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The Research of small wave basis ANN algorithm and 5-class decision factor AI

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Abstract: The accuracy and reliability of continuous space curve estimation is the key to global exploration. An improved artificial intelligence algorithm is proposed for the analysis of continuous space. First, small wave basis ANN algorithm is proposed to solve discretization strategy in continuous space: The hidden layer node transfer function in BP neural network is substituted with wavelet basis function, while the replaced BP neural network is composed of wavelet neural network. Secondly, improved wolf algorithm is set up. The core wolf system ensures the precision of whole exploration. Finally, the main and auxiliary double cores and five-class decision factor is used to establish a population classification model to solve the convergence of the algorithm.

Key words: small wave basis ANN, main and auxiliary double core, 5-class decision factor, AI

1. Introduction

In nature, ants, wolves, etc. although their individual intelligence is not high, they show high group intelligence. Swarm intelligence refers to any method and scattered problem solution plan in the interest of obtaining collective foraging of social insect groups and other animal groups. Group intelligence, with its simplicity, flexibility, distribution and robustness, has shown great potential and advantages in the research fields such as combinatorial optimization, knowledge discovery, communication network, robot and so on, and promotes the development of complex science.

Ant colony algorithm is a swarm intelligence mimic algorithm. It is another heuristic intelligent optimization algorithm. Ants is capable of seeking out the shortest distance between the nest and the food without any hint, and can adaptively search new paths to produce new choices as the environment changes. The fundamental reason is that ants can release a special secretion pheromone on the way they walk, and the substance gradually volatilized over time, and the possibility of path choice later increases with the amount of the pheromone on the way. When much more ants travels on the way, the pheromones that they leave are more and more, and the chance that ants travel the path is much more, thus increasing the pheromone intensity on the path. Pheromones with strong intensity will have a strong appeal to more ants, thus producing a positive feedback mechanism. By this effective feedback method, ants can finally produce the shortest route. The ant colony algorithm is from the Italy scholar. They firstly proposed and successfully applied to solve Traveling Salesman Problem, QA Problem, graph coloring, vehicle scheduling, integrated circuit design and communication network load and other issues. The ant colony algorithm is very popular for its outstanding performance in discrete combinatorial optimization during ten years.

Although ant colony algorithm has been around in various fields at present, the application of the algorithm still needs to be popularized. It needs to be developed from simple application to complex comprehensive application, such as multicast routing and data mining. It can be imagined that as the research is deep, the ant colony algorithm will also get higher performance and become

more widely used as well as other analog evolutionary algorithms. Of course, from the situation encountered in the previous field, the theoretical imperfection does not interfere with the application, and sometimes the application will go ahead of the theory, and promote the theoretical research, the ant colony algorithm is also the same.

The ant colony algorithm is modified and used to the TSP problem; thus, the convergence speed is accelerated and the performance of the algorithm is promoted successfully [1-6]. However, another disadvantage of the ant colony algorithm is that it is difficult to deal with the optimization problem of continuous space. Because the selection of each ant at each stage is always limited, it requires discrete solution space. It is very applicable to discrete optimization problems such as combinatorial optimization, and it cannot be applied directly to the optimization problem of continuous space such as linear and nonlinear programming. GiBlchve utilized genetic algorithm to solve the optimization problem of continuous space in engineering design, with the use of ant colony algorithm to preliminary results obtained by the genetic algorithm, which achieved good results, but the ability of ant colony algorithm to settle the optimization continuous space problem is relatively weak. An improved ant colony algorithm is proposed to solve the problem mentioned above. In this approach, the solution space is divided into several subsections. During each step of ant colony algorithm, the subsection of the solution is calculated first according to the amount of information, and then the specific value of the solution is determined in the existing solution in the subsection. Our algorithm is very different from that from the literature [9], which is only a mixture of genetic algorithm and ant colony algorithm. They applied the ant colony algorithm to perform local search and use genetic algorithm to perform global search. This algorithm is entirely based on improved ant colony algorithm. The method shows better convergence speed than the use of simulated annealing algorithm and genetic algorithm.

