

Optimal Configuration of Expressway Charging Piles and Vehicle Charging Guidance Technology Based on Genetic Algorithm

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Abstract. With the intensification of urbanization and environmental problems, it is a consensus that new energy vehicles will replace fuel vehicles, but the development of their charging facilities is lagging, and the short battery life and uncoordinated charging facilities lead to "mileage anxiety" on expressways. The existing DC charging piles of expressways in China are difficult to meet the demand due to the problems of large load and uneven distribution. Based on the analysis of traffic flow and charging behavior of electric vehicles, this study constructs a short-term traffic flow and charging demand forecasting model that integrates the attention mechanism LSTM, and establishes a charging pile configuration model with optimal operating cost and a charging guidance model with optimal travel time under multi-constraint conditions by combining genetic algorithm. The research findings are of great significance for improving pricing convenience, promoting industrial development, and protecting the ecological environment.

Keywords: Genetic Algorithm, Expressway Charging Piles, Electric Vehicles.

1. Introduction

The usage of new energy vehicles has grown in popularity as a result of technological advancements and increased environmental consciousness. Emerging research areas include charging advice and the design and arrangement of electric car charging systems. The overall number of charging stations is far from enough, and the growth rate of charging stations in our nation is significantly slower than that of electric cars. The growth of new energy cars and the distribution of charging resources greatly depend on the creation of the best possible charging pile layout and electric vehicle charging guiding technology.

A model of the locations and capacities of electric car charging stations in the area was developed by Kou Lingfeng et al. The simulated annealing approach was used to solve the model, which established the scale and position of charging stations [1]. Jun Bi and colleagues proposed a prediction model of available charging piles in the charging station based on the combination of long-term and short-term memory networks and a fully connected network, which successfully combined the historical charging state sequence and related characteristics [2]. Li Hengjie and his research team proposed an optimized charging guidance strategy for electric vehicles based on mixed-integer linear programming (MILP), which has demonstrated high effectiveness across various practical scenarios. [3].

Ma S C and Fan Y investigate the intrinsic connections among electric vehicles, charging infrastructure, and public interest using a panel vector autoregression framework, incorporating five policy measures as external factors for model regulation and construction [4]. Chen and colleagues introduced a multi-level coordination framework for electric vehicle charging management, incorporating shared charging infrastructure. The model employs quantum-behaved particle swarm optimization enhanced by real-time adaptive feedback, ensuring robust convergence characteristics during the optimization process. [5]. Li D and Gao W developed an efficient real-time forecasting approach for grid load induced by electric vehicle charging, integrating fluid dynamics principles with EV adoption scenarios. [6]. Pochhi Ad et al. incorporate both vehicle arrival time estimation and queuing duration limitations into their analytical framework, formulating an optimization model to reduce charging infrastructure deployment expenses. [7]. Kurani Kenneth S and Sanguinetti Angela

categorized electric vehicle operators within U.S. multinational corporations into seven distinct groups, developing a comprehensive multivariate framework that correlates weekly driving duration with corporate charging patterns. Their analysis reveals a significant association between operational mileage and charging frequency [8]. Wang Y and colleagues developed a dynamic traffic-responsive optimization framework for charging infrastructure deployment, achieving cost minimization while satisfying both energy provider requirements and EV user demands. [9].

Existing research has typically treated quantitative planning of charging points as secondary to their spatial distribution planning. It mostly focused on the planning results obtained based on the actual charging demands of vehicles. This study integrates multiple constraints and obtains multi-objective optimal solutions by constructing mathematical models, which can better fit the actual situation and comprehensively consider factors such as user demands and profit demands of service areas. The existing charging pile guidance systems have the drawbacks of only considering the site selection and capacity determination of charging piles, and mostly focusing on the spatio-temporal demand prediction of static charging. This study, however, has the innovative point of dynamic charging demand prediction and the optimization guidance of charging stations, which realizes the coverage of dynamic charging demand changes.

2. Model construction

2.1. Traffic flow prediction utilizing an LSTM neural network architecture enhanced with attention mechanism integration

Develop an attention-based LSTM neural network to forecast expressway ramp traffic volumes (both upstream and downstream) and subsequently estimate electric vehicle traffic flow [10]. The neural network model utilizes historical traffic flow data as input to generate predictive outputs for future traffic conditions.

