Original Research Article

Forecasting of road traffic flow based on harris hawk optimization and XGBoost

ABSTRACT

With the development of society and economy, people's living standards are improving day by day. The number of private cars is increasing, and the problem of urban traffic congestion is becoming more and more serious. Short-term traffic flow prediction is crucial to assist intelligent transportation system decision-making, solve congestion problems, and improve road capacity. In order to effectively improve the prediction accuracy and improve the generalization performance of the model, this paper combines extreme gradient boosting (XGBoost) and harris hawk optimization (HHO) to propose a multi-step prediction hybrid model. When building a hybrid model, the hyperparameter selection of the XGBoost model is converted into an optimization problem, and the optimization problem is solved through HHO. The solution to the final optimization problem is the optimal parameter combination of the XGBoost model. In order to verify the performance and competitiveness of the model, this study applies the proposed model to traffic flow prediction together with seven other representative models. The results show that the model has high accuracy and stability in practical applications.

Keywords: {Taffic flow, Extreme gradient boosting, Harris hawk optimization, Multi-step forecast }

1. INTRODUCTION

1.1 Backgroud

With the progress of urbanization in the world and the popularization of automobiles, traffic problems are increasing daily, such as traffic congestion, frequent traffic accidents, and traffic environment deterioration. Frequent traffic accidents and traffic congestion will prolong people's travel time and cause more traffic accidents to a certain extent. With the development of society and economy, the desire of human beings for a better life continues to breed, resulting in an increasing trend of owning one private car per capita rather than one private car per household[1]. With the gradual increase of personal vehicles, urban traffic congestion is becoming more and more serious, and traffic accidents are increasing year by year. Traffic congestion causes severe pollution to the environment and has a tremendous negative impact on human health[2].

The intelligent transportation system relies on the monitoring and guidance of the running state of the driving vehicles to optimize the distribution of traffic flow in the road network[3], which can effectively alleviate road traffic congestion and traffic accidents. It is currently the most effective way to solve traffic problems recognized by the world. As one of the key technologies intelligent transportation research, traffic flow prediction has become a research hotspot at home and abroad.

Traffic flow prediction is the basis for realizing traffic guidance and reasonable traffic control, and it is a prerequisite for the realization of intelligent transportation. However, the

randomness and dynamic characteristics of traffic flow determine the difficulty of prediction, which has always been a hot and challenging spot in traffic flow research.

1.2 Related work

Up to now, a large number of researchers have carried out a lot of research work on the short-term forecast of traffic flow, using the knowledge of various disciplines, and proposed a variety of forecasting theories and methods. According to the nature of the prediction method itself, the current traffic flow prediction models can be roughly classified into the following categories: statistical models, machine learning models, deep learning models, and gray system models.

Mario Cools, Elke Moons, Geert Wets Using Autoregressive Integrated Moving Average (ARIMA) Models with Explanatory Variables (aka ARIMAX Model) and Methods Using Seasonal Autoregressive Integrated Moving Average (SARIMA) Models and SARIMA with Explanatory Variables model (i.e., the SARIMAX model), analyzed using data collected in 2003, 2004, and 2005 for single-inductive loop detectors, showing that both the ARIMAX and SARIMAX modeling methods are effective frameworks for identifying and quantifying possible impacts[4]. Guoqiang Yu et al. modeled the traffic flow as a higher-order Markov chain, and the case study results demonstrate the applicability and effectiveness of their proposed model[5]. Mengzhang Li and Zhanxing Zhu proposed a novel spatiotemporal fusion graph neural network (STFGNN) for traffic flow prediction. Experimental results on several public transportation datasets show that the proposed method consistently achieves optimum performance[6]. Wentian Zhao et al. studied Temporal Convolutional Networks (TCN)[7]. They proposed a deep learning framework based on the TCN model, which was applied to short-term traffic forecasting across the city. State-of-the-art performance with improved accuracy. Jiawei Cao et al. proposed a short-term traffic flow prediction model based on extreme gradient ascent. The experimental results revealed the model's superiority by comparing it with traditional prediction models[8]. Li Yuanyuan and Xu Weixiang used the improved KNN algorithm to reconstruct the phase space, wait until the input data, and then use the SVR model to predict the data. The best experimental results show that the model has better prediction performance[9]. Huiming Duan and Xinping Xiao introduced the cyclic truncation accumulation and generation operation to realize rolling prediction and proposed a dynamic tensor rolling inhomogeneous discrete gray model (DTRNDGM). The results show that the simulation and prediction results of DTRNDGM are good[10]. Huiming Duan, Xinping Xiao, Qinzi Xiao proposed three new inertial grey discrete models (IDGMs) and used them for short-term traffic flow estimation based on traffic flow data mechanics and characteristics and traffic state characteristics. The evolution process of mechanical data decomposition is applied to the modeling process, making the modeling process more reasonable and the structure more stable, which solves the shortcomings of traditional gray DGM parameter estimation[11].

