**International Journal of Ambient Computing and Intelligence**
Volume 15 • Issue 1

# Management of New Automatic Ticket Vending Machine System in Urban Rail Transit

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## ABSTRACT

The technology of automatic fare collection system for urban rail transit is an important technology for achieving automatic fare collection for public transportation facilities such as urban subways. This article studies the relevant characteristics of the AFC system. Through introducing queuing models, simulation comparative experiments, and neural network debugging, it is found that the automatic fare collection system for urban rail transit not only effectively helps station staff to allocate tickets in a timely and reasonable manner, adjust station ticket supply, but also facilitates station passengers to query tickets, and passengers can freely choose whether to take the train according to their actual needs. The experiment shows that the AFC system can effectively help passengers avoid traffic congestion during peak hours, greatly improve management level, and reduce labor intensity.

## KEYWORDS

Automatic Ticketing System, New Technology Application, Ticket Management, Urban Rail Transit

Urban rail transit, usually in the form of railways or subways, is an integral public transportation system within a city used to transport passengers between locations. According to the latest data released by the China Urban Rail Transit Association, as of December 31, 2022, 55 cities in China have opened urban rail transit systems, covering a total operating length of 10,287.45 kilometers. With the gradual expansion of operating cities, urban passenger volume continues to grow, leading to the demand for passenger services and higher expectations for travel experience (Mesch, 2022).

In May 2018, the Ministry of Transport of China issued the Regulations on the Operation and Management of Urban Rail Transit, advocating for the adopting of innovative technologies like big data analysis and mobile internet to enhance service quality. Urban rail transit operations should organize and implement these technologies and facilities, promoting the use of the One Card payment system in accordance with relevant standards and promoting cross regional and cross transportation mode interconnectivity (Shah et al., 2022).

DOI: 10.4018/IJACI.344796
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Therefore, operators are encouraged to establish sound data analysis systems to collect and analyze passenger travel data, traffic flow data, and other information. This data-driven approach can better demand prediction, operational management, and decision-making to improve the overall performance of the system. However, operators and policymakers should establish strict data security policies and privacy protection measures to ensure that passenger data is not abused or leaked. This aspect needs careful attention in the future development of rail transit.

Urban rail transit is characterized by safety, reliability, punctuality, high efficiency, and large passenger volume, as well as complex passenger flow structures (Elliott & Kittner, 2022). The automatic fare collection system (AFC) is an important factor that affects the efficiency of station passenger transportation. Carelessness in managing this system can result in long queues forming in front of the automatic gate machine (AGM) as passengers try to purchase tickets (Lei et al., 2014).

In recent years, the widespread application of new technologies like cloud computing, big data, mobile internet, and mobile payment in daily life has created continuous innovation and development in AFC systems. This advancement has also driven the upgrading of transportation payment methods. Thus, relevant enterprises are trying to improve their ticketing management methods and work levels to meet the urgent needs of passengers for mobile payments. By providing more convenient ticketing services, the improvements can provide better travel experiences for passengers (Neves et al., 2022). Therefore, understanding the relevant knowledge of AFC systems is very important in this landscape.

This article focuses on the relevant characteristics of the AFC system through the use of queuing models, simulation comparative experiments, and neural network debugging methods. Research has found that the AFC system helps station staff better manage ticket supply while also offering passengers more convenient ticket purchasing methods and ticket query services. The experimental results indicate that the application of AFC systems not only helps passengers avoid traffic congestion during peak hours but also significantly improves management levels and reduces labor intensity. This study has positive significance for further optimizing the urban rail transit systems and improving the overall travel experience.

## RELATED MATERIALS

### AFC System Overview

The AFC system is an automated solution to provide efficient and convenient ticketing services, thereby enhancing ticketing management efficiency (Toffolo et al., 2021). The system integrates computer technology, information collection and processing technology, and mechanical manufacturing, using computer, communication, network, and automatic control technologies (Volinski, 2018). With is strong intelligent functionalities, the AFC system can automate ticket sales, ticket checking, billing, charging, statistics, sorting, and management processes (Lott et al., 2021).

Compared to traditional paper ticket sales modes, the AFC system overcomes shortcomings of traditional models, such as slow speeds, financial loopholes, high error rate, and significant labor requirements (Yin et al., 2022). Moreover, it can effectively prevent issues like counterfeit tickets and staff negligence, greatly improving management levels and reducing labor intensity (Wang et al., 2022).

This advanced management system has been applied in rail transit across developed countries (Qiu et al., 2022). Initially imported from abroad (Aglibar et al., 2022), AFC equipment for rail transit systems in China has witnessed a large amount of research and development in recent years, leading to constant technological improvements (Mathews, 1989). This progression reflects the evolution of the domestic rail transit AFC system, which has evolved from its earliest stages to an improved method (Ferreira et al., 2021).

As the AFC system finds widespread application in passenger transport management of urban rail transit stations, it has become an important system in the rail transit system. It directly impacts public experience and interaction (Wang et al., 2021). Not only is it a trend in the development of the subway and transportation system, but it is also an important symbol of urban information construction (Wu et al., 2021).

