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Mixed parking demand assignment in hub parking lots based on regression modeling

ZHANG Chu[1,2], CHEN Kehan[1], CHEN Jun[2], CHEN Jiayi[1]

(1. School of Transportation, Southeast University, Nanjing 211189, China; 2. Jiangsu Key Laboratory of Comprehensive Transportation Planning and Simulation, Southeast University, Nanjing 211189, China)

Abstract: To adapt to the unique demand-supply features of accessory parking lots at passenger transport hubs, a mixed parking demand assignment method based on regression modeling is proposed. First, an optimal model aiming to minimize total time expenditure is constructed. It incorporates parking search time, walking time, and departure time, focusing on short-term parking features. Then, the information dimensions that the parking lot can obtain are evaluated, and three assignment strategies based on three types of regression models—linear regression (LR), extreme gradient boosting (XGBoost), and multilayer perceptron (MLP)—are proposed. A parking process simulation model is built using the traffic simulation package SUMO to facilitate data collection, model training, and case studies. Finally, the performance of the three strategies is compared, revealing that the XGBoost-based strategy performs the best in case parking lots, which reduces time expenditure by 29.3% and 37.2%, respectively, compared with the MLP-based strategy and LR-based strategy. This method offers diverse options for practical parking management.

Key words: parking areas assignment; hub parking lot; regression-based modeling; extreme gradient boosting (XGBoost)

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Urban passenger transport hubs play a vital role in managing the convergence and dispersion of urban passenger flows. With the rapid development of online ride-hailing services in China, supportive infrastructure must be appropriately equipped. As the primary distribution place for vehicles, including those associated with online ride-hailing services, a hub parking lot (HPL) considerably differs from general parking lots in terms of parking demand and facility supply.

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Biographies: Zhang Chu (1989—), female, doctor; Chen Jun (corresponding author), male, doctor, professor, chenjun@seu.edu.cn.

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As an auxiliary facility of passenger transport hubs, HPLs continue to serve passenger flows within the hub. Site investigations reveal that short-term parking dominance is a key demand feature that distinguishes vehicles in passage areas (primarily for online ride-hailing purposes) and those in regular parking slots. This distinction has led to increased demand for innovative parking arrangements, impacting how parking spaces are assigned. From a supply perspective, HPLs in China, which allow online ride-hailing services to pick up passengers, are characterized by providing roadside parking areas segregated from the main parking zones. These areas are designed to accommodate the growing number of ride-hailing vehicles. However, during actual operations, HPL faces challenges such as low turnover efficiency and difficulties for vehicles to quickly find suitable parking spaces because of differences in driving behaviors.

Therefore, parking in HPLs faces challenges. Given that the possibility of increasing parking supply is limited, HPLs call for the optimization of the parking demand assignment method in such a specific setting[1]. The parking demand assignment method should provide the location (where to park) and path (how to get there) for the entering vehicles to complete parking behavior, that is, to facilitate the parking area assignment and the path guidance. With the goal of minimizing parking expenses, Kim et al.[2] analyzed parking costs based on parking rates and duration and used mixed-integer programming to solve the parking assignment model. Shao et al.[3] proposed a simple model for a shared parking platform, using binary integer linear programs to maximize parking profits. Wang et al.[4] proposed a chance-constrained optimization model aimed at maximizing parking utilization. A rule-based mixed-integer linear programming was used to seek a satisfying solution to this model. Sun et al.[5] estimated potential parking demand using historical parking data and proposed an integer linear programming model for the dynamic reservation and allocation of regional parking spaces. In addition, the allocation of parking spaces can also be studied from the perspective of game theory, where the vehicle is set as a player, and the player chooses the best parking area during the game. Ayala et al.[6] presented a

game-theoretic framework to analyze parking scenarios. Mejri et al. [7] modeled the parking problem as a congestion game, minimizing the whole network cost. Although the game-based model complies with the actual parking scene, the noncooperative game will sacrifice the collective interest and run counter to the needs of administrators. Although the classical accurate algorithms are usually applied for solving optimization problems[8], the approximate solution method, such as heuristic approaches, has a better application effect[9-10].

