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Automatic Scheduling Method for Customs Inspection Vehicle Relocation Based on Automotive Electronic Identification and Biometric Recognition

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Abstract: This study presents an innovative automatic scheduling method for the relocation of customs inspection vehicles, leveraging Vehicle Electronic Identification (EVI) and biometric recognition technologies. With the expansion of global trade, customs authorities face increasing pressure to enhance logistics efficiency. Traditional vehicle scheduling often relies on manual processes and simplistic algorithms, resulting in prolonged waiting times and inefficient resource allocation. This research addresses these challenges by integrating EVI and biometric systems into a comprehensive framework aimed at improving vehicle scheduling. The proposed method utilizes genetic algorithms and intelligent optimization techniques to dynamically allocate resources and prioritize vehicle movements based on real-time data. EVI technology facilitates rapid identification of vehicles entering customs facilities, while biometric recognition ensures that only authorized personnel can operate specific vehicles. This dual-layered approach enhances security and streamlines the inspection process, significantly reducing delays. A thorough analysis of the existing literature on customs vehicle scheduling identifies key limitations in current methodologies. The automatic scheduling algorithm is detailed, encompassing vehicle prioritization criteria, dynamic path planning, and real-time driver assignment. The genetic algorithm framework allows for adaptive responses to varying operational conditions. Extensive simulations using real-world data from customs operations validate the effectiveness of the proposed method. Results indicate a significant reduction in vehicle waiting times—up to 30%—and an increase in resource utilization rates by approximately 25%. These findings demonstrate the potential of integrating EVI and biometric technologies to transform customs logistics management. Additionally, a comparison against state-of-the-art scheduling algorithms, such as NSGA-II and MOEA/D, reveals superior efficiency and adaptability. This research not only addresses pressing challenges faced by customs authorities but also contributes to optimizing logistics operations more broadly. In conclusion, the automatic scheduling method presented represents a significant advancement in customs logistics, providing a robust solution for managing complex vehicle scheduling scenarios. Future research directions will focus on refining the algorithm to handle peak traffic periods and exploring predictive analytics for enhanced scheduling optimization. Advancements in the intersection of technology and logistics aim to support more efficient and secure customs operations globally.

Keywords: automotive electronic identification; biometric recognition; customs vehicle relocation; automatic scheduling; dynamic resource allocation

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1. Introduction

With the continuous growth of global trade, customs authorities face increasing pressure to enhance the efficiency of vehicle inspection and management processes. Traditional scheduling methods often rely on manual operations and simplistic algorithms, leading to prolonged vehicle waiting times, inefficient resource allocation, and overall operational delays. As customs operations grow in complexity, innovative solutions are urgently needed to streamline these processes, resulting in long vehicle waiting times, low scheduling efficiency, and wasted resources. In recent years, To solve these problems, automatic scheduling technology and intelligent scheduling algorithms have been extensively studied and applied, providing new solutions for customs vehicle management [1–3]. However, most of these approaches remain in the simulation testing phase.

The development of automatic scheduling methods has primarily focused on optimizing scheduling algorithms and improving scheduling efficiency. Traditional methods, such as First-Come, First-Served (FCFS) and heuristic algorithms, have been gradually replaced by automated scheduling approaches utilizing artificial intelligence and machine learning technologies [4–6]. Recent advancements in vehicle scheduling, particularly those incorporating deep reinforcement learning, have significantly enhanced scheduling efficiency and system adaptability, although they remain constrained by the operational rules of the research subjects [7]. Additionally, multi-objective optimization algorithms, such as Genetic Algorithms (GA), Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO), have been widely used in complex vehicle scheduling problems [8–10]. These algorithms optimize scheduling optimization by comprehensively considering various constraints (e.g., vehicle arrival time, priority, yard capacity), significantly improving scheduling efficiency and reducing both vehicle waiting time and yard resource occupancy. Automatic scheduling is crucial in addressing these challenges. By leveraging advanced technologies, customs can optimize vehicle relocation and inspection processes, thereby significantly reducing waiting times and enhancing resource utilization. The integration of Vehicle Electronic Identification (EVI) and biometric recognition technologies represents a novel approach to achieving these objectives. This method not only enhances the accuracy of vehicle identification but also improves security by ensuring that only authorized personnel can operate specific vehicles.

Significant progress has been made in automatic scheduling technology for customs vehicle relocation. A blockchain-based EVI solution has been proposed to enhance the security and transparency of vehicle identification systems [11]. Scheduling methods that combine EVI technology with biometric recognition technology have emerged as a research hotspot. EVI technology enables real-time vehicle identification and positioning via RFID or OBU, while biometric recognition technology is used for driver identity verification and access management [12–14]. The synergy of these technologies improves the automation in vehicle scheduling and enhances the security and reliability of the management system. In practice, many customs and logistics parks have gradually implemented automatic scheduling systems to address increasingly complex vehicle scheduling needs. For instance, intelligent scheduling systems based on EVI and biometric recognition technology have demonstrated effectiveness at several large ports, effectively reducing manual intervention and improving scheduling accuracy [15,16]. These systems automate scheduling processes, enhance accuracy, and effectively manage high volumes of vehicle entry and exit during peak periods.

Research on automatic scheduling methods for customs vehicle relocation has increasingly focused on effectively combining EVI technology, biometric recognition technology, and multi-objective optimization algorithms [17–19]. Roberts et al. proposed a hybrid optimization algorithm that integrates genetic algorithms and deep learning technologies to improve scheduling robustness in complex environments [20]. Furthermore, blockchain-based scheduling methods have also begun to be utilized in customs settings, enhancing both security and transparency in the scheduling process [21]. Simulations and real-world application indicate that these methods can significantly enhance the scheduling efficiency of customs inspection vehicles [22–25].

This research is motivated by the identified gaps in current methodologies, particularly the lack of effective automated solutions that can adapt to the dynamic nature of customs operations. While various studies have explored scheduling techniques, few have comprehensively integrated EVI and biometric systems into a cohesive framework. This research aims to address this gap by developing an automatic scheduling method that leverages these technologies to enhance logistics management efficiency.

The problem statement for this study is as follows: how can we develop an effective automatic scheduling method for relocating customs inspection vehicles that optimizes resource allocation while significantly reducing vehicle waiting times? The objective is to propose a solution that enhances the operational efficiency in customs management within a rapidly evolving trade environment. To effectively address the challenges of driver and inspection vehicle identification, this study proposes an automatic scheduling method based on EVI and biometric recognition technology, considering factors such as vehicle arrival time, priority, and yard capacity. By employing genetic algorithms for multi-objective optimization, the method aims to tackle complex vehicle scheduling issues, achieve dynamic scheduling and optimal path planning, and ultimately improve scheduling efficiency and reduce vehicle waiting times.

The structure of this study is as follows: Section 2 reviews the relevant literature, highlighting existing approaches and contributions. Section 3 outlines the methodology, providing a detailed description of the proposed scheduling algorithm and its implementation. Section 4 presents experimental results, demonstrating the effectiveness of the method and comparing it to state-of-the-art solutions. Finally, Section 5 concludes the study and discusses future research directions.

2. Vehicle and Driver Identification Methods

2.1. Application of Vehicle Electronic Identification in Customs Inspection Vehicle Identification

In modern customs management, efficient and accurate vehicle identification is crucial for improving work efficiency and ensuring security. Vehicle Electronic Identification (EVI) technology has emerged as an essential tool for addressing the shortcomings of traditional identification methods.

EVI technology comprises two core components: Radio Frequency Identification (RFID) tags and On-Board Units (OBUs). RFID tags are small devices embedded with microchips and antennas that transmit data via radio frequency signals. OBUs are installed on vehicles that communicate with customs systems in real-time through gantries or roadside reading and writing devices [2]. EVI technology enables automatic vehicle identification without manual intervention, quickly transmitting information to readers through radio waves [7]. Additionally, to ensure data security during transmission, RFID systems transmit vehicle information to a central database through a wireless communication link. To ensure data security during transmission, RFID systems send vehicle information to a central database via a wireless link, employing encryption technology to prevent unauthorized access and tampering [22]. Additionally, data transmission includes integrity checks and error correction to maintain information accuracy [18]. In the central database, vehicle information is matched against system records for identity verification. The system can detect anomalies in real-time, and provide decision support through data analysis. For instance, if vehicle information does not meet expectations, the system automatically triggers an alarm to alert customs personnel for further inspection [23]. Moreover, system integration technology facilitates seamless collaboration among RFID readers, OBUs, and central databases, enhancing identification and scheduling efficiency [3].

The vehicle data collection method using EVI involves installing comprehensive sensing stations at critical locations, such as key intersections, parking lot entrances and exits, inspection laboratory entrances, and roll-on/roll-off ship loading and unloading points. Induction loops are installed 15 m from these key locations to detect vehicles passing by, while gantries equipped with vehicle recognition devices are set up 15 m from the loops for automatic license plate recognition. EVI technology allows antenna on the gantry to read the information from vehicles equipped with electronic tags. When a vehicle triggers the induction loop, it sends two signals: one to the high-definition video camera and another to the EVI antenna reader, capturing the license plate and reading the EVI information simultaneously. The collected data are then uploaded to the integrated sensing's processing computer for further analysis.

The integrated sensing station system comprises a license plate recognition system and an EVI reading and writing system. This comprehensive deployment enables efficient data collection, verification, transmission, and processing in practical applications. By strategically selecting monitoring locations for gantry installation, placing induction loops 15 m away, and equipping gantries with EVI antennas, HD cameras, and supplemental lighting, the system ensures effective data capture. The EVI antennas connect to the EVI reader and writer controller via cables, while the cameras interface with the front-end computer or switch through a network.