### Performance Index

The low-level controller (LCC) system availability is 99.9997, with a mean time to repair standing at about 18 minutes. Upon the initial stage of system opening, the central computer system can ensure that the resource utilization rate will not exceed 50% (Javadinasr et al., 2021). Similarly, the disk array can ensure that the resource utilization rate will not exceed 30% at the initial stage of the system's opening. For data backup, the hourly backup capacity is set at 432GB/h, with daily business data backup taking four seconds. The recovery time of data backup is one hour. Furthermore, the LCC data accuracy reaches 99.99% (Mo et al., 2022).

### Ticketing Center

The ticketing center includes various functions for smooth operation, including ticket distribution, recycling, deployment, personalization, cleaning, and disinfection. It also monitors system status, generates corresponding statistical reports, manages ticket purchase, initialization, counting, and packaging, oversees ticket scrapping and tracking audits, prepares issuance plans, adjusts parameters and settings, conducts self-diagnosis, synchronizes clocks, manages authorities, updates software, and manages data, tasks, and emergency stops.

Within the AFC system, different tickets are found in each layer, ensuring operation management. The ACC has a ticket center for key management, system management, inventory management, and allocation management. LCC features a ticket center, managing online inventory, supervising station inventory production, and overseeing the allocation of tickets online.

At the station level, the station control (SC) is equipped with a station ticket office to manage terminal equipment tickets and the allocation of tickets in the station. The station integrated control room is responsible for monitoring equipment inventory and authorizing the station attendant to replace the ticket box.

### Equipment Functions

The AFC system facilitates transaction data collection and the comprehensive statistics and analysis of the line. It manages data, parameters, coding, and authority maintenance centrally, preventing illegal entry, interference, and replication.

Data management includes collection, processing, and security measures to safeguard information and confidentiality.

System operation management includes equipment monitoring and control, passenger flow tracking, system mode monitoring, expansion of the operational mode, and schedule management to ensure smooth operations.

Revenue management includes cash accounting, ticket agency sales, nonimmediate refund application, ticket refund and replacement, revenue accounting and statistics, and reconciliation.

Additionally, the system manages composition, generation, processing, deletion, download, validation, and processing of ticket blacklists to improve security measures (Yao et al., 2021).

### System Function

The station fare collection equipment uses real-time monitoring, which ensures clock synchronization between the station computer and equipment within specified time intervals. Monthly statistics on passenger flow, ticketing, and financial revenue are compiled by the computer system. Self-diagnosis features are integrated into the system, allowing for proactive maintenance. The station computer can work offline and has extensive hard disk storage capacity. Maintenance functions are provided, including a data backup function onto floppy disks. A half-hour uninterruptible power supply (UPS) system is installed to support the operation of the station computer system. Operation logs and system alarms are recorded. Data transfer functions are available for information exchange. Equipment monitoring includes tracking the operation status of equipment, transactions, communication status, alarms, and the overall system mode. Special pass mode processing, degraded mode handling, and system operation mode management are also included in the system's functionalities. Emergency mode methods include using the emergency button, fire alarm system triggers, station computer commands, and manual power cut interventions.

### *AFC Field Terminal Equipment*

The ticket vending machine provides an array of functions, including networking operation, road network operation, operation display, ticket selling, stored value ticket processing, audit functions, coin handling, change provision, and security maintenance. In addition, semiautomatic ticket vending machines offer functions of ticket processing alongside basic equipment methods.

Automatic AGMs support equipment networking operation, road network operation, operation display, ticket checking, integrated circuit card processing, access control, audit, ticket recovery, emergency mode activation, two-way ticket checking, and security maintenance. While less frequently used, ticket checkers can serve as ticket inquiry, system introduction, user guidance, and announcements. Portable ticket detectors are used to effectively verify various tickets and display ticket information.

## Urban Rail Transit Ticket Work

The main task of the ticket management department within urban rail transit enterprises is to establish and improve ticketing rules and regulations, overseeing ticket card management, conducting revenue reviews, supervising ticket operations, and facilitating internal and external coordination. Some departments may also be responsible for the maintenance and management of the AFC system (Tyndall, 2022). Stations are frontline units of urban rail transit ticketing work. Station ticket operation involves ticket sales, zero exchanges, passenger ticket affairs, emergency procedures, and more (Li et al., 2022). In addition, ticket operations are closely related to other departments, particularly in the following:

1. **Traffic Organization:** In case of an emergency like a fire in the train or the station, the station will coordinate passenger evacuations via the AFC system emergency mode.
2. **Maintenance and Repair:** Timely reports are made related to the failure of ticket vending machines or other system equipment.
3. **Ticket Management:** The ticket management department handles ticket inspections, income audits and other regulatory work.

Thus, the island effect of traditional urban rail transit AFC systems is relatively apparent. These systems manage the entire ticketing process of urban rail transit, including ticket sales, ticket checking, billing, charging, statistics, and settlement (including settlement with citywide cards). The application of mobile internet and mobile payment technologies has also impacted traditional urban rail transit ticketing operations, prompting urban rail transit enterprises to improve their ticketing management functions. This is reflected in:

1. **Upgrading and Reconstruction:** The software and hardware of the traditional AFC system will be upgraded by means of equipment asset upgrading and reconstruction to support the application of new pass payment technologies like QR code scanning, mobile payment, and ticket purchase.
2. **Station Ticket Operations:** The application of the new AFC system traffic payment technology requires urban rail transit enterprises to strengthen the training of station staff and ensure they master AFC system equipment and passenger transaction processing according to the new requirements.

