Intelligent Logistics Vehicle Scheduling Based on MPHIGA

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***Abstract*—The current intelligent logistics vehicle scheduling faces challenges, including the difficulty of obtaining real-time location data and the need for manual intervention in emergencies. To address these issues, a modified multi-population hybrid genetic algorithm is proposed, along with an intelligent scheduling model constructed through the reconstruction of domain generation strategies. Experimental results show that the model stabilizes the total cost at 7864 yuan within 49 iterations, whereas the dual-population hybrid genetic algorithm requires 51 iterations, making convergence more time-consuming. Moreover, when the scheduling frequency is two, the research model successfully allocates three company vehicles, whereas the comparison algorithm can only allocate two. Overall, the research model offers significant advantages in reducing operating costs and enhancing dynamic response capabilities, providing effective technical support for the digital transformation of logistics companies.**

***Keywords*—Multi-population hybrid improved genetic algorithm; domain generation algorithm; logistics vehicles; co-evolution; scheduling management**

I. Introduction

With rapid technological advancements, intelligent systems are increasingly integrated into various industries. Intelligent vehicle management is a key factor in improving operational efficiency in logistics and transportation [1]. Scientific scheduling of logistics vehicles optimizes routes and vehicle allocation, while also enabling real-time tracking of logistics resources, thus improving efficiency based on vehicle status and road conditions [2,3]. Although current intelligent logistics vehicle scheduling uses machine learning and big data analysis to predict demand fluctuations and optimize route selection, challenges remain [4]. Data silos significantly affects overall scheduling performance, while factors such as weather changes and uneven resource distribution make it harder to matching vehicles with cargo [5]. Some intelligent logistics vehicle scheduling systems cannot fully monitor and manage vehicle safety, limiting their ability to provide comprehensive data reports and statistics, which limits enterprises in conducting in-depth analysis and optimization [6]. To address these challenges, this study integrates the Domain Generation Algorithm (DGA) with the Multi-Population Hybrid Improved Genetic Algorithm (MPHIGA). The proposed model aims to improve intelligent logistics vehicle scheduling. DGA generates random domain names, which are introduced into MPHIGA for population initialization and mutation operations, enhancing the algorithm's global search capability. This study aims to improve real-time monitoring and positioning in logistics vehicle scheduling, enhance the profitability of logistics enterprises, and support the transformation of the logistics industry.

This study consists of four sections. Section II summarizes domestic and international research on MPHIGA and logistics vehicle scheduling. Section III focuses on optimizing MPHIGA with DGA to develop the scheduling model. Section IV evaluates the performance and practical application of the proposed model. Finally, Section V presents the study's conclusions.

II. Related Works

MPHIGA is an improved genetic algorithm that uses multiple populations for simultaneous optimization, enhancing global search capabilities and preventing premature convergence. Many researchers have explored its core characteristics. For example, Yu et al. proposed an algorithm based on a hybrid genetic algorithm to reduce the total response time between cloud data centers and medical devices. By combining the genetic algorithm with a hybrid metaheuristic method and conducting simulation experiments, the study demonstrated the effectiveness of this approach [7]. Sun H's team introduced a particle swarm optimization method based on genetic algorithms for inverse lithography technology. This method improved lithographic imaging performance through iterative optimization. Experimental results showed that it had better convergence capability compared to traditional genetic algorithms [8]. Additionally, DGA enhances search efficiency and solution quality through the cooperation of two populations. Its strong search ability has led to its adoption by some researchers. Fang et al. developed a novel interval prediction method for photovoltaic power generation to improve forecasting timeliness. Applying an integral dual-domain decomposition method for learning and prediction, the study found that the error values were significantly reduced [9]. Zhang's team proposed a wave source localization method for harmonic analysis. By analyzing harmonic and non-harmonic sources from a time-domain perspective, simulation experiments verified the effectiveness of this approach [10]. Zhan et al. investigated the freshness of sensory data in unmanned aerial vehicles and introduced a domain generation algorithm-based strategy to obtain near-optimal solutions. By enabling rapid decision-making, this approach improved computational efficiency. Results showed that the algorithm exhibited strong flexibility [11].

Intelligent logistics vehicle scheduling plays a key role in transportation and has been widely applied by logistics enterprises in recent years. Effective scheduling models allows for efficient resource allocation. Cho's team addressed the limitations of traditional logistics research by proposing a heuristic scheduling algorithm. By introducing various cost functions to evaluate scheduling results, experiments showed that this method effectively reduced delivery costs [12]. Elgharably et al. developed a hybrid search algorithm based on the vehicle routing problem in operations research. This algorithm solves solve multi-objective problems with balance trade-offs. Simulation experiments verified its feasibility and effectiveness [13]. Berghman et al. introduced a general model for outbound vehicle routing and conducted a review of comprehensive scheduling problems using an integrated approach. The study confirmed that this method provided valuable data references for future research directions [14]. Ding's team proposed a novel vehicle scheduling method to recommend optimal routes for electric vehicles, aiming to mitigate traffic congestion. By integrating multiple interactive modules for iterative decision-making, results demonstrated the feasibility of this approach [15]. Shen and Yan examined the impact of bus services on traffic and introduced a dynamic vehicle scheduling method. Using hybrid dynamic control, the method handled abnormal operating conditions effectively. Experimental results indicated strong flexibility and timeliness [16].