2.2. Application of Biometric Recognition Technology in Driver Identification for Customs Inspection Vehicles

The application of biometric recognition technology in driver identification for customs inspection vehicles significantly enhances the security and efficiency of identity verification. This study employs a multi-modal recognition approach, incorporating three modalities: facial recognition (for identity recognition) [26], fingerprint recognition (for identity recognition) [27], and behavior recognition (for determining responsibility for vehicle damage during relocation) [28]. By fusing these characteristics, the accuracy of identity verification and overall system security can be significantly improved. The multi-modal recognition method leverages the complementary nature of different biometric features to enhance the system's comprehensive recognition capability, thus providing more reliable identity verification services. This study uses an adaptive spatial feature fusion method for data integration, focusing on the adaptively learning the fusion spatial weights of each scale feature map. The main steps of this method are as follows:

Step 1: Adaptive fusion.

The vector at the spatial position (i, j) after data fusion is a weighted fusion of the vectors at the same position across the three feature maps prior to fusion. The fusion coefficients are adaptively learned by the network and shared among all channels. Let $x_{ij}^{n\to l}$ denote the feature vector at the location (i, j) adjusted from level n to level l, and the fusion method of the level l features is expressed as below:

$$y_{ij}^{l} = \alpha_{ij}^{l} \cdot x_{ij}^{1\to l} + \beta_{ij}^{l} \cdot x_{ij}^{2\to l} + \gamma_{ij}^{l} \cdot x_{ij}^{3\to l} \quad (1)$$

where $1 \to l$, $2 \to l$, $3 \to l$ are the feature maps obtained through 1×1 convolution, allowing them to be learned via standard backpropagation, that is, $\alpha_{ij}^{l} + \beta_{ij}^{l} + \gamma_{ij}^{l} = 1$ and $\alpha_{ij}^{l}, \beta_{ij}^{l}, \gamma_{ij}^{l} \in [0, 1]$. The spatial importance weights of the three different levels to level l are $\alpha_{ij}^{l} = \frac{e^{\lambda_{\alpha_{ij}}^{l}}}{e^{\lambda_{\alpha_{ij}}^{l}} + e^{\lambda_{\beta_{ij}}^{l}} + e^{\lambda_{\gamma_{ij}}^{l}}}$, $\beta_{ij}^{l} = \frac{e^{\lambda_{\beta_{ij}}^{l}}}{e^{\lambda_{\alpha_{ij}}^{l}} + e^{\lambda_{\beta_{ij}}^{l}} + e^{\lambda_{\gamma_{ij}}^{l}}}$, and $\gamma_{ij}^{l} = \frac{e^{\lambda_{\gamma_{ij}}^{l}}}{e^{\lambda_{\alpha_{ij}}^{l}} + e^{\lambda_{\beta_{ij}}^{l}} + e^{\lambda_{\gamma_{ij}}^{l}}}$, respectively, which are computed as control parameters.

Step 2: Deep learning optimization.

A deep neural network is employed to further learn and optimize the fused features, enhancing recognition accuracy [29]. This study utilizes feature concatenation and fusion [30], along with an attention mechanism [31], to design a multi-modal deep network architecture that integrates hybrid convolutional and recurrent networks for processing diverse modal data [32]. Ultimately, the prediction results of multiple deep learning models are combined, leveraging the strengths of different models to improve overall recognition performance [33].

Step 3: Text output.

Following feature fusion and the extraction of non-text data, such as internal and external traffic conditions and driver expression information, the continuous nature of the time-aligned data allows for the establishment of a complete monitoring data chain through data sequence synchronization. This synchronization ensures that time-aligned data streams from different sources are integrated and analyzed cohesively. By doing so, the system can accurately reflect real-time conditions and provide continuous monitoring, offering a comprehensive view of driving dynamics, potential hazards, and driver states to improve decision-making in autonomous systems.

3. Driver-Inspection Vehicle Automatic Scheduling Method

To enhance the efficiency of relocation operations, this study proposes an automatic scheduling method utilizing Vehicle Electronic Identification (EVI) and biometric recognition. This method comprehensively considers the driver's authority, vehicle status, and real-time environmental data to achieve optimal scheduling. The main steps are as follows:

Step 1: Driver identity verification and authority confirmation.

Biometric recognition technology is employed to verify the driver's identity, which is then matched with the corresponding vehicle information. Only verified drivers are granted the authority to operate specific vehicles. This step ensures the safety and legality of the association between drivers and vehicles.

Step 2: Identification and path confirmation of inspection vehicles.

Through EVI and roadside equipment, vehicles awaiting inspection are assigned a temporary identity unique to the authorized timeframe. The optimal relocation path is determined to effectively arrange and utilize the space in the transit area.

Step 3: Combining vehicle status and scheduling requirements.

Once identity verification is completed, the system dynamically matches drivers with vehicles based on their authority and vehicle status to ensure optimal relocation operations. The vehicle status information provided by EVI (e.g., vehicle location, current task status) is integrated with the driver's identity and behavior data to generate a dynamic scheduling plan. This study proposes a multi-objective optimization-based scheduling algorithm that comprehensively considers the following factors:

① Priority of vehicles waiting for inspection: the system automatically generates vehicle priorities based on customs inspection requirements, arrival times, and vehicle types, matching them with suitable drivers.

② Driver idle time and skill matching: the relationship between drivers and vehicles is dynamically adjusted based on the driver's current status, skill level, and historical operation records to ensure optimal resource allocation.

③ Path optimization: utilizing genetic algorithms, dynamic planning of relocation paths minimizes the distance and time required for vehicle movement, thereby enhancing overall scheduling efficiency.

Step 4: Dynamic scheduling.

By thoroughly analyzing the vehicle priorities, current yard status, and the driver's capabilities, the scheduling plan is dynamically adjusted to optimize the relocation paths and reduce waiting times. The scheduling scheme is modified in real-time using multi-objective optimization algorithms. The scheduling scheme considers not only the vehicle's status and location but also the driver's current task status and operational capability, ensuring both efficiency and safety in scheduling. During execution, the system continuously monitors the status of drivers and vehicles to facilitate smooth implementation of the scheduling scheme. In the event of anomalies (e.g., abnormal driver status or changes in vehicle status), information fusion and scheduling adjustments are conducted in real-time. The global view of the proposed solution is shown in Figure 1.

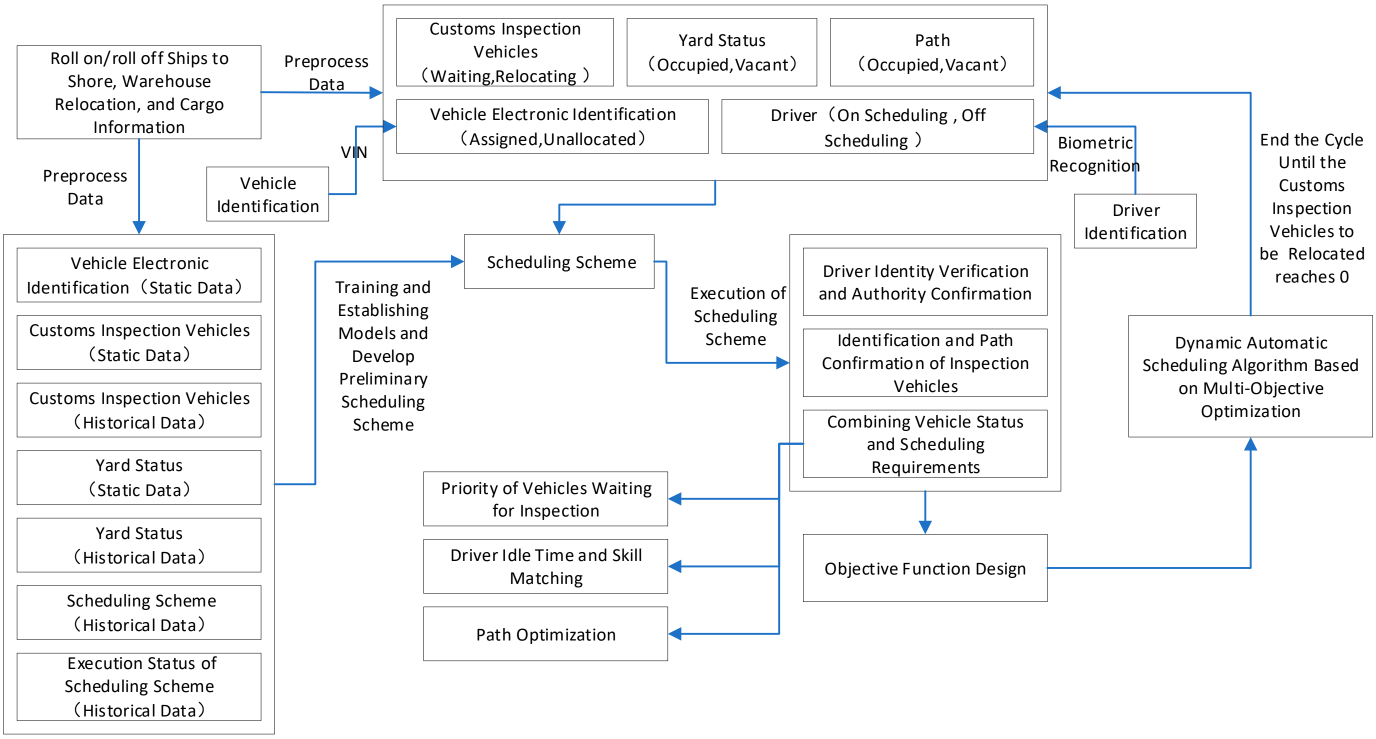


Figure 1. Global view of the proposed solution.