Shortest-path search is a common and basic method for path induction in graph networks, which considers the weights of edges in the network as a determining factor to complete path allocation[11]. Jonkers et al. [12] defined road weights considering path distance, road quality, and slot availability when assigning paths based on the improved Dijkstra shortest-path algorithm. The Dijkstra algorithm adopts the method of traversal with high computational complexity. In order to reduce the search space, some scholars used the heuristic search method to conduct the shortest-path search. Vital et al. [13] used the A* search algorithm to assign the shortest path to guide trucks on highways to service point parking spaces, whereas Xie et al. [14] enhanced shared parking guidance for autonomous vehicles using an improved A* shortest routing method. Regarding routing optimization models, Zhao et al. [15] established a low-carbon school routing optimization model considering vehicle detours. This problem was addressed using an improved ant colony algorithm based on Lin-Kernighan heuristic algorithm and Levy flight operator.

Predicting the availability of parking slots is an important part of dynamic parking demand assignment, and machine learning is effective for accurate predictions[16-17]. Zhang et al. [18] used multiagent deep reinforcement learning for connected vehicle parking allocation. Lu et al. [19] proposed a predication-based parking allocation framework. This framework uses regression to predict and select low-cost empty slots, which effectively reduce parking costs and improve parking success rates.

Existing studies have not fully addressed the unique dynamics of HPLs in the online ride-hailing system of China. The parking demand assignment method often fails to consider how short-term parking durations influence vehicle preferences for parking locations. In addition, the effective allocation of parking areas with accessible entry and exit routes within HPLs remains insufficient. To address these gaps, this paper proposes a mixed parking demand assignment method tailored for the specific design of HPLs. This model aims to enhance management efficiency and improve parking turnover by minimizing total time expenditure while incorporating constraints such as available parking spaces and feasible pathways. The study employs regression-based strategies, evaluating the efficacy of linear regression (LR), EXtreme gradient boosting (XGBoost), and multilayer perceptron (MLP) approaches through the simulation results.

This assignment method can be combined with advanced vehicle navigation technology and applied to the intelligent parking management system[1]. This approach facilitates the optimal placement of vehicles by guiding them through a suitable path to reasonable parking spaces within HPLs, ensuring efficient entry and exit routes.

1 Model Formulation

1.1 Estimated total time expenditure of parking areas

The total parking cost in HPLs is calculated by combining three key components: parking search time, departure time, and pedestrian walking time to the exit. These elements are weighted and summed to determine the total parking cost for each space. Each parking area within an HPL also has its own total time expenditure, defined similarly by considering the key components. The specific cost is influenced by factors such as the position of the parking area, the road network structure, the occupancy of parking spaces, and the volume of vehicles within the parking lot.

Thus, the total time expenditure for parking in area k within the parking lot can be defined as follows:

$$c_k = \alpha t_{ck} + \beta t_{pk} + \eta t_{ek} \tag{1}$$

where α, β, and η are weights representing the importance of different factors in parking area allocation; t_{ck} (parking search time) is the travel time from the parking lot entrance to the k-th parking area p_k, $k \in [1, K]$, where K is the total number of parking areas; t_{pk} (pedestrian walking time) refers to the time required to walk from p_k to the pedestrian exit; t_{ek} (departure time) is the travel time from p_k to the parking lot exit. In general, departure time t_{ek} has a small influence on the allocation decision; thus, $\eta < \alpha < \beta$. This study assigns the weights as follows: $\alpha = 0.3$, $\beta = 0.6$, $\eta = 0.1$.