Existing research has made progress in reducing logistics costs and optimizing logistics services. However, challenges such as information delays and inaccuracies remain. To address these limitations, this study integrates DGA with MPHIGA to develop a novel intelligent logistics vehicle scheduling model. Each scheduling scheme undergoes a fitness function, and individuals are selected for genetic and crossover operations based on fitness values. The study employs a multi-population hybrid improved genetic algorithm, primarily addressing the issues of traditional genetic algorithms in logistics scheduling, such as falling into local optima and insufficient population diversity. By introducing domain name generation algorithms to optimize dynamic coding strategies, it resolves the decoding efficiency bottleneck under complex constraints. Compared to existing models, its multi-population co-evolution mechanism simultaneously optimizes vehicle allocation and route generation, making it suitable for high-dimensional logistics scheduling. This approach aims to enable rapid adjustments to scheduling strategies in response to changing logistics demands, providing flexible logistics solutions.

III. The Multi-Population Hybrid Improved Vehicle Scheduling Model for Intelligent Logistics

A. *Intelligent Logistics Vehicle Scheduling Strategy Based on MPHIGA*

Compared with the traditional genetic algorithm, MPHIGA breaks away the framework of single-population genetic evolution and assigns different control parameters to different populations through simultaneous optimization searches [17]. In MPHIGA, multiple populations achieve collaborative evolution through specific operational factors, enhancing global search capability and prevents premature convergence compared to the traditional genetic algorithm [18,19]. MPHIGA is applied to intelligent vehicle scheduling strategies, automatically calculating the optimal vehicle scheduling plan based on multiple factors such as vehicle location, real-time road conditions, and cargo volume. The workflow of MPHIGA is shown in Fig. 1.

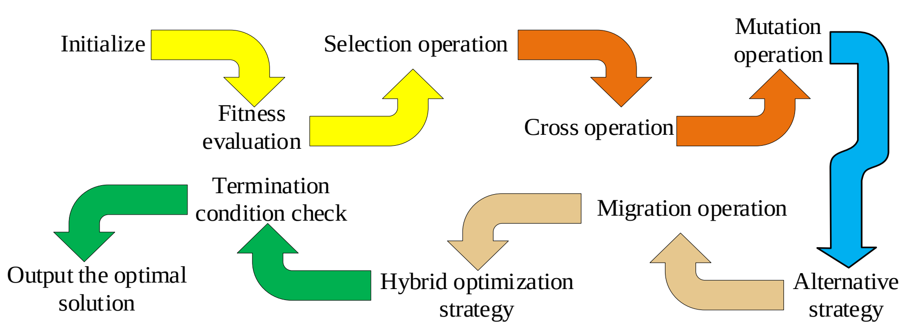


Fig. 1. Schematic diagram of MPHIGA workflow.

As shown in Fig. 1, MPHIGA first initializes the population size and the scale of each population randomly. The number of sub-populations is set according to the problem complexity and resource constraints. The fitness function evaluates each individual in the sub-population based on the problem requirements. In the selection process, individuals with higher fitness values are more likely to be selected. The crossover and different crossover strategies can be used to maintain diversity. The fitness function is given in Eq. (1).

$$f_j = \begin{cases} F(G_{ej}), x' = 1 \\ F(G_{ej}) + M_0, x' = 0 \end{cases} \quad (1)$$

In Eq. (1), $F(G_{ej})$ and $x' = 1$ represent the objective function value and the feasibility of the decoded solution as a binary variable, respectively. M_0 is assigned a finite integer. x' and $x' = 0$ are binary variables and represent an infeasible decoded solution. When applying MPHIGA to the intelligent logistics vehicle scheduling strategy, the intelligent scheduling dynamically adjusts the transportation plan based on demand, reducing empty mileage and transportation time. The key components of intelligent logistics vehicle scheduling are shown in Fig. 2.