3.1. Objective Function Design

In multi-objective optimization problems, it is necessary to design objective functions that comprehensively consider different goals. Combining the business requirements of relocating customs inspection vehicles, this study defines the following objective functions:

① **Minimizing vehicle waiting time**

The objective is to minimize the total waiting time of vehicles during customs inspection, thereby reducing queuing and waiting times in customs areas and enhancing scheduling efficiency.

The calculation of vehicle waiting time involves two key factors: vehicle arrival time and actual relocation start time. The formula is as follows:

$$f_{wait} = \sum_{i=1}^{N} W_i \tag{2}$$

where W_i is the waiting time of the i-th vehicle.

$$W_i = \max(0, T_{start,i} - T_{arrival,i}) \tag{3}$$

where $T_{start,i}$ is the arrival time of the i-th vehicle at customs, and $T_{arrival,i}$ is the start time of relocation for the i-th vehicle.

To optimize this objective function within a multi-objective framework, primary strategies include improving scheduling methods (thereby reducing idle and waiting times) and introducing priority scheduling for high-priority vehicles to further decrease their waiting times.

② **Minimizing relocation path length**

The objective is to minimize the total path length from the arrival point to the destination yard for all vehicles. The formula for calculating path length D_i is given by the following:

$$D_i = \sum_{j=1}^{M} d_{ij} \tag{4}$$

where d_{ij} is the length of the j-th segment of the path for the i-th vehicle, and M is the total number of segments in the paths. The overall objective function for all vehicle path lengths is defined as the sum of these segment lengths.

To optimize this objective function within a multi-objective framework, strategies primarily include employing the shortest path algorithm to compute the shortest route, along with real-time data adjustment to modify path planning based on current traffic conditions.

③ **Maximizing resource utilization rate**

The objective is to maximize the efficiency of yard and related resource utilization. The formula for calculating resource utilization is as follows:

$$f_{resource} = \frac{1}{M}\sum\nolimits_{k=1}^{M}\frac{U_k}{C_k} \tag{5}$$

where U_k is the actual capacity used by the k-th yard, C_k is the total capacity of the k-th yard, and M is the number of yards.

To optimize this objective function within a multi-objective framework, strategies include dynamic resource allocation (dynamically adjusting yard assignments based on real-time demand) and capacity prediction (utilizing predictive models to estimate future resource needs and adjusting strategies accordingly).

④ **Balancing driver workload**

The objective is to balance the workload of all drivers to ensure equitable workload distribution. The formula for calculating workload L_k is as follows:

$$L_k = \sum\nolimits_{i \in S_k} T_{work,i} \tag{6}$$

where S_k is the work time spent by the k-th driver on vehicle relocation, $T_{work,i}$ is the total finishing time of relocation for the i-th vehicle. The objective function is defined as the difference between the maximum and minimum workload among all drivers, that is,$f_{load} = \max_{1,2,\ldots,K} L_k - \min_{1,2,\ldots,K} L_k$.

To optimize this objective function within a multi-objective framework, methods include workload prediction (using data analysis to forecast workloads and adjust scheduling strategies) and dynamic scheduling (adapting driver task allocation based on actual workload).

⑤ **Minimizing relocation time**

The objective is to minimize the total time from vehicle arrival at customs to the completion of relocation, encompassing parking time, the time drivers take to return to the dispatch point, and other necessary actions to complete all tasks. The total relocation time includes waiting time and actual movement time $T_{total,i}$, defined as follows:

$$T_{total,i} = T_{end,i} - T_{start,i} \tag{7}$$

where $T_{end,i}$ is the time the i-th vehicle completes relocation, and $T_{start,i}$ is the time the i-th vehicle arrives at customs. The objective function $f_{time} = \sum_{i=1}^{N} T_{total,i}$ is defined as the total relocation time for all vehicles.

To optimize this objective function within a multi-objective framework, strategies include optimizing the scheduling sequence (adjusting the order of tasks to reduce overall relocation time) and real-time adjustment (optimizing scheduling strategies based on live data).

⑥ **Minimizing scheduling uncertainty**

The objective is to minimize uncertainties in the scheduling process, such as errors arising from unforeseen events. The measure of scheduling uncertainty σ_i^2 can be calculated using error variance:

$$f_{uncert} = \sum\nolimits_{i=1}^{N} \sigma_i^2 \tag{8}$$

where σ_i^2 is the error variance in the scheduling process for the *i*-th vehicle.

To optimize this objective function within a multi-objective framework, strategies primarily include uncertainty modeling (establishing a model for scheduling uncertainty that can be dynamically adjusted) and redundancy planning (reserving extra resources to manage uncertainties effectively).

⑦ **Minimizing operational costs**

The objective is to minimize overall operational costs, encompassing labor, energy consumption, and maintenance costs. The operational cost is defined as follows:

$$f_{\cos t} = \sum\nolimits_{i=1}^{N} C_i \tag{9}$$

where C_i represents the relocation cost of the *i*-th vehicle, including fuel, labor, maintenance, and parking fees.

To optimize this objective function within a multi-objective framework, strategies mainly include cost control (implementing measures to manage and reduce operational costs) and resource optimization (enhancing resource usage to reduce unnecessary expenses).

⑧ **Optimizing vehicle scheduling consistency**

The objective is to optimize the consistency of scheduling and reduce discrepancies and errors. Scheduling consistency can be generally calculated by comparing the planned scheduling time and actual scheduling time:

$$f_{consistency} = \sum\nolimits_{i=1}^{N} \left| T_{scheduled,i} - T_{actual,i} \right| \tag{10}$$

where $T_{scheduled,i}$ is the planned scheduling time for the *i*-th vehicle, and $T_{actual,i}$ is the actual scheduling time for the *i*-th vehicle.

To optimize this objective function within a multi-objective framework, strategies mainly include consistency checks (establishing mechanisms to minimize scheduling changes) and scheduling optimization (improving scheduling accuracy through refined scheduling algorithms).

⑨ **Additional objective functions**

Additional objective functions include the following:

Maximizing system throughput: this objective aims to maximize the number of vehicles processed per unit time. The system throughput is defined as follows:

$$f_{throughtput} = \frac{1}{f_{total}} \sum\nolimits_{i=1}^{N} Throughput_i \tag{11}$$

where $Throughput_i$ represents the number of vehicles processed, and T_{total} is the total processing time. To optimize this objective function in multi-objective optimization, efficient scheduling algorithms can be employed to increase processing speed and improve system throughput.

Improving system service efficiency: this objective seeks to enhance the overall service capacity by minimizing timeouts or improving processing scheduling efficiency across various scenarios. The system service efficiency is defined as follows:

$$f_{service} = \frac{1}{N} \sum\nolimits_{i=1}^{N} \left(\frac{T_{service,i}}{T_{\max}} \right) \tag{12}$$

where $T_{service,i}$ is the service time of the *i*-th vehicle, and $T_{\max}$ is the maximum allowable service time. Efficient scheduling algorithms can be utilized to accelerate processing and enhance overall system service efficiency.

Enhancing system flexibility and responsiveness: This objective focuses on improving the system's ability to respond to unexpected events and maintain flexibility. System responsiveness is defined as follows:

$$f_{flexibility} = \frac{1}{N}\sum_{i=1}^{N} T_{response,i} \tag{13}$$

where $T_{response,i}$ is the response time for the i-th vehicle under an emergency. To optimize system flexibility and responsiveness, adaptable scheduling strategies can be implemented to effectively manage emergencies, along with predictive and early warning systems to reduce response time.

These objectives are designed to ensure that the system can effectively handle a variety of situations while maintaining high performance across multiple dimensions. By balancing these objectives, the scheduling system can achieve optimal performance in complex, dynamic environments.

3.2. Dynamic Automatic Scheduling Algorithm Based on Multi-Objective Optimization

In managing the relocation of customs inspection vehicles, the scheduling system must optimize multiple objectives simultaneously, including minimizing vehicle waiting time, optimizing relocation paths, maximizing resource utilization, and balancing driver workload. These objectives often conflict, making the pursuit of an optimal balance a central challenge for this algorithm. To address the multi-objective optimization problem, this study adopts a hybrid intelligent optimization algorithm framework that combines the advantages of Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE) algorithms. This combination ensures both a robust global search capability and an effective local optimization capability.

In the dynamic automatic scheduling algorithm based on multi-objective optimization, Pareto selection is employed to identify and maintain a set of solutions that are not strictly dominated by any other solutions across all objectives. Specifically, the algorithm integrates multi-objective optimization techniques with Pareto optimal selection to generate and filter effective scheduling schemes. The specific steps and combinations of the algorithm are outlined as follows:

Step 1: Initial population generation.

The initial population is generated based on random initialization and diversity control [34]. Heuristic generation methods, based on established rules or strategies, are employed to enhance the quality of initial solutions. In vehicle scheduling problems, initial solutions can be derived using known priority rules or simple scheduling strategies, improving the quality and optimizing overall efficiency.

The scheduling problem is represented as the vector $X = [x_1, x_2, \cdots, x_n]$, where each element x_i represents the specific scheduling order of the i-th inspection vehicle. To avoid generating infeasible solutions, an integer encoding method is adopted, with each x_i value range corresponding to the set of possible vehicle sequences [35]. The initial population is generated through random initialization, denoted as $P(0)$. Specifically, the initialization method is:

$$P(0) = \left\{X^1, X^2, \cdots, X^N\right\} \tag{14}$$

where N represents the population size to ensure diversity, X^i represents the i-th individual in the population, and each individual's value on each objective function is calculated, including vehicle allocation, path selection, resource allocation, and driver tasks [36].

To elucidate the operation of the genetic algorithm's operation, it provides a detailed account of chromosomes within the optimization framework. Each chromosome represents a potential solution to the scheduling problem and comprises several key components:

Vehicle priorities: each chromosome encodes the priorities of vehicles waiting for inspection, ensuring that higher-priority vehicles are scheduled first based on their urgency and inspection requirements.