### Overview of Urban Public Transportation Situation

Urban public transport is a large service industry, consisting of light rail, subway systems, and more. It is a comprehensive transportation network with a three-dimensional structure, operating underground, at ground level, and above ground (Lu et al., 2022). It is integral to the lives of citizens in cities, becoming an important symbol of the modernization of a city and even a country (Stecker et al., 2009). However, at present, serious traffic congestion plagues provincial capitals and economically developed cities in China, with urban traffic emerging as a main factor restricting social and economic development (Srivastava & Agrawal, 2014).

In the past, the operation and management of urban rail transit relied on manual processes, such as Beijing Metro Lines 1 and 2. However, with the increasing passenger flow of urban rail transit, outdated ticket operations, selling, checking, and settlement methods have brought many inconveniences and problems to passengers, operating companies, and government departments. Cash-based ticket purchases and manual ticket sales are slow, prone to human error, and susceptible to other inefficiencies, causing serious congestion during rush hours of commuting or holidays, thereby inconveniencing the public. Ticketing has evolved into a tedious task for all operating companies.

The AFC system can address these problems by classifying ticket prices based on the attributes of passengers, such as student status, age, disability, and weekday vs. weekend travel. Different fare classifications can be distinguished through smart cards or applications, allowing for the fees to be calculated based on fare policies. The AFC system can provide personalized services and ticket prices based on different needs and policies. This improves the efficiency of the public transportation system, reducing road congestion, and better meets the needs of diverse passenger groups.

The traditional manual ticket selling process is very large, unable to realize reasonable and rapid fare collection or prevent ticket evasion and internal malpractice by ticketing staff. The operating enterprise must also be equipped with a considerable number of cashiers, which not only undermines employees' well-being but also increases the pressure on enterprise operation. Due to technical limitations, the general one-ticket system or simple section charging is unreasonable, making it impossible to enhance the competitiveness of the operating company through cumulative discount strategies.

The backwardness of the management mode makes it impossible for the operating enterprises to obtain timely insights, hindering their ability to allocate transport capacity according to real-time needs. This results in high operating costs, difficulty in improving production efficiency, and the lack of accurate basic data for transportation authorities to make macro-level decisions. Therefore, addressing the modern city's requirements for public transport system through high-tech means has become a critical issue faced by traffic management and operational departments.

## METHODS

### Queue System of Gate

The M/M/1 queuing system is a fundamental model in queuing theory, specifically used to describe a single-server queuing system. In this model, the first M signifies that customer arrivals follow a Poisson distribution, meaning that the intervals between arrivals are random and follow a Poisson process. The second M indicates that service times also follow an exponential distribution, meaning that the service time of customers at the service desk is random and follows an exponential distribution. The 1 means there is only one service desk in the system.

A Poisson flow is a continuous process of events at a specific rate, with the time intervals between the events following a Poisson distribution. In the urban rail transit system, passengers undergo queuing when they use ticket gates to enter. Here, passengers are customers in the queuing system, while the gates represent the service desks within the queuing system. Therefore, passengers and gates constitute a queuing system within the urban rail transit system.

For the M/M/1/queuing system, the customer flow is defined as a Poisson process with the parameter of brother, where brother represents the number of customers arriving per unit time (arrival rate). Thus, the interval between customer arrivals follows the negative exponential distribution with parameter brother, and the probability density function is denoted as a(t).

With only one service desk, the service time v for serving a customer follows the negative exponential distribution with a parameter of knife, where λ refers to the average number of customers served per unit time (service rate) when the service desk is busy. If the distribution density function for service time is denoted as b(t).

It is important to note that the service time at the desk is independent of the arrival interval of the customer, meaning that the customer arrival is independent of the work of the service desk. See equation (1).

$$\rho = \lambda / \mu \tag{1}$$

where ρ is called service strength.

In equations (2) and (3), let $N(t)$ denote the number of customers in the queuing system at time t, including customers receiving services, $N(t) \in [00\}$.

$$p_k(t) = P(N(t) = k) \tag{2}$$

$$p_k = \lim_{t \to \dot{\omega}} p_k(t) \tag{3}$$

By solving the formula of Markov birth and death process, as shown in equation (4), we get:

$$p_{k-} = \frac{\lambda_{k-1}\lambda_{k-2}\cdots\lambda_0}{\mu_k\mu_{k-1}\cdots\mu_1} p_0 = \left(\frac{\lambda}{\mu}\right)^k p_0 \tag{4}$$

as long as the stationary distribution exists and can be obtained, as shown in equation (5).

$$p_0 = \left[\sum_{\omega}^{k=0}\left(\frac{\lambda}{\mu}\right)^{k-1}\right]^{-1} = 1 - \rho \tag{5}$$

The stationary distribution is geometric, as shown in equation (6).

$$p_k = (1-\rho)\rho^k \tag{6}$$

P0 = 1-P is the probability that the server console is idle. ρ is the probability that the server is busy. The bigger, the busier the service desk.

