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# Multi-Objective Intelligent Vehicle Routing Optimization by Dynamic Complex Neutrosophic Particle Swarm

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***Abstract:***

The multi-objective scheduling optimization problem is one of the important research problems in intelligent vehicle scheduling systems. For scheduling optimization problem of seafood intelligent vehicles, a scheduling optimization model based on the Dynamic complex Neutrosophic Particle Swarm (DNPS) is proposed. Experimental comparison with traditional genetic and immune was conducted, and the experimental data showed that the average distance was shortened by 1.15km, the average waiting time was shortened by 56s in the process of seafood intelligent vehicle scheduling. It can effectively ensure the freshness problem of seafood and improve the quality of delivery service.

***Keywords:****Scheduling optimization,Dynamic particle swarm,Complexneutrosophic set, Multi-objective*

## I. INTRODUCTION

In the intelligent vehicle research and application fields, the problem of scheduling optimization of multi-objective intelligent vehicles has become a hot and difficult problem for research[1]. In industry, automatic guided vehicles can improve cargo handling efficiency and reduce production costs in the operation of automated warehouses, intelligent ports, terminals, workshops[2]. In the transportation of terminal freight intelligent vehicles, the presence of special cargoes such as fresh and dangerous goods increases the difficulty of scheduling optimization problems of intelligent vehicles[3]. In foreign countries, some scholars use swarm intelligence such as genetic and immune to carry out the path optimization problem of storage and transportation vehicles[4]. The behavior of the whole population is coordinated by collecting and analyzing local information and using it to solve problems that are difficult to formalize models and complex combinatorial optimization problems that are difficult or impossible to solve exactly. Pollaris researched Iterated local search for the capacitated vehicle routing problem with sequence based pallet loading and axle weight constraints[5]. Swarm intelligence are widely used in scheduling and scheduling optimization problems due to their superiority in search. Masdari et al. studied the scheduling of particle swarm in cloud computing[6]. Hjp studied Particle swarm optimization with time buffer insertion for robust berth scheduling[7]. Islam combined particle swarm optimization (PSO) and variable neighborhood search (VNS) and proposed a new hybrid metaheuristic to solve the cluster vehicle path CluVRPproblem[8]. The domestic research on intelligent vehicle path optimization problem started late but

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developed rapidly. Lu and Teng et al. did a thorough study on vehicle path planning and optimization for storage complex operations and hazardous materials transportation, and achieved good application results[9-10].Ge used the Dynamic Event-Triggered Scheduling and Platooning Control Co-Design for Automated Vehicles Over Vehicular Ad-Hoc Networks[11]. All these studies are devoted to the direct use of improved swarm intelligence for scheduling problems and scheduling optimization problems, providing more stable and better search performance. However, for multi-objective optimization, the weights of the objectives are only set using empirical values, and no data analysis and decision is given for the weights of the objectives. neutrosophic set gives a reasonable basis for the weight setting of multi-objectives, and the existing research on neutrosophic set. Jin proposed a flexible job shop scheduling (TLBO) based on neutral sets, which gives a modeling and optimization method for IPPS problems with uncertain processing[12].LUU applied the neutrosophic set to a multi-objective green supplier decision problem[13]. It can be seen that the neutrosophic set has good adaptability for solving multi-objective optimization problems. For the multi-objective vehicle scheduling optimization problem, different values of weight settings have a certain influence on the convergence speed of the swarm intelligence. Therefore, in this study, the objective is firstly analyzed by using the CMI set and used in the objective function of the algorithm to adapt the vehicle scheduling optimization with different objectives.

## II. PROBLEM DESCRIPTION

The neutrosophic fuzzy set contains a total of three affiliation functions, which are true value affiliation function, uncertain affiliation function and distortion value affiliation function, each belongs to the [0,1] interval, and the sum of the three affiliation functions belongs to the [0,3] interval, which has a larger affiliation space and is more suitable for describing uncertain fuzzy information compared with the previous fuzzy sets and intuitionistic fuzzy sets[14-15]. In the study of intelligent vehicle path problems, decision makers often face some fuzzy and uncertain choice information for decision making, and sometimes intelligent vehicles give the weights between attribute criteria, but more often, it is never possible to obtain the exact attribute weights of alternative paths, and the study of path selection problems, a class of multi-criteria decision problems, is particularly important under these conditions.