Optimal scheduling path: the chromosome includes a sequence of scheduled actions for each vehicle, detailing the path from the arrival point to the inspection yard, influenced by capacity and vehicle types.

Driver assignments: each chromosome encodes driver assignments for each vehicle, considering driver skills, current workloads, and availability to ensure optimal matching.

Resource allocation: elements indicating the allocation of resources (e.g., inspection lanes and equipment) necessary for processing each vehicle are incorporated into the chromosomes.

Performance metrics: additional components may include fitness scores reflecting the expected performance of the scheduling plan encoded within the chromosome, facilitating the selection process during genetic operations.

By structuring the chromosome in this manner, the genetic algorithm effectively explores a diverse solution space, enabling continuous evolution and enhancement of scheduling efficiency across successive generations.

Step 2: Pareto selection and non-dominated sorting.

The fitness of individuals is evaluated based on the objective functions [37]. Non-dominated sorting is performed on the individuals in the population $P(0)$, assigning different levels of non-dominance to the individuals. The Pareto level of each individual $r(x_i)$ is determined by the number of individuals it dominates, with lower levels indicating a solution closer to the Pareto front.

Level 1: contains all individuals not dominated by any other solution.

Level 2: contains individuals only dominated by solutions in Level 1, and so on.

The roulette wheel selection method is employed to select individuals based on their fitness values, calculated as follows:

$$F(x) = \frac{f(X^i)}{\sum_{j=1}^{N} f(X^j)} = \frac{1}{1 + r(x_i)} \tag{15}$$

where $f(X)$ is the fitness function for an individual and $r(x_i)$ is the rank of an individual x. An elite retention strategy ensures that the current optimal individuals directly progress to the next generation, preventing the loss of optimal solutions.

For each individual on the Pareto front, its crowding distance is calculated to maintain population diversity. The crowding distance $d(x_i)$ is determined by measuring the distance between that individual and its nearest neighbors:

$$d(x_i) = \sum_{j=1}^{m} \left(\frac{f_j(x_{i+1}) - f_j(x_{i-1})}{f_j^{\max} - f_j^{\min}} \right) \tag{16}$$

Step 3: Genetic operations and local search.

Genetic operations, including crossover and mutation operations, are performed, alongside local search strategies, combining Particle Swarm Optimization (PSO) and Differential Evolution (DE) to enhance solution quality [38].

Crossover employs a combination of single-point and multi-point crossover methods, with a crossover probability of p_c. New individuals are generated by the following formula:

$$X^{new} = Cross(X^i, X^j) \tag{17}$$

where X^i and X^j are the parent individuals involved in crossover, and X^{new} is the offspring individual generated [39].

Mutation is achieved by randomly altering one or more genes of an individual to increase diversity, with a mutation probability of p_m. The mutated individual is denoted as follows:

$$X^{mut} = Mutate(X^i) \tag{18}$$

where X^i is the individual undergoing mutation, and X^{mut} is the mutated individual [40].

In the case of single-point crossing, for each pair of parental chromosomes selected for crossing, a random crossing point is chosen. After this point, all genes of one parent are exchanged with the corresponding genes of the other parent. This method promotes the mixing of genetic information while maintaining some structural integrity of chromosomes. For multi-point crossing, after performing single-point crossing, multiple crossover points are selected within the chromosome. The segments between these points are exchanged between the two parents, allowing for greater variation and exploration of the solution space. In the combined strategy, single-point crossover is applied first, followed by multi-point crossover on the offspring generated from the first operation. This two-step process leverages the strengths of both methods, encouraging a broader search for optimal solutions while maintaining convergence. Regarding parameter settings, the crossover probability of both single-point and multi-point methods is uniformly set to 0.8 in this study. This ensures that a sufficient number of offspring inherit diverse features from their parents. By utilizing this combination of crossover methods, the genetic algorithms effectively explore the solution space while preserving high-quality genetic material from the parental chromosomes.

PSO enables each particle to navigate in the solution space while continuously updating its position and velocity to converge on the optimal solution. The position of each particle in the solution space is denoted by d_i, and its velocity is denoted by v_i. The particle's update depends on the individual best position $pbest_i$ and the global best position $gbest_i$. The position and velocity update methods for each particle are given as follows:

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 (pbest_i - x_i(t)) + c_2 r_2 (gbest_i - x_i(t)) \tag{19}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{20}$$

where ω is the inertia weight controlling the influence of the particle's historical velocity; c_1 and c_2 are acceleration constants, typically ranging from 1.5 to 2.5, controlling the speed of the particle approaching the individual best position and global best position; and r_1 and r_2 are random numbers between 0 and 1, used to introduce randomness [41].

In practical applications, multiple objective functions often need to be optimized, which can lead to conflicts among them. PSO can be adapted for multi-objective optimization by employing a non-dominated sorting mechanism to rank particles and select solutions on the Pareto front. The density of particles on this front is evaluated to maintain solution diversity. By integrating PSO with multi-objective optimization techniques, the algorithm effectively preserves a set of non-dominated solutions in each iteration, enhancing the robustness of the search process.

Differential Evolution (DE) is utilized in this study to generate new solutions by leveraging the differences between individuals. This method can be effectively extended to multi-objective optimization problems, enabling the resolution of complex issues with multiple conflicting objectives and facilitating the identification of Pareto optimal solution sets to support decision-making.

In DE, three different individuals are selected for differential operations,

$$v_i(t+1) = x_{r1} + F(x_{r2} - x_{r3}) \tag{21}$$

where F is the scaling factor, typically ranging from 0.5 to 1. After the crossover operation, the new individuals generated are compared with the original individuals, and those exhibiting better fitness are retained for the next generation. The crossover operation is defined as follows:

$$u_i(t+1) = \begin{cases} v_i(t+1), r < CR \\ x_i(t), otherwise \end{cases} \tag{22}$$

where CR is the crossover probability [42], controlling the mixing degree of the mutant vector and the current individual. By comparing the trial vector's fitness with that of the current individual, the algorithm selects the better-performing individuals for the subsequent generation. The DE algorithm concludes based on predefined termination criteria, which may include reaching a maximum number of iterations or achieving the convergence of the objective function.

Step 4: Multi-objective optimization and pareto selection.

Non-dominated sorting and crowding distance metrics are employed to select optimal solutions that form the Pareto front solution set [35]. In multi-objective optimization, each objective function is assigned a specific priority or weights; however, these objectives often conflict with one another. Thus, it is essential to evaluate the performance of all objectives rather than focusing solely on the minimum or maximum value of an individual objective function.

To address multi-objective optimization problems, the Pareto selection method is utilized to assess the relative advantages and disadvantages of different schemes. Specifically, the Pareto front comprises a set of solutions that cannot be dominated by any other solution across all objectives. The selection strategy involves the following:

Non-dominated sorting: For all individuals in the current population, the number of individuals dominated by each one is calculated, and the individuals are ranked based on dominance relationships. The parent population is merged with the new generation population to form a combined population, followed by another round of non-dominated sorting and crowding distance calculations.

Pareto front update: All non-dominated solutions are retained as Pareto optimal solutions, and dominated solutions are discarded. This ensures that the final solution set contains a diversified array of optimal schemes. Specifically, individuals with the lowest non-dominance rank and the highest crowding distance are selected to form a new population for the next iteration.

By integrating multi-objective optimization and Pareto selection, the algorithm generates a diversified Pareto front solution set, providing decision-makers with a variety of options based on actual needs.

Step 5: Termination condition judgment.

The algorithm assesses termination conditions to determine when to stop the optimization process. Termination occurs when either the preset number of iterations is reached or when the convergence criteria are satisfied. Upon meeting these conditions, the final Pareto optimal solution set is generated and outputted for further analysis and decision-making [43].

The algorithm continually checks whether the termination conditions are met, including reaching the maximum number of iterations or satisfying the convergence criteria for the Pareto front. If these conditions are fulfilled, the final Pareto front solution set is output; otherwise, the iteration process continues until one of the conditions is met.

A pseudocode of the proposed algorithms is shown as follows (Algorithm 1):

Algorithm 1: Dynamic Automatic Scheduling Algorithm

```
Input:
    -Vehicle data (EVI, biometric recognition information)
    -Custom inspection criteria
    -Scheduling constraints
    -Vehicle attributes (type, priority, et al.)
    -Resource availability (inspectors, equipment, et al.)
Output:
    -Optimized vehicle scheduling scheme
1. Initialize scheduling parameters
2. Define multi-objective functions:
    2.1 Minimize total wait time
    2.2 Minimize inspection cost
    2.3 Maximize resource utilization
    2.4 Minimize vehicle downtime
    2.5 Minimize the number of inspections per inspector
```

Algorithm 1: *Cont.*

2.6 Maximize the throughput of inspections
2.7 Minimize the variance in inspection times
2.8 Maximize compliance with inspection deadlines
2.9. . .. . .
3. While (vehicles are pending inspection)
3.1 Collect real-time vehicle data
3.2 For each vehicle in the queue:
3.2.1 Evaluate compliance with inspection criteria
3.2.2 Calculate objective function values for each vehicle:
-f1: Total wait time
-f2: Inspection cost
-f3: Resource utilization
-f4: Vehicle downtime
-f5: Inspections per inspector
-f6: Throughput
-f7: Variance in inspection times
-f8: Compliance with deadlines
-f9:. . .. . .
3.3 Apply multi-objective optimization algorithm (e.g., Genetic Algorithm)
3.3.1 Generate new scheduling solutions based on objective functions
3.3.2 Evaluate new solutions against objective functions
3.3.3 Select the best scheduling solution using Pareto dominance
4. Update scheduling plan with selected solution
5. Output the optimized vehicle scheduling scheme

The convergence of the multi-objective optimization algorithm is defined based on the following criteria:

Objective function stability: Monitoring the values of the objective functions over successive iterations. The algorithm is considered to have converged when the improvement in these objective function values falls below a specified threshold (1% change over 10 consecutive iterations). This indicates that the algorithm is no longer making significant progress toward better solutions.