Here, the value of the search time t_{ck} and departure time t_{ek} of the vehicle in the parking lot is affected by factors such as the parking lot network and vehicle volume, which could not be explicitly expressed. For pedestrian walking time t_{pk}, pedestrians are assumed to cross passageways and parking slots in a straight line without considering the heterogeneity of pedestrians. Therefore, this value is equal to the Euclidean distance from the center of the parking area to the pedestrian exit, l_{pk}, divided by the average walking speed of pedestrians, s_p, as shown below:

$$t_{pk} = \frac{l_{pk}}{s_p} \tag{2}$$

Considering that t_{ck} and t_{ek} are retrospective values,

the selection of a parking area was based on the estimated total time expenditure $\tilde{c}_k$, defined as follows:

$$\tilde{c}_k(v) = \frac{\alpha}{d_v^{\text{norm}}}\tilde{t}_{ck} + \frac{\beta}{d_v^{\text{norm}}}t_{pk} + \eta\,\tilde{t}_{ek} \tag{3}$$

where $\tilde{t}_{ck}$ is the estimated parking search time and $\tilde{t}_{ek}$ is the estimated departure time. The coefficients of $\tilde{t}_{ck}$ and t_{pk} change relative to t_{ck} and t_{pk} in Eq. (1), reflecting the relationship between parking area allocation and expected parking duration. In general, vehicles expecting a long parking duration are less sensitive to parking search time and pedestrian walking time. Therefore, $\tilde{t}_{ck}$ and t_{pk} can be scaled based on the expected parking duration d_v. d_v^{norm} is the normalized d_v, ranging from 0 to 1, with min-max normalization as the default.

With the above definition of the estimated total time expenditure $\tilde{c}_k(v)$ for parking areas, vehicles can be reasonably allocated to appropriate parking areas.

1.2 Parking area demand assignment model

For any vehicle v with an expected parking duration d_v, the vehicle aims to park in the area with the minimum estimated total time expenditure $\tilde{c}_k(v)$. This assignment is subject to constraints like the number of vacant parking spaces in the area and the accessibility of the internal road network of the parking lot. The assignment model is formulated as follows:

$$\min_{k,l_1,l_2} \tilde{c}_k(v, l_1, l_2) = \frac{\alpha}{d_v^{\text{norm}}}\tilde{t}_{ck}(l_1) + \frac{\beta}{d_v^{\text{norm}}}t_{pk} + \eta\,\tilde{t}_{ek}(l_2) \tag{4}$$

$$\text{s. t.} \quad \sum_n p_{kn} \oplus 0 < N_k \quad n \in [1, N_k] \tag{5a}$$

$$L_{1k} \neq \varnothing,\ L_{2k} \neq \varnothing \tag{5b}$$

$$l_1 \in L_{1k},\ l_2 \in L_{2k} \tag{5c}$$

Eq. (4) is the objective of this model that selects the parking area k, search path l_1, and departure path l_2 with minimum total time expenditure. Eq. (5) represents the constraints of the model; Eq. (5a) ensures that the parking spaces are vacant, with $p_{kn} \oplus 0 = 0$ if vacant and $p_{kn} \oplus 0 = 1$ otherwise. Eqs. (5b) and (5c) represent feasible path conditions, which can be obtained through breadth-first search or depth-first search. L_{1k} is the set of feasible search paths to reach p_k, and L_{2k} is the set of feasible departure paths from p_k. The expected parking duration was obtained from statistical data on the parking lot usage. Approximately 40% of vehicles are parked for less than 5 min, 50% of vehicles are parked for 5-15 min, 5% of vehicles are parked for 15-30 min, and another 5% of vehicles are parked for more than 30 min.

The parking area assignment model operates through three main stages: input, parameter calibration, and output, as illustrated in Fig. 1. The structured process is as follows:

(1) Input. The model requires three hyperparameters (α, β, η) representing the weights and the expected parking duration (d_v) for each vehicle v.

(2) Parameter calibration. The model calibrates various parameters, including estimated travel times for each parking area ($\tilde{t}_{ck}$, t_{pk}, $\tilde{t}_{ek}$), passage usage information (p_{kn}), and L_{1k}, L_{2k}. Here, the environmental information is gathered to determine the occupancy of each parking area and other relevant factors. This calibration process ensures that the objective function is accurately estimated for generating the decision variable in the allocation strategy.

(3) Output. If the generated allocation scheme meets all constraints, it is outputted as the final allocation plan. Otherwise, it is regenerative and allows for adjustments and recalibration until a valid allocation is achieved.