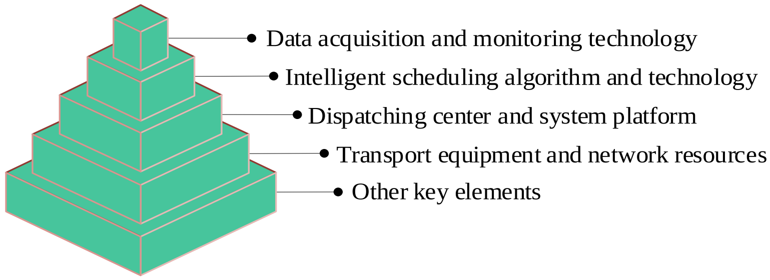


Fig. 2. Schematic diagram of the components of intelligent logistics vehicle scheduling.

$$F(l)=\begin{cases}\sum_{I=1}^{n-1}\sqrt{(X_I+1-X_I)^2+(y_I+1-y_I)^2}+num\times p_{punish1} \\ I=1,2,3,......,n-1\end{cases} \tag{2}$$

As shown in Fig. 2, the key components of intelligent logistics vehicle scheduling consist of five main parts. The data collection and monitoring technology uses sensors and onboard intelligent devices. Sensors collect real-time key data from logistics vehicles, while onboard intelligent devices monitor vehicle status to ensure accurate execution of scheduling instructions and enhance transportation safety. The intelligent scheduling algorithm uses big data and artificial intelligence to optimize logistics scheduling, with cloud computing and big data analysis providing efficient data storage and processing capabilities. The dispatch center and system platform include the intelligent dispatch center, user interface, and operating system. The dispatch center receives and processes data from sensors and onboard devices, generating scheduling instructions based on intelligent algorithms and transmitting them in real-time to drivers and vehicles. The evaluation function for the total path length in logistics vehicle scheduling is given in Eq. (2) [20].

In Eq. (2), X_I and l represent the midpoint of the line segment connecting the start and end points and the path, respectively. num and $p_{punish1}$ are the number of infeasible segments in the path and the penalty value. y_I represents the vertical coordinate when the two-dimensional path encoding is converted into one-dimensional encoding. By sorting the selection probabilities assigned to individuals, the cumulative probability equation is given in Eq. (3).

$$p_{\sum i}=\sum_{i=1}^{NP}p_i \tag{3}$$

Transportation equipment and logistics networks ensure the execution of logistics transportation tasks and support the implementation of intelligent logistics vehicle scheduling. Other key elements include real-time detection and early warning systems, which reduce transportation risks. The intelligent logistics vehicle scheduling strategy based on MPHIGA is shown in Fig. 3.

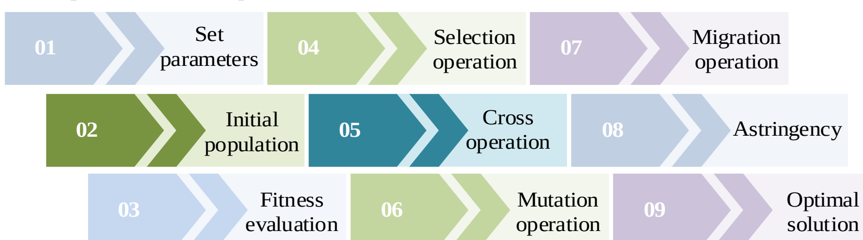


Fig. 3. Intelligent logistics vehicle scheduling strategy based on MPHIGA.

As shown in Fig. 3, in the MPHIGA-based intelligent logistics vehicle scheduling strategy, each individual represents a potential scheduling plan. After setting the basic parameters of the genetic algorithm, each sub-population is randomly initialized. The fitness function defines and evaluates individuals and scheduling plans based on the vehicle scheduling problem requirements and multiple indicators. Within each sub-population, the crossover operation generates new offspring. The mutation operation is usually random, and individuals from different sub-populations exchange information to enhance capabilities. The exchange strategies include both synchronous and asynchronous communication. The threshold value in the exchange strategy is given in Eq. (4).

$$E=\frac{1}{N}\sum_{i=1}^{N}\left|f_i-f_{avg}\right| \tag{4}$$

In Eq. (4), f_i, N, and f_{avg} represent the fitness value of the i-th individual in the population, the number of individuals in the population, and the average fitness value. The crossover probability equation is given in Eq. (5).

$$p_c = \begin{cases} p_{c1} - (p_{c1} - p_{c2}) \dfrac{f_{\max} - f'}{f_{\max} - f_{avg}} & f' \geq f_{avg} \\ p_{c1} & f' < f_{avg} \end{cases} \quad (5)$$

In Eq. (5), $f_{\max}$ and p_{c1} represent the fitness value of the optimal individual in the population and the maximum mutation probability. f' and p_{c2} represent the larger fitness value and the minimum mutation probability of the two chromosomes to be crossed.

B. Construction of the Intelligent Logistics Vehicle Scheduling Model with DGA

Although applying MPHIGA to intelligent logistics vehicle scheduling allows precise environmental recognition through high-precision sensors and visual recognition technologies, it may still prematurely converge to local optima when facing complex problems due to ineffective selection strategies. For large-scale problems, MPHIGA requires multiple iterations to generate and evaluate populations, which leading to increased computational time and resource consumption [21]. Therefore, DGA is introduced to optimize MPHIGA, allowing the search process to adapt dynamically and avoid premature convergence. DGA is an algorithm that generates a large number of random and short-lived domain names. It can generate different domain names as needed, offering flexibility and adaptability. The domain generation process of DGA is shown in Fig. 4.