Pareto front consistency: In multi-objective optimization, convergence is also assessed by examining the stability of the Pareto front. If the set of non-dominated solutions remains stable and exhibits minimal variation over several generations, it will think that the algorithm has reached convergence.

Iteration limit: Additionally, a maximum number of iterations for the algorithm will be imposed. If this limit is reached, the algorithm terminates, and the current best solutions are returned, even if the convergence criteria have not been fully met.

Performance metrics: Evaluating convergence not only by the stability of the objective functions and Pareto front but also by tracking key performance metrics such as computational time and resource utilization. A balance between these metrics and convergence indicators is essential to ensure the efficiency of the scheduling solution.

Implementing these criteria can ensure that our algorithm effectively approaches optimal solutions while balancing the trade-offs inherent in multi-objective optimization.

4. Experiments and Analysis

This section presents the experimental design, results, and analysis of the automatic scheduling method for relocating customs inspection vehicles based on Vehicle Electronic Identification (EVI) and biometric recognition. The experiments integrate simulation and real data to assess the effectiveness of the proposed multi-objective optimization scheduling algorithm, focusing on metrics such as vehicle scheduling efficiency, resource utilization, driver workload balance, and other aspects.

4.1. Dataset

To verify the effectiveness of the proposed method, experiments were conducted within a simulated customs logistics scenario. The scenario encompasses multiple vehicles waiting for inspection, alongside yards characterized by various resource constraints such as yard capacity and vehicle type restrictions, as well as dynamic factors, including vehicle arrival times and driver statuses. Vehicle identification is facilitated through EVI technologies, including Radio Frequency Identification (RFID) and On-Board Units (OBU), ensuring real-time vehicle tracking and positioning. Driver identity verification employs multi-modal biometric recognition methods, including facial, fingerprint, and behavior recognition, to ensure accurate identity verification authority management.

The dataset is sourced from the actual operational records of Xinsha Port at Huangpu Customs, including vehicle arrival times, vehicle types, yard information, inspection requirements, and driver information, which provides a comprehensive representation of vehicle movements and inspection processes. It utilized a dataset derived from actual customs operations, capturing vehicle movements and inspection processes over the period of 2020–2023. This dataset serves as a comprehensive representation of the dynamic nature of customs vehicle management. The dataset stored 2,879,256 historical records, which provides detailed records of vehicle entries, inspection requirements, and processing times. This real-world dataset ensures that our findings are grounded in practical applications.

The dataset includes several important features: vehicle types (various categories such as passenger cars, trucks, and specialized vehicles, each with distinct inspection requirements that influence the scheduling process), arrival patterns (detailed records of vehicle arrivals, highlighting peak and off-peak periods, which are critical for evaluating scheduling efficiency and understanding operational challenges), and inspection requirements (information on different inspection protocols that must be followed based on vehicle type and cargo, providing insight into how these requirements impact overall processing times).

The dataset is unique in that it encompasses diverse operational conditions, including the following: variability in traffic volume (the dataset captures variations in traffic volume during different times of the day and week, enabling a thorough analysis of how scheduling strategies can be adapted to changing conditions), resource availability (the dataset records fluctuations in resource availability, such as the number of inspection lanes and available personnel, allowing us to assess how resource constraints affect scheduling decisions), and domain context (this dataset is particularly relevant to customs logistics management, as it reflects the complexities and challenges faced by customs authorities in real-world scenarios. By analyzing these data, we aim to develop solutions that enhance operational efficiency and improve the overall effectiveness of customs inspections. The insights gained from this dataset will inform the algorithm's design, ensuring that it is well-suited to address the specific needs of customs operations).

To simulate various scheduling scenarios, multiple datasets were generated to assess the algorithm's performance under different conditions. These datasets included driver authorization through multi-modal biometric data, comprising facial, fingerprint, and behavioral data, which were used to train deep learning models for efficient driver identity verification and management. Independent variables of the experiment included vehicle arrival time, vehicle type, yard capacity, inspection requirements, and driver workload. Evaluation indicators comprised vehicle waiting time, relocation path length, resource utilization, and driver workload balance, among others.

4.2. Experiments and Application Effect Analysis

After preprocessing the original data obtained from customs, including normalizing EVI data and biometric data, the parameters of the multi-objective optimization algorithm were initialized (e.g., population size, number of iterations, objective weights), and the multi-objective optimization algorithm, based on improved PSO, was applied for dynamic scheduling. The algorithm began by generating an initial population, then iteratively optimizes through the multi-objective evolutionary process to produce the final Pareto optimal solution set. During each iteration, objective function values were calculated based on the requirements of current scenario, which included vehicle waiting time, relocation path length, resource utilization, driver workload balance, relocation time, scheduling uncertainty, vehicle scheduling consistency, system throughput, and other indicators. The population was updated according to the selection strategy. Experimental results, including the values of the objective functions for each generation during the optimization process and the final Pareto front solution set, were collected. These results were compared with benchmark methods to validate the effectiveness of the improved algorithm.

Figure 2 illustrates the Pareto front solution sets under different objective combinations. The results indicate that the proposed multi-objective optimization algorithm can effectively balance multiple objectives. For instance, solutions aimed at reducing vehicle waiting time often resulted in an increase in relocation path length, highlighting the trade-offs between resource utilization and driver workload balance.

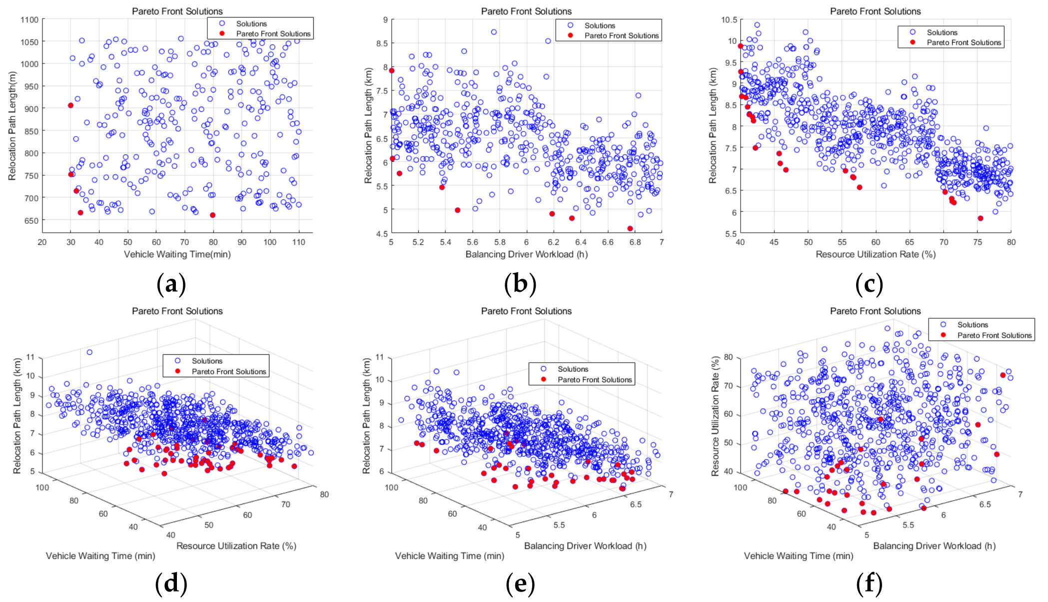


Figure 2. Pareto front solution. (**a**) Pareto Front Solution between Vehicle Waiting Time and Relocation Path Length; (**b**) Pareto Front Solution between Balancing Driver Workload and Relocation Path Length; (**c**) Pareto Front Solution between Resource Utilization Rate and Relocation Path Length; (**d**) Pareto Front Solution between Resource Utilization Rate, Vehicle Waiting Time, and Relocation Path Length; (**e**) Pareto Front Solution between Balancing Driver Workload, Vehicle Waiting Time, and Relocation Path Length; (**f**) Pareto Front Solution between Balancing Driver Workload, Vehicle Waiting Time, and Resource Utilization Rate.

Table 1 shows the results for eight objective indicators in two scenarios based on real business data from a working day in August 2024. It should be noted that the data in the table are the average values of all complete business data for the day, and they have been compared and validated against benchmark methods (manual scheduling algorithms and simple heuristic algorithms).

The distribution of the Pareto front shows that the proposed method achieves a good balance among multiple objectives. The proposed method outperforms the benchmark methods in vehicle waiting time and relocation path length, while also showing excellent performance in resource utilization and driver workload balance. In some solution sets, vehicle waiting time and relocation path length are significantly optimized, while in others, resource utilization and driver workload achieve better balance. These results indicate that the proposed algorithm can flexibly adjust according to actual needs to meet different scheduling requirements.

Table 1. Comparison of objective function values.

No.	Scenario Content	Objective Indicator	Manual Scheduling Algorithm	Simple Heuristic Algorithm	Proposed Method
1	Berth 11 to Parking Lot 2	Vehicle Waiting Time (min)	21.04	19.15	17.59
2		Relocation Path Length (m)	2325.24	2298.25	2017.29
3		Resource Utilization (%)	76.32	78.24	80.41
4		Driver Workload Balance (h) *	1.28	1.18	0.89
5		Relocation Time (min)	38.89	34.28	30.07
6		System Throughput (/h)	328.24	344.28	375.36
7		Scheduling Uncertainty (min)	18.25	17.58	16.38
8		Vehicle Scheduling Consistency (min)	9.24	8.68	8.04
9	Parking Lot 6 to Inspection Lab 1	Vehicle Waiting Time (min)	16.52	15.21	14.21
10		Relocation Path Length (m)	1208.26	1106.32	1028.57
11		Resource Utilization (%)	80.56	83.24	84.29
12		Driver Workload Balance (h) *	0.85	0.78	0.69
13		Relocation Time (min)	24.89	23.92	21.08
14		System Throughput (/h)	369.69	402.98	415.26
15		Scheduling Uncertainty (min)	13.25	12.06	10.88
16		Vehicle Scheduling Consistency (min)	10.85	9.25	8.85

* Calculated as variance of work time.