There are two problems of multi-objective decision making and scheduling optimization for the intelligent vehicle scheduling problem of fresh and dangerous goods at terminals. The scheduling objectives for deciding smart vehicles mainly include features such as delivery cost, customer receipt time, green and low-carbon, etc. In this case, in addition to the commonly used features, two additional features, cargo loss and customer satisfaction, are added for fresh food delivery in multiple distribution centers at the terminal. The importance of features is not the same for different goods and different distribution centers, so how to give the target of final goods distribution reasonably is the first link to be solved. Here, according to the grade rating and weight setting of each feature given, a reasonable decision is given by using neutrosophic. On this basis, based on the above decision results, particle swarm with inertia factor is used to realize the link of multi-objective scheduling optimization. For the intelligent vehicle scheduling problem at the terminal, the vehicles need to deliver different goods to n storage centers from the starting point. For each storage center, the starting point is the location of the cargo source, and there may be 1 or more sections to pass through. If the goods are delivered to both the nth and n+1th storage center from the

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starting point, then for the nth storage center, its road section can be set as the road section n from the starting point to n, while for the nth+1st storage center, it is the road section n plus the road section n+1. Here the order of distribution centers is relatively uncertain, so the road section is not determined. When an intelligent vehicle starts from the starting point, the scheduling result determines its direction and travel, and each intelligent vehicle has an independent travel route. In the overall scheduling, the conditions to satisfy the optimization scheme are set according to the specific conditions of the scheduling optimization problem, and the target parameters of the goods are ensured to be satisfied during the delivery process.

## III. MODEL ESTABLISHMENT

The whole solution is divided into two main parts, firstly, the decision phase for the multi-objective complex neutrosophic fuzzy set. The decision objective vectors generated in the first stage for different storage centers are used as velocity vectors for the particle swarm scheduling optimization model with inertia factors to design and implement the scheduling model.

### 3.1 Multi Objective Intelligent Decision Model

The running path of the intelligent vehicle is divided into $m$ segments according to the optional path, $R = \{R_i | i = 1,2, \dots, m\}$ is the segment, $m$ is the number of segments, the length of the segment where each particle is located constitutes an m-dimensional vector $X_{i,j} = \{x_{1,j}, x_{2,j}, \dots, x_{m,j}\}$. Denote the set of $J$ storage centers as $N = \{n_j | j \in J\}$. Consider the five factors influencing the arrival of each storage center mainly including price/cost($F_1$), urgency($F_2$), security factor ($F_3$), cargo loss ($F_4$) and green low-carbon($F_5$), and generate the factor vector $F = \{F_1, F_2, F_3, F_4, F_5\}$,where the evaluation rank and importance weight of each factor of each storage center are different, the interval-valued neutral hesitation set of each factor's evaluation rating is $LS = \{VL, L, F, G, VG\}$, respectively, and it is assumed that the fuzziness is evaluated by the scheduling team based on $o$ importance of $q$ ratings of $P$ factors affecting $J$ storage centers; where the ratings and importance of the influencing factors are evaluated using the interval-valued complex fuzzy set (IVCNS) method is used to describe the ratings and importance of the influencing factors. The steps of the proposed multi-objective routing optimization decision-making (MORODM), as shown in Equation 1.

$$F_{j,p} = [F_j^s, F_j^b].\, e^{j\pi\,[\varphi^s(p), \varphi^b(p)]} \qquad (1)$$

Where, the criteria for the influencing factors are $F_{j,p}$. Here,$j$ represents the $j$th distribution center, $s$ represents the minimum value, $b$ represents the maximum value, $P$ represents the $P$th factor,$\varphi^s(p)$ represents the minimum value derived from the evaluation of the factor, and $\varphi^b(p)$ represents the maximum value derived from the evaluation of the factor. Here the impact factor indicators are given using the IVCNS method. Where the interval wise set of the rank assessment is denoted, as shown in Equation 2.

$$W_{p,q} = [W_p^s, W_p^b].\, e^{j\pi\,[\varphi^s(q), \varphi^b(q)]} \qquad (2)$$

The integration impact factor of the jth distribution center is given by integration, as shown in Equation 3.