Using the stationary distribution, several important quantities, including the average queue length, the average waiting queue length, the average waiting time, and the average stay time under statistical equilibrium can be obtained, as shown in equation (7). Here, 10,000 represents the team leader under statistical balance. N represents the average team leader:

$$\bar{N} = E[N] = \sum_{\infty}^{r=0} kp_{l} = \frac{\rho}{1-\rho} \tag{7}$$

## Parallel Queuing Model of Gate

Using M to analyze the queue system of the gate, we can consider the queue system of the gate as n standard M, rM, r1/r0 queue systems in parallel. For each subsystem, the arrival rate of passengers is as shown in equation (8).

$$\lambda = G \,/\, n \tag{8}$$

The service rate of the channel is as shown in equation (9).

$$\mu = 1 \,/\, T \tag{9}$$

In a constant situation, on the one hand, increasing n can reduce p, meaning that more channels in the gate unit set are set as entrance channels. However, the space of the entrance and exit of the actual rail transit station is limited, so the number of gates that can be placed is also limited. Thus, the number of channels is also limited. Therefore, ρ can only be increased to the maximum value feasible within the actual channel capacity.

On the other hand, reducing the size of Luo can also reduce the size of the corpse, which means reducing the passage time of passengers. Therefore, by creating reasonable gates, the time required for ticket checking can be reduced, facilitating smoother passenger flow. There are many ways to reduce the processing time of the gate, including improving the performance of hardware devices like using a faster read/write card reader, enhancing the efficiency of internal control (for example, considering real-time properties when designing the control module), and designing the gate's intelligent recognition system to maximize recognition speed without compromising recognition results. This article focuses on the intelligent recognition system of the gate, considering recognition speed during system design and development.

## Variable Standardization

When conducting multibehavior feature analysis, it is important to standardize the data to ensure that the results of subsequent data analysis will not be affected by differences in dimensions and units among behavior features. The standardization transforms the data into dimensionless ratios, ensuring that all behavior features are within the same range and comparable. There are three common methods for variable standardization:

1. One-pot coding for discrete variables;
2. Z-normalize for continuous variables;
3. Min-max normalize for continuous variables.

Due to the large amount of data and calculation for data standardization, programming is usually used for calculations. Fortunately, this is a small step in a large analysis and can be completed with just a few lines of code. Here, the article introduces the principle, but these will be reflected in the subsequent clustering analysis.

### One-Pot Encoding

This method ensures that the absolute value of the result vector is 1, indicating that the coding result is standardized and requires no further processing. The advantage of this approach is that the distance between each vector in the classification variable is maintained. This meets the requirements when the eigenvalues are different and cannot be sorted.

### Deviation Standardization

The original data can be linearly transformed so that the result falls between [0,1]. A group of samples $X = \left[x_1, x_2, \ldots, x_n\right]$ are as shown in equation (10):

$$y_i = \frac{x_i - \min\left(x_j\right)}{\max\left(x_j\right) - \min\left(x_j\right)} \tag{10}$$

The deviation standardization method ensures that each quantity in the new matrix is within the interval [0,1] and is dimensionless. This is achieved by scaling each value based on the maximum and minimum values of sample data. However, this standardization method has two obvious defects. First, when new data is added, the maximum and minimum values may change, requiring that the entire formula be redefined. Second, if there is a single data outlier and it is the maximum or minimum value, most of the standardized data may be concentrated in a small interval.

### Standardization of Standard Deviation

The standardization of standard deviation is applicable when the maximum and minimum values of the original data are unknown or individual data outliers exceed the value range. This, in turn, optimizes the drawbacks of deviation standardization, as shown in equation (11).

$$s = \sqrt{\frac{1}{n-1}\sum\left(x_i - \bar{x}\right)^2} \tag{11}$$

After obtaining the frequency, calculate the similarity coefficient between the two variables λ according to equation (10), as shown in equation (12).

$$\lambda = \frac{\sum_{m}^{i=1}\max\left(n_{ij}\right) - \max\left(n_{\max(i)j}\right)}{n - \max\left(n_{\max(i)j}\right)} \tag{12}$$

## EXPERIMENTAL RESULTS AND ANALYSIS

### Analysis of Simulation Results

CloudSim is a cloud computing simulation software launched by the Grid Laboratory of the University of Melbourne, Australia. It models and simulates the core functions of the cloud, such as job/task queues, event processing, the creation of cloud data centers, data center proxies, communication between entities, and the implementation of proxy strategies.

Before deploying the simulation software CloudSim, it is necessary to install some dependent software tools in the running environment. The hardware environment and software tool versions