2. Wolf Algorithm

Based on bionic natural wolf hunting behavior Liu .etc. proposed wolf group algorithm (Wolf Colony Algorithm, WCA). The algorithm abstracts wolves search behavior, siege behavior and wolf group updating behavior. The simulation experiment proves that the WCA algorithm possesses higher accuracy, faster convergence speed. Consequently, the WCA algorithm is applied to robot path planning. Wu Husheng and so on proposed the wolf group algorithm (Wolf Pack Algorithm, WPA), which is different from the WCA algorithm search strategy on the basis of the characteristics of the collaborative seeking activities of the wolves. The method analyzes the mode of predator behavior and the distribution of prey, and abstracts the 3 acts of walking, calling, and siege and the wolf group updating mechanism of "winner is king" and "strong person survival", and based on Markov chain theory, the global optimal solution of the algorithm with probability 1 convergence problem is proved. Finally, the experiment shows that the Wolf Pack Algorithm has stronger robustness and global optimization ability compared with classic Fish-Swarm Algorithm (FSA), PSO algorithm and GA algorithm, especially in the processing of multi peak and high dimensional complex functions. Zhou Qiang and so on [33] introduce leader strategy and propose a leader strategy based wolf swarm algorithm (Wolf Colony search Algorithm base on the strategy of the Leader, LWCA), which leads the wolf group to evolve through competitive selection of the head wolf. Literature 4 encodes the position, step length of artificial wolves by defining the operator, and proposes a binary wolf group algorithm. It has successfully solved the 0-1 knapsack problem and has a good solution stability to solve the problem the large scale 0-1 knapsack

problem, which has obvious advantages and extends the application of wolf group algorithm.

WA is a swarm intelligence optimization algorithm that simulates wolves' predation. It mainly solves the global optimization problem of variables. The algorithm mainly simulates 3 processes of predator prey: 1) hunting process: using the mountain climbing method to search the local optimal value near the current position of the wolf individual; 2) the siege process: searching the global optimal value by using the information of the best wolf individual in the group; 3) food distribution process: the wolf individual whose target function is poor in the group can be replaced by a random new individual, which can increase the diversity of the group and avoid the local optimal algorithm. First, it is necessary to improve its coding mode. Moreover, considering the data initialized by the wolf colony algorithm, the effect of subsequent optimization process will be greatly affected. In the course of the WA algorithm, wolves in the wolf pack drive the prey to the head of the wolf, but this will reduce the diversity of the wolves and make the algorithm access to fall into the local optimum. For this reason, this paper proposes a hierarchical wolf swarm algorithm, which divides the wolves before food distribution, in order to ensure the superiority of the wolf, and expel the other wolf individuals in the group, so that the diversity of wolves in the wolves is improved, and the efficiency of the calculation is greatly improved.

3. Continuous space discretization algorithm based on ANN

Supposed there are m inputs and n outputs (or n ants) in continuous space. Wavelet transform is a multi-scale analysis of signals through translation and scale expansion, so that the local information of the signal can be extracted more effectively. For neural network, it has good adaptability, good self-learning ability and strong fault tolerance, and can be used to approximate real condition function.

The hidden layer node transfer function in BP neural network is substituted with wavelet basis function, and the replaced BP neural network is composed of wavelet neural network. The topology of wavelet neural network is shown in the following figure.