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$$F_j = \frac{1}{p} \otimes (F_{j,1}.W_{1,q} \otimes F_{j,2}.W_{2,q} \otimes \ldots \otimes F_{j,p}.W_{p,q}) \quad (3)$$

3.2 Model Distance Calculation

For a factor in the above complex neutrosophic multi-objective decision model, when two decision makers give two different evaluated values, a neutrosophic distance is generated between the two evaluated values. For two values $F_{j,s}$ and $F_{j,t}$ of this factor $F_j$, the distance is given using the Manhattan distance as shown in Equation 4.

$$D(F_{j,s}, F_{j,t}) = \left[F_{j,s}^{s} - F_{j,t}^{s}, F_{j,s}^{b} - F_{j,t}^{b}\right]. e^{j\pi\,[\varphi_s^s(p)-\varphi_t^s(p),\varphi_s^b(p)-\varphi_t^b(p)]} \quad (4)$$

Here, $0 \le D(F_{j,s}, F_{j,t}) \le 1, D(F_{j,s}, F_{j,t}) = D(F_{j,t}, F_{j,s})$, $D(F_{j,s}, F_{j,t}) = 0$, when $F_{j,t} = F_{j,s}$,The values given by different decision makers can be measured by the distance and similarity between the two measures of their degree of difference. The values after discretizing their distances can be used as other particles of this factor to participate in the optimization search of the model.

3.3 Scheduling Dynamic Particle Swarm Optimization Model

For the multi-objective path optimization problem, an $m$-dimensional vector is used, i.e., a population of $m$ road sections with a population of $J$ distribution center particles. At a certain moment $t$: the position of the $j$th particle is an $m$-dimensional vector $X_{i,j}(t) = \{x_{1,j}, x_{2,j}, \ldots, x_{m,j}\}$, and the flight velocity of the $j$th particle is also an m-dimensional vector $V_{i,j}(t) = F_{i,j,p}(t)$, which is fitted according to the CIW hesitation set distribution center's influence factor, which constitutes a $J$-dimensional vector $V_{i,j}(t) = \{v_{1,j}, v_{2,j}, \ldots, v_{m,j},\}$ of $J$ storage centers in $m$ road sections. The vector is used as the flying speed of the particles in $m$ road sections, where the vector values of $k$ road sections belonging to the same distribution center are the same. The optimal position (i.e., the individual extremum) searched so far by the $i$ th particle is $T_i = (t_{i,1}, t_{i,2}, \ldots, t_{i,m})$, and the optimal position (i.e., the global extremum) searched so far by the whole particle population is $T_g = (t_{g,1}, t_{g,2}, \ldots, t_{g,m})$, the objective function $f(i)$ calculates the fitness $f(X_{i,j}(t))$ of each particle, and the measures the merit of the particle according to the fitness size.

where the particle is updated using the inertia factor as in Equation 5.

$$\begin{cases} V_{i,j}(t+1) = \omega V_{i,j}(t) + C_1 r_1 \left(T_i - X_{i,j}(t)\right) + C_2 r_2 \left(T_g - X_{i,j}(t)\right) \\ X_{i,j}(t+1) = X_{i,j}(t) + V_{i,j}(t+1) \end{cases} \quad (5)$$

$C_1$ and $C_2$ are non-negative constants called learning factors, and $r_1$ and $r_2$ are random numbers on [0,1]. $\omega$ is the inertia factor, which decreases linearly from the maximum weighting factor $\omega_{max}$ to the minimum weighting factor $\omega_{min}$ as the number of iterations increases. $\omega_{max}$ is initially set to 0.9 and ω_min is initially set to 0.4. The first term in equation (4) is called the "momentum" part. The first term is

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called the "momentum" part, which reflects the tendency of the particle to maintain its previous velocity, and is therefore also called the "inertia" part. The second term of the first article is the "cognitive" part, which reflects the particle's memory or recollection of its own historical experience and represents the tendency of the particle to approach its best historical position. The third item of the first article is the "collaboration" part of the particle, which reflects the group historical experience of collaboration and knowledge sharing among particles, and represents the tendency of the particle to approach the best position in the group or neighborhood history.