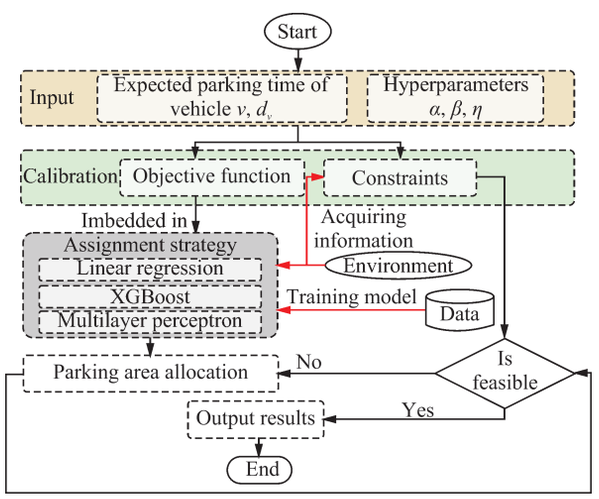

Fig. 1 Process of the parking area demand assignment model from input to output

2 Regression-Based Assignment Strategy

The core of parking demand assignment in HPLs involves assigning vehicles to parking areas with the lowest estimated total time expenditure. The accuracy of this estimate directly impacts the reasonableness of the assignment, making it crucial to employ a strategic approach tailored to the simulation environment of the parking lot.

Accurate estimation of total time expenditure is vital for efficiently managing parking demand allocation in HPLs. Two primary methods are employed: deep reinforcement learning (DRL) and regression modeling. DRL requires real-time data, such as the current occupancy status of each parking area. However, its implementation is challenging because of the need for high levels of informatization as well as the complexity of algorithms and computational resources required. By contrast, regression modeling is more flexible and can be adapted to various types of data, including historical data and simulation data. This method is preferred when real-time data is unavailable as it allows for offline train-

ing and model adjustments based on the data type available. It is pragmatic, given the constraints of real-time data access and computational limitations.

Linear egression (LR) is the most fundamental regression model, known for its simplicity in training. However, it cannot effectively handle nonlinear relationships. By contrast, XGBoost offers enhanced adaptability, making it suitable for complex variable interactions, such as the relationship between the state of a parking lot and total time expenditure[20]. Similarly, the MLP excels in nonlinear situations. By incorporating more types of parking lot state data, MLP enables the development of strategies that can address increasingly intricate scenarios. However, its implementation demands a higher level of parking lot informatization[21]. The following section outlines the assumptions underlying each of these regression models.

2.1 LR

The basic assumptions underlying the LR-based strategy are as follows: (1) HPL can obtain the total internal parking vehicle counts, the total parked vehicle counts, and detailed data on parking time, parking location, and departure time for vehicles. (2) A linear relationship exists between the number of vehicles in the parking lot and the total time expenditure for each area. (3) The error between the estimated and the actual total time expenditure follows a normal distribution with constant variance. (4) Observations are independent of each other.

2.2 XGBoost

The XGBoost-based allocation strategy requires specific data collection efforts. HPL is assumed to obtain the total internal parking vehicle counts, the total parked vehicle counts, and detailed information, including parking time, parking location, and departure time for individual vehicles.

Based on these assumptions, the XGBoost-based allocation model uses similar data to the LR-based strategy as its foundation. Its independent variables include the total vehicle count in the lot at each specific time point, D_t, and the combined time cost of each parking area for that particular time point.

2.3 MLP

The assumption of the allocation strategy based on multilayer sensors is that the parking lot can obtain the occupancy status of each parking area and the spatial saturation of each channel. Thus, for this assumption, the input data for MLP is defined as follows:

$$\begin{cases} \boldsymbol{X}_1 = \boldsymbol{P} = [o_{\mathrm{p}1}, o_{\mathrm{p}2}, \cdots, o_{\mathrm{p}k}, \cdots, o_{\mathrm{p}K}]_{1\times K} \\ \boldsymbol{X}_2 = \boldsymbol{E} = [o_{\mathrm{e}1}, o_{\mathrm{e}2}, \cdots, o_{\mathrm{e}m}, \cdots, o_{\mathrm{e}M}]_{1\times M} \end{cases} \tag{6}$$

where $\boldsymbol{P}$ is a vector representing the occupancy of all parking areas in the parking lot, $o_{\mathrm{p}k}$ represents the occupancy of the k-th parking area, $\boldsymbol{E}$ represents the spatial occupancy of all passages in the parking lot, o_{em} represents the spatial occupancy of the m-th aisle, K is the number of parking areas in the parking lot, and M is the number of aisles in the parking lot.