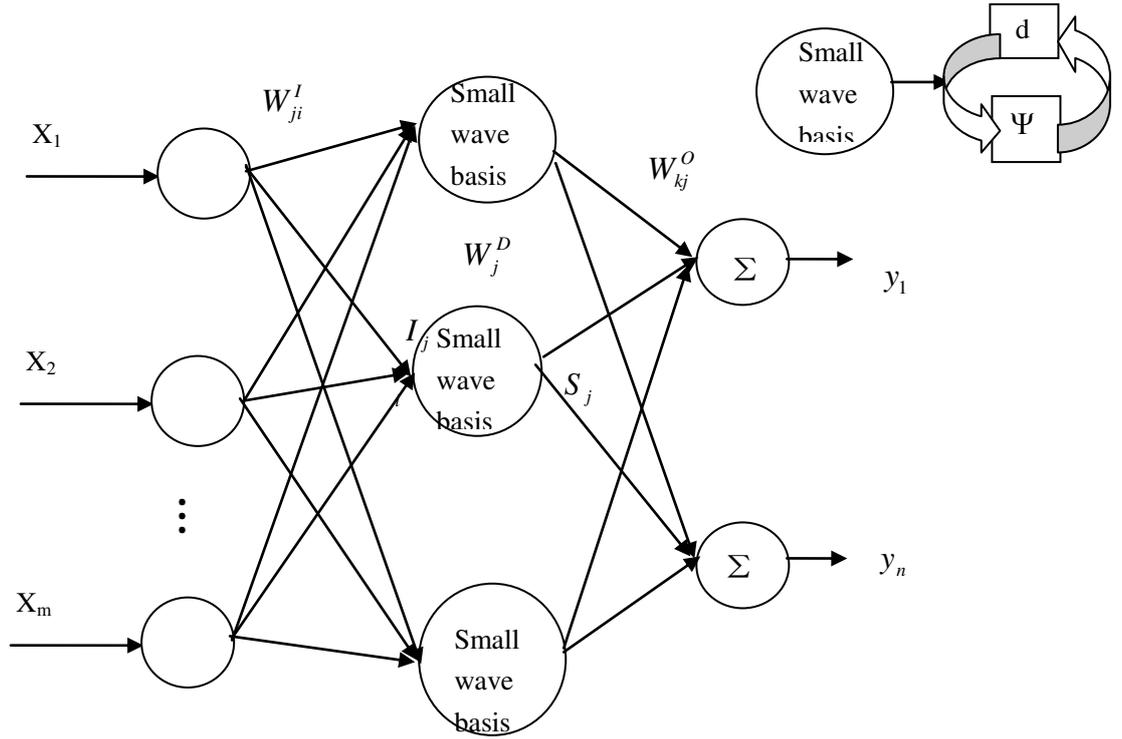


Fig.1 ANN topology

As shown in Figure 1, the mathematical model of the entire network is:

$$\begin{cases} \bar{y}_k(t) = y_k(t) + e_k(t) = \sum_j w_{jk}^o S_j(t) + e_k(t) \\ S_j(t) = \psi(I_j(t)) \\ I_j(t) = \sum_i w_{ji}^I x_i(t) + w_j^D S_j(t-1) \end{cases}$$

Among them, $x_i(t)$ is the i^{th} input for the network; $I_j(t)$ is the sum of the j^{th} input wavelet basis function; $S_j(t)$ is the output of the j wavelet. ψ is the wavelet function. $\bar{y}_k(t)$ and y_k are the k^{th} output node for the network. $e_k(t)$ is the model error. w_{ji}^I is the coefficient value of the input to the hidden. w_{kh}^o is the coefficient value of the hidden to the output. w_j^D is

1. The hidden layer nodes reflect the dynamic characteristics of the system by introducing a first-order self-feedback link. In this way, the dynamic performance of the algorithm can be represented by the input and output of M and N, which can describe the dynamic characteristics of the system, and the number of the input nodes of the network can be reduced to a large extent without the traditional multi-layer dynamic forward network. The input of the hidden layer is composed of the input of the current time and the output of the previous moment, and the output at the first time is the function of the input at the moment, and the input of the previous moment contains the output of the previous moment, so the infinite recurrence is formed and the memory of the information is infinite. Therefore, compared with the multi-layer dynamic feed forward network, the first-order delay structure can better reflect the dynamic characteristics of the system,

and does not increase the number of input nodes of the network.