## IV. DESCRIPTIONOFDNPS

Dynamic Neutrosophic Particle Swarm (DNPS) seeks the most optimal solution in the problem space based on cross-comparison and analysis between different complex neutrosophic sets of data. Ordinary particle swarm do not have the ability to select, crossover and mutate the particles themselves, and it is impossible to search the rest of the problem space when the particle cluster is located near some local extrema. The DNPS adopts changing the overall initialization scheme and importing crossover and mutation to improve the arithmetic power of the basic PSO. The mutation here mainly adopts the method of neutrosophic set interval discretization, and the efficient organic integration of the basic PSO with other algorithms can not only increase the diversity of the particle swarm to improve the particle arithmetic power as well as accuracy. The specific algorithmic procedure is described below.

Step1: Randomly initialize the particle swarm, i.e., randomly assign a location $X_{i,j}(0)$ and a velocity $V_{i,j}(0)$ to each particle at t=0.

Step2: Calculate the fitness value $f(X_{i,j}(t))$ for each particle, and the vector consisting of the latest as of time of all feasible sections of distribution centers is the iterative particle.

Step3: Compare the current fitness value $f(X_{i,j}(t))$ and individual optimal value $f(T_i)$ of each particle, if $f\left(X_{i,j}(t)\right) > f(T_i)$, then $T_i = X_{i,j}(t)$.

Step4: Compare the current fitness value $f(X_{i,j}(t))$ and the global optimum $f(T_g)$ of each particle, if $f\left(X_{i,j}(t)\right) > f(T_g)$, then $T_g = X_{i,j}(t)$.

Step5: Calculate the Manhattan distance D between particles of each generation.

Step6: Discretize the edges of the neutrosophic interval so that the particles in the neutrosophic set are mutated.

Step7: Crossover the hesitations in different neutrosophic sets.

Step8: Change the velocity and position of each particle according to the distance D update formula.

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Step9: If the abort condition is satisfied, output $T_g$, otherwise, $t = t + 1$,and go to step2.

## V. COMPARISION EXPERIMENT

The experiments are based on the parameters of the actual storage center intelligent vehicle scheduling, firstly, the vector that determines the speed in the particle swarm is derived according to the neutrosophic decision model. Combined with the existing storage center roadway scheduling vectors, the multi-objective dynamic complex neutrosophic particle swarm scheduling optimization experiments for intelligent vehicles are given. The following comparison data and analysis are given from the experimental data, the complex neutrosophic decision and the particle swarm scheduling optimization process with inertia factor, and the later genetic and immune.

5.1 Experimental Data

For the decision making part of complex neutrosophic, here, the evaluation level data for multiple factors are set as follows: VL=Very Low=$[0.1,0.2]e^{j\pi\,[0.6,0,7]}$, $[0.7,0.8]e^{j\pi\,[0.8,0,9]}$, $[0.6,0.7]e^{j\pi\,[0.9,1.0]}$, L=Low=$[0.3,0.4]$ $e^{j\pi\,[0.6,0,7]}$ , $[0.6,0.7]$ $e^{j\pi\,[0.8,0,9]}$ , $[0.5,0.6]$ $e^{j\pi\,[0.9,1.0]}$ , F=Fair=$[0.4,0.5]$ $e^{j\pi\,[0.6,0,7]}$ , $[0.5,0.6]e^{j\pi\,[0.8,0.9]}$, $[0.5,0.6]e^{j\pi\,[0.9,1.0]}$, G=Good=$[0.7,0.8]e^{j\pi\,[0.8,0.9]}$, $[0.7,0.8]e^{j\pi\,[0.9,1.0]}$, $[0.8,0.9]e^{j\pi\,[0.9,1.0]}$, VG=Very Good=$[0.9,1]e^{j\pi\,[0.8,0.9]}$, $[0.9,1]e^{j\pi\,[0.9,1.0]}$, $[0.9,1]e^{j\pi\,[0.7,0.8]}$. The interval CMI set of importance weights for each factor is $W = \{UI, QI, I, VI, AI\}$ , where, UI=Unimportant=$[0.1,0.2]$ $e^{j\pi\,[0.6,0,7]}$ , $[0.1,0.2]e^{j\pi\,[0.8,0,9]}$, $[0.1,0.2]e^{j\pi\,[09,1,0]}$, OI=Ordinary Important=$[0.3,0.4]e^{j\pi\,[0.6,0,7]}$, $[0.3,0.4]e^{j\pi\,[0.8,0,9]}$, $[0.3,0.4]e^{j\pi\,[09,1,0]}$, I=Important =$[0.5,0,6]e^{j\pi\,[0.6,0,7]}$, $[0.5,0,6]e^{j\pi\,[0.8,0,9]}$, $[0.5,0,6]e^{j\pi\,[0.9,1.0]}$, VI=Very Import=$[0.7,0.8]$ $e^{j\pi\,[0.6,0,7]}$ , $[0.7,0.8]$ $e^{j\pi\,[0.8,0,9]}$ , $[0.7,0.8]$ $e^{j\pi\,[0.9,1,0]}$ , AI=Absolutely Important=$[0.9,1.0]e^{j\pi\,[0.6,0,7]}$, $[0.9,1.0]e^{j\pi\,[0.8,0,9]}$, $[0.9,1.0]e^{j\pi\,[0.9,1.0]}$.