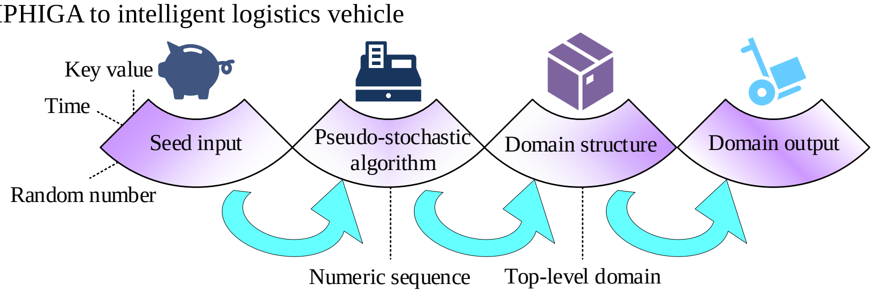


Fig. 4. Schematic diagram of DGA domain name generation.

As shown in Fig. 4, DGA initializes a pseudo-random algorithm using one or more specific parameters as seeds, which typically include key values, time, and random numbers. Different seeds generate different domain sequences. During the execution of the pseudo-random algorithm, DGA generates a series of numerical sequences based on the input seed, forming part of the domain names. The generated sequences are then combined into one or more domain names. These domain names are often used by malware or attackers to communicate with servers or other targets. DGA-generated domain names exhibit high unpredictability and randomness, allowing attackers to periodically change the seed to alter the generated domain sequences. The calculation method for the consecutive number ratio is given in Eq. (6).

$$C_d = \frac{N_{cd}}{L} \quad (6)$$

In Eq. (6), N_{cd} and L represent the number of consecutive number pairs and domain name length, respectively. The equation for domain name length is given in Eq. (7).

$$L = len(domain) \quad (7)$$

In Eq. (7), $domain$ and $len()$ represent the domain name string and its length. The dynamic generation mechanism of DGA is used to adjust the search strategy of MPHIGA, and the optimization process is shown in Fig. 5.

As shown in Fig. 5, DGA generates a large number of random domain names through its randomness generation mechanism. This randomness is introduced into MPHIGA for population initialization and mutation operations, enhancing the global search capability. MPHIGA already has strong global search capabilities through hybrid improvement strategies, and introducing DGA further strengthens the ability to explore optimal solutions in a broader solution space. The entropy value of domain names is given in Eq. (8).

$$H = -\sum_{z=1}^{n} p_z \log p_z \quad (8)$$

In Eq. (8), p_z represents the frequency of character z. The number of numeric characters is calculated using Eq. (9).

$$Nd = \sum_{z \in digits} count(z) \quad (9)$$

In Eq. (9), $digits$ represents the set of numeric character z. The user interface provides an intuitive interface for seamless integration with other logistics management systems, facilitating monitoring, collaboration, and data sharing. The randomness of DGA helps prevent MPHIGA based on premature convergence to local optima. By continuously introducing new random elements, the algorithm maintains exploration within the solution space and ultimately finds the optimal solution. The intelligent logistics vehicle scheduling model based on DGA-MPHIGA is shown in Fig. 6.

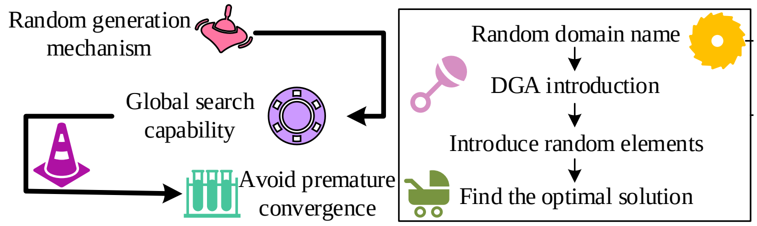


Fig. 5. Schematic diagram of DGA optimization of MPHIGA.

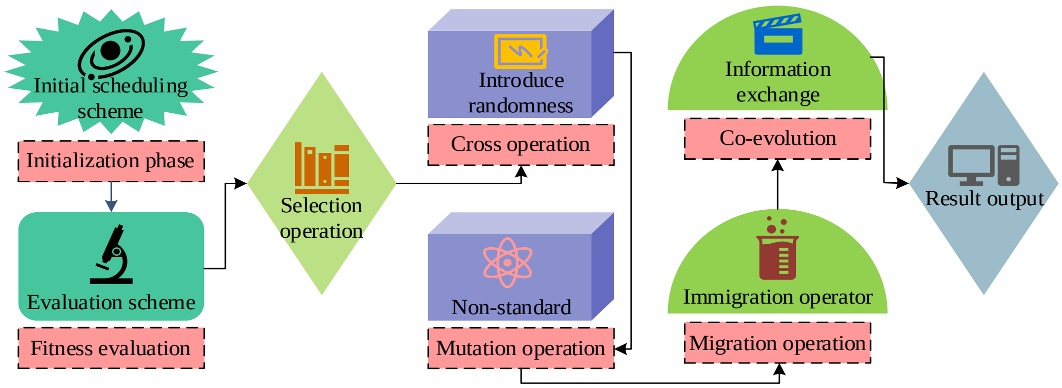


Fig. 6. Intelligent logistics vehicle scheduling model based on DGA-MPHIGA.