4. The strategy based on dual core and 5-class decision factor

4.1 Wolves coding initialization

First, based on the discreteness of the target optimization, a double coding method is introduced to express the solution, that is, to use the (x, s) to represent the wolf individual. Among them, x is the location vector, that is, iterative search in this search vector; s is binary vector, indicating the placement of vertices.

Wolves coding and initialization steps are as follows: step 1: suppose that the total number of all nodes is n , and numbered 1 to n . Step 2: take the wolf i in the wolf pack as an example ($i = 1, 2 \dots P$) P is the total number of wolves), and their corresponding solutions can be expressed as: $p_i = (x_i, s_i)$. The location vector x_i is a real number array generated from interval $[x_{down}, x_{up}]$, and its dimension components can be generated by the following methods.

First set the vector:

$$\phi = \left(\frac{1}{n+1}, \frac{2}{n+1}, \dots, \frac{n}{n+1} \right).$$

Then the order of the components in the Φ and get the vector Φ' is disrupted.

Φ' is used to initialize the position of wolves.

$$x_{i,j} = \phi'_j (x_{up} - x_{down}) + x_{down}$$

$$x_{i,j} = \phi'_j (x_{up} - x_{down}) + x_{down}$$

$$s_{i,j} = sig(x_{i,j}) = \frac{1}{1 + e^{-x_{i,j}}}$$

Where $s_{i,j}$ is $x_{i,j}$ is binary coded from upper equation.

During upper equation, the threshold value ε and interval $[x_{down}, x_{up}]$ are needed.

If $sig(x_{i,j}) > \varepsilon$, then the component $s_{i,j} = 1$. A vertices is arranged at the position of the node.

If $sig(x_{i,j}) < \varepsilon$, then the component $s_{i,j} = 0$. There is no vertex arranged at the position of the

node. In this manuscript, $x_{down} = -6$; $x_{up} = 6$. Since the effective wolf individual needs to satisfy the coding requirement, in order to ensure the effectiveness of the wolf individual produced by the initialization, a method based on the probability method to determine the threshold value ε is proposed. With the j dimension component $P_{i,j}$ of the wolf individual P_i as an example, the probability of the $S_{i,j}$ value of 1 is n_s/n , while the probability of $S_{i,j}$ is 0 of the $1 - n_s/n$, which can ensure that the generated wolf individual satisfies the coding requirements. If $x_{down} < x_{i,j} < -x_{th}$,

then $s_{i,j} = 0$, the probability of a corresponding $s_{i,j}$ value of 0 is $1 - n_s/n$. If $-x_{th} < x_{i,j} < x_{up}$,

then $s_{i,j} = 1$, the probability of a corresponding $s_{i,j}$ value of 0 is n_s/n . therefore, x_{th} is given

by:

$$x_{th} = (n_s/n)(|x_{down}| + |x_{up}|) - |x_{up}|$$

The interval $[x_{\text{down}}, x_{\text{up}}]$ is segmented by means of x_{th} , so the suitable value of ε is $1 / (1 + e^{x_{th}})$. This method can not only speed up the production of effective initial wolves, but also ensure the uniformity of individual components of wolves.

4.2 hunting process

Wolves in the wolves are all involved in hunting for prey. Before each step, the wolf individual calculates the position of one step forward to the surrounding h direction, and then finds the optimal position in the H position, pos_A . if pos_A is better than the current position, then the wolf moved forward to the best position and searched forward with pos_A as the current position. If no better location is found, the wolf maintains the current position. The hunting equation of a wolf individual can be expressed as:

$$y_{c,j} = x_{i,j} + (2x_{rand} - 1)x_{st}$$

Where x_{rand} is a random number in $[0, 1]$; x_{st} is the search step; $x_{i,j}$ is the j component of the wolf i individual; $y_{c,j}$ is the j component of the c location around $x_{i,j}$.

