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Research on the Optimization Method of Bus Travel Safety Considering Drivers' Risk Characteristics

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Abstract: Bus drivers have an important role in ensuring road safety, as their driving circumstances fluctuate due to the combined influence of physiological, psychological, and environmental dynamics, which can cause complex and varied driving dangers. Quantifying and assessing drivers' risk characteristics under various scenarios, as well as finding the best fit with their work schedules, is critical for enhancing bus safety. This research first uses the entropy weight method, which is based on historical warning data, to examine the risk characteristics of bus drivers in various complicated contexts. It then creates an objective function targeted at minimizing the operational risk for a specific bus route. This function uses the quasi-Vogel approach and an improved simulated annealing algorithm to optimize and restructure the scheduling table, taking individual driver risk characteristics into account. Finally, the analysis is confirmed and examined with actual operational data from the Zhenjiang Bus Line 3. The data show that enhanced bus operations resulted in a 7.22% gain in overall safety and a 33.76% improvement in balancing levels. These insights provide valuable theoretical guidance as well as practical references for the safe operation and administration of public buses.

Keywords: urban traffic; public transport safety; bus driver; driving behavior risk; safety enhancement; simulated annealing algorithm

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1. Introduction

In recent years, there have been frequent bus safety accidents in China, making the effective prevention and control of bus operation risks a hotly debated issue. Bus drivers, as the most important factor in ensuring driving safety, are prone to certain fluctuations in their driving state due to the coupling effects of dynamic factors, such as driving behavior [1–4], physiology and psychology [5,6], and external environments [7,8]. These fluctuations can, in turn, induce complex and dynamic driving risks [9]. Quantifying and analyzing the differences in bus drivers' safety under various driving scenarios and developing scientifically reasonable bus scheduling plans to achieve optimal matching between drivers and their corresponding working environments and conditions is of great significance for enhancing the fine management level of bus driving safety.

Driver scheduling [10], as a crucial aspect of bus operation planning and safety management, directly influences the overall level of bus safety. The problem of bus driver scheduling is a typical nondeterministic polynomial time hardness (NP-hard) issue. Classified from the perspective of algorithms, currently, bus vehicle scheduling methods mainly encompass exact algorithms [11,12] and heuristic approaches [13–15]. In terms of addressing driver scheduling problems, the current approaches are primarily categorized into generate-and-select methods [16,17], construct-and-evolve methods [18], and integrated scheduling methods [19–22]. Ryan [23] was an early pioneer in introducing integer programming theory into the problem of driver scheduling, and by adding over-constraints, he simplified the original problem to obtain a lower bound solution for practical issues. Smith [24] and his colleagues were the first to model the driver scheduling problem as a set covering problem (SCP), and based on practical experience, they reduced the computational scale of set partitioning to obtain an approximate solution to the problem. The set covering model has since been widely used. Norris [25] divided the personnel scheduling problem into multiple stages and solved each stage using the set covering model, achieving an approximate solution that was only 2% away from the optimal solution. Heuristic algorithms, based on the idea of probabilistic optimization, can efficiently search the feasible region of the objective function to obtain approximate solutions. Clement [26] and his colleagues were among the first to apply heuristic algorithms to the problem of bus driver scheduling, systematically introducing the characteristics and applicability of typical algorithms, such as simulated annealing, genetic algorithms, and greedy algorithms. Kwan [27] and his team designed a driver scheduling method based on an improved genetic algorithm, demonstrating its better computational efficiency, robustness, and suitability for handling large-scale data compared to integer programming models. Liu Haoxiang [28] and his colleagues divided the driver scheduling problem into a set covering master problem and a resource-constrained shortest path subproblem and used a column generation heuristic algorithm to obtain integer feasible solutions. Chen Mingming [29] and his team designed a heuristic algorithm based on generating initial solutions for the problem of crossline scheduling of bus attendants and utilized a tabu search algorithm to find approximate solutions to the problem. The optimization problem of bus driver scheduling is characterized by large-scale computations and complex constraints, making it difficult to obtain an exact solution within a limited time. Considering that bus schedules are generally fixed, practical problems can be simplified, and heuristic algorithms can be designed to obtain approximate solutions.

A reasonable bus driver scheduling plan is a critical factor in ensuring the normal operation of public transportation, and it is also an important aspect for reducing operating costs and enhancing resource utilization efficiency. Perumal [21] et al. focused on the bus driver scheduling problem considering employee vehicles and the corresponding mathematical solution, with examples demonstrating the reduction in bus operating costs. Kang [30] emphasized the study of a single-line bus driver scheduling model considering mealtime windows, with optimization results improving driver resource utilization and reducing work delays. Some scholars have optimized bus operation safety and reliability by considering bus risk factors as constraints when solving the bus driver scheduling problem. Andrade-Michel [22] et al. proposed a scheduling optimization model considering driver reliability, with simulation results showing that the model can reduce driver absenteeism and ensure service levels. Sun Bo [31] et al. introduced an optimization model for regional bus driver scheduling that considers drivers' familiarity with routes, which can enhance the reliability of scheduling plans while reducing scheduling costs. Wang [32] et al. presented a reconstruction model for bus driver schedules considering the risk of fatigue driving, with simulation results indicating that the optimized scheduling plan can reduce the incidence of bus collisions by approximately 30%.

