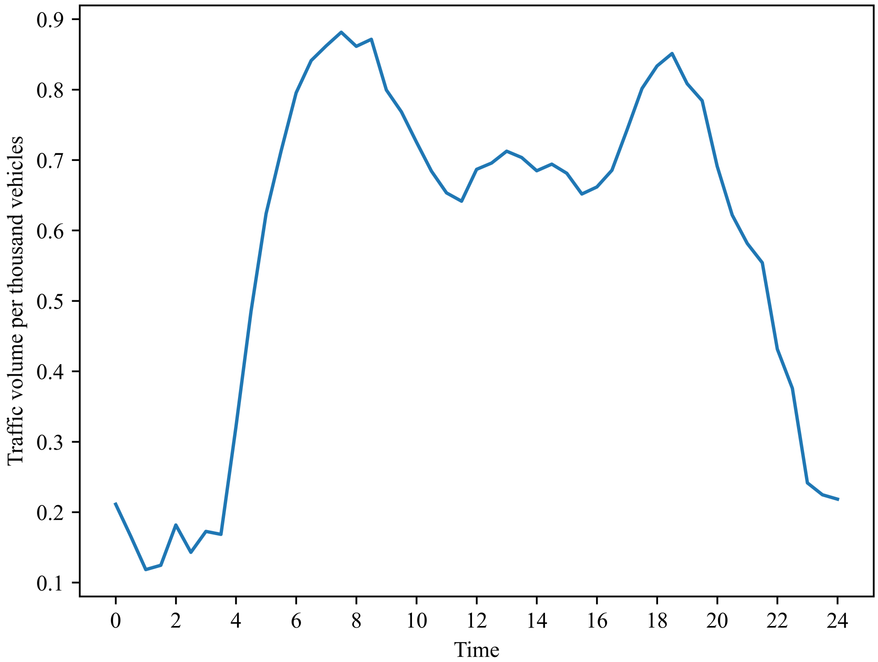

Figure 3. Predicted traffic volume for the road segment

absolute error and is less affected by extreme values, also assessing prediction accuracy. The formulas for these metrics are as follows:

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - \hat{x}_i| \tag{13}$$

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2} \tag{14}$$

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_i - \hat{x}_i}{x_i}\right| \times 100\% \tag{15}$$

Using this information, it is possible to conduct an analysis of the prediction performance of various methods.

4.2. **Test Results and Analysis.** Based on the above, this paper conducted a comparative analysis of three models' performance, and the obtained data information is shown in Table 1.

Table 1. Analyzed the results of predicting model

Prediction Model	**MAPE/%**	**RMSE**	**MAE**
SVM	26.99	7.22	5.63
BPNN	23.56	6.76	4.56
QGA	20.03	5.53	4.02

The test results indicate that the proposed prediction model optimized by quantum genetic algorithm outperforms the SVM and BPNN models in terms of prediction error and prediction accuracy. It can be considered that using the quantum genetic algorithm to optimize the prediction model effectively improves its performance. This model is a better method for prediction, with higher accuracy and practicality. Figure 4 offers a visual comparison of the three methods.

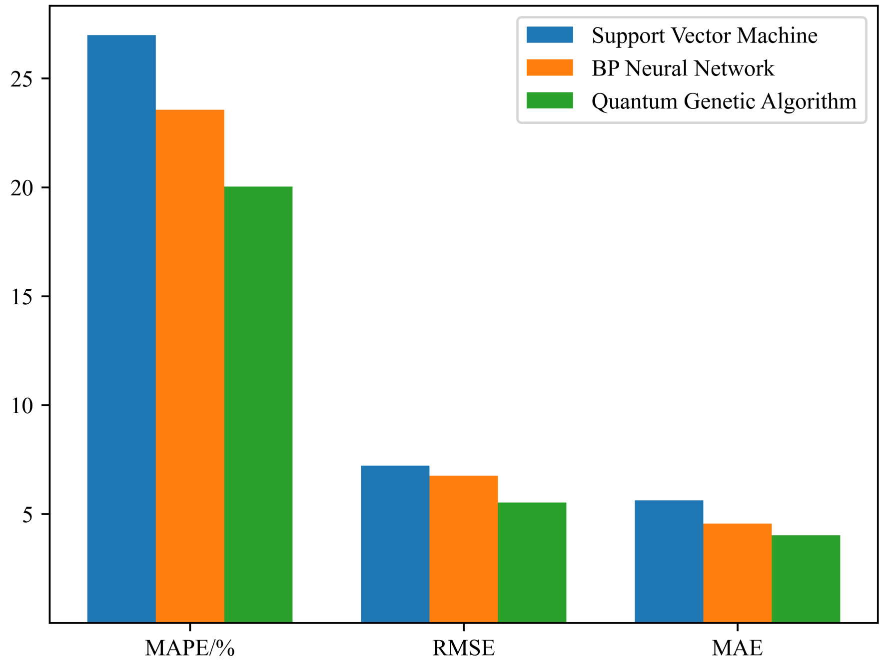

Figure 4. Experimental data comparison chart

5. **Conclusion.** In conclusion, this paper introduces a novel approach to city short-term traffic flow prediction by incorporating quantum genetic optimization. The utilization of the quantum genetic optimization algorithm aims to enhance the accuracy and robustness of traffic flow prediction. By designing and implementing the proposed model, as well as conducting thorough experiments and result analysis, we have demonstrated the improved performance of our model in terms of accuracy and robustness compared to existing methods. Moving forward, there are promising opportunities for further research on optimizing and adapting the model to address the dynamic challenges observed in urban traffic. This includes exploring additional techniques and algorithms to improve the prediction accuracy and adaptability of the model in real-time scenarios. Ultimately, the continuous refinement and application of advanced prediction models like the one presented in this study will contribute to the development of more efficient and intelligent urban transportation systems, benefiting both public safety and transportation optimization.

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