From the literature review results, it can be seen that traffic flow prediction is a very open field that can use a variety of models and methods. However, it is worth noting that most scholars use a single model to predict traffic flow, but the stability and prediction performance of a single model has limitations. Therefore, to effectively improve the stability of the prediction and the reliability of the prediction results, this study proposes a new hybrid model combining the intelligent optimization algorithm and the machine learning algorithm and selects the hyperparameters of the model through the optimization algorithm.

2. METHODOLOGY

2.1 Extreme Gradient Boosting

XGBoost is a decision tree-based algorithm proposed by Chen Tianqi et al. in 2016[12]. It efficiently implements the GBDT algorithm and makes many improvements in algorithm and engineering. It is widely used in Kaggle competitions and many other machine learning competitions and achieved good results.

The core idea of XGBoost is based on Boosting, and the general process is shown in the Eq.1.

$$\begin{aligned}
&\hat{y}_i^{(0)} = 0 \\
&\hat{y}_i^{(1)} = f_1(x_i) = \hat{y}_i^{(0)} + f_{1(x_i)} \\
&\hat{y}_i^{(1)} = f_{1(x_i)} + f_{2(x_i)} = \hat{y}_i^{(1)} + f_{2(x_i)} \\
&\vdots \\
&\hat{y}_i^{(t)} = \sum_{k=1}^{t} f_k(x_i) = \hat{y}_i{}^{(t-1)} + f_{t(x_i)}
\end{aligned} \tag{1}$$

Where $\hat{y}_i^{(t)}$ represents the forecasting result of the t-th round model, and $\hat{y}_i^{(t-1)}$ is the forecasting result of the $t-1$ round model. What's more, the objective function of XGBoost is mainly composed of two parts: loss function, regularization term, such as Eq.2.

$$\begin{aligned}
obj^{(t)} &= \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t)}\right) + \sum_{i=1}^{t} \Omega(f_i) \\
&= \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f(x_i)\right) + \Omega(f_t) + C
\end{aligned} \tag{2}$$

Where $\Omega(f) = \gamma T + \frac{1}{2}\lambda||w||^2$, C is a constant. We use the second-order expansion of Taylor's formula to approximate the objective function, remove the constant term simultaneously, and expand ω. Besides, map all samples to the tree structure through the function $q(x)$ to obtain Eq.3:

$$\begin{aligned}
obj^{(t)} &= \sum_{i=1}^{n} [g_i f_t(x_i) + h_i f_t^2(x_i)] + \Omega f(t) \\
&= \sum_{i=1}^{n} \left[g_i \omega_{q(x)} + h_i \omega_{q(x)}^2\right] + \gamma T + \frac{\lambda}{2}\sum_{j=1}^{T} \omega_j^2 \\
&= \sum_{j=1}^{T} \left[\left(\sum_{i \in I_j} g_i\right)\omega_j + \frac{1}{2}\left(\sum_{i \in I_j} h_i + \lambda\right)\omega_j^2\right] + \gamma T
\end{aligned} \tag{3}$$

Where $I\_j = \{i|q(x_i) = j\}$ as the set of subscripts of the samples on each leaf node j. Define $G_j = \sum_{i \in I_j} g_i$, $H_j = \sum_{i \in I_j} h_i$:

$$obj^{(t)} = \sum_{j=1}^{T} \left[G_j \Omega_j + \frac{1}{2}\left(H_j + \lambda\right)\omega_j^2\right] + \gamma T \tag{4}$$

When the structure of the tree $q(x)$ is determined, the optimal weight of the leaf can also be easily calculated. At this time, the objective function value can be calculated by Eq.5.

$$obj^{(t)} = -\frac{1}{2}\sum_{j=1}^{T} \frac{G_j}{H_j + \lambda} + \gamma T \tag{5}$$

The result of Eq.5 is used to evaluate the quality of the tree structure. The smaller the result, the better the tree structure.