Existing driver scheduling methods primarily focus on enhancing the economic benefits and service efficiency of bus operations or on solving algorithms for scheduling optimization problems, with less consideration given to bus safety and comfort. There is still a lack of safety-oriented driver optimization models and solution methods. How to propose optimization methods to improve driving safety based on drivers' risk characteristics in different situations has been rarely studied. This paper comprehensively utilizes multisource historical warning data to quantitatively analyze the characteristics of individual drivers. Meanwhile, for all drivers on a specific bus route, it optimizes the scheduling combination from the perspective of improving driving safety and verifies the effectiveness of the method.

To help readers better understand the structure and content of this paper, Figure 1 illustrates the technical roadmap of the chapter content. Below is a brief overview of each chapter.

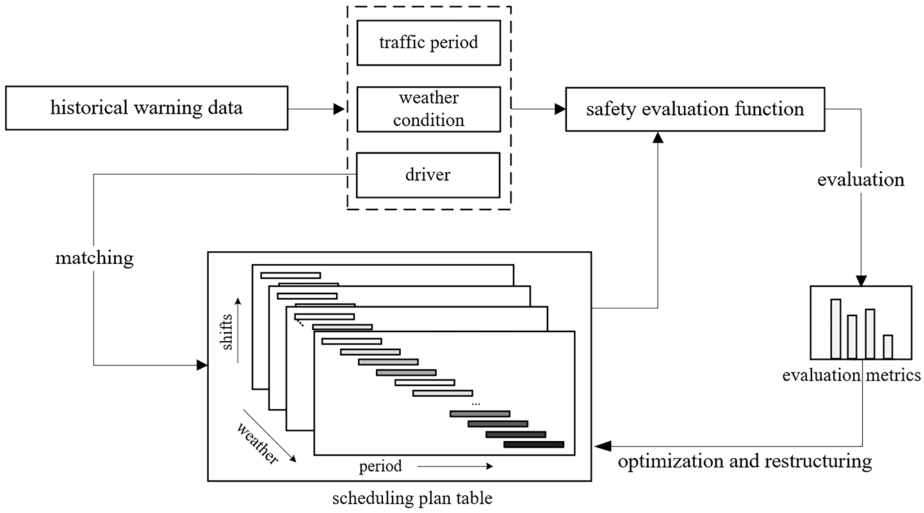

Figure 1. Flowchart of driving safety analysis and scheduling optimization method.

Section 2 integrates historical warning data generated by bus drivers during their driving to quantitatively express the driving safety of bus drivers under different driving scenarios. Furthermore, considering the feasibility, fairness, rationality, and safety of driver scheduling, an optimization model for safety-oriented bus driver scheduling is established.

Section 3 designs an initialization strategy based on the improved Vogel's approximation method, ensuring that the initial results can better meet the requirements. The basic principle is that if the safety difference between a driver's optimal and second-optimal time periods is significant, this driver should be prioritized for scheduling to reduce the safety loss caused by not being able to assign them to a more favorable position. Conversely, if the safety difference between a driver's optimal and second-optimal time periods is minimal, assigning them to the second-optimal time period will result in very little safety loss.

Sections 4 and 5 provide descriptions of the road data and driver data used, and through specific case studies, they verify that the safety optimization method proposed in this paper can effectively enhance the overall safety and risk balance of bus operations.

2. Driver Scheduling Model

2.1. Quantitative Evaluation of Driver Driving Safety

To compare the differences in driving safety among drivers under various working environments, this paper quantitatively evaluates the driving safety of bus drivers based on their historical warning data from bus operations. Assuming that the set of warning types contained in the historical bus warning data is denoted as $A = \{a_1, a_2, \cdots a_m\}$, then the probability of risk events occurring for driver d_k in different scenarios can be obtained based on the naive Bayes formula. The calculation formula is as follows:

$$\begin{aligned} P^k_{a|c} &= P^k(a|c) \\ &= \frac{P^k(c|a)\cdot P^k(a)}{P^k(c)} \end{aligned} \quad (1)$$

In this context, c denotes the driving scenario, a denotes the driving warning event, and thus, $P(a|c)$ represents the probability of the warning event a occurring under the driving scenario c.

Then, using the entropy weight method, the characteristic weight $W_{a|c}$ corresponding to the warning event a under the driving scenario c is obtained.

$$W_{a|c} = \frac{1-e_{a|c}}{\sum_{a=1}^{m}(1-e_{a|c})} \tag{2}$$

$$e_{a|c} = -\frac{1}{\ln n}\sum_{k=1}^{n} P_{a|c}^{k} \ln(P_{a|c}^{k}) \tag{3}$$

In the formula, n represents the total number of drivers; m represents the number of driving warning event categories; and $e_{a|c}$ denotes the information entropy corresponding to the warning event a under scenario c.

In this paper, the driving scenario c is mainly divided into driving periods p and driving weather w. Assuming that they are independent of each other, the combined risk of driver d_k in different environments can be expressed as:

$$\begin{aligned} r_{ij}^{k} &= \frac{\sum\limits_{a=1}^{m}\sum\limits_{p\in p_{ij};w\in w_{ij}}(\dfrac{W_{a|p}+W_{a|w}}{2})\cdot P_{a|p\cdot w}^{k}}{N} \\ &= \frac{\sum\limits_{a=1}^{m}\sum\limits_{p\in p_{ij};w\in w_{ij}}(W_{a|p}+W_{a|w})\cdot P_{a|p}^{k}\cdot P_{a|w}^{k}/P_{a}^{k}}{2N} \end{aligned} \tag{4}$$

In the formula, r_{ij}^{k} represents the combined risk value of driver d_k under $s_{i,j}$; p_{ij} denotes the risk value and safety evaluation value corresponding to driver k under the shift chain $s_{i,j}$; and N represents the length of the shift chain.