As shown in Fig. 6, the random generation mechanism of DGA produces an initial set of scheduling plans. After evaluating the fitness of each scheduling plan, the best individuals are selected for genetic and crossover operations. Mutation operations are usually random, with their probability and intensity adjusted according to the scenario. Within sub-populations, replacement strategies ensure continuous optimization of the population. DGA enables non-standard crossover and mutation operations with a certain probability, and the migration operator facilitates information exchange and collaborative evolution among populations. The model terminates when the stopping condition is met or the preset iteration count is reached, ultimately obtaining the optimal logistics vehicle scheduling plan. The equation for computing the probability distribution of chromosomes in the population is given in Eq. (10).

$$p_i = \begin{cases} p\times(1-p)^{i-1}, & i=2,\cdots,NP \\ (1-p)^{i-1}, & i=1 \end{cases} \tag{10}$$

In Eq. (10), i and NP represent the individual's ranking and the population size. p represents a constant within the range of $(0,1)$. The optimal path equation is given in Eq. (11).

$$MinZ = \sum_{w=1}^{W}\left\{\sum_{u=1}^{A_w} C_W D_{k_{w(u-1)}k_{wi}} D_{k_{mnw}k_{w0}} sign(A_w)\right\} \tag{11}$$
$$w = 1, 2, \cdots W$$

In Eq. (11), A_w and k_w represent the number of customer points served by vehicle w and the w-th path, respectively. k_{wi} and k_{w0} are the sequence positions of customer points in path w, while C_W and D represent the cost per unit travel distance of vehicle w and the maximum allowable travel distance. The vehicle transportation cost equation is given in Eq. (12).

$$M = h\sum_{s,q=1}^{m} x_{sq} d_{sq} \tag{12}$$

In Eq. (12), h and d_{sq} represent the transportation cost per unit distance and the transportation distance between customer s and customer q. m represents the total number of customers.

IV. Performance Verification of the DGA-MPHIGA Intelligent Scheduling Model

A. *Performance Analysis of the Intelligent Logistics Vehicle Scheduling Model*

To analyze the performance of the intelligent logistics vehicle scheduling model based on DGA-MPHIGA, the study used intelligent logistics vehicle scheduling models based on MPHIGA, Simple Genetic Algorithm (SGA), and Dual Population Hybrid Genetic Algorithm (DPHGA) as comparison models. The experiments were conducted on a Windows XP SP3 operating system with a Pentium(R) 4 2.66 GHz CPU and 12 GB of RAM. The experimental datasets included the TSPlib dataset and the Solomon dataset. The TSPlib dataset was used as the training set, containing specific city coordinates and distance matrix information for solving the traveling salesman problem and routing problems in vehicle scheduling. The Solomon dataset was used as the test set, providing detailed parameters such as customer location coordinates, time windows, and demand quantities. The study first compared the scheduling costs of the four models on the training and test sets, and the results are shown in Fig. 7.

As shown in Fig. 7(a), when the scheduling frequency reached five times, the cost of the proposed model was only 0.112 million yuan. However, the cost of the MPHIGA scheduling model had already reached 0.128 million yuan when the scheduling frequency was three times. Fig. 7(b) shows that the DGA-MPHIGA scheduling model maintained lower cost consumption than the comparison models in the test set. When the scheduling frequency was four times, the cost of the MPHIGA and DPHGA scheduling models was 0.137 million yuan and 0.159 million yuan, respectively, while the cost of the SGA scheduling model was the highest among the four models at 0.188 million yuan. These results indicated that the DGA-MPHIGA scheduling model exhibited lower cost consumption in both the training and test sets, demonstrating higher resource utilization. Next, the study conducted a comparative analysis of the scheduling time of the four models on the TSPlib dataset, with results shown in Fig. 8.