2.2 Harris Hawk Optimization

Inspired by the predation behavior of Harris Eagle in 2019, Heidari et al. proposed the Harris Hawk Optimization[13]. The algorithm is mainly composed of three parts: search, conversion and development of search, and development, and has strong global searchability.

2.2.1 Exploration phase

In HHO, Harris Hawk is the candidate solution, and the best candidate solution in each step is considered the expected prey or close to the optimal solution. Harris Hawks will perch somewhere randomly and find prey through two strategies:

$$E(i+1)=\begin{cases} E_{rand}(i)-c_1|E_{rand}(i)-2c_2E(i)|, q\geq 0.5 \\ \left[E_{food}(i)-E_m(i)\right]-c_3[lb+c_4(ub-lb), q<0.5 \end{cases} \quad (6)$$

Where $E(i)$ and $E(i+1)$ are the position of the individual at the current and next iteration, respectively, i is the number of iterations and $E_{rand}(i)$ is an individual randomly selected from the population, $E_{food}(i)$ is the prey position. Besides, $c1$, $c2$, $c3$ and q are random numbers inside[0,1]. $E_m(i)$ is the average position of the current population of hawks. which can be calculated by Eq.7.

$$E_m(i)=\sum_{k=1}^{M}E_k(t)/M \quad (7)$$

$E_k(t)$ represents the position of each individual in the Kth iteration, and M represents the population size.

2.2.2 Transition from exploration to exploitation

The HHO algorithm switches between searching and different exploitation behaviors according to the escape energy of the prey, which is defined as:

$$W=2W_0(1-\frac{i}{I}) \quad (8)$$

Among them, W_0 is the initial energy of the prey, which is a random number between $[-1,1]$, which is automatically updated at each iteration, and I is the maximum number of iterations. Enter the search phase when $|E|\geq 1$, and enter the development phase when $|E|<1$.

2.2.3 Exploitation phase

Define r as a random number between [0,1]. When $0.5\leq|W|<1$ and $r\geq 0.5$, a soft siege strategy is adopted to update the position:

$$E(i+1)=\Delta E(i)-W|LE_{food}(t)-E(i)| \quad (9)$$

When $|W|<0.5$ and $r\geq 0.5$, adopt a hard siege strategy for position update:

$$E(i+1)=E_{food}(i)-W|\Delta E(i)| \quad (10)$$

When $0.5\leq|W|<1$ and $r<0.5$, the soft encircling strategy of asymptotic fast dive is adopted to update the position:

$$E(i+1)=\begin{cases} Y, f(Y)<f(E(I)) \\ Z, f(Z)<f(E(I)) \end{cases} \quad (11)$$

where $Y=E_{food}(i)-W|LE_{food}(i)-E(i)|$, $Z=Y+S*Tf(2)$. f is a fitness function, S is a two-dimensional vector, and its elements are random numbers in $[0,1]$, TF is the mathematical expression of Levi's flight.

When $|W|<0.5$ and $r<0.5$, adopt the hard encircling strategy of asymptotic fast dive to update the position:

$$E(i+1) = \begin{cases} Y, f(Y) < f(E(I)) \\ Z, f(Z) < f(E(I)) \end{cases} \quad (12)$$

where $Y = E_{food}(i) - W|LE_{food}(i) - E_m(i)|$.

In the above four formulas, $\Delta E(i) = E_{food}(i) - E(i)$ represents the difference between the prey position and the individual's current position, and L is $[0, 2]$ between random numbers.

2.3 Establishment of a novel hybrid model

The optimization of hyperparameters is a difficult and hot issue in machine learning. The quality of a model depends mainly on the choice of hyperparameters. Most of the time, researchers adjust the hyperparameters based on their own experience, but this method is highly subjective and may not be able to obtain satisfactory results. Therefore, in this study, we introduce an intelligent optimization algorithm to optimize the model's hyperparameters.