2.2. Optimization of Bus Operation Safety

Let $D = \{d_1, d_2, \cdots, d_n\}$ be the set of available drivers. Define a repeated sequence of driver numbers, composed of drivers for consecutive departures, as a "duty sequence" denoted as $L = [l_1, l_2, \cdots, l_m]$. Here, $l = l(d)$ represents the driver number, and each number corresponds to a unique driver. Conversely, a single driver can have multiple numbers.

Define a "shift" composed of k duty sequences as $L|_1^k = [l_1^{(1)}, \cdots, l_m^{(1)}, l_1^{(2)}, \cdots, l_m^{(2)}, \cdots, l_1^{(k)}, \cdots, l_m^{(k)}]$, and the minimum shift is termed the "standard shift", denoted as $L|_i^{i+k_{\min}}$, $i \in Z^+$, $k_{\min} = 2e, e \in Z^+$, which ensures that the bus driver starts and finishes work at the same station, and it sets the minimum number of working shifts for each driver. The duty sequences of the same driver in a standard shift are collectively referred to as a "shift chain", denoted as $s = l|_i^{i+k_{\min}}$. Based on the above definitions, the bus driver scheduling table can be represented by the following matrix:

$$S = [s_{ij}]_{u\times v} = \begin{bmatrix} s_{1,1} & s_{1,2} & \cdots & s_{1,v} \\ s_{2,1} & s_{2,2} & \cdots & s_{2,v} \\ \cdots & \cdots & \cdots & \cdots \\ s_{u,1} & s_{u,2} & \cdots & s_{u,v} \end{bmatrix} \tag{5}$$

where S is the scheduling table matrix; $s_{i,j}$ is the i shift chain on the j day; $u = \mathrm{H}/k_{\min}$ is the total number of shift chains on a single day; H is the total number of daily departures from a single station; and v is the number of scheduling days. The S matrix can be viewed as a collection of multiple equal-length sequences. The column vectors of the matrix represent the train sequence within a day, and modifications to this sequence primarily impact the driving periods of the drivers. The row vectors of the matrix, on the other hand, represent the train sequence for the same period each day, and changes to this sequence only affect the working weather of the drivers, without influencing their driving periods.

This paper assumes that the driving safety of individual drivers in a specific environment is generally consistent. Based on historical warning data, a safety evaluation function related to drivers and their working environment is established. To facilitate the scoring of the safety of drivers' working environments, the highest score is set to 100.

$$f_{ij}^k = (1 - r_{ij}^k) * 100 \tag{6}$$

In summary, the safety-oriented driver scheduling optimization problem can be described as utilizing the set of drivers d_k to completely cover the scheduling table S under certain constraints. Simultaneously, it aims to match each driver d_k with suitable weather conditions w_{ij} and corresponding traffic time periods p_{ij} to maximize $\sum_{i=1}^{u} \sum_{j=1}^{v} f_{ij}$.

2.3. Optimization of Driver Scheduling Based on Bus Operation Safety

The scheduling of bus drivers differs from that of regular vehicle drivers. Bus drivers cannot switch shifts along the route but must complete the entire bus route and change shifts at designated starting and ending stations. Figure 2 illustrates the hierarchy of daily bus operations. From the figure, it can be observed that a vehicle enters a rest period after completing a route and undergoes a change in direction during this rest period. Since the departure and return vehicles are equivalent in this problem, to simplify matters, this paper only considers the scheduling of drivers departing from a single station.

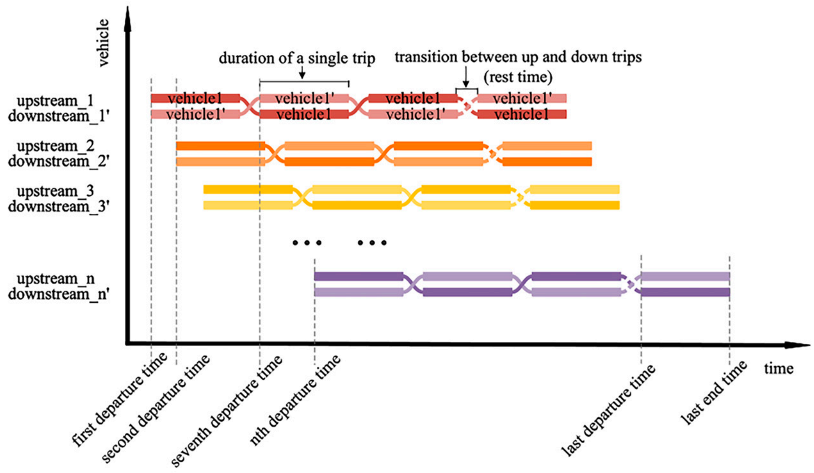

Figure 2. Hierarchy diagram of daily bus operations.

Building upon the analysis of individual driver characteristics, this paper focuses on enhancing the driving safety of a bus route as the primary objective. Simultaneously considering requirements such as economic efficiency and fairness, the study conducts an optimization combination for driver scheduling.