For accurate traffic forecasting, the network's weight parameters must be optimized. This requires training neural network models with historical traffic data containing known input-output pairs. The ideal weight configuration is achieved when the discrepancy between predicted and actual outputs is minimized.

The LSTM architecture employs three gating mechanisms - the input gate, output gate, and forget gate - which collectively enable temporal memory retention through adaptive weighting of both historical states (previous inputs/outputs) and current inputs [11].

The attention mechanism replicates the human brain's selective information processing capabilities, enhancing neural networks' ability to prioritize relevant information. At its core, this approach learns an adaptive weighting scheme for input features, which it then applies to amplify critical features while attenuating less important ones. By dynamically adjusting focus according to feature significance, the mechanism optimizes information processing efficiency, mirroring how human cognition naturally filters and prioritizes sensory input. This biologically-inspired weighting process enables models to concentrate computational resources on the most informative aspects of the data, significantly improving task performance through intelligent feature selection [12]. After adding the attention network to the input sequence, let the input sequence vector be $\mathbf{E} = [\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_t]$.

The attention mechanism can highlight the features of significant influence, enabling the model to make better choices and improve the accuracy of prediction. It is finally determined that the model consists of a five-layer structure, namely the input layer, the fully connected layer, the LSTM layer, the attention layer, and the output layer, as shown in Figure 1.

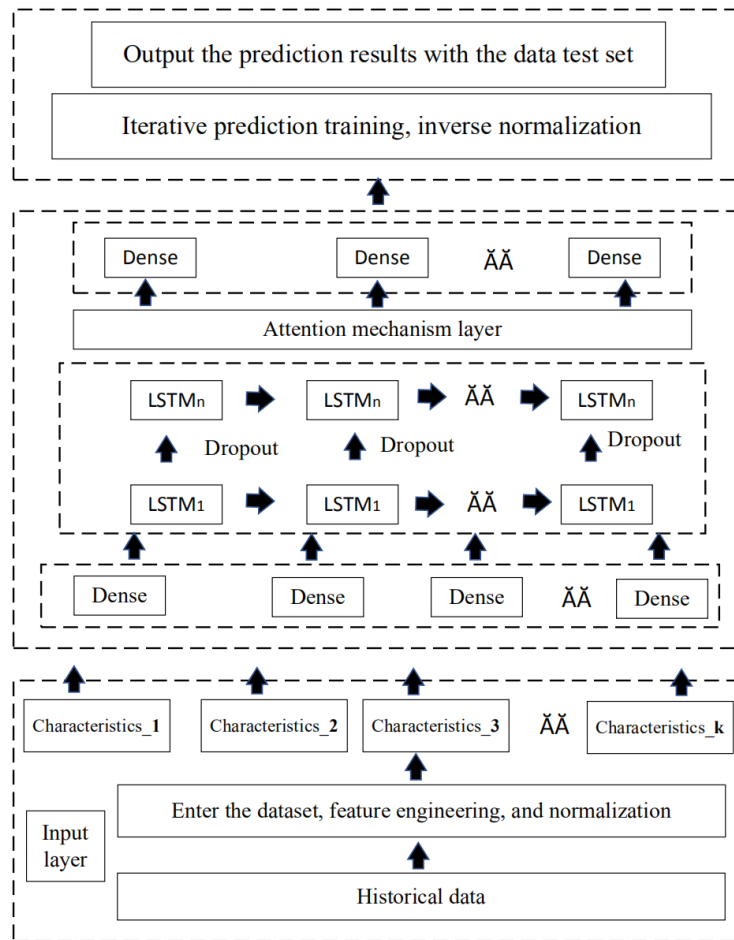


Figure 1. Overall model diagram

Calculate the number X of new energy vehicles based on the number of new energy vehicles in use, the number of cars in use, and the predicted traffic volume.

$$\alpha = \frac{E}{V} \beta \quad (1)$$

$$X = \alpha V_w \quad (2)$$

where α is the proportion of new energy vehicles, E represents the number of new energy vehicles in use, V represents the number of cars in possession, β represents the proportion adjustment coefficient of new energy vehicles on expressways; V_w represents the short-term traffic forecast volume of a certain expressway.