4.3. Comparison of Algorithm Performance and Analysis

To verify the effectiveness of the proposed multi-objective optimization algorithm for the automatic scheduling method of relocating customs inspection vehicles based on EVI and biometric recognition, a comparative analysis of the convergence performance of various algorithms was conducted. The experimental results demonstrated that, with an increasing number of generations, the multi-objective optimization algorithm converged rapidly, successfully identifying solutions that closely approximated the Pareto optimal set in a short time frame. Notably, the multi-objective optimization algorithm achieved convergence after only tens of iterations, highlighting its efficiency. Figure 3 illustrates the convergence curves of the algorithm under different iteration counts. As shown, the improved PSO algorithm exhibits significant enhancements in both computational efficiency and convergence speed compared to traditional algorithms. The results indicate that the proposed method can effectively balance multiple objectives, optimizing the scheduling process while reducing vehicle waiting times and improving resource utilization.

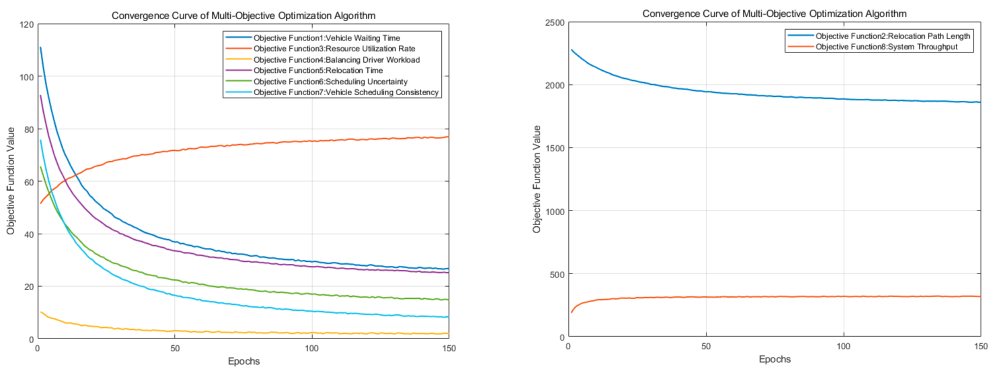


Figure 3. Convergence curve of algorithm proposed.

The proposed multi-objective optimization algorithm exhibits a rapid convergence feature in optimizing vehicle waiting time. In the early iterations, the objective function value drops sharply, indicating that the algorithm can quickly identify better solutions during the initial optimization phase. As the iterations progress, the convergence curve smoothens, approaching the optimal solution, which demonstrates good stability.

Similarly, the convergence curve of the relocation path length also showcases a fast initial convergence speed, marked by a significant decrease in the objective function value during the early iterations. This indicates that the algorithm is effective in reducing vehicle relocation path length. In the subsequent optimization process, the convergence curve maintains a high degree of smoothness without significant fluctuations, underscoring the algorithm's robustness across multiple experimental runs.

The convergence curve for optimizing resource utilization shows the clear advantages of the proposed algorithm during the convergence process. The algorithm rapidly improves resource utilization in the early iterations, demonstrating a strong global search capability. As the number of iterations increases, the proposed algorithm gradually approaches the Pareto front, and the curve stabilizes, indicating a good convergence performance and solution quality.

The convergence curve for optimizing driver workload balance shows a rapid decrease in the objective function value during the initial iterations, signifying the algorithm's ability to find better solutions early on. This decline is steep in the early stage. In the middle iterations, the curve begins to flatten, indicating that the algorithm is progressively approaching the Pareto front, with solution quality steadily improving. At this point, the algorithm has commenced local exploration around high-quality solutions to ensure further optimization. In the late iterations, the convergence curve becomes nearly flat as it approaches the Pareto front, illustrating the superiority and stability of the solution. Across multiple experimental runs, the solution quality remains concentrated in the optimal region, showing good robustness. The advantages of the proposed algorithm in optimizing driver workload balance are evident through rapid initial convergence, minimal oscillation during iterations, a high final solution quality, and a concentrated solution distribution. These characteristics collectively demonstrate the effectiveness of the proposed algorithm in tackling complex multi-objective optimization problems.

To validate the effectiveness of the proposed multi-objective optimization algorithm for the automatic scheduling method of customs inspection vehicles based on VEI and biometric recognition, an experimental analysis of the convergence performance of various algorithms was conducted. The same training and testing samples were used, and the results of the first 150 iterations were selected to display the convergence curves of the proposed algorithm and classical algorithms (NSGA-II, MOEA/D) under different objective functions, as shown in Figure 4.

As shown in Figure 4a, the proposed algorithm exhibits rapid convergence characteristics in optimizing vehicle waiting time (Objective 1). In the first 50 iterations, the algorithm's objective function value decreases rapidly, indicating that it can quickly find better solutions in the early stages of optimization. In contrast, the NSGA-II and MOEA/D algorithms converge more slowly with the same number of iterations, as their objective function values decrease more gradually, suggesting a lower search efficiency in the initial phase. In subsequent iterations (from the 50th to the 150th), the convergence curve of the proposed algorithm becomes smoother and approaches the optimal solution, demonstrating good stability. NSGA-II experiences some oscillation in the later iterations, indicating fluctuations in solution quality during the optimization process, while the convergence curve of MOEA/D remains relatively stable, but its final solution quality is lower than that of the proposed algorithm.

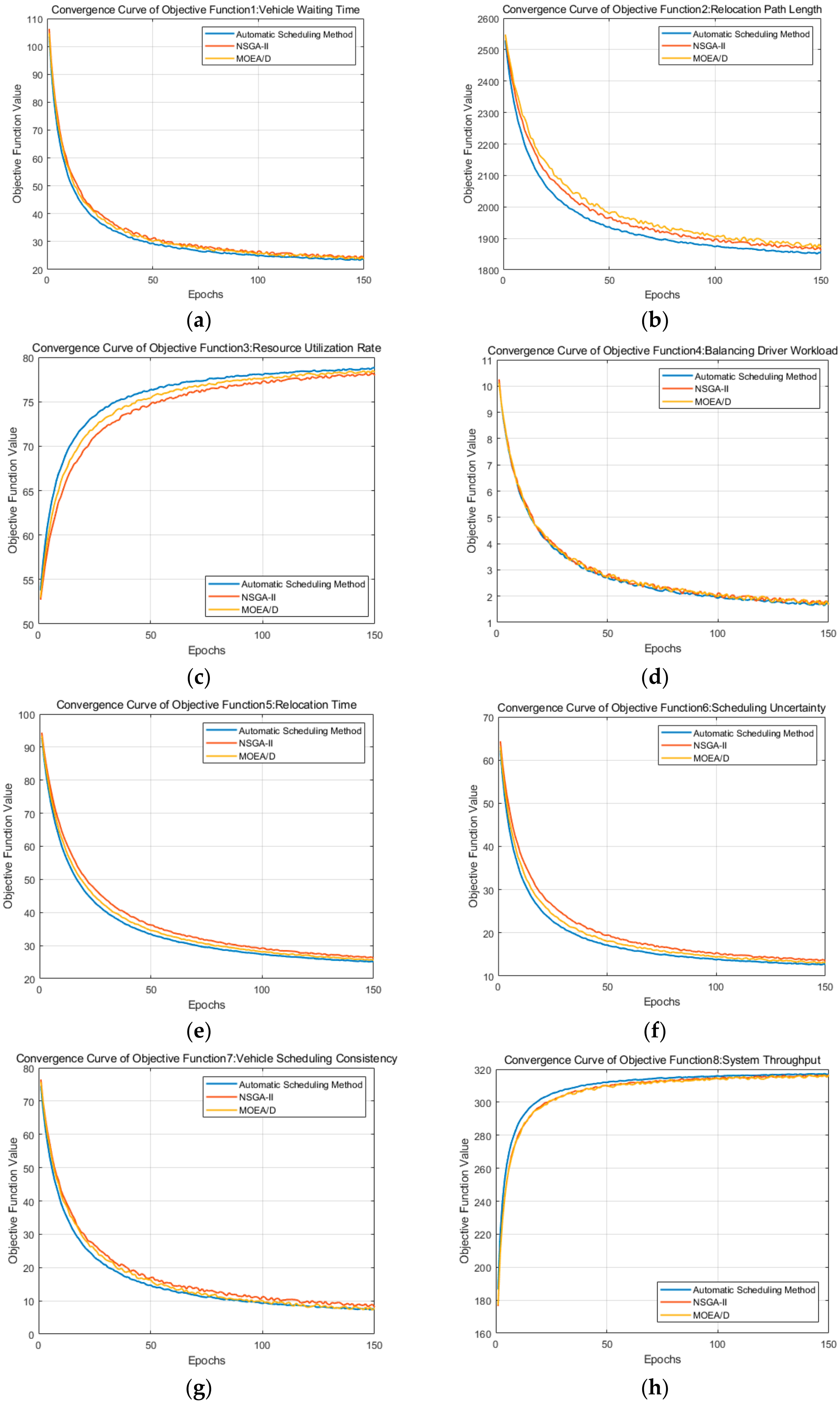


Figure 4. (**a**) Convergence curve of objective Function 1. (**b**) Convergence curve of objective Function 2. (**c**) Convergence curve of objective Function 3. (**d**) Convergence curve of objective Function 4. (**e**) Convergence curve of objective Function 5. (**f**) Convergence curve of objective Function 6. (**g**) Convergence curve of objective Function 7. (**h**) Convergence curve of objective Function 8.