The construction process of the novel prediction model based on HHO and XGBoost is mainly divided into the following five steps: (1) Determining model parameters and initialization algorithm. (2) Define the objective function of HHO, (3) Continuously update the position based on the objective function value. (4) If the iteration meets the maximum number of iterations, continue to run the algorithm. Otherwise, return the step(3). (5) Obtain the optimal model and apply the model to predict traffic flow. The detailed process of the model construction is shown in Figure.1.

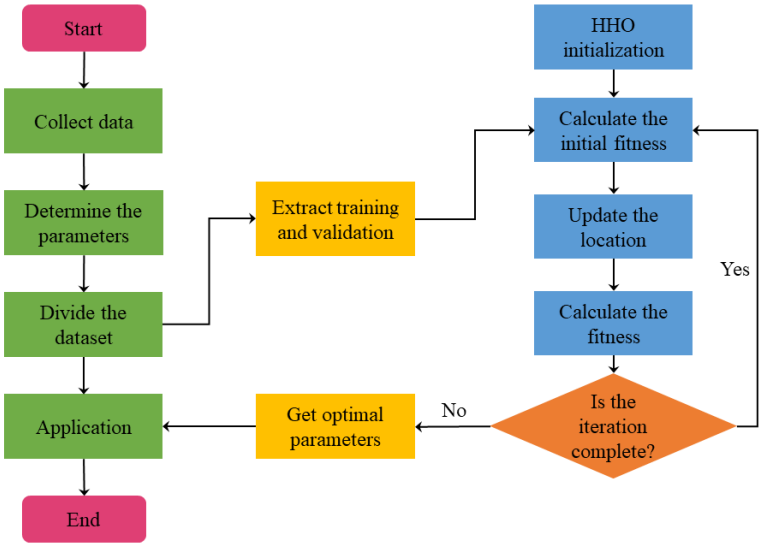


Figure 1 The construction process of HHO-XGBoost model

3. RESULTS AND DISCUSSION

3.1 Data description

The quality of a model depends largely on its generalization. In this study, our data is derived from the OpenITS[14]. The data comes from the Whitemud Drive Highway in Canada, where road traffic information is collected every twenty-second. In our research, the data is processed into two granularities of ten minutes and twenty minutes.

The relevant information and some statistical characteristics of the two datasets are shown in Table 1.

Table 1 Some statistical features of the dataset

The time granularity of the dataset	Mean	Standard Deviation	Median	Skewness coefficient	Kurtosis coefficient
10 minutes	835.861	552.897	924.000	0.049	-1.117
20 minutes	778.058	518.233	813.000	0.093	-1.088

3.2 Forecasting result

In order to quantitatively analyze the prediction performance of the model, we introduce the Mean Absolute Percentage Error (MAPE) to evaluate the prediction results of the model. The smaller the MAPE, the better the prediction performance. In addition, in order to verify the competitiveness of the proposed model, a variety of models and algorithms were introduced in this study for comparison, including Salp swarm algorithm (SSA), Random Forest (RF), LightGBM, Multilayer Perceptron (MLP), and Support Vector Regression (SVR).

We apply the proposed model to two datasets, respectively. One step of prediction on the dataset with a time granularity of 10 minutes represents the prediction of road traffic flow in the next ten minutes. One step of prediction on the dataset with a time granularity of 20 minutes represents the prediction of road traffic flow in the next 20 minutes. This study predicted the road traffic flow for the next fifty minutes and the next hundred minutes. The detailed prediction results are shown in Table 2.

Table 2 MAPE(\%) of prediction results for both datasets

Dataset	Model / Step	HHO-XGB	SSA-XGB	XGB	HHO-RF	HHO-LGB	SVR	MLP
10 minutes	1-step	7.611	16.693	20.963	72.438	80.284	17.101	11.606
	2-step	7.942	20.709	23.505	73.857	81.767	18.811	11.45
	3-step	7.474	23.716	25.761	75.416	83.398	21.493	11.263
	4-step	7.631	26.161	28.949	76.429	84.456	24.213	12.426
	5-step	7.564	28.722	33.163	77.728	85.814	26.977	12.912
20 minutes	1-step	10.985	13.884	13.578	28.384	17.832	43.043	11.016
	2-step	12.779	14.558	14.906	29.208	21.517	42.863	13.844
	3-step	13.88	14.362	16.095	33.475	25.368	42.679	15.641
	4-step	15.29	14.916	17.01	36.094	29.942	42.639	16.939
	5-step	16.857	15.596	18.554	40.056	34.742	42.636	18.759

As can be seen from the table, HHO-XGBoost has a very prominent advantage among all competitors. It is worth mentioning that in the two datasets with different statistical characteristics, the results of the HHO-XGBoost model are better than other competitors, which also shows from the side that our proposed novel model not only has excellent prediction performance. It also has perfect generalization and can be applied to various situations.