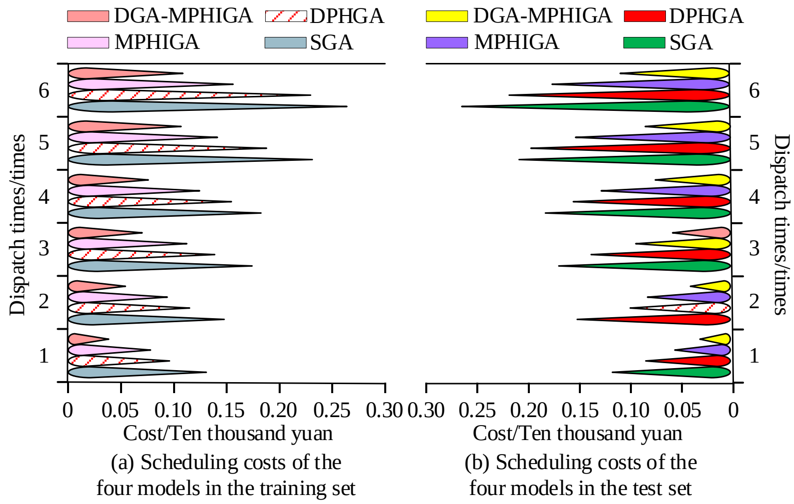


Fig. 7. Comparison of the scheduling costs of four models in training and test sets.

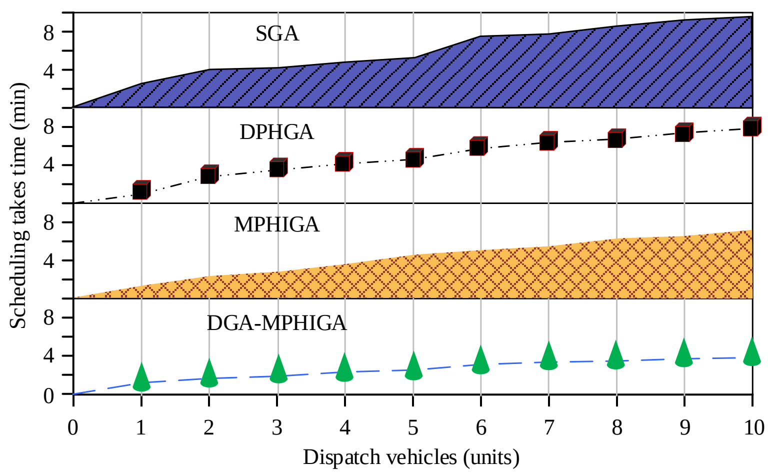


Fig. 8. Comparison of the scheduling time of four models in the TSPlib dataset.

As observed in Fig. 8, when the number of scheduled vehicles was two, the scheduling time of the DGA-MPHIGA and MPHIGA models was 1.24 minutes and 2.67 minutes, respectively. When the number of scheduled vehicles reached ten, the scheduling time of the DGA-MPHIGA model was 3.98 minutes, while the scheduling time of the SGA model was 5.94 minutes longer than that of the proposed model. Meanwhile, the scheduling times of the MPHIGA and DPHGA models were 7.31 minutes and 7.98 minutes, respectively. These results indicated that the DGA-MPHIGA model achieved the shortest scheduling time among the four models. The model was capable of computing the optimal vehicle scheduling solution in a shorter time, significantly improving overall logistics efficiency. Additionally, the shorter scheduling time allowed the model to quickly adapt to new order demands and traffic conditions. Finally, the study analyzed the vehicle distribution route length and time of the four models on the training and test sets, with results shown in Table I.

TABLE I COMPARISON OF VEHICLE DELIVERY ROUTE LENGTH AND TIME

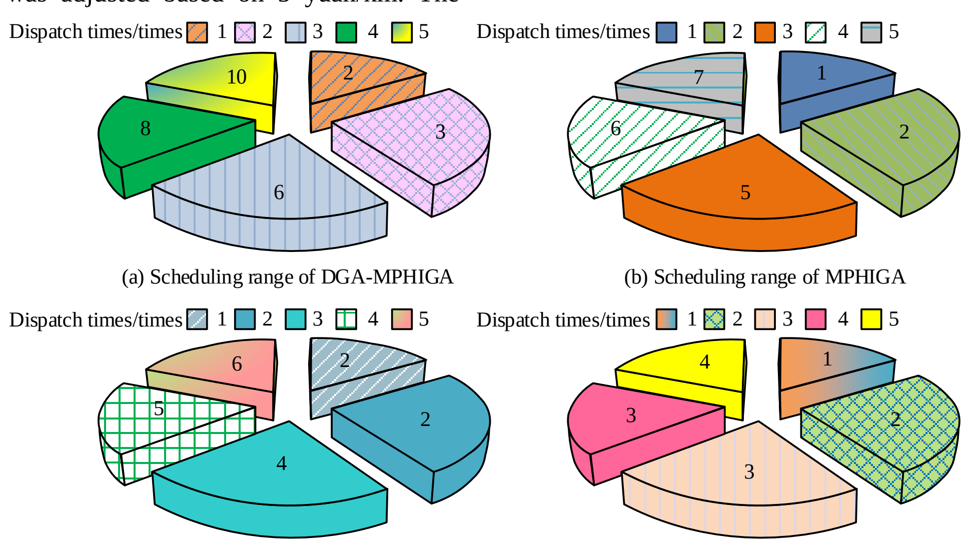
Data set	Scheduling model	Average calculated path length (km)	Optimal path distance length (km)	Running time (s)
Training set	DGA-MPHIGA	411.32	410.84	9.54
	MPHIGA	423.15	419.27	14.36
	DPHGA	435.81	425.33	18.24
	SGA	449.25	437.41	21.39
Test set	DGA-MPHIGA	412.94	408.57	9.21
	MPHIGA	427.35	424.35	14.17
	DPHGA	436.87	431.23	19.34
	SGA	451.29	439.78	22.17