**Table 1. Experimental Environment Configuration**

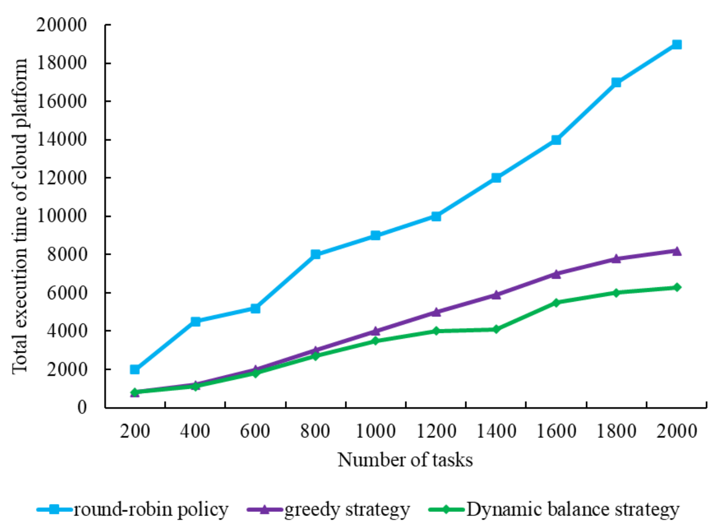
| Environmental Configuration | Parameter |
|---|---|
| Operating System | Window 8 |
| Memory | 4G |
| Development Tool | Eclipse jee Kepler |
| JDK Version | 1.7 |
| Maven Version | 3.2.5 |
| CloudSim Version | 4.0 |

used in this article's experiment are shown in Table 1. CloudSim software is used to simulate the environment of the cloud platform of the AFC system, conducting several groups of comparative experiments under the set parameters. To improve the accuracy of simulation results, the average value of 10 experimental results is taken as the simulation result.

The loop method aims to obtain numerical solutions through gradual approximation until predetermined accuracy or conditions are met. The greedy method, on the other hand, seeks a local optimal solution under given constraints, although it may not necessarily be a global optimal solution. Dynamic balancing strategies, commonly used in distributed and parallel computing environments, focus on effectively allocating tasks between multiple computing nodes or processors to reduce computational time and improve performance. The research data in this article were simulated using these three algorithms to obtain the optimal strategy. The simulation results were processed to obtain the total execution time () of the cloud platform for the three load balancing strategies under different task numbers. A comparison chart of the platform's total execution time is $\max\left\{T_j\right\}, j = 1, 2, \cdots \mathrm{m}$, as shown in Figure 1.

According to Figure 1, the total execution time of the cloud platform under the three strategies increases linearly with the number of tasks. Notably, the polling strategy has significantly longer execution times compared to the greedy strategy and dynamic balance strategy. Taking n = 1000 as

**Figure 1. Comparison of Total Execution Time of Cloud Platforms Under Three Strategies**



an example, the polling strategy is 8,812 seconds, while the greedy and dynamic balance strategies only take 3,785 seconds and 1,689 seconds, respectively, accounting for 42.9% and 19.2% of the polling strategy time. Figure 2 shows the ratio of the total execution time of the cloud platform of the greedy strategy, dynamic balance strategy, and polling strategy. The greedy strategy's time ranges from 29.6% to 47.6% of the polling strategy, while the dynamic balance strategy's time consumption ranges from 21.7% to 34.7% of the polling strategy.

When designing and implementing strategies, greedy strategies may be simpler as they are typically based on static rules. Dynamic balancing strategies, however, may require more complex algorithms and resource management to achieve real-time load balancing. The polling strategy is usually relatively simple; however, it may require complex task allocation rules in certain scenarios. In addition, dynamic balancing strategies can usually allocate resources more effectively, reducing resource waste and improving resource utilization. In contrast, the greedy and polling strategies may lead to resource imbalances, affecting the full utilization of resources. Moreover, dynamic balancing strategies typically have good scalability, accommodating loads of different scales. The performance of greedy and polling strategies may decrease as the load increases.

It can be seen that the dynamic balance strategy is superior, effectively shortening the data processing time and saving costs. This stems from its real-time adaptability, task priority consideration, resource allocation flexibility, and task scheduling efficiency. However, dynamic balancing strategies typically require more complex algorithms and logic to adjust task and resource allocation in real-time. This may increase the computational cost and complexity of the system, requiring more computing resources to support the decision-making process. Nonetheless, in practical applications where the load fluctuates, a cloud platform that adopts a dynamic balancing strategy can better adapt to this fluctuation, ensuring acceptable performance under high loads.

According to Figure 2, when the polling strategy is adopted, there is a notable disparity in execution time distribution across virtual machines. This is especially evident with a large number of tasks. For instance, the execution time difference on 20 virtual machines is large. Taking n = 2,000, the 13th virtual machine has the longest execution time at T13 = 17,871 seconds, while the ninth virtual machine records the shortest execution time at T9 = 4439 seconds. Thus, the ninth virtual machine is idle for 13,432 seconds before all tasks are complete, accounting for 75.2% of the total