Datas of the given factor ratings and importance weights are shown in TableI and TableII. The 16-dimensional particle velocity vectors for 12 distribution centers in some of these multiple sections are derived by taking the weighted mean values according to Equation 3, as follows.

**TABLE I. Ratings values of Factor**

| Factor | Centers | Ratings Values |
|---|---|---|
| $F_1$ | $N_1$ | $[0.533,0.642]e^{j\pi\,[0.739,0.819]}$, $[0.474,0.566]e^{j\pi\,[0.913,0.99]}$, $[0.31,0.403]e^{j\pi\,[0.81,0.9]}$ |
| | $N_2$ | $[0.210,0.341]e^{j\pi\,[0.718,0.823]}$, $[0.502,0.623]e^{j\pi\,[0.901,0.982]}$, $[0.305,0.498]e^{j\pi\,[0.823,0.894]}$ |
| | … | … |
| | $N_{12}$ | $[0.721,0.742]e^{j\pi\,[0.812,0.902]}$, $[0.231,0.298]e^{j\pi\,[0.913,0.990]}$, $[0.11,0.173]e^{j\pi\,[0.634,0.658]}$ |
| $F_2$ | $N_1$ | $[0.6,0.742]e^{j\pi\,[0.739,0.819]}$, $[0.474,0.566]e^{j\pi\,[0.964,1.0]}$, $[0.304,0.473]e^{j\pi\,[0.891,0.957]}$ |
| | $N_2$ | $[0.340,0.415]e^{j\pi\,[0.758,0.893]}$, $[0.7,0.823]e^{j\pi\,[0.941,0.986]}$, $[0.199,0.232]e^{j\pi\,[0.898,0.976]}$ |
| | … | … |
| | $N_j$ | $[0.586,0.552]e^{j\pi\,[0.912,0.992]}$, $[0.431,0.512]e^{j\pi\,[0.823,0.819]}$, $[0.332,0.473]e^{j\pi\,[0.629,0.780]}$ |
| $F_3$ | $N_1$ | $[0.579,0.562]e^{j\pi\,[0.739,0.819]}$, $[0.424,0.587]e^{j\pi\,[0.89,0.919]}$, $[0.314,0.493]e^{j\pi\,[0.681,0.797]}$ |
| | $N_2$ | $[0.387,0.454]e^{j\pi\,[0.622,0.732]}$, $[0.698,0.720]e^{j\pi\,[0.871,0.892]}$, $[0.295,0.308]e^{j\pi\,[0.962,0.996]}$ |
| | … | … |
| | $N_{12}$ | $[0.621,0.723]e^{j\pi\,[0.931,1.0]}$, $[0.331,0.390]e^{j\pi\,[0.803,0.82]}$, $[0.221,0.317]e^{j\pi\,[0.637,0.608]}$ |