Figure 4b displays the convergence performance of different algorithms in optimizing relocation path length (Objective 2). Compared to other algorithms, the proposed algorithm also shows a fast convergence speed in the initial phase, with the objective function value sharply decreasing in the first 70 iterations, indicating its effectiveness in reducing vehicle relocation path length. In the subsequent optimization process, the convergence curve of the proposed algorithm continues to exhibit high smoothness without significant fluctuations, demonstrating robust performance across multiple experimental runs. In contrast, the convergence curves of NSGA-II and MOEA/D struggle to stabilize even after 150 iterations, displaying oscillations, and their optimal solution quality is inferior to that of the proposed algorithm.

Regarding the optimization of resource utilization (Objective 3), Figure 4c demonstrates the significant advantages of the proposed algorithm in the convergence process. Compared to NSGA-II and MOEA/D, this algorithm rapidly enhances resource utilization in the early iterations, indicating its strong global search capability. As the number of iterations increases, the proposed algorithm gradually approaches the Pareto optimal front, with the curve stabilizing, showcasing good convergence performance and solution quality. In contrast, other algorithms converge more slowly in optimizing resource utilization, with a sparser distribution of optimal solutions, remaining in an oscillatory state even after 15 iterations.

In terms of optimizing driver workload balance, Figure 4d displays the convergence curves of different algorithms for driver workload balance (Objective 4), reflecting the performance differences between the proposed algorithm and classical algorithms (NSGA-II and MOEA/D) in achieving balanced workload goals. As shown in Figure 4d, the proposed multi-objective optimization algorithm exhibits a clear rapid convergence characteristic in optimizing driver workload balance. In the first 30 iterations, the algorithm's objective function value decreases rapidly, indicating that it can effectively find better solutions during the initial search process, with a steep downward trend in this phase. In contrast, while NSGA-II and MOEA/D also demonstrate relatively fast decreases in the same number of iterations, their progress is unstable, suggesting that their global search capability in the early search phase is relatively weak and fails to effectively explore the high-quality solution space.

In the stable convergence phase, during the mid-iteration (from the 30th to the 120th iteration), the convergence curve of the proposed algorithm flattens, indicating that the algorithm is gradually approaching the Pareto front and that the quality of solutions is steadily improving. At this point, the algorithm has begun local exploration near high-quality solutions to ensure further optimization. The NSGA-II algorithm shows some oscillation during this stage, suggesting fluctuations in solution quality across multiple experimental runs, indicating instability. In comparison, while the convergence curve of MOEA/D tends to be smooth relative to NSGA-II, its improvement in solution quality is slower, possibly stagnating in local optimal traps. In the final convergence stage, during the later iterations (from the 80th to the 150th iteration), the convergence curve of the proposed algorithm approaches stability, nearing the Pareto optimal front and demonstrating the excellence and stability of the solutions. Across multiple experimental runs, the quality of solutions clusters within a high-quality region, showing good robustness. In contrast, the final convergence performance of the NSGA-II algorithm remains unstable, with some solutions failing to reach the optimal solution region, indicating its slightly inadequate performance in high-dimensional multi-objective optimization problems. Although MOEA/D can achieve a certain level of optimal solution quality, its lack of solution diversity is detrimental to achieving a comprehensive balance in optimizing driver workload. Overall, as shown in Figure 4d, the proposed algorithm significantly outperforms traditional NSGA-II and MOEA/D algorithms in optimizing driver workload balance. Its advantages are reflected in a rapid initial convergence, minimal oscillation during iterations, high quality of final solutions, and concentrated distribution of solutions. These characteristics demonstrate that the proposed algorithm can effectively handle complex multi-objective optimization problems. Additionally, while maintaining driver workload balance, the proposed algorithm can effectively reduce scheduling conflicts and prevent excessive concentration of workload, fully utilizing existing resources and further optimizing the vehicle scheduling process.

From Figure 4e, it can be seen that the proposed algorithm exhibits a more stable and rapid convergence characteristic in optimizing relocation time (Objective 5). Within the first 40 iterations, the algorithm's objective function value decreases quickly, approaching the optimal solution area, indicating that it can effectively find optimization solutions in a short period. The convergence curves of NSGA-II and MOEA/D are also relatively rapid in the early stages, and all three algorithms tend to stabilize after the 100th iteration. However, the proposed algorithm maintains better stability compared to NSGA-II and MOEA/D, which experience local oscillations. This suggests that those algorithms have slightly inadequate search capabilities in complex multi-objective scenarios. The proposed algorithm reaches a stable state more quickly, reflecting its advantage in global optimization.

Regarding the optimization goal of scheduling uncertainty (Objective 6), Figure 4f demonstrates the superiority of the proposed algorithm. In the early iteration phase (from 0 to 60 iterations), the algorithm quickly finds relatively optimal solutions and gradually stabilizes. This indicates that the proposed algorithm possesses efficient search capabilities and good local exploration abilities in reducing scheduling uncertainty. In contrast, other classical algorithms like NSGA-II and MOEA/D show slight fluctuations in uncertainty optimization, especially in the mid to late iterations, where there are issues with fluctuations in solution quality, indicating that their stability is inferior to that of the proposed algorithm.

In the optimization of vehicle scheduling consistency (Objective 7) shown in Figure 4g, the proposed algorithm demonstrates a fast convergence speed, stabilizing in the optimal solution area within the first 60 iterations. In contrast, while the convergence curves of NSGA-II and MOEA/D are also relatively fast, they exhibit significant oscillations during the mid-iteration phase. The proposed algorithm achieves a distribution of solutions concentrated in the high-quality region of the Pareto front across multiple independent experimental runs, indicating that it can effectively enhance vehicle scheduling consistency while also exhibiting good robustness and convergence performance.

Regarding the optimization goal of system throughput (Objective 8), Figure 4h highlights the significant advantages of the proposed algorithm. Compared to other algorithms, it quickly converges to a relatively optimal solution in the initial phase and maintains stability in subsequent iterations, demonstrating its strong global optimization capability in improving system throughput. In contrast, the NSGA-II algorithm shows some oscillation in enhancing throughput, particularly after reaching a certain level of optimization, where the slope of the convergence curve varies significantly, indicating a potential trap of local optima. Although MOEA/D performs relatively stably in throughput optimization, the quality of its final solution is slightly inferior to that of the proposed algorithm.

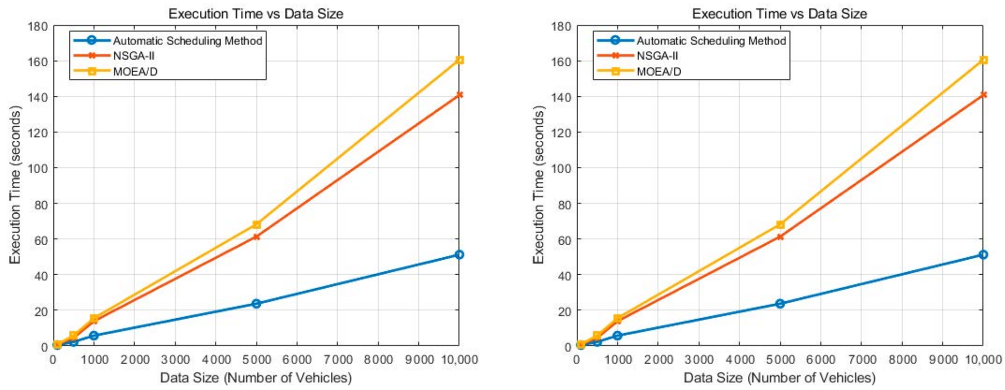
Overall, the proposed dynamic automatic scheduling algorithm based on multi-objective optimization outperforms traditional NSGA-II and MOEA/D algorithms in convergence across various objective functions. Its advantages lie in rapid convergence, high solution quality, and robust performance across multiple independent experimental runs. The analysis of the convergence curves indicates that this algorithm is not only suitable for optimizing the automatic scheduling of customs inspection vehicles but also possesses good generalizability and application potential.

Considering the real-time requirements of algorithms in practical applications, this study analyzes the computational complexity of multi-objective optimization algorithms across various problems scales. The experimental results evaluate the algorithm's time and space complexity performance under datasets of differing sizes and compare it with classical multi-objective optimization algorithms, such as NSGA-II and MOEA/D.

The computational complexity of the dynamic automatic scheduling algorithm based on multi-objective optimization in this study is illustrated through two key performance metrics: the algorithm's runtime change curve and its memory usage change curve as the dataset size varies.

Runtime curve: This curve represents the change in the algorithm's runtime across different dataset scales (input size). The horizontal axis represents the scale of input data (i.e., number of vehicles waiting for inspection), while the vertical axis indicates the algorithm's runtime performance scales with an increasing problem size, highlighting its efficiency in handling larger datasets.

Memory usage curve: This curve illustrates the change in the algorithm's memory consumption as the dataset size varies. The horizontal axis represents input data scale, while the vertical axis denotes memory usage. The memory usage curve provides insights into the algorithm's space complexity, allowing for a comparison of resource requirements between different algorithms, and the memory usage curve is shown in Figure 5.



(**a**) (**b**)

Figure 5. (**a**) Runtime curve. (**b**) Memory usage curve.