(1) Objective Function

This paper aims to maximize the overall safety of the bus schedule as the optimization objective. In other words, it establishes a 0–1 programming model to maximize the sum of safety evaluations for all shift chains in the schedule.

$$\max z = \sum_{i=1}^{u} \sum_{j=1}^{v} x_{ij}^k f_{ij}^k, x_{ij}^k \in \{0, 1\}, x_{ij}^k \in Z^+ \tag{7}$$

where x_{ij}^k is whether the driver dk is included in the shift chain $s_{i,j}$ (1 if yes, 0 if no), and f_{ij}^k is the safety estimation value for driver d_k under the shift chain $s_{i,j}$.

(2) Constraint Conditions

This paper, driven by actual data, establishes safety-oriented rules for bus scheduling management. The specifics are as follows:

① Independent full coverage constraint: each driver must be able to cover all assigned shift chains, and each shift chain should be completed by only one driver.

$$\sum_{k=1}^{n} x_{ij}^{k} = 1 \tag{8}$$

② Nonoverlapping time constraint: the working hours of drivers should not overlap during the optimization process of driver scheduling.

$$\sum_{i=\max\{1,h-m\}}^{\min\{h+m,u\}} x_{ij}^{k} \leq 1 \tag{9}$$

where h is the row index indicating any shift chain.

③ Labor regulation constraint: safety-oriented and aimed at preventing bus drivers from fatigue driving and illegal overtime, it is necessary to limit the working hours of drivers.

$$\mathrm{L} < \sum_{i=1}^{u} x_{ij}^{k} \leq \mathrm{U} or \sum_{i=1}^{u} x_{ij}^{k} = 0 \tag{10}$$

where U is the maximum number of shifts a driver can work in a single day; L represents the minimum number of shifts a driver must undertake if they work; otherwise, they do not work on that day.

④ Labor fairness constraint: the sum of working shifts for drivers should be approximately equal over a sufficiently long scheduling period, or the sum of working shifts for drivers should be exactly equal within a long scheduling cycle.

$$\lim_{v \to \mathrm{M}} \sum_{i=1}^{u} \sum_{j=1}^{v} x_{ij}^{k} - \frac{1}{n} \sum_{k=1}^{n} \sum_{i=1}^{u} \sum_{j=1}^{v} x_{ij}^{k} = 0 \tag{11}$$

$$\left| \sum_{i=1}^{u} \sum_{j=1}^{v} x_{ij}^{k} - \frac{1}{n} \sum_{k=1}^{n} \sum_{i=1}^{u} \sum_{j=1}^{v} x_{ij}^{k} \right| \leq \theta \tag{12}$$

where M is a very large number or a long scheduling period, and θ is the tolerance for fairness within a short period; empirically, it is generally chosen from the range $\theta \in [0, 5/T]$, where T is the number of weeks.

⑤ Risk balancing constraint: to ensure the safety of individual drivers, it is necessary to consider the balance of driving risks.

$$\left| 1 - \frac{\sum_{i=1}^{u} \sum_{j=1}^{v} x_{ij}^{k} r_{ij}^{k}}{\frac{1}{n} \sum_{k=1}^{n} \sum_{i=1}^{u} \sum_{j=1}^{v} x_{ij}^{k} r_{ij}^{k}} \right| < \varphi \tag{13}$$

where φ is the tolerance for risk balance. It is not advisable to set φ too small, as it would make it challenging to make the risks borne by each driver completely consistent and reduce the flexibility of scheduling. Conversely, setting it too large might lead the model to sacrifice individual driver safety in pursuit of overall optimization. Empirically, it can be set as $\varphi \in [0.18, 0.22]$.

3. Simulated Annealing Algorithm Based on Vogel's Approximation Method for Solution [33,34]

Firstly, Vogel's approximation method is utilized to reconstruct the original scheduling table, obtaining a relatively optimal initial feasible solution. Subsequently, an improved simulated annealing algorithm is employed to transform the current solution, assess its feasibility, and filter the solution that optimizes the objective function value. This process is iterated to progressively optimize the driver scheduling table until the model converges.

The scheduling optimization algorithm proposed in this paper for the safety operation of buses consists of three main modules: solution initialization, new solution generation, and feasibility assessment of solutions.

(1) Solution Initialization

To find an initial feasible solution that satisfies hard constraints and has a relatively optimal objective function value, this paper extends the commonly used preoptimization method, Vogel's approximation method, to the bus driver scheduling optimization problem. The basic idea is that when a driver cannot match suitable working time periods, their driving safety will be significantly compromised. Therefore, priority should be given to placing them in the scheduling table. Conversely, if a suitable time period is available, there is no need to prioritize them. In this case, the initialized result will be significantly better than a random strategy. The specific steps are as follows.