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| | | |
|---|---|---|
| $F_4$ | $N_1$ | $[0.569,0.629]e^{j\pi\,[0.893,0.9]}$, $[0.424,0.516]e^{j\pi\,[0.939,1.01]}$, $[0.30,0.41]e^{j\pi\,[0.887,0.956]}$ |
| | $N_2$ | $[0.760,0.841]e^{j\pi\,[0.528,0.693]}$, $[0.312,0.473]e^{j\pi\,[0.971,0.999]}$, $[0.21,0.306]e^{j\pi\,[0.826,0.897]}$ |
| | … | … |
| | $N_{12}$ | $[0.691,0.734]e^{j\pi\,[0.878,0.994]}$, $[0.421,0.598]e^{j\pi\,[0.863,0.887]}$, $[0.21,0.387]e^{j\pi\,[0.548,0.606]}$ |
| $F_5$ | $N_1$ | $[0.508,0.621]e^{j\pi\,[0.734,0.843]}$, $[0.491,0.542]e^{j\pi\,[0.933,1.0]}$, $[0.432,0.498]e^{j\pi\,[0.83,0.92]}$ |
| | $N_2$ | $[0.382,0.492]e^{j\pi\,[0.628,0.733]}$, $[0.629,0.721]e^{j\pi\,[0.9,0.972]}$, $[0.345,0.409]e^{j\pi\,[0.833,0.854]}$ |
| | … | … |
| | $N_{12}$ | $[0.603,0.714]e^{j\pi\,[0.722,0.802]}$, $[0.231,0.298]e^{j\pi\,[0.823,0.819]}$, $[0.311,0.472]e^{j\pi\,[0.763,0.858]}$ |

**TABLE II. The weight of Factors**

| Centers | Factor | Weight values |
|---|---|---|
| $N_1$ | $F_1$ | $[0.097,0.103]e^{j\pi\,[0.138,0.172]}$, $[0.103,0.176]e^{j\pi\,[0.187,0.190]}$, $[0.641,0.687]e^{j\pi\,[0.132,0.165]}$ |
| | $F_2$ | $[0.092,0.098]e^{j\pi\,[0.143,0.184]}$, $[0.132,0.203]e^{j\pi\,[0.174,0.183]}$, $[0.601,0.672]e^{j\pi\,[0.163,0.158]}$ |
| | $F_3$ | $[0.13,0.154]e^{j\pi\,[0.122,0.198]}$, $[0.174,0.198]e^{j\pi\,[0.094,0.124]}$, $[0.534,0.643]e^{j\pi\,[0.163,0.158]}$ |
| | $F_4$ | $[0.098,0.172]e^{j\pi\,[0.097,0.102]}$, $[0.231,0.243]e^{j\pi\,[0.091,0.119]}$, $[0.568,0.626]e^{j\pi\,[0.103,0.134]}$ |
| | $F_5$ | $[0.193,0.245]e^{j\pi\,[0.172,0.196]}$, $[0.264,0.298]e^{j\pi\,[0.093,0.194]}$, $[0.598,0.674]e^{j\pi\,[0.133,0.168]}$ |

In particle swarm optimization, the population size is set to 30, the number of particles is 100, the vector length of particles is 16, C_1 and C_2 are equal and equal to the regular 2. When the iteration reaches the maximum number of iterations or the deviation of the solution satisfies the requirement that the average time difference of scheduling is less than 2s, the program is aborted.

$$\begin{bmatrix} 0.23 & 0.29 & 0.29 & 0.76 & 0.76 & 0.64 & 0.45 & 0.52 & 0.52 & 0.08 & 0.08 & 0.37 & 0.43 & 0.72 & 0.81 & 0.83 \\ 0.31 & 0.37 & 0.37 & 0.69 & 0.79 & 0.19 & 0.59 & 0.59 & 0.62 & 0.62 & 0.09 & 0.38 & 0.67 & 0.67 & 0.76 & 0.74 \\ 0.17 & 0.17 & 0.27 & 0.27 & 0.87 & 0.45 & 0.45 & 0.13 & 0.65 & 0.85 & 0.85 & 0.76 & 0.32 & 0.28 & 0.28 & 0.65 \\ 0.53 & 0.56 & 0.56 & 0.13 & 0.76 & 0.67 & 0.67 & 0.15 & 0.66 & 0.43 & 0.43 & 0.85 & 0.72 & 0.72 & 0.32 & 0.76 \\ 0.43 & 0.18 & 0.34 & 0.34 & 0.75 & 0.75 & 0.13 & 0.13 & 0.08 & 0.76 & 0.13 & 0.13 & 0.72 & 0.54 & 0.54 & 0.65 \\ 0.81 & 0.76 & 0.76 & 0.53 & 0.18 & 0.77 & 0.65 & 0.16 & 0.16 & 0.62 & 0.62 & 0.23 & 0.71 & 0.71 & 0.86 & 0.52 \\ 0.56 & 0.23 & 0.23 & 0.76 & 0.53 & 0.53 & 0.66 & 0.76 & 0.76 & 0.12 & 0.12 & 0.08 & 0.08 & 0.13 & 0.13 & 0.83 \\ 0.13 & 0.19 & 0.19 & 0.88 & 0.88 & 0.09 & 0.13 & 0.25 & 0.34 & 0.76 & 0.13 & 0.13 & 0.80 & 0.77 & 0.77 & 0.14 \\ 0.09 & 0.09 & 0.68 & 0.67 & 0.67 & 0.32 & 0.75 & 0.24 & 0.24 & 0.77 & 0.13 & 0.45 & 0.45 & 0.23 & 0.3 & 0.16 \\ 0.87 & 0.14 & 0.14 & 0.11 & 0.11 & 0.76 & 0.76 & 0.31 & 0.65 & 0.16 & 0.16 & 0.87 & 0.87 & 0.34 & 0.43 & 0.86 \end{bmatrix}$$