**Figure 2. Task Execution Time of Each Virtual Machine Under Polling Policy (unit: s)**

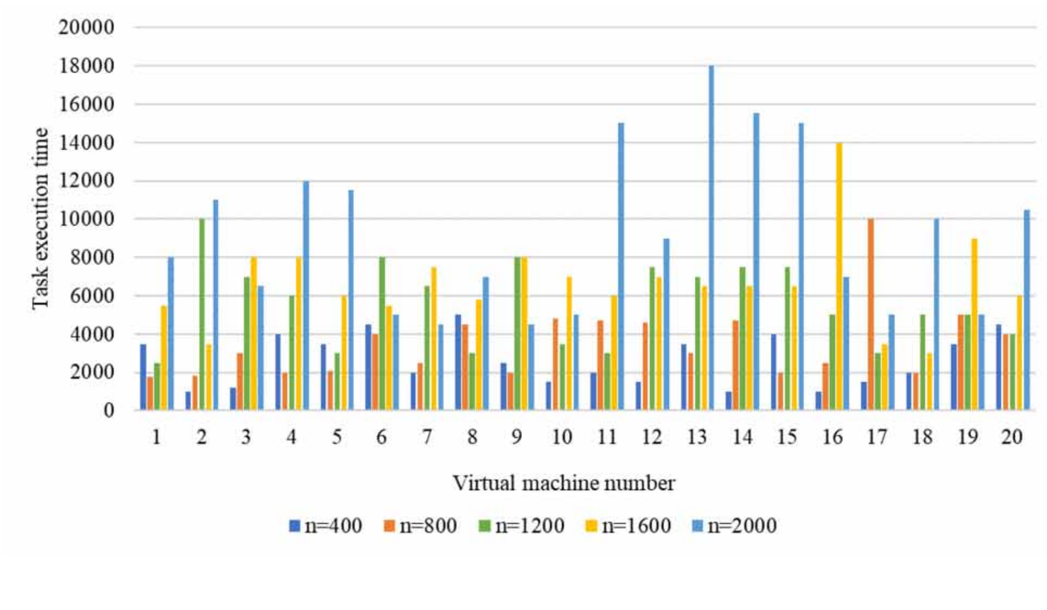
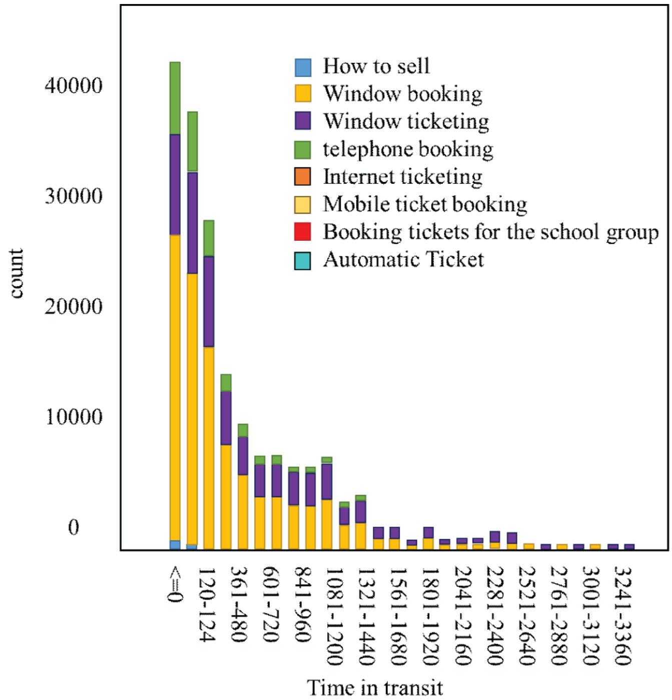


Figure 3. Stacking Chart of In-Transit Time and Sales Method




execution time of the cloud platform. This discrepancy is because the polling policy aims to run an equal number of tasks across all virtual machines.

## STATISTICAL ANALYSIS

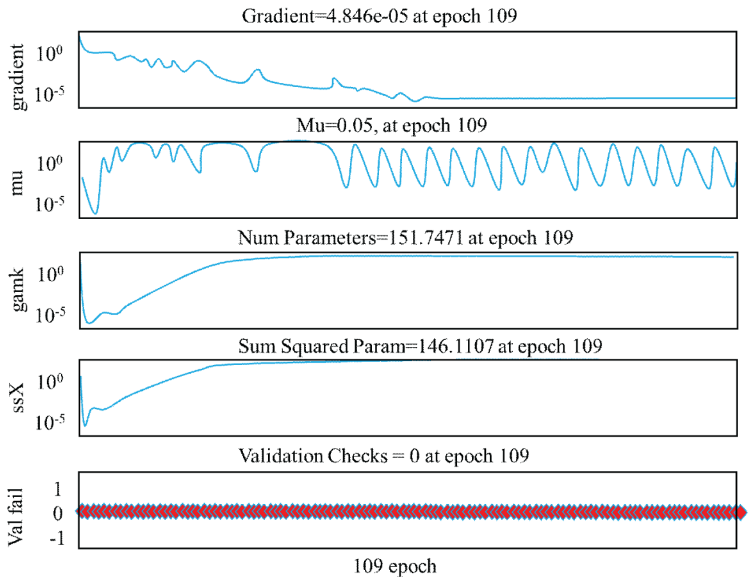
The in-transit time and sales method are made into a stack chart for visual analysis, as shown in Figure 3.

The proportion of classification factors within the scope of each segment can be clearly seen by using the area stack diagram. However, due to the small proportion of telephone booking and group booking window booking, their contribution is not visible. Upon examining the stack diagram, a trend emerges: for shorter travel times, more student passengers tend to buy tickets directly at the ticket window, whereas for longer travel times, they are more likely to use mobile phones or online ticket sales. Moreover, the shorter the travel time corresponds to a higher the proportion of passengers choosing window ticket sales and automatic ticket sales, as well as a higher preference for purchasing high-speed rail tickets.