3 Case Study

The validity of the usability of the assignment framework can be demonstrated through a specific case analysis. This research focused on HPLs that align with the supply-demand features identified in this study. HPLs were primarily categorized into two main types based on their internal structural characteristics: nonlinear HPLs and linear HPLs. The nonlinear type represents a more typical structure of HPL, while the linear type is a simplified variation of the nonlinear type. Both representative HPL types were selected for the case study analysis.

3.1 Case description

The P2 and P5 parking lots at Nanjingnan Railway Station were selected as templates for nonlinear and linear HPLs, respectively. A simulation road network was developed using the SUMO platform, with demand data employed to configure simulation parameters for experimental purposes. The layouts of P2 and P5 are illustrated in Figs. 2(a) and (b), respectively.

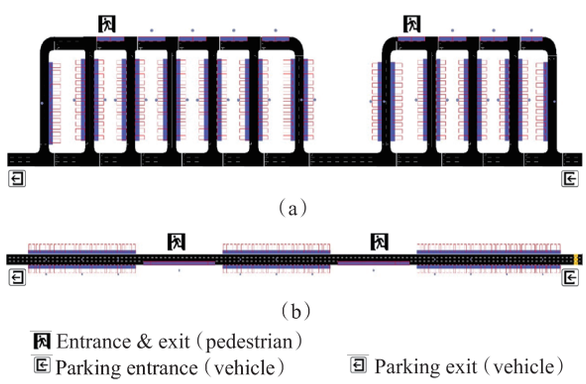

Fig. 2 Inner structure of Case HPLs. (a) Nonlinear HPL structure (P2); (b) Linear HPL structure (P5)

Regarding demand-input settings, vehicle entry demand and parking duration must be defined. Field surveys indicate the peak-hour vehicle entry rates of 848 veh/h for the nonlinear parking lot (P2) and 432 veh/h for the linear parking lot (P5). Vehicle arrivals were modeled using a Poisson distribution. Parking duration was assumed to follow an exponential distribution, with approximately 90% of vehicles staying for less than 15 min, 5% staying between 15 and 30 min, and 5% remaining parked for over 30 min.

After conducting simulations to collect data on actual parking durations, parking search time, departure time, and pedestrian walking time for parked vehicles, the to-

tal time expenditure for each parking area can be calculated. Fig. 3 visually demonstrates the differences in total time expenditure across parking areas. According to Fig. 3, the assignment strategy should prioritize allocating spaces to areas with lower total time expenditure (represented in green) while assigning spaces to areas with high total time expenditure (represented in red) as the last priority.

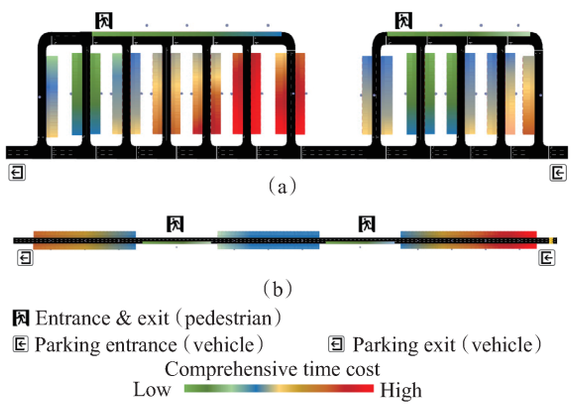

Fig. 3 Total time expenditure of each parking area. (a) Nonlinear HPL; (b) Linear HPL

3.2 Feasibility analysis

In this study, three demand assignment strategies were developed using linear, XGBoost, and MLP regression models for demand prediction and allocation. The training of these models relied on incremental datasets derived from field surveys and simulation experiments, which collected parking data from a total of 220 000 vehicles and detailed information about their parking status at the time of entry. Regarding model settings, the primary hyperparameter adjusted for XGBoost was the maximum depth, which was set to 3 to prevent overfitting. For MLP, the hyperparameters depended on the input dimensions specified by $\boldsymbol{X}_1 = \boldsymbol{P}$ and $\boldsymbol{X}_2 = \boldsymbol{E}$, defined as $1 \times K$ and $1 \times M$, respectively, according to Eq. (6). In this study, K and M are provided in Table 1. Across all models, the learning rate was uniformly set to 0.001 during training.