Step 1: Initialize parameters. Set the iteration count $k = 1$.
Step 2: Calculate the safety values for each driver in different time period chains and sort them in descending order $[\mathrm{f}_1, \mathrm{f}_2, \ldots, \mathrm{f}_\mathrm{n}]$.
Step 3: Calculate the differential sequence of safety values for each driver $[\mathrm{d}_{\mathrm{f}1}, \mathrm{d}_{\mathrm{f}2}, \ldots, \mathrm{d}_{\mathrm{fn}-1}, \mathrm{d}_{\mathrm{fn}}]$, where $\mathrm{d}_{\mathrm{fn}} = 0$.
Step 4: Sort the drivers in ascending order based on d_{fk}.
Step 5: While ensuring the feasibility of the scheduling table, prioritize placing the drivers at the front of the sorted list into the schedule. Match the time period corresponding to the maximum safety value of the driver with the respective shift. Record the number of unmatched shifts for each driver. If all drivers are matched, terminate.
Step 6: Set $k = k + 1$ and go back to Step 4.

(2) Generation of new solutions

Considering that row and column transformations of the schedule can change the driving weather and traffic time periods for drivers, a roulette wheel selection method is applied to perform row–column crossover or mutation on the old solution, generating new solutions.

(3) Feasibility assessment

Based on a neighborhood search method, the feasibility of shift chains is assessed. It iterates through the shift chains at the transformed positions in the new solution, checking whether there is a working time overlap within the minimum number of shifts above and below. If an overlap exists, a new solution is generated; otherwise, the current feasible solution is retained.

4. Data Description

To control variables and make the research more targeted, this study selects Zhenjiang Line 3 as a typical research subject among the 72 bus lines in Zhenjiang City, Jiangsu Province, as shown in the Figures 3 and 4. This line is approximately 13,500 m long, with consistent routes for both directions and does not pass through any tunnels or other low-signal areas. Additionally, it has sufficient departure frequencies, which is conducive to data analysis and error control.

This study collected 112,000 bus warning data from November 2020 to February 2021 on Bus Route 3 in Zhenjiang City. It quantitatively evaluated the driving safety of 24 drivers on this route in different working environments. The driver scheduling plan for the week of 7 December to 13 December 2020 was selected as the analysis instance.

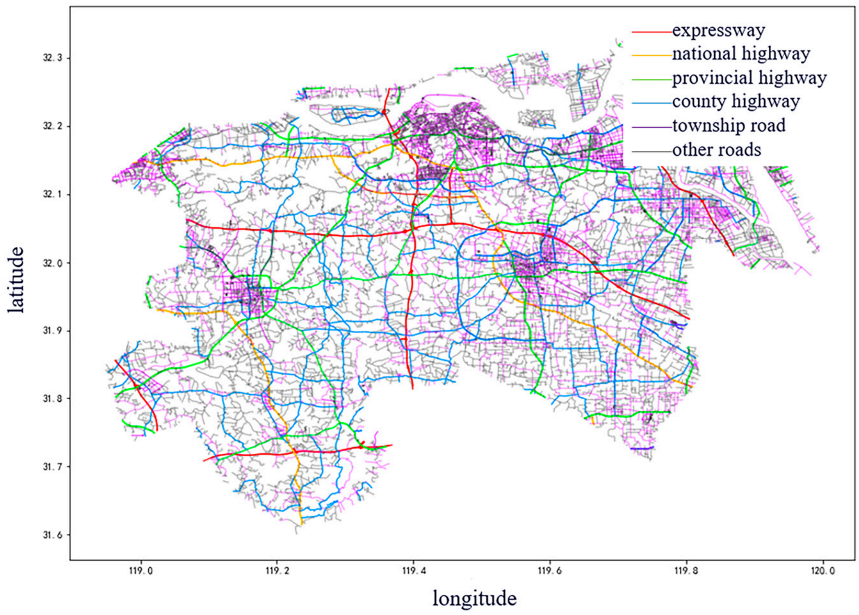

Figure 3. Zhenjiang road data map.

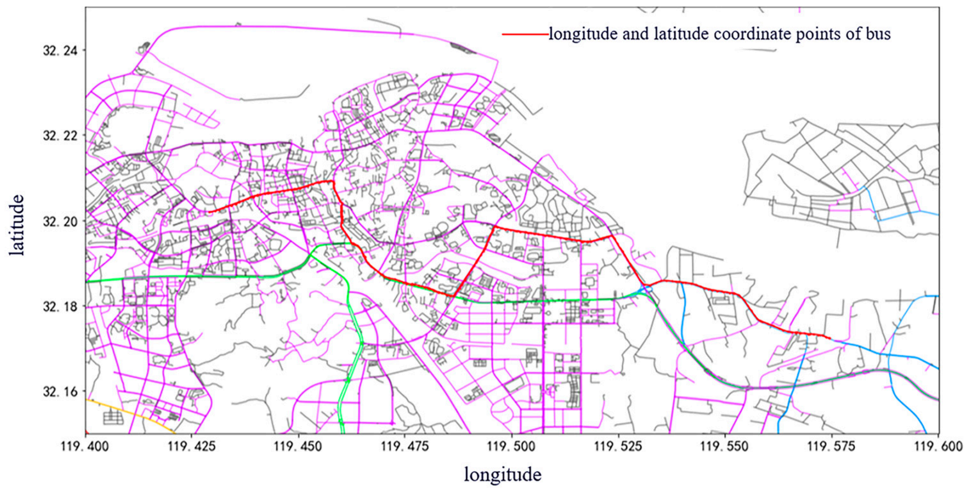

Figure 4. Route map of Zhenjiang bus line 3.

The bus driver scheduling data records information such as the route, bus vehicle, actual departure time, and actual arrival time of the drivers' work. A sample of the driver scheduling data is shown in Table 1.

Table 1. Bus driver scheduling data.