2.2. Service Area Charging Pile Configuration Model under the Optimal Operating Cost

There are x electric vehicles with charging needs at different locations on the expressway every day, and there is a total of y service areas on this expressway that can provide charging services, while ensuring the stability of the power grid [13]. For expressway service stations, the minimum daily operating cost function is:

$$\min C = \sum_{j=1}^y k_j [(C_1 + C_2) + P_j(C_{p1} + C_{p2})] \quad (3)$$

where k_j denotes the quantity of charging stations within the service area, C_1 corresponds to the unit construction cost per charging station, C_2 signifies the unit operation and maintenance (O&M) cost per charging station. Additionally, C_{p1} represents the capital expenditure per unit power capacity, C_{p2} indicates the O&M cost per unit power, P_j defines the rated power capacity of charging stations in service area j .

The model's primary constraints include: Equation (7) imposes limitations on grid charging load capacity, Equation (8) enforces electric vehicle charging demand requirements, and Equation (4) establishes permissible service time thresholds for EV users.

$$\sum_{j=1}^y \sum_{i=1}^x \frac{\lambda P_{ij} E_{ij}}{T/T_{ij3}} \leq P_r \quad i = 1, 2, \dots, x \quad j = 1, 2, \dots, y \quad (4)$$

$$K_j P_j \geq Q_j \quad j = 1, 2, \dots, y \quad (5)$$

$$\left(\frac{V_j}{k_j} + 1\right) \times \frac{0.5E_e}{P_j} \leq T' \quad j = 1, 2, \dots, y \quad (6)$$

where λ serves as a correction factor for pure EV charging load calculations, T denotes the operational duration of charging services in the service area, P_n specifies the maximum permissible grid load capacity for the expressway's power network, Q_j quantifies the EV charging demand at service area, V_j estimates the number of EVs expected to arrive for charging at j , E_e represents the battery capacity of individual EVs, T' defines the maximum service time tolerance for users.

2.3. Electric Vehicle Charging Demand Model Considering Travel Time Cost

The highway EV charging user model developed in this study seeks to minimize total travel time costs, which consist of three components: the travel time includes the in-vehicle driving time T_{ij1} for electric vehicle i , the queuing delay T_{ij2} at the charging station j in the service area, and the actual charging time T_{ij3} .

$$\min T = \sum_{j=1}^y \sum_{i=1}^x \left[\frac{d_{ij1} + d_{ij2}}{V} + \left(\frac{V_j}{k_j} + 1\right) \frac{0.5E_e}{P_{ij}} + \left(\frac{0.8E_{i,e} - E_{e,ij}}{P}\right) \right] E_{ij} \quad (7)$$

where d_{ij1} represents the travel distance that the i -th electric vehicle needs to travel from the starting point to the charging station when choosing service area j for charging, d_{ij2} represents the subsequent journey distance from station to the destination when the i -th electric vehicle selects service area j for charging, The constant V indicates the vehicle's travel speed, E_{ij} is the decision variable for whether electric vehicles charge in service area j , k_j represents the number of charging piles in the service area. Battery characteristics include $E_{i,e}$ for the vehicle's total battery capacity; $E_{e,ij}$ for its remaining charge upon reaching station j ; The charging process is quantified by P_{ij} , denoting the charging power delivered to vehicle i in service area j [13].

Equation (8) establishes user travel time limitations, while Equations (9) and (10) define the electric vehicle range restrictions based on battery capacity. The service area's maximum throughput constraint is formulated in Equation (11), and Equation (12) enforces safe charging power thresholds for EV batteries.