Table 1 Values of parameters setting in MLP

Parameter	Linear HPL	Nonlinear HPL
K	22	24
M	1	43

Table 2 presents the mean values of MAPE indicators for each modeling method across all parking areas. The results indicated that MAPE values for regression methods remained below 10% when estimating search time and departure time, regardless of whether the parking lot is nonlinear or linear. Among these methods, LR exhibited the poorest performance, while XGBoost demonstrated superior accuracy. In general, supported by extensive simulation data, an incremental learning approach was employed to address each demand scenario individually. This approach ensured that the accuracy of various models met the required standards.

Table 2 MAPE of two types of parking lots in different modeling methods and usage scenarios

Modeling method	Usage scenario	MAPE/%	
		Nonlinear parking lot	Linear parking lot
MLP	Search time estimation	0.583 141	0.521 536
	Departure time estimation	1.094 385	1.195 106
LR	Search time estimation	3.881 775	3.922 011
	Departure time estimation	9.782 232	3.879 476
XGBoost	Search time estimation	1.021 942	0.231 834
	Departure time estimation	1.129 369	0.268 607

3.3 Effect comparison of strategies

To evaluate the impact of these parking strategies, a total time expenditure indicator was employed, combining search time, departure time, and pedestrian walking time. In particular, an LR model was established with the total vehicle count in the parking lot as the independent variable and the three time components (parking time, departure time, and walking time) as dependent variables. The weighted slope and intercept of the model were used to estimate the overall time cost under various demand scenarios.

During training, a clustering-based feature point acquisition method was implemented. This approach involved dividing the independent variable data D (total vehicle count) into segments of 50 vehicles each. Within each segment, DBSCAN density clustering identified cluster centers, eliminating the need for predefined cluster numbers. Subsequently, LR was applied to fit the clustered center points, resulting in three regression models.

For the case parking lot, Table 3 presents the MAPE values from the training of each strategy. The results indicated that the regression models estimating parking search time and walking time based on the total vehicle count D performed well, with MAPE remaining below 10%. However, the model estimating departure time based on D exhibited relatively lower accuracy, though all models achieved MAPE within 15%. Given the minimal impact of departure time estimation errors on the total time expenditure, in conclusion, all models were valid and applicable.

The regression slopes (change in corresponding time (unit: s) per vehicle increase) and intercepts (time when the parking lot is empty) are provided in Table 4 for nonlinear and linear parking lots.

3.4 Results analysis

Fig. 4 is generated using data from Table 4 to analyze

Table 3 MAPE of the regression model with two types of parking lots in different strategies

Parking lot type	Regression strategy	MAPE/%		
		Search time estimation model	Walking time estimation model	Departure time estimation model
Nonlinear	LR	0.830 915	10.874 030	2.106 701
	XGBoost	0.468 463	11.923 420	2.629 242
	MLP	2.275 092	0.492 872	0.378 797
Linear	LR	2.278 905	2.930 625	0.412 012
	XGBoost	2.112 312	0.343 480	3.063 596
	MLP	0.418 943	4.371 458	2.083 381