Observe the change of neural network training error Figure 4 and note that the model error gradient gradually decreases to $4.85\times10^{-5}$. Analyzing the data fitting shown in Figure 4, it is evident that the correlation coefficients R for the training set, test set, and total data are 0.99868, 0.97176, and 0.99544, respectively. These coefficients are greater than 0.95, indicating a strong predictive performance of the model.

After analyzing the influencing factors of the intercity railway underground station, selecting and screening variables, designing and debugging the BP neural network structure, and comparing and selecting Bayesian regularization algorithm as the training algorithm, this research has completed the construction of the intercity railway underground station neural network model. Overall, this research achieves a high level of accuracy.

**Figure 4. Training Error Diagram of Neural Network**




According to the actual situation of Beijing West Passenger Station, factors like the distance between facilities, pedestrian flow, and passenger characteristics are considered for simulation. For instance, the distance between the high-speed railway exit and transfer facilities is 55m. Selected simulation objects include four security check machines, three ticket vending machines, and two automatic ticket checkers. Additionally, the dimensions of connecting channels between the ticket vending machine and security check machine is 10m long and 3m wide. The connecting channel between the security check machine and the automatic ticket checker is 58m long and 3m wide. The connecting channel allows pedestrians to walk in multiple rows.

Passenger characteristics, including luggage size, gender, and age, are considered as inputs for the neural network model. They are divided into 12 categories. Among the transfer passengers, children account for 1% to 2%; thus, children's passenger flow is not considered. The size of the luggage is categorized into small, medium, and large. Gender is divided into male and female categories, while age is divided into adult passengers and elderly passengers. Fifty samples of each type of passenger are selected to obtain the average traveling speed of passengers. Then, the model aims to analyze how different passenger types impact the security check, optimizing the station security process and strategies for the station.

The traffic capacity calculations for facilities at Beijing West Passenger Station are considered. For instance, the traffic capacity is 1,400 people per hour, the service time for queuing is 2.8 seconds, the traffic capacity of the security check machine is 1,750 people per hour, the service time for queuing is 2 seconds, the traffic capacity of the ticket vending machine is 1,950, and the service time for queuing is 11 seconds.

Constructing neural network models for underground stations to improve accuracy presents several challenges. First, obtaining real underground station data, including accurate passenger flow data like types of passengers, behaviors, numbers, locations, and speed of movement, may require time and resources. Second, accurately simulating the behavior and interaction of different types of passengers can be complex. The walking speed, path selection, and queuing behavior of passengers should be comprehensively considered. Additionally, building an accurate neural network model requires consideration of multiple variables and parameters, which may lead to model complexity and training difficulties.

Verifying the accuracy of the model may require field experiments or comparison with actual data, involving time, resource costs, and controllable experimental environments. Moreover, the situation of underground stations, affected by unpredictable factors like emergencies and weather conditions, adds another layer of complexity.

Addressing these challenges requires interdisciplinary collaboration among data scientists, engineers, domain experts, and decision-makers to ensure the feasibility, accuracy, and practical applicability of the model. In addition, adaptability and flexibility are key to handling the constantly changing environment of underground stations.

## CONCLUSION

The AFC system in urban rail transit is pivotal for automating fare collection in public transport facilities like subways. This article studies the relevant characteristics of the AFC system, introducing queuing models, simulation comparative experiments, and neural network debugging. It is found that the AFC system not only effectively helps station staff to allocate tickets and adjust ticket supply but also facilitates station passengers to query tickets and choose their travel options according to their needs. The experiments show that the AFC system can effectively help passengers avoid traffic congestion during peak hours and reduce labor intensity.

In the future, the system could evolve toward "senseless" payment and passage by automatically identifying passengers and deducting fees. This method improves passenger convenience while reducing congestion and queuing times. In addition, embracing advanced technologies like artificial intelligence, machine learning, and deep learning can achieve a more intelligent and adaptive automatic ticketing system. This would further improve ticketing efficiency and accuracy, creating an intelligent and adaptive automatic ticketing system.

## DATA AVAILABILITY

The figures used to support the findings of this study are included in the article.

## CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

## FUNDING STATEMENT

This work was not supported by any funds.

## ACKNOWLEDGMENT

The authors thank those techniques that have contributed to this research.

## PROCESS DATES

This manuscript was initially received for consideration for the journal on 05/14/2023, revisions were received for the manuscript following the double-blind peer review on 04/15/2024, the manuscript was formally accepted on 01/22/2024, and the manuscript was finalized for publication on 04/16/2024.

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## REFERENCES

Elliott, M., & Kittner, N. (2022). Operational grid and environmental impacts for a V2G-enabled electric school bus fleet using DC fast chargers. *Sustainable Production and Consumption*, *30*, 316–330. doi:10.1016/j.spc.2021.11.029

Ferreira, M. C., Dias, T. G., & Cunha, J. F. (2021). ANDA: An innovative micro-location mobile ticketing solution based on NFC and BLE technologies. *IEEE Transactions on Intelligent Transportation Systems*, *23*(7), 6316–6325. doi:10.1109/TITS.2021.3072083

Javadinasr, M., Mohammadian, A., & Parsa, A. (2021). A deep-learning based optimization approach to address stop-skipping strategy in urban rail transit lines. In *International Conference on Transportation and Development 2022* (pp. 165–176).