Date	Route ID	Vehicle ID	Driver ID	Departure Time	Arrival Time
8 December 2020	31	37007	3698	5:40:11	6:27:34
8 December 2020	31	37015	3632	5:40:40	6:33:44
8 December 2020	31	37008	3828	5:50:05	6:35:04
8 December 2020	31	37004	3664	5:50:35	6:39:33
8 December 2020	31	37013	3506	6:00:25	6:48:33
8 December 2020	31	37009	3688	6:01:17	6:50:25
8 December 2020	31	35513	3700	6:10:07	6:57:49

This paper obtained real-time weather data for the Zhenjiang area through the open-source API interface [35] of the Hefeng Weather website. This website can record over

60 types of weather conditions in real time, along with information such as temperature, humidity, wind force, precipitation, and visibility. A sample of the weather data is shown in Table 2.

Table 2. Weather data.

Time	Weather	Temperature (°C)	Wind Force (Scale)	Wind Speed (m/s)	Humidity (%)	Rainfall (mm)	Visibility (km)
12:00:30	Rain	6	5	30	93	1.6	8
13:00:28	Rain	5	5	29	93	1.2	12
14:00:26	Rain	4	5	35	90	0.5	12
15:00:27	Snow	3	5	31	93	0.8	3
16:00:28	Snow	3	7	61	94	1.1	4
17:00:30	Snow	1	7	53	93	0.8	3
18:00:30	Snow	3	4	27	75	8.4	2
19:00:30	Snow	−1	5	30	93	0.6	2

Vehicle alarm data are collected by the auxiliary warning system installed on public transit buses. This system consists of multiple components, including forward short-wave radar and GPS positioning terminals, and is capable of issuing alerts for vehicle anomalies, such as forward collisions and deviation from the intended route. A sample of the alarm data collected by the public transit warning system is shown in Table 3.

Table 3. Alarm data from bus vehicle onboard warning equipment.

Time	Lon	Lat	Driver ID	Vehicle ID	Line ID	Alarm Type
7:00:10	119.55196	32.182868	3791	37006	31	Forward collision
7:17:50	119.480024	32.18325	3664	37015	31	Forward collision
7:40:09	119.541976	32.185138	3688	35504	31	Lane Departure
8:24:13	119.488928	32.185848	3664	37015	31	Lane Departure
9:07:52	119.472816	32.185544	3069	35515	31	Lane Departure
9:37:27	119.461704	32.195846	3772	35516	31	Forward collision

The scheduling table was optimized and reconstructed, with model parameter calibration values as shown in Table 4.

Table 4. Calibration of model parameters.

Symbol	Meaning	Value Range	Calibration Value
θ	fairness tolerance/shift	[0, 5/T]	1
φ	balance tolerance/1	[0.18, 0.22]	0.2
p_1	row exchange probability/1	[0, 1)	0.4
p_2	column exchange probability/1	[0, 1)	0.4
p_3	mutation probability/1	[0, 1)	0.2
U	number of rows in scheduling table/shift	--	96
L	minimum sequential shifts/shift	--	4
T_0	initial temperature/degree	--	1000
α	temperature decay coefficient/1	[0.9, 1)	0.98

5. Results

The bus company aims to enhance driver safety by assessing driving risks under different extreme weather and driving periods. This is to prevent bus accidents caused by scheduling factors, so three performance measures were utilized in this study, as follows:

1. Calculation of bus driver risk indicators: assessing driving risks for each bus driver under different conditions, particularly focusing on extreme weather situations and driving periods that warrant attention.

2. Individual safety variation of drivers: comparing the safety levels of individual bus drivers between the original scheduling plan and the optimized scheduling plan to measure the extent of improvement in individual safety values.
3. Overall change in bus operation safety: comparing the overall safety levels between the original scheduling plan and the optimized scheduling plan to evaluate the extent of improvement in system safety values.

5.1. Driver Safety Assessment

Based on historical bus warning data, a quantitative evaluation of bus driver safety under different adverse weather and traffic time periods was conducted. A safety assessment database for each driver in different driving environments was established, as shown in Table 5. It can be observed that the safety of driving behavior fluctuates for the same driver under different driving environments, indicating significant variations in individual drivers' sensitivity to different conditions.

Table 5. Safety database for each driver under different driving environments.

UID	W_1P_1	W_1P_2	W_1P_3	W_2P_1	W_2P_2	W_2P_3	W_3P_1	W_3P_2	W_3P_3	W_4P_1	W_4P_2	W_4P_3
01	81.82	75.77	81.96	86.57	78.09	86.34	85.59	75.46	85.42	83.07	76.82	83.14
02	71.14	72.63	79.52	72.00	73.91	83.08	67.63	70.41	81.49	72.16	73.62	80.64
03	73.57	69.61	74.44	81.93	75.91	82.34	79.88	72.83	80.59	82.02	77.41	82.33
04	84.26	85.86	88.47	83.68	85.86	89.34	82.04	84.85	89.05	93.27	94.27	96.94
05	34.08	30.06	35.92	72.55	63.72	71.56	68.31	58.12	67.58	84.16	76.6	82.61
06	65.16	65.06	70.89	67.04	66.73	74.5	61.52	61.74	71.13	66.36	66.16	72.12

Comparing the weights of acceleration risk and deceleration risk, it is evident that the weight of acceleration risk for bus drivers is generally higher than the corresponding weight of deceleration risk. This indicates significant differences in acceleration risk among drivers, warranting closer attention. When comparing the weights of indicators for different weather conditions and time periods, it can be observed that the weights for each time period are relatively high and similar. Regarding the weights for different weather conditions, those for low temperature and low visibility are higher, suggesting that these two weather conditions may lead to sudden incidents and should be given more attention.