$$T_{ij} E_{ij} \leq T_{y,ij} \quad i = 1, 2, \dots, x; \quad j = 1, 2, \dots, y \quad (8)$$

$$E_{e,ij} = r_i E_{i,e} - \gamma d_{ij1} \quad i = 1, 2, \dots, x; \quad j = 1, 2, \dots, y \quad (9)$$

$$E_{e,ij} \geq 0 \quad i = 1, 2, \dots, x; \quad j = 1, 2, \dots, y \quad (10)$$

$$N_{qj} + \sum_{i=1}^x E_{ij} \leq C_{r,j} \quad j = 1, 2, \dots, y \quad (11)$$

$$P_i^{\min} \leq P_{ij} \leq P_i^{\max} \quad i = 1, 2, \dots, x; \quad y = 1, 2, \dots, y \quad (12)$$

where $T_{y,ij}$ denotes the user's scheduled travel duration, $E_{e,ij}$ indicates the remaining battery capacity of EV i upon arrival at service area j , r_i represents the SOC value of the i battery of an electric vehicle, γ quantifies the energy consumption rate per kilometer, N_{qj} represents the number of electric vehicles in the service area before electric vehicle i arrives at service area j , $C_{r,j}$ specifies the maximum vehicle capacity of service area j [14].

3. Results

3.1. Traffic Flow Forecast based on Long Short-Term Memory Models

In this study, the traffic data of machine-loaded expressways obtained from the OD survey conducted by enterprises were used for analysis to construct the optimal configuration of expressway charging piles and vehicle charging guidance technology based on a genetic algorithm. The Jihe Expressway starts from Shenzhen Bao'an International Airport in Bao'an District in the west and ends at He'ao Village in Longgang District in the east. The total length of the route is approximately 44 kilometers, with a designed speed of 100 kilometers per hour. There are 14 interchanges in total.

Write the Python code of the LSTM long short-term memory neural network model, introducing the attention mechanism to predict the short-term traffic volume upstream and downstream of each ramp on the Jihe Expressway.

The prediction results are as follows in Table 1:

Table 1. Predicted traffic volumes (pcu/h) for each section of machine load height

Section of the road	Two-way traffic volume	Section of the road	Two-way traffic volume
Guangshen-Hezhou	3133.65	Ban Lan-Xiufeng	8435.75
Hezhou-Tangtou	6666.6	Xiufeng-Pinghu	8820.75
Tangtou-Shiyan	7369.6	Pinghu-Bainikeng	8498.85
Shiyan-Xizhigu	7064.35	Bainikeng-Paibang	7511.65
Xizhigu-Shui Lang	7268.25	Paibang-Shuihe	7051.85
Shui Lang-Fumin	8074.25	Shuihe-He 'ao	5828.6
Fumin-Qinghu	8341.95	He 'ao-Huiyan He 'ao	3713.95
Qinghu-Ban Lan	8435.75	Huiyan He 'ao-East of He 'ao in Huiyan	3713.55

3.2. Service area charging pile allocation model under optimal operation cost

Considering the constraints of grid load, utilization efficiency of charging piles, and construction cost of charging stations, the genetic algorithm is used, and the high-performance Python Genetic Algorithm Toolkit Geatpy is called for the genetic algorithm solution, and the objective function is close to convergence in the amount of iterations 80 times. Both Figure 2 and Figure 3 below show the iteration results for the charging pile configuration.