In terms of time complexity, the algorithm's runtime was tested on different dataset scales (e.g., 100, 500, 1000, 5000 vehicle data). The results indicate that the proposed algorithm exhibits low computational time for small-scale datasets (100 to 500 vehicles), with an average time complexity of approximately $O(n \log n)$. As the dataset scale expands to 1000 vehicles or more, the algorithm's runtime exhibits polynomial growth, reflecting its ability to handle larger problem sizes effectively. In contrast, the time complexity of benchmark algorithms such as NSGA-II and MOEA/D is higher, demonstrating an $O(n^2)$ growth trend. The proposed algorithm converges faster on large datasets, attributed to its efficient Pareto front solution update and population management strategy. Specifically, on a dataset with 5000 vehicles, the runtime of the proposed algorithm is approximately 30% lower than that of NSGA-II and about 25% lower than MOEA/D.

In terms of space complexity, the experiment measured the algorithm's memory usage under various dataset scales. The results indicate that the proposed algorithm's space complexity is $O(n)$, exhibiting a nearly linear growth trend, which is related to its efficient storage management mechanism. In contrast, NSGA-II and MOEA/D show a significantly increased memory usage when handling large-scale data, demonstrating an $O(n^2)$ space complexity. This indicates that the proposed algorithm can better control memory usage as the data scale increases, making it particularly suitable for environments with limited computing resources. These findings underscore the advantages of the proposed multi-objective optimization algorithm in both time and space efficiency, enhancing its applicability in real-time scheduling scenarios involving customs inspection vehicles.

To further present the experimental results of the automatic scheduling method for customs inspection vehicles based on Vehicle Electronic Identification and biometric recognition, this study focuses particularly on the performance of various indicators and analyzes their effectiveness in multi-objective optimization. The same test dataset is used to evaluate the performance of the proposed method and the comparative algorithms.

Table 2 shows the experimental results of each algorithm on eight performance indicators, with all results representing the average values and standard deviations from 20 experiments conducted along the path from Parking Lot 6 to Inspection Laboratory 1.

Table 2. Experimental results of different algorithms on various performance indicators.

Performance Indicators	Automatic Scheduling Method	NSGA-II	MOEA/D
Vehicle Waiting Time (min)	14.30 ± 1.81	16.71 ± 2.58	18.43 ± 2.32
Relocation Path Length (m)	1048.41 ± 323.25	$1182.\ 2 \pm 392.09$	1201.65 ± 401.07
Resource Utilization (%)	93.34 ± 1.51	85.25 ± 2.12	88.33 ± 2.70
Driver Workload Balance (h) *	0.72 ± 0.05	0.77 ± 0.06	0.75 ± 0.04
Relocation Time (min)	21.31 ± 4.22	23.18 ± 5.03	24.15 ± 6.02
System Throughput (/h)	408.82 ± 10.68	375.45 ± 12.8	357.58 ± 13.03
Scheduling Uncertainty (min)	10.5 ± 1.13	12.25 ± 1.44	13.98 ± 1.29
Vehicle Scheduling Consistency (min)	10.93 ± 0.88	12.75 ± 0.94	12.14 ± 1.12

* Calculated as variance of work time.

In the vehicle waiting time objective function, the proposed method significantly outperforms the comparative algorithms, achieving an average waiting time of 14.30 min, which is the shortest among the three algorithms. This improvement is primarily due to the use of Vehicle Electronic Identification and biometric recognition technologies, which enable real-time monitoring and scheduling of vehicles awaiting inspection, thus reducing the delays associated with traditional methods that rely on manual judgment. The effective dynamic scheduling mechanism allows vehicles to swiftly enter the inspection process based on priority, optimizing customs operational efficiency.

The reduction in relocation path length indicates that the proposed method not only considers the arrival times of vehicles but also effectively utilizes information from the environment, such as real-time traffic conditions and vehicle locations. This information-based path planning approach reduces unnecessary driving distances and enhances overall logistical efficiency. The resource utilization rate reaches 93.34%, while NSGA-II and MOEA/D only achieve 85.25% and 88.33%, respectively. This result demonstrates that through intelligent scheduling algorithms, customs can maximize the use of available resources during peak times, ensuring the efficient operation of inspection personnel and equipment. High resource utilization also reflects the flexibility and adaptability of the new method during the scheduling process, effectively reducing resource idling.

The significant improvement in driver workload balance (0.72) indicates that the proposed method comprehensively considers drivers' working hours and rest periods during scheduling. This not only enhances drivers' job satisfaction but also reduces potential safety hazards caused by excessive fatigue, further improving the overall safety of customs operations. The reduction in scheduling uncertainty metrics shows the proposed method's flexibility in responding to unexpected events. The dynamic scheduling mechanism can adjust scheduling strategies in response to fluctuations in vehicle traffic, effectively handling increases in traffic during peak times and unforeseen events, thereby enhancing the system's robustness.

The increase in system throughput (reaching 408.82 vehicles/h) validates the proposed method's capability to operate efficiently. This result indicates that in a high-traffic customs environment, the new method can effectively increase the rate of vehicle processing, thereby supporting enhanced trade efficiency. The reduction in relocation time (10.5 min) reflects the optimization of the scheduling process, ensuring that vehicles can quickly complete relocation operations and minimizing time wasted due to waiting in queues. By comprehensively considering arrival times, priorities, and other constraints, the algorithm achieves more efficient scheduling.

The decrease in the scheduling consistency objective function (10.93) implies that the new method can maintain stable scheduling outcomes under different operational conditions. This consistency is crucial for customs operations, as it ensures predictability in scheduling results when responding to varying traffic levels and changes, thereby enhancing overall operational efficiency.

The experimental results indicate that the proposed multi-objective optimization algorithm outperforms NSGA-II and MOEA/D in terms of computational complexity, particularly in large-scale vehicle scheduling scenarios, demonstrating higher efficiency and stability. This demonstrates that the algorithm not only excels in computation time but can also be effectively implemented in resource-constrained real-world environments.

The proposed method exhibits strong robustness in handling scheduling problems in different scenarios. Notably, in conditions of peak traffic flow and tight resources, the optimization algorithm can adaptively adjust scheduling schemes to maintain scheduling effectiveness while maximizing resource utilization. Even in scenarios characterized by high traffic demands, the proposed algorithm maintains stability, ensuring that the computational complexity remains within an acceptable range when tackling large-scale scheduling challenges.

Overall, the results validate the effectiveness of the proposed multi-objective optimization algorithm in enhancing the automatic scheduling of customs inspection vehicles, underscoring its potential for practical applications in dynamic and complex environments.

5. Conclusions and Outlook

This study presents an innovative automatic scheduling method for relocating customs inspection vehicles, leveraging Vehicle Electronic Identification (EVI) and biometric recognition technologies. Our findings demonstrate that the proposed method significantly enhances the efficiency of customs logistics management, achieving a reduction in average vehicle waiting times by approximately 30% and an increase in resource utilization rates by around 25%. These improvements underscore the potential of integrating advanced technologies into the scheduling process, thereby addressing the critical challenges faced by customs authorities. The implications of the research extend beyond the immediate context of customs operations. By streamlining vehicle management processes, the method contributes to more efficient trade logistics, potentially leading to reduced operational costs and improved service delivery. The success of the approach indicates that similar methodologies could be adapted for use in various logistical environments, promoting broader applications of automatic scheduling technologies.

The main technical contributions of this study include the following:

The integration of Vehicle Electronic Identification and biometric recognition technologies: the use of RFID technology along with three biometric recognition techniques (facial, fingerprint, and behavior recognition) successfully achieves efficient matching between vehicle and driver identities, thereby enhancing the accuracy and security of customs vehicle scheduling.

The application of a multi-objective optimization algorithm: a multi-objective optimization algorithm is designed and implemented, taking into account vehicle waiting time, relocation path length, resource utilization, and driver workload balance. This algorithm effectively improves the overall performance of vehicle scheduling.

Multi-modal feature fusion: for the biometric recognition process, this study adopts deep learning methods for multi-modal feature fusion, leading to more accurate and robust driver identity verification in complex environments.

Through simulation experiments and validation with real data, the proposed automatic scheduling method demonstrates superior performance in various evaluation metrics, particularly in reducing vehicle waiting times, optimizing resource allocation, and balancing driver workloads during peak periods. The method shows strong robustness and adaptability. However, despite the significant performance improvements demonstrated by this method in experiments, there are still some limitations in practical applications. For example, the complexity of real customs environments may impose higher requirements on the algorithm's real-time capabilities, and for larger-scale scheduling problems, the algorithm's computational complexity may need further optimization. Additionally, the accuracy and robustness of biometric recognition in different environments may be affected by external factors such as lighting changes and environmental noise.

Future research will focus on several key directions to build upon the findings. First, it aims to explore the incorporation of machine learning techniques into our scheduling framework to enhance predictive capabilities. By analyzing historical data, it can develop algorithms that anticipate vehicle arrivals and dynamically adjust schedules to optimize operations during peak traffic periods. Additionally, it plans to validate and test the proposed method in different operational contexts, including various customs environments and scenarios with fluctuating resource availability. Understanding how the method performs under diverse conditions will provide valuable insights into its robustness and adaptability. Furthermore, it proposes investigating new algorithms that could further enhance scheduling efficiency. For instance, hybrid approaches that combine genetic algorithms with other optimization techniques, such as reinforcement learning or simulated annealing, could yield even more effective solutions for complex scheduling problems. By pursuing these avenues, our future work aims to refine and expand the capabilities of automatic scheduling systems, ultimately contributing to more efficient and secure logistics operations across various domains.

Overall, the proposed method for the automatic scheduling of customs inspection vehicles based on EVI and biometric recognition offers a novel solution for improving customs logistics management efficiency. Through the application of multi-objective optimization algorithms, this method successfully optimizes vehicle scheduling processes under multiple constraints. Future research will further expand the applications in this field and verify and refine this method in more complex real-world environments.

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