Lei, T., Zuo, Y., Wang, Y., & Liu, H. (2014). Study on tobacco leave lean production management system. *Agricultural Science and Technology*, *15*(9), 1602.

Li, M., Zhou, X., Wang, Y., Jia, L., & An, M. (2022). Modelling cascade dynamics of passenger flow congestion in urban rail transit network induced by train delay. *Alexandria Engineering Journal*, *61*(11), 8797–8807. doi:10.1016/j.aej.2022.02.022

Lott, J. S., Young, S., & Zhu, L. (2021). Safe operations at roadway junctions: Design principles from automated guideway transit. *SAE International Journal of Advances and Current Practices in Mobility, 4*(2021-01-1004), 260–269.

Lu, Y., Chen, L., Zhou, P., & Wu, S. F. (2022). Experimental validations of reconstructed excitation forces acting inside a solid enclosure. Part I: Exterior region. *Journal of Theoretical and Computational Acoustics*, *30*(03), 2250008. doi:10.1142/S2591728522500086

Mathews, J. T. (1989). Redefining security. *Foreign Affairs*, *68*(2), 162–177. doi:10.2307/20043906 PMID:12343986

Mesch, S. K. (2022). Air Force eyes new battle management system to protect air bases. *Inside the Air Force, 21*(7), 10–14.

Neves, M. E., Vieira, E., & Serrasqueiro, Z. (2022). Management or market variables in the assessment of corporate performance? Evidence on a bank-based system. *International Journal of Accounting & Information Management*, *30*(3), 372–390. doi:10.1108/IJAIM-12-2021-0251

Qiu, S., Yang, C. H., Wu, L., Wang, K. C., & Pan, J. Z. (2022). Machine-vision-based spindle positioning system of grinding-wheel-saw automatic replacement system. *Sensors and Materials*, *34*(2), 789–801. doi:10.18494/SAM3638

Shah, K. J., Singh, A. V., Tripathi, S., Hussain, T., & You, Z. (2022). Environmental management system as sustainable tools in water environmental management: A review. *Current Chinese Science*, *2*(1), 48–56. doi:10.2174/2210298102999211228114721

Srivastava, S. D., & Agrawal, R. (2014). Automated people movers: A futuristic approach to modern transportation planning. *IOSR Journal of Mechanical and Civil Engineering, 11*(3), 01–11.

Stecker, M. S., Balter, S., Towbin, R. B., Miller, D. L., Vañó, E., Bartal, G., Angle, J. F., Chao, C. P., Cohen, A. M., Dixon, R. G., Gross, K., Hartnell, G. G., Schueler, B., Statler, J. D., de Baère, T., & Cardella, J. F.CIRSE Standards of Practice Committee. (2009). Guidelines for patient radiation dose management. *Journal of Vascular and Interventional Radiology*, *20*(7), S263–S273. doi:10.1016/j.jvir.2009.04.037 PMID:19560006

Toffolo, C., Gentili, R., Banfi, E., Montagnani, C., Caronni, S., Citterio, S., & Galasso, G. (2021). Urban plant assemblages by land use type in Milan: Floristic, ecological and functional diversities and refugium role of railway areas. *Urban Forestry & Urban Greening*, *62*, 127175. doi:10.1016/j.ufug.2021.127175

Tyndall, J. (2022). Complementarity of dockless mircomobility and rail transit. *Journal of Transport Geography*, *103*, 103411. doi:10.1016/j.jtrangeo.2022.103411

Volinski, J. (2018). Reflections on the future of public transportation. *Journal of Public Transportation*, *21*(1), 13. doi:10.5038/2375-0901.21.1.13

Wang, J., Zhang, N., Peng, H., Huang, Y., & Zhang, Y. (2022). Spatiotemporal heterogeneity analysis of influence factor on urban rail transit station ridership. *Journal of Transportation Engineering. Part A, Systems*, *148*(2), 04021115. doi:10.1061/JTEPBS.0000639

Wang, L., Ma, W., Wang, L., Ren, Y., & Yu, C. (2021). Enabling in-depot automated routing and recharging scheduling for automated electric bus transit systems. *Journal of Advanced Transportation*, *2021*, 1–15. doi:10.1155/2021/5531063

Wu, Y., Zhao, L. Y., Jiang, Y. X., Li, W., Wang, Y. S., Zhao, H., Wu, W., & Zhang, X. J. (2021). Research and application of intelligent monitoring system platform for safety risk and risk investigation in urban rail transit engineering construction. *Advances in Civil Engineering*, *2021*, 1–10. doi:10.1155/2021/9915745

Yao, E., Hong, J., Pan, L., Li, B., Yang, Y., & Guo, D. (2021). Forecasting passenger flow distribution on holidays for urban rail transit based on destination choice behavior analysis. *Journal of Advanced Transportation*, *2021*, 1–13. doi:10.1155/2021/9922660

Yin, D., Huang, W., Shuai, B., Liu, H., & Zhang, Y. (2022). Structural characteristics analysis and cascading failure impact analysis of urban rail transit network: From the perspective of multi-layer network. *Reliability Engineering & System Safety*, *218*, 108161. doi:10.1016/j.ress.2021.108161