Take the m^{th} wolf individual position vector X_m in wolf pack as an example; the hunting steps are as follows:

- h new locations around X_m are generated by the upper equation.
- The f value of the target function for each y_c ($y_{c,1} \dots y_{c,n}$) is calculated. If the optimal position in the h new positions is superior to the previous position, the position vector of the wolf individual is changed to this vector; conversely, the individual position of the wolf remains the same.
- Repeat steps above 1 and 2 until the number of searches is set number N_h .

4.3 Siege process

When the hunted wolf individual finds its prey, it first determines the position of the prey, and then recruits the other wolf individuals through howling, and the wolf individual in the group drives the prey to the wolf's position, realizing the siege strategy for the prey. The siege equation is as follows:

$$\Delta x_{(i,j)d} = x_{rand} x_{stb} (x_{best,j,d} - x_{i,j,d})$$

$$\Delta x_{\min} \leq \Delta x_{i,j,d} \leq \Delta x_{\max}$$

Where x_{stb} is the step length of a wolf's individual siege preying; $x_{best,j,d}$ is the j component of the head wolf in the D iteration; $x_{i,j,d}$ is the j component of the i^{th} wolf individual in the D iteration. $\Delta x_{i,j,d}$ is the siege distance of the j component of wolf i except head in the D iteration. In order to prevent the wolves from missing the global optimum in the siege process due to the siege distance, the threshold Δx_{\min} and Δx_{\max} are used to limit the siege distance of the

wolf individuals. If $\Delta x_{i,j,d} \geq \Delta x_{\max}$, then $\Delta x_{i,j,d} = \Delta x_{\max}$. If $\Delta x_{\min} \geq \Delta x_{i,j,d}$, then

$\Delta x_{i,j,d} = \Delta x_{\min}$. Hence

$$x_{i,j,d+1} = x_{i,j,d} + \Delta x_{i,j,d}$$

Where $x_{i,j,d}$ and $x_{i,j,d+1}$ is the j component of wolf i before and after siege.

Therefore, the siege steps are as follows:

Step 1: calculate the value of the wolf's target function and select the best wolf individual as the wolf x_h .

Step 2: takes the 1 wolf individual apart from head wolf in the wolf group as an example, and uses the above two equations to update the position of the individual wolf in the group to get the updated individual position of the wolf.

4.4 social classifications

By reference of labor division and cooperation and hierarchy of animals, and the whole group is divided into five categories according to the function division of the individual. The individual acts according to their own will, the individual acts according to the wishes of others, and the individual negative action is eliminated by the whole group.

On this basis, the decision factor β is introduced as a strong evaluation value for the individual's willingness to act independently: the greater the value, the stronger the self-determination and the increase of the influence of the other individuals. In reverse, the smaller the value of the individual is, the weaker the self-determination will be. It is also easy to be affected when it cannot affect other individuals.

The decision factor β is given by:

$$\beta_i = opt_i / opt_{\max}$$

β_i is the decision factor of individuals, opt_{\max} is the best fitness, and opt_i is the fitness of individuals. According to the predetermined threshold and the individual decision factor, the whole social group can be divided into 5 categories, namely, the main and auxiliary head, the leader, the followers and the elimination.

The overall calculation method of adaptive ant colony algorithm based on dynamic level is shown in the following graph. After the completion of the path construction of all ants,, the ant is classified by the dynamic classifier, and after the effect of the wolf influence strategy, two classifying is carried out.

Dynamic pheromone updating strategy is also proposed according to the classification. This information will be retained as the basis for the next iteration of ant colony construction. When the termination condition is reached, the current optimal path and path length information are output.