## 5.2 Experimental Results

In order to avoid the precocious phenomenon that occurs in multi-objective optimization problems, the inertia factor is introduced into the dynamic complex neutrosophic particle swarm scheduling optimization. The data shows that the scheduling optimization based on neutrosophic particle swarm, compared with genetic algorithm, runs the program efficiently due to the absence of crossover and mutation operations in genetic algorithm. In comparison with genetic algorithm(GA) and immune algorithm(IA), it is easier to search for the global optimum and less likely to fall into the local optimum solution.

For the distribution of goods in 16 sections of 12 distribution centers, after one month of distribution plan optimization, the comparison of the distribution time, distribution satisfaction, and green low-carbon index of each distribution center is shown in Fig. 1 using the DNPS based particle scheduling method with

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genetic and immune. The experiment shows that among the three algorithms, the distribution time optimization rate of dynamic neutrosophic particle swarm is 6%, the satisfaction rate is increased by 8.9%, and the green low-carbon index is increased by 12%, which achieves the expected effect.

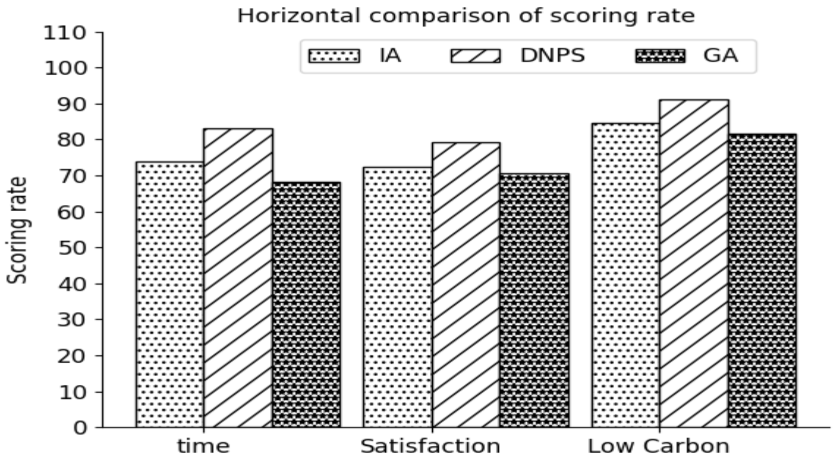


**Fig 1: Comparison of DNPS, immune and genetic**

The average routing times over 100 iterations of the three methods were compared and are shown in Figure 2. As can be seen from Figure 2, the average routing time of DNPS is lower than that of the GA and IA algorithms, although the time of DNPS iterations is slightly longer than that of the other methods.