Table 4 Slopes and intercepts of LR models for each allocation strategy

Coefficient	Parking lot type	Regression strategy	Search time estimation model	Walking time estimation model	Departure time estimation model	Weighted time estimation
Slope/ ($s \cdot veh^{-1}$)	Nonlinear	LR	0.432 30	0.216 82	0.446 41	0.304 42
		XGBoost	0.295 45	0.086 45	0.503 06	0.190 81
		MLP	0.313 27	0.287 23	0.035 78	0.269 90
	Linear	LR	0.223 80	0.393 17	0.332 65	0.336 31
		XGBoost	0.215 07	0.029 63	0.221 10	0.104 41
		MLP	0.233 85	0.267 88	0.250 98	0.255 98
Intercept/s	Nonlinear	LR	−0.677 94	−0.034 10	−0.264 16	−0.250 26
		XGBoost	−0.400 02	0.655 31	0.083 92	0.281 57
		MLP	−0.659 22	−0.180 19	0.800 71	−0.225 81
	Linear	LR	0.116 40	0.945 64	1.133 91	0.715 69
		XGBoost	0.464 75	0.308 15	0.032 29	0.327 54
		MLP	0.762 89	−0.261 67	0.152 24	0.087 09

the slopes and intercepts of the regression models. The following analyses can be made:

(1) Regarding the slopes, nonlinear and linear parking lots exhibited positive slopes across various allocation strategies, indicating that as vehicle counts in the parking lot increased, parking search time, walking time, and departure time also increased. This trend aligns with operational expectations for parking lot management.

(2) Concerning intercept values, the values are relatively consistent across all allocation strategies, suggesting that at lower occupancy rates, different regression-based methods yielded comparable results.

When the weighted intercepts of fitted models are closely aligned across strategies, the weighted slope represents the marginal impact on total parking time expenditure. A smaller slope value indicates that changes in vehicle count have less effect on overall time cost. Analysis from Fig. 4 reveals the following:

(1) Based on ranked weighted slopes, the XGBoost-based assignment strategy performed best, regardless of HPL type (nonlinear or linear). For instance, in nonlinear HPL, using XGBoost to assign demand resulted in a 0.19 s increase in total time expenditure per vehicle, which was 29.3% lower than that of MLP and 37.2% lower than that of LR, as shown in Table 3.

(2) Under the XGBoost strategy, a comparison of slopes across stage-specific models (parking search, walking, departure) showed that the slope for walking time was consistently lower, regardless of parking lot type. This finding indicates that walking time was rela-

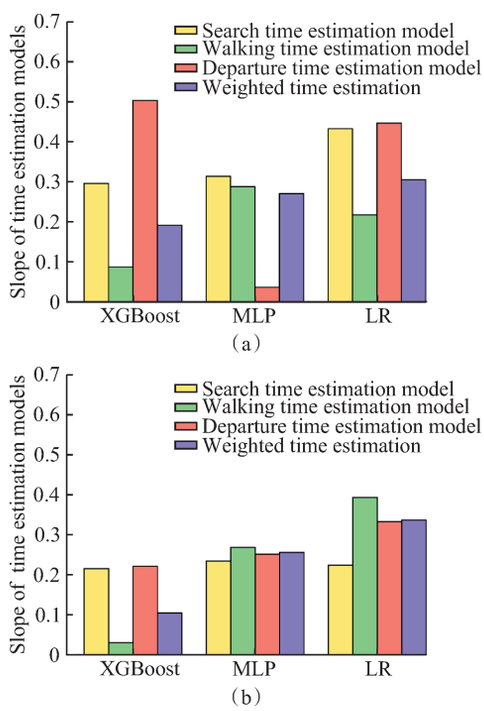

Fig. 4 Slopes of vehicle count versus search time, departure time, and walking time regression models for each assignment strategy. (a) Nonlinear parking lot; (b) Linear parking lot

tively less affected by total vehicle count, aligning with practical expectations.

(3) The analysis of slopes across stages (parking, walking, and departure) in nonlinear and linear HPLs under XGBoost showed consistent patterns, demonstrating the stable performance of XGBoost across different scenarios and highlighting its applicability.

(4) Comparing slope values between HPL types, the linear lot exhibited more balanced slopes across all stages owing to its single-channel structure from entrance to parking and exit, which simplified path selection during demand assignment.