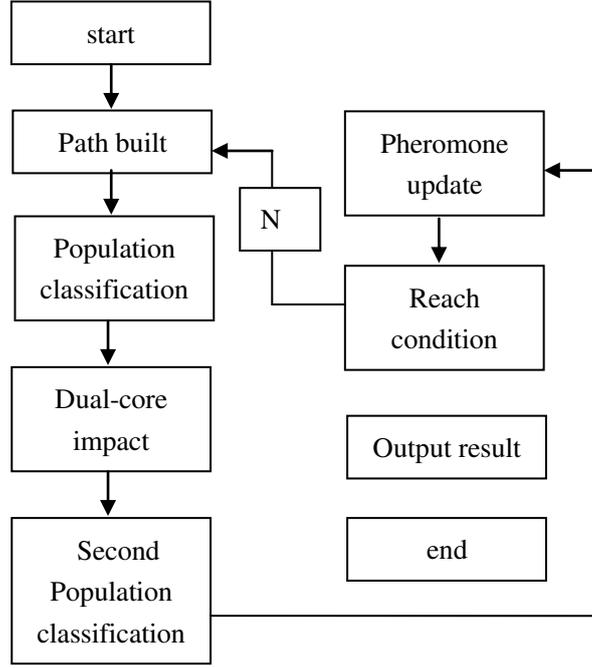


Fig.2 algorithm process

4.5 5-class decision factor

A 5-class decision algorithm is proposed, which divides the whole population into 5 different grades based on individual fitness.

The rank of individual A_i is L_i , and the grade is determined by decision factor β_i . In path planning, the individual's degree of excellence is determined by the length of the route. The longer path length individuals are considered to be excellent individuals. Under this premise, the grading factor is defined as follows:

$$\beta_i = length_i / length_{\max}$$

Where, $length_i$ is the path length of an individual, and $length_{\max}$ is the shortest path length in the current iteration, and β_i is determined by the ratio of $length_i$ to $length_{\max}$.

The individual is divided by the following equation:

$$L_i = \begin{cases} main & \text{if } \beta_i = 1 \\ auxiliary & \text{if } \beta_i \approx 1 \\ elite & \text{if } cl \leq \beta_i \leq 1 \\ ordinary & \text{if } ce \leq \beta_i \leq cl \\ Elimination & \text{if } \beta_i \leq ce \end{cases}$$

The whole population is divided into 5 categories:

- When $\beta_i = 1$, the rank L_i of individual A_i is defined as main core. Such individual is similar to head wolf, which can guide the whole population.
- When $\beta_i \approx 1$, the rank L_i of individual A_i is defined as auxiliary core. Such individual is similar to vice head wolf or wife wolf, which can ensure the whole population if head wolf is gone. The auxiliary core also avoids the endless loop while the main core meets singularity. In general the auxiliary core and main core guide the population
- When $cl \leq \beta_i \leq 1$, the individual level is defined as elite, and cl is the grading threshold of this class. Individuals belonging to this class who are outstanding in the population individuals are less affected by main and auxiliary cores, and their experience can be more individuals, and may become new main core.
- When $ce \leq \beta_i \leq cl$, the level of the individual is defined as ordinary, and ce is the lower limit of ranking. They can be similar to fierce wolves. They are ordinary members of the population and the main components of the population. They are influenced by main and auxiliary cores, but also retain their own characteristic.
- When $\beta_i \leq ce$, individuals are defined as elimination. These individuals are considered to be the obsolete. They will be guided by main and auxiliary cores and will not function in updating information elements.

Hierarchical decision making is the basis of dual core impact strategy and information element updating strategy, which embodies the strict classification of wolves' algorithm. At the same time, the number of individuals in each level is not fixed. It will adjust the scale according to the situation of each iteration.

4.6 dual core impact strategy

The effect of dual core on other rank members can be reflected in a variety of ways. This algorithm is set by the head wolf influence strategy--- directly replacing the path fragment which by randomly selecting the two intersection points of the path of the head path and the other members of the class, path segmentation and fragment replacement is utilized to preserve the individual's own experience, and reflect the influence of core.

As shown in flowing figure, when there are two or more intersection points outside the starting point and the end of the path, the intersection point A and B of the path of the head path and the other rank members are randomly selected, and the AB path of the other rank members is replaced with the head AB path after dividing the paths connected by the A and B points. While reflecting the guiding role of head, it retained the experience of other members.