As presented in Table I, in the training set, the average computed path length and optimal path length of the DGA-MPHIGA model were 411.32 km and 410.84 km, respectively, both lower than those of the comparison models. The SGA model exhibited the highest average computed path length at 449.25 km, with a runtime of 21.39s. The optimal path length of the MPHIGA model in the training set increased compared to previous results, reaching 424.35 km, with a runtime of 14.17s. At this point, the optimal path length of the DGA-MPHIGA model was only 408.57 km, with its runtime being the shortest among the four models, at just 9.21s. These results demonstrated that the DGA-MPHIGA model had the shortest average computed path length and optimal path length, leading to faster delivery speeds and enabling the rapid computation of optimal logistics routes.

B. *Evaluation of the Practical Effectiveness of the Intelligent Scheduling Model*

To further validate the effectiveness of the intelligent logistics vehicle scheduling model in real-world applications, the study set the number of foreign trade enterprise vehicles to ten, along with ten loading points and thirteen unloading points. The transportation time was set to two hours, and the unit transportation cost was adjusted based on 5 yuan/km. The penalty coefficients for exceeding the time window and the vehicle's rated load were set to 200 and 10,000, respectively. The study first analyzed the scheduling range of the four models when scheduling ten enterprise vehicles, with results shown in Fig. 9.

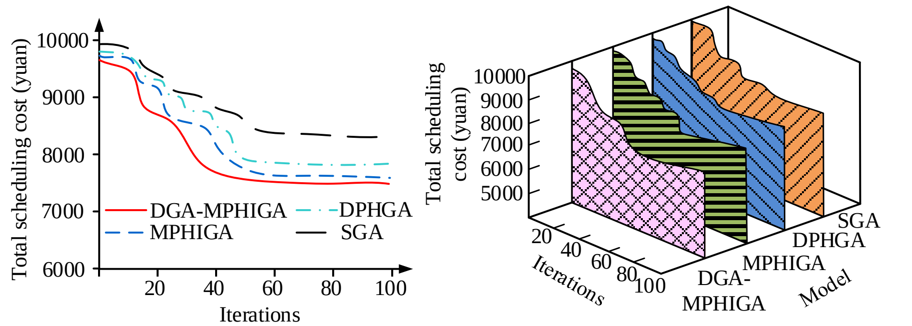
As shown in Fig. 9, the DGA-MPHIGA model achieved a significantly wider scheduling range than the other three comparison models under the same scheduling frequency. When the scheduling frequency was two times, the DGA-MPHIGA model scheduled three enterprise vehicles. When the scheduling frequency increased to four times, the SGA model scheduled three enterprise vehicles, while the DPHGA and MPHIGA scheduling models scheduled five and six enterprise vehicles, respectively. At this point, the DGA-MPHIGA model was capable of scheduling eight enterprise vehicles. When the scheduling frequency reached five times, the model successfully scheduled all ten enterprise vehicles. These results indicated that the DGA-MPHIGA model demonstrated excellent vehicle scheduling capabilities, handling broader and more complex logistics transportation tasks. The study then analyzed the total cost optimization iterations of the four models under different vehicle demand scenarios, with the iterative change curves shown in Fig. 10.



(a) Scheduling range of DGA-MPHIGA (b) Scheduling range of MPHIGA

(c) Scheduling range of DPHGA (d) Scheduling range of SGA

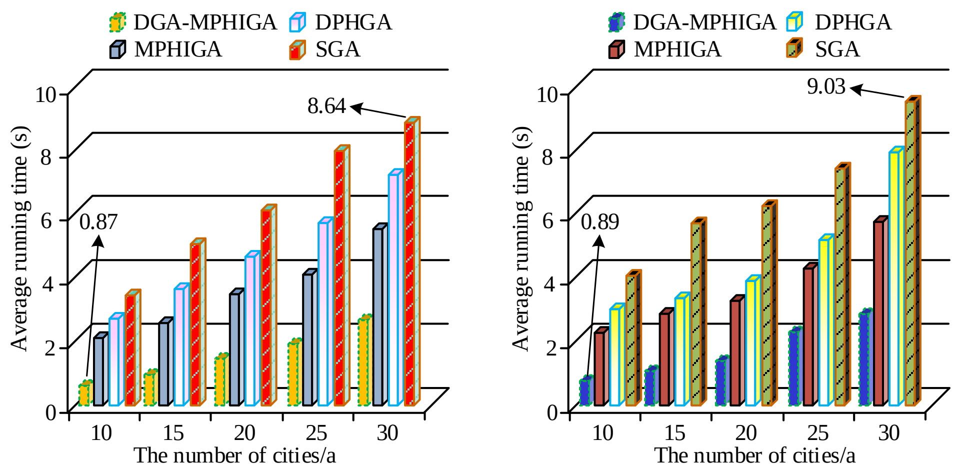
Fig. 9. Result diagram of scheduling range for dispatching enterprise vehicles.