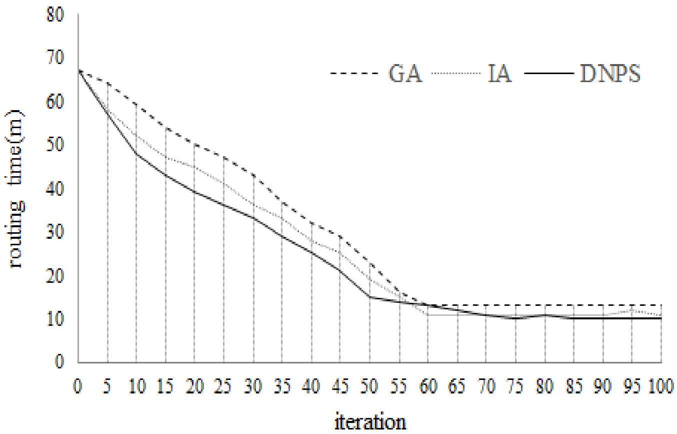


**Fig 2: Comparison of optimization process**

Population diversity is an important indicator to ensure that it can find the optimal solution. The population diversity oscillogram is shown in Figure 3. In the oscillogram of population diversity of the iterations, the immune has a certain advantage in terms of the average diversity of the three methods, but the optimized DNPS has slightly more population diversity at the peaks than the others. The population diversity of the genetic has more values at the peaks and valleys.

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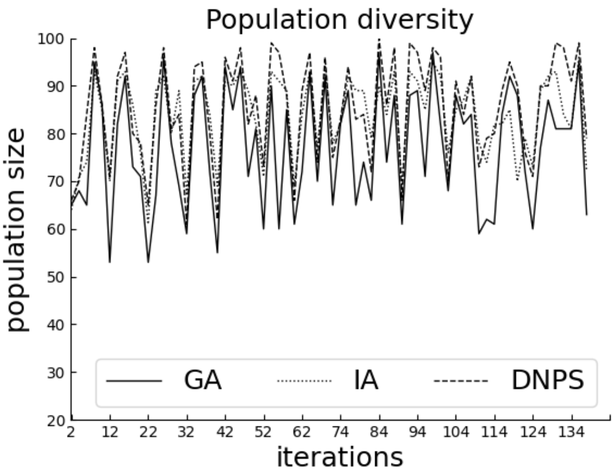


**Fig 3: Population diversity**

## VI. CONCLUSION

With the continuous progress of driverless technology and the development of smart vehicle application fields, the path design of smart vehicles in different fields needs further research. Good path planning capability is an important indicator for the wide application of smart vehicles and is crucial to meet the application requirements. In order to better serve customers and ensure the usability and versatility of smart vehicles, this study proposes a multi-objective path planning scheme for smart vehicles. In addition, we give a CMI particle swarm to find the optimal solution for the path of smart vehicles. The main contributions of this study are as follows.

•Based on the multi-objective intelligent vehicle scheduling problem, a multi-objective dynamic complexneutrosophic particle swarm scheduling optimization is studied, and a multi-objective decision method for complexneutrosophic hesitant set is given to fit the objective vector of multiple storage centers. Different weights of the objectives and distance calculation analysis are given in the method, and the case study shows that the model can guarantee the objectivity of the optimization objectives.

•In order to get the path that satisfies the scheduling objective, the velocity vector and inertia factor of the particle swarm are given for iteratively generating the sequence of scheduling paths for intelligent vehicles with multiple storage centers and variable road sections based on the objective vector of multiple storage centers.

•Comparing with the traditional genetic algorithm and immune algorithm, the results show that the method is highly adaptable to the multi-storage center intelligent vehicle scheduling problem. The path sequence obtained in this study can effectively improve the scheduling efficiency, save the scheduling cost and have better customer satisfaction. However, the weights of the multi-objective part need to be decided in combination with the decision maker's questionnaire, which means that the implementation of the thesis model needs to be better intelligent.

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•This study adopts the particle swarm combined with the CMI set, which gives the inertia factor and speeds up the convergence of the original particle swarm. It is simple and practical, with wide application prospects, and can be used as a reference for other multi-objective path finding problems.

•In this paper, the model is simulated and studied based on the actual data of the terminal multi-storage center. The simulation results verify the effectiveness and feasibility of the model, which can be used in the scheduling path finding of multiple intelligent vehicles.

Finally, it is worth noting that the approximate optimal solution of the path optimization problem can be obtained by using the proposed CMI particle swarm. However, the real-time performance needs to be improved, and the timeliness guarantee for the real-time scheduling problem is a research direction for the next step. Secondly, this study only considers the multi-objective scheduling optimization problem of one intelligent vehicle, and the coordination and cooperation problem between multiple intelligent vehicles is also one of the directions being studied.

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