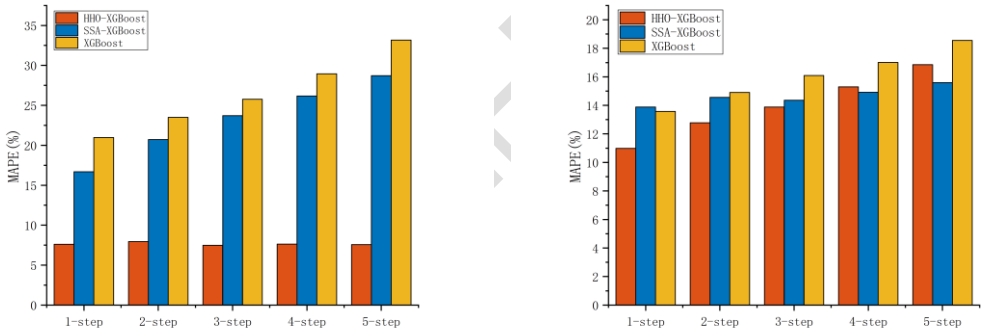
Among all the comparison models, we not only selected random forest and lightGBM, which belong to the same decision tree model as XGBoost but also selected SVR and MLP, which are completely different from the XGBoost principle, which is enough to illustrate the

powerful predictive ability model of XGBoost and can be applied to traffic field of flow prediction.

3.3 Discussion

In this section, we have a separate discussion on intelligent optimization algorithms. Figure 2(a) shows the MAPE of the three models, HHO-XGBoost, SSA-XGBoost, and XGBoost. It can be seen from the figure that the optimization algorithm has an excellent effect on improving the accuracy of the model. This is enough to show that the intelligent optimization algorithm is reasonable and effective for the parameter adjustment of the machine learning model. Figure 2(b) shows the error drop graph of the HHO and SSA algorithms with the increase of the number of iterations. It can be clearly seen from the figure that compared with SSA, HHO has a faster decrease speed. When the number of iterations is only 60, the second time, the HHO algorithm has reached the optimal value, which indicates that the global search ability of HHO is stronger than that of SSA.

To sum up, it is a very effective method to use the intelligent optimization algorithm to optimize the hyperparameters of machine learning. Compared with the traditional GridSearchcv and empirical parameter tuning, it has the advantages of faster speed, minor memory consumption and better prediction accuracy, high characteristic. However, it is worth mentioning that in some data sets, because the intelligent optimization algorithm is too focused on achieving the optimum on the validation set, it is prone to overfitting when making predictions.



(a) 10 minutes (b) 10 minutes

Figure 2 Algorithm tuning and comparison of default parameters

4. CONCLUSION

In order to solve the existing problems in traffic flow prediction and effectively improve the prediction accuracy and generalization performance of the model, in the research, we use HHO to optimize the hyperparameters of XGBoost and propose a new HHO-XGBoost to predict the traffic flow on the road. In order to demonstrate the good enough predictive ability of the hybrid model, we compare the prediction results of HHO-XGBoost with the prediction results of seven other representative models. Finally, we also discuss the intelligent optimization algorithm used in the study.

To sum up, we can draw the following three conclusions: (1) The HHO-XGBoost algorithm shows strong prediction ability and generalization performance in different prediction steps and different datasets, which shows that the HHO-XGBoost model has a strong application in traffic flow. The prediction field has strong potential (2) The prediction performance of the

two-hybrid models HHO-XGBoost and SSA-XGBoost are better than that of XGBoost. It can be concluded that the parameter adjustment of the machine learning model based on the intelligent optimization algorithm is an effective means to improve the accuracy of the machine learning model. (3) HHO has a stronger global search ability than SSA and can find the optimal global solution with fewer iterations.

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