In addition, the allocation method based on regression modeling can obtain the results of Fig. 5 in the case parking lot. By classifying vehicle parking durations and analyzing the spatial distribution of parked vehicles, the following observations were made: short-term parked vehicles (red, less than 15 min) were exclusive to the passage parking area. However, their proportion remained below 90%, likely owing to their high turnover rate, brief time occupying spaces, and frequent departures. Meanwhile, long-staying vehicles (green and blue, accounting for over 5%) occupied designated berths owing to their low turnover rates and extended parking durations.

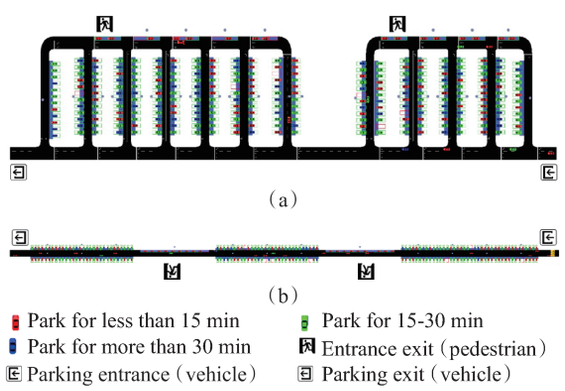

Fig. 5 Spatial distribution of vehicles in Case HPLs. (a) Nonlinear HPL; (b) Linear HPL

In summary, using the P2 and P5 parking lots at Nanjingnan Railway Station as case studies, this research simulated demand assignment processes for nonlinear and linear parking lots using three assignment strategies based on three types of regression models, LR, XGBoost, and MLP. A comparative analysis of regression model slopes relative to vehicle counts and time expenditure across operational stages revealed that XGBoost was the most stable, universal, and optimal strategy for mixed parking demand assignment in HPLs.

4 Conclusions

(1) This research explores parking demand assignment strategies at large passenger transport hubs by establishing an optimization model that aims to minimize the total time expenditure of parking areas. In the results analysis, an LR model was used to quantify the effectiveness of the strategy by relating the parking lot vehicle count to the time expenditure. The slope of the model effectively quantifies how the time cost changed with vehicle count, providing valuable insights into strategy performance under high occupancy.

(2) From the perspective of large passenger transport hubs, previous studies on parking demand assignment failed to consider their unique parking demand and corresponding facility supply. By contrast, this study focused on linear and nonlinear HPLs, considering factors such as temporary parking needs and the corresponding supply of roadside parking. The analysis showed that XGBoost regression modeling emerged as an optimal strategy for managing these complex parking scenarios, where traditional methods may fall short.

(3) In application, this method can be integrated with navigation software to enhance user experience, providing better routing and optimal parking space suggestions based on real-time data. Efficient parking management aligns with broad transportation goals, such as station-city integration, aiming to reduce urban congestion by improving connections between transportation modes.

(4) However, the intercept of the LR model in the results analysis lacked realistic interpretability owing to the potential exclusion of low-occupancy scenarios in the dataset. This limitation highlights the usage of LR in scenarios where parking lots are not busy.

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基于回归建模的枢纽停车场内混合停放需求分配

张楚[1,2], 陈可涵[1], 陈峻[2], 陈嘉毅[1]

(1.东南大学交通学院,南京 211189; 2.东南大学江苏省综合交通运输规划与仿真重点实验室,南京 211189)

摘要: 为了适应客运枢纽配建停车场的特殊供需特征,提出了一种基于回归建模的枢纽停车场内部混合停放需求分配方法。首先,充分考虑寻泊、步行及离场时间,并关注短时停放特性,建立以综合时间成本最小为目标的分配模型。其次,估计停车场可获取的信息维度,提出3种基于回归建模的分配策略,回归模型分别采用线性回归、XGBoost和多层感知机3类模型。同时,利用交通仿真软件SUMO构建停车场停放过程仿真模型,为数据收集、模型训练及案例研究提供有力支持。最后,通过在案例中比较3种策略效果发现,基于XGBoost回归的分配策略在停车场中实现了最优分配,消耗的时间成本较基于多层感知机回归和线性回归的策略分别下降29.3%和37.2%。这为实际应用中的停车管理提供了多样化的选择。

关键词: 停车区域分配;枢纽停车场;回归建模;极致梯度提升(XGBoost)

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