5.2. Enhancing Safety Through Driver Scheduling Optimization

Using Formula (2) to calculate the quantitative indicators of driving safety for each bus driver and analyzing the assessment values of driving safety before and after scheduling optimization, the results are shown in Figure 5. It can be seen that the safety scores of all 24 drivers have been improved to varying degrees after optimization. Especially for drivers with lower safety scores, the improvement is more significant. For drivers with original safety scores below 75, the average safety has increased by 11.08 after scheduling optimization. However, for drivers with original safety scores exceeding 80, the safety indicators have only increased by 1 to 3 after optimization. This indicates that the model prioritizes matching drivers with lower safety scores to driving conditions that suit them, thereby reducing the occurrence of extreme safety accidents.

For further analysis of the optimization results, Table 6 shows the main indicators of overall driver safety. After optimization, the overall safety of bus operations has increased by 7.22%. The minimum safety value has risen from 38.80 to 62.07, and the standard deviation of safety assessment values has decreased by 33.76%. Overall, the safety of the bus scheduling plan has been effectively improved and significantly enhanced.

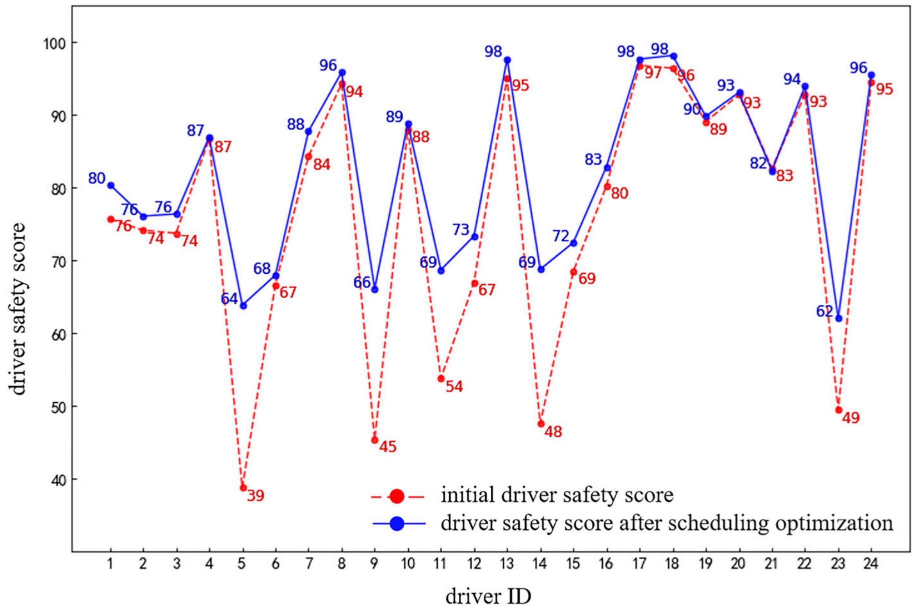

Figure 5. Comparison of safety evaluation values of each driver.

Table 6. Comparison of the overall safety evaluation values of bus operation.

	Mean	Standard Deviation	Maximum Value	Minimum Value
Before optimization	76.46	17.77	96.83	38.80
After optimization	81.98	11.77	98.21	62.07
Difference	5.52	−6.00	1.38	23.27
Rate of Change	7.22%	−33.76%	1.43%	59.97%

It is evident that after optimization, the overall safety of bus operations has improved by 7.22%, which translates to a reduction of approximately 264 instances of abnormal speed changes per hour across the entire route, resulting in a total reduction of 44,352 instances per week. The standard deviation of the scores decreased by 6 points, indicating a more balanced overall safety level among drivers and a more reasonable scheduling scheme. The increase in the maximum score is relatively small at 1.43%, which may be due to the limited optimization scope caused by the presence of high scores in the original schedule. The minimum score has increased from 38.80 to 62.07, indicating a significant improvement in the safety of low-scored chains, thereby reducing bus safety incidents.

Table 7 presents the drivers' working sequences before and after the shift scheduling optimization on 7 December 2020. This scheduling result can fulfill all the constraint conditions mentioned previously and can automatically generate a shift scheduling plan oriented towards bus operation safety. Figure 6 displays the changes in safety for each shift chain before and after the scheduling. It can be observed from the figure that the overall safety has increased from 75.5 to 86.1 after the optimization, with a significant improvement in the safety of low-safety shift chains; however, there is also a slight decrease in the safety corresponding to some shift chains. This indicates that due to the limited number of available drivers, it is not possible to ensure an increase in safety for all shift chains. Nevertheless, to guarantee the individual safety and risk balance among drivers, it is necessary to control the damage caused by individual safety reductions through penalty terms.

Table 7. Driver scheduling sequence.