(a) Iterative changes in the total cost optimization of the four models when four vehicles are required

(b) Iterative changes in total cost optimization for the four models when 8 vehicles are required

Fig. 10. Total cost optimization iteration curve under different requirements.



(a) The average operating time of the four models when four vehicles are required

(b) The average operating time of the four models when eight vehicles are required

Fig. 11. Comparison of average running time under different requirements.

As shown in Fig. 10(a), when the vehicle demand was four, the DGA-MPHIGA model exhibited a shorter convergence time. When the iteration count reached 37, the total scheduling cost of the model gradually stabilized, converging faster than the comparison models. The DPHGA model had the longest convergence time, reaching 51 iterations. Fig. 10(b) shows that when the vehicle demand was eight, the total scheduling cost optimization curves of all four models exhibited a downward trend as the iteration count increased, eventually stabilizing at different iteration points. The convergence time and iteration count of the DGA-MPHIGA model were both shorter than those of the comparison models. These results indicated that the DGA-MPHIGA model learned data patterns faster and reached stability with lower computational resource consumption. Finally, the study compared the scheduling time of the four models under different vehicle demand scenarios, with results shown in Fig. 11. As summarized in Fig. 11, the average runtime of the DGA-MPHIGA model under different vehicle demand scenarios was the lowest among the four models. When the vehicle demand was four, and the number of cities was ten, the shortest average runtime of the DGA-MPHIGA model was 0.87 seconds. At this point, the average runtime of the SGA model was 3.02 seconds, while those of the MPHIGA and DPHGA models were 1.97 seconds and 2.28 seconds, respectively. When the vehicle demand reached eight, the average runtime of all four models increased as the number of cities increased. When the number of cities reached 25, the average runtime of the DGA-MPHIGA and SGA models was 3.94 seconds and 6.89 seconds, respectively, while the runtime of the DPHGA model was 4.86 seconds. The SGA model exhibited an average runtime of 9.03 seconds when the number of cities reached 30. These results indicated that the DGA-MPHIGA model made scheduling decisions more quickly when handling different vehicle demands, ensuring faster delivery of goods from the starting point to the destination.

V. Conclusion

To address the shortcomings of current intelligent logistics vehicle scheduling methods in dynamic data acquisition and managing security, this study combined DGA and MPHIGA in an intelligent logistics vehicle scheduling model. By leveraging the dual-population mechanism of DGA and the hybrid strategy of MPHIGA, the model achieved information sharing and co-evolution, balancing global search and local exploitation with the feasible vehicle scheduling solution is represented as an individual in genetic algorithm by chromosome coding. The results showed that the optimal path length of the MPHIGA model in the training set increased, reaching 424.35 km, with a running time of 14.17s. At this point, the optimal path length of the DGA-MPHIGA model is only 408.57km, with the shortest running time among the four models, at just 9.21s. When the number of scheduling instances reaches 5, the cost of the research model is only 0.112 million yuan. However, when the MPHIGA scheduling model has 3 instances, the cost has already reached 0.128 million yuan. Based on the above results, the proposed DGA-MPHIGA model outperformed the comparison models in scheduling time, cost, and range, demonstrating excellent vehicle scheduling capability and handling more complex logistics transportation tasks. The proposed model overcomes the limitations of traditional algorithms in multi-model scheduling and dynamic order response through multi-population co-evolution and dynamic coding optimization, provides an expandable decision framework for building highly flexible intelligent logistics systems, and helps reduce the empty load rate of cold chain transportation. The differences in results between various datasets stem from the structural characteristics of the TSPlib and Solomon datasets. The TSPlib dataset focuses on classic path optimization, while the Solomon dataset includes complex constraints such as time windows and dynamic demands, better reflecting the challenges of real-time logistics scenarios. The proposed algorithm enhances global search capabilities through multi-population co-evolution mechanisms, combined with domain generation algorithms to dynamically adjust coding rules, demonstrating significant advantages when handling high-dimensional constraints. However, as the number of cities increased, the average runtime of the model continued to rise, indicating that its performance still required improvement. Future work will focus on further optimizing the model.

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