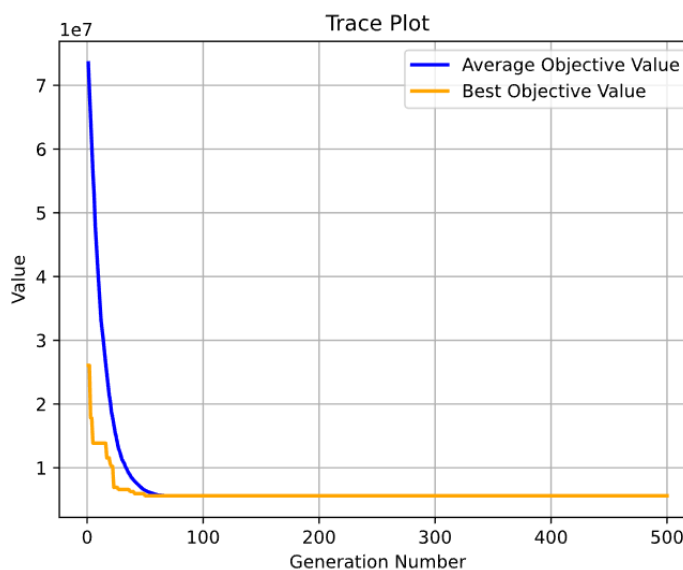


Figure 2. Iterative map of charging pile configurations

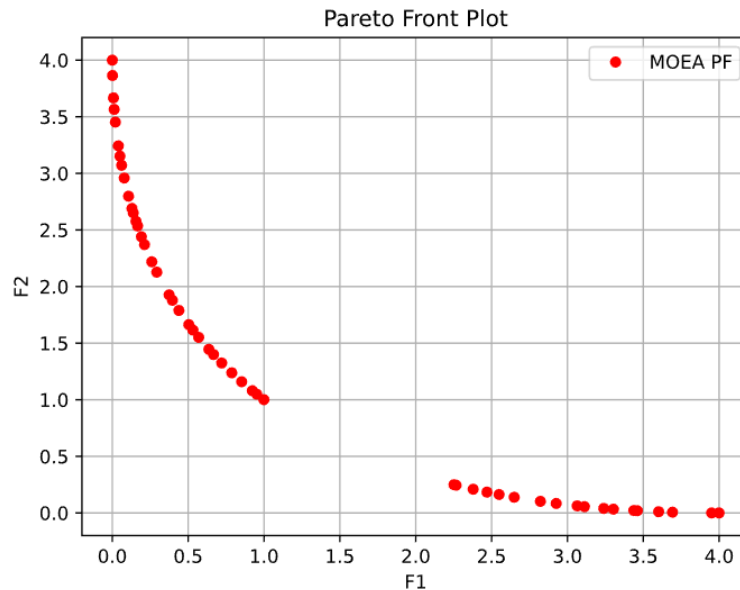


Figure 3. Iterative map of charging pile configurations

It is concluded that charging piles are set up in four service areas, respectively, and the amount of charging piles configured in each service area is: 7, 4, 4, 2, respectively, and the minimum value of operating cost is 5.61 million yuan.

3.3. Considering the cost of travel time to establish the charging demand model

Considering the constraints of user travel time, electric vehicle range power, charging station capacity, driving mileage, charging pile power, using the genetic algorithm, calling the high-performance Python genetic algorithm toolbox Geatpy for genetic algorithm solving, the objective function in the number of iterations is 20 times closer to convergence. Figure 4 below shows the iteration results of the charging pile demand.

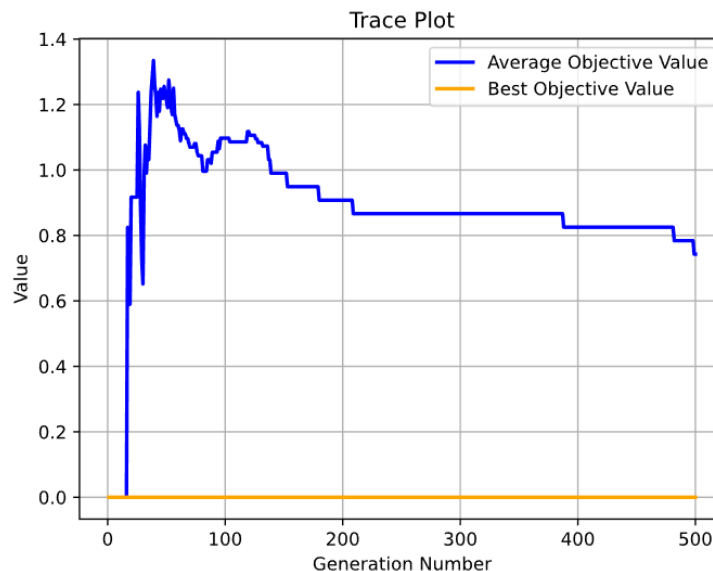


Figure 4. Iterative map of charging pile demand

Five electric vehicles are made to generate charging demand at different sections of the highway, and they are guided to four service areas using the established model. The parameter settings are shown in Table 2, and the simulation result is shown in Table 3:

Table 2. Parameter calibration

Electric Vehicle Battery Capacity	35KWh
Power of the charging pile	30kw
Number of charging piles in the charging station	7 4 4 2
Distance between charging stations	55km 60km 50lm

Table 3. Simulation result

Electric Vehicle	Guiding service area
1	2
2	3
3	1
4	2
5	2

4. Conclusions

The charging facilities in the expressway service area are insufficient. The problems of uneven distribution of charging piles, low charging utilization rate and long charging time are increasingly prominent, which hinder the development of new energy vehicles. On the basis of considering the user's charging demand, the optimization strategy of user's charging in expressway service area and the optimization strategy of charging pile operating cost are obtained by using genetic algorithm.