Status	Shift Chain Sequence	Overall Safety
Before optimization	16→8→13→18→22→4→3→15→19→20→21→10→14→23→9→11→1→5→12→7→17→24→2→6	75.5
After optimization	3→11→5→14→9→23→2→20→6→16→10→4→18→17→13→8→22→16→18→4→19→20→13→24	86.1

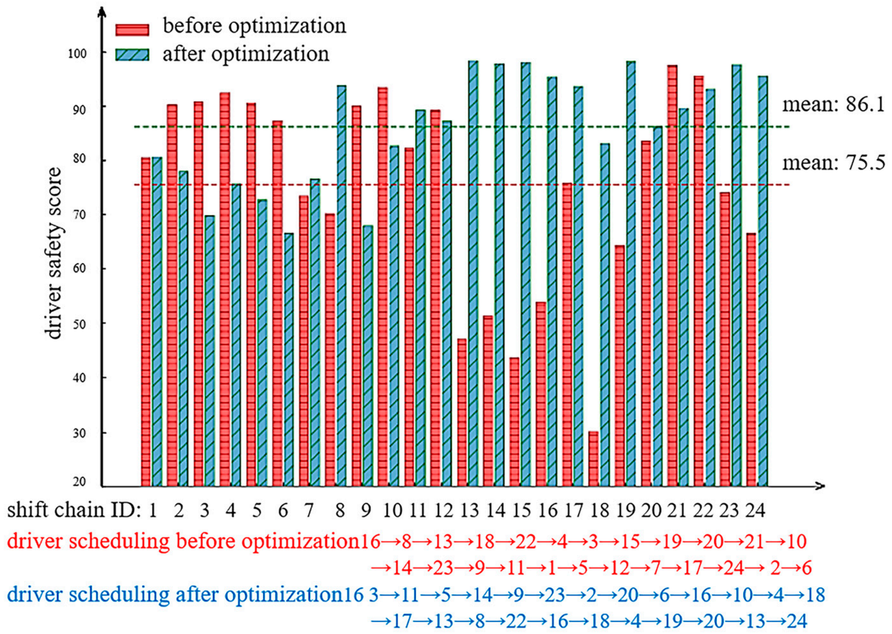

Figure 6. Comparison of safety evaluation values of each shift chain**.**

It can be observed that there is a significant adjustment in the scheduling order after optimization. The safety assessment mean value for all drivers in this shift increased from 75.5 to 86.1, indicating that the model has good global optimization capabilities. After optimization, the overall safety of shift chains with a safety score mean value below 60 increased by more than 40%. For some shift chains with safety scores exceeding 80, there was a slight decrease in safety scores after optimization. This suggests that while optimizing overall safety, the model may increase the risk level of some shift chains, but this can be controlled through the model's risk balance tolerance parameter.

6. Discussion

The article aims to reduce bus operational risks, enhance the safety of bus operations, optimize scheduling and dispatch plans, and save operational and maintenance costs. It focuses on cutting-edge research on the safety issues of bus operations. Based on relevant research progress at home and abroad, as well as the analysis of urban bus operational safety needs, it comprehensively explores and analyzes multisource data, such as bus trajectory, alarms, and weather. With the goal of improving bus operational safety, the article reconstructs the scheduling plan with the risk characteristics of drivers in their actual work as constraints. Through the identification and proactive management of bus operational risks, it aims to reduce potential safety hazards, enhance safety levels, and promote the development of bus operation management towards a more information-intensive and intelligent direction, but there are still shortcomings that need further improvement in future research. The improvements in future research can be made in several aspects:

(1) This paper only considers weather and traffic periods as influencing factors in the study of drivers' abnormal behaviors. However, in reality, drivers' abnormalities are

closely related to their physiological and psychological states, as well as current decisions. Subsequent research will comprehensively consider the influence characteristics of various factors to further optimize and improve the model.

(2) The optimization of driver scheduling presented in this paper is only the analytical result of theoretical modeling. Reconstructing the driver scheduling may disrupt the original work patterns of drivers, leading to new changes in driving characteristics. Subsequent research will further verify and analyze the application model to enhance its feasibility in practical applications.

7. Summary

This paper investigates the safety-oriented optimization problem in bus operations. Firstly, based on historical bus warning data, the individual driving risk differences of bus drivers in different environments are quantitatively evaluated. Then, with the optimization goal of improving bus operation safety, the scheduling table is reconstructed, considering the risk characteristics of drivers in real-world work as constraints. Finally, a quasi-Newton algorithm with an improved simulated annealing approach is designed and applied to presolve the target problem and find an approximate optimal solution. Results from the case study indicate that the optimization in the first four iterations accounts for 95% of the overall optimization, demonstrating strong reconstruction performance and good convergence of the scheduling optimization model. After optimization, the overall safety of bus operations has increased by 7.22%, and the standard deviation of safety assessment values has decreased by 33.76%. Moreover, shift chains with higher risk have seen a safety improvement of over 40%, showing that the proposed safety optimization method effectively enhances the overall safety and risk balance of bus operations.

The findings of this study can be used to evaluate the driving risks of drivers in extreme weather and special time periods, assist government departments and public transportation companies in optimizing the scheduling of bus drivers from the perspective of safe operation, coordinate resource allocation, and assign appropriate working hours and working times for drivers, in order to reduce the safety hazards of public transportation operation and improve service quality.

However, this study mainly focuses on all drivers on a single bus route, optimizing scheduling combinations from the perspective of improving driving safety. It lacks consideration of the entire bus network in a coordinated manner, future research will further explore this aspect.

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