The research of this project provides some guidance for the optimal configuration of charging piles and the design of a charging pile guidance system. However, there are still some assumptions and schemes in this project that do not take reality into account well. Based on this project, we can add more factors (such as vehicle speed, environmental temperature, etc.) that affect the power consumption, and continue to study in depth in terms of optimization or specialization of parameter settings, to improve the shortcomings of this paper.

References

- [1] Kou Lingfeng, Liu Zifa, Zhou Huan. Model and algorithm of regional electric vehicle charging station planning [J]. *Modern Electric Power*, 2010,27 (04): 44-48.
- [2] Jun Bi, Wang Jianing, Wang Yongxing. Short-term operation state prediction of charging stations based on LSTM-FC model [J]. *Journal of South China University of Technology (Natural Science Edition)*, 2025, 53(02): 58-67.
- [3] Li Hengjie, Hu Zhehui, zhou yun, et al. Optimization strategy of electric vehicle charging guidance based on mixed integer linear programming [J/OL]. *Power grid technology*, 1-22 [2025-05-09].
- [4] Ma S C, Fan Y. A deployment model of EV charging piles and its impact on EV promotion[J]. *Energy Policy*, 2020, 146: 111777.
- [5] Chen J, Huang X, Cao Y, et al. Electric vehicle charging schedule considering shared charging pile based on Generalized Nash Game[J]. *International Journal of Electrical Power & Energy Systems*, 2022, 136: 107579.
- [6] Li D, Gao W. Modeling and Analysis of the Impact of Charging Electric Charged Vehicles on the Grid Load in the Expressways[C]// *Green Connected Automated Transportation and Safety: Proceedings of the 11th International Conference on Green Intelligent Transportation Systems and Safety*. Springer Singapore, 2022: 1-20.
- [7] Pochhi A, Lohia A, Chakraborty N. Optimizing Electric Vehicle Charging Stations and Charging Ports for Highways and Expressways[C]// *Proceedings of the 15th ACM International Conference on Future and Sustainable Energy Systems*. 2024: 492-493.
- [8] Kurani Kenneth S. and Sanguinetti Angela. Patterns of electric vehicle charging on transportation network companies in the US[J]. *Transportation Research Part D*, 2023, 116.

- [9] Wang Y, Zhao Y, Gan S, et al. Optimization of charging stations integrated with dynamic transportation systems in metropolises[J]. *Transportation Research Part D: Transport and Environment*, 2023, 119: 103726.
- [10] Peng Yuwen, Lin Zhenhong, Huang Jingyuan, et al. Short-term wind power forecasting method based on EEMD and BiGRU-Attention [J/OL]. *Southern Power Grid Technology*, 1-10[2025-05-10].
- [11] Xiao Zhang. "Research on Photovoltaic Power Prediction Method Based on TCN-BiLSTM Neural Network." 2023 IEEE 6th International Conference on Automation, Electronics and Electrical Engineering (AUTEEE). IEEE, 2023.
- [12] Fu, Zuan, et al. "Photovoltaic Power Prediction Based on Gray-scale Satellite Cloud Image and Optimized LSTM." 2022 IEEE 6th Conference on Energy Internet and Energy System Integration (EI2). IEEE, 2022.
- [13] Xianlong Ge. "Urban Transportation Energy Supply Network", Springer Science and Business Media LLC, 2024.
- [14] Zhang M, Lou S, Wu Y, et al. Research on charging station planning method considering electric vehicle charging queuing[C]//2022 IEEE 3rd China International Youth Conference on Electrical Engineering (CIYCEE). IEEE, 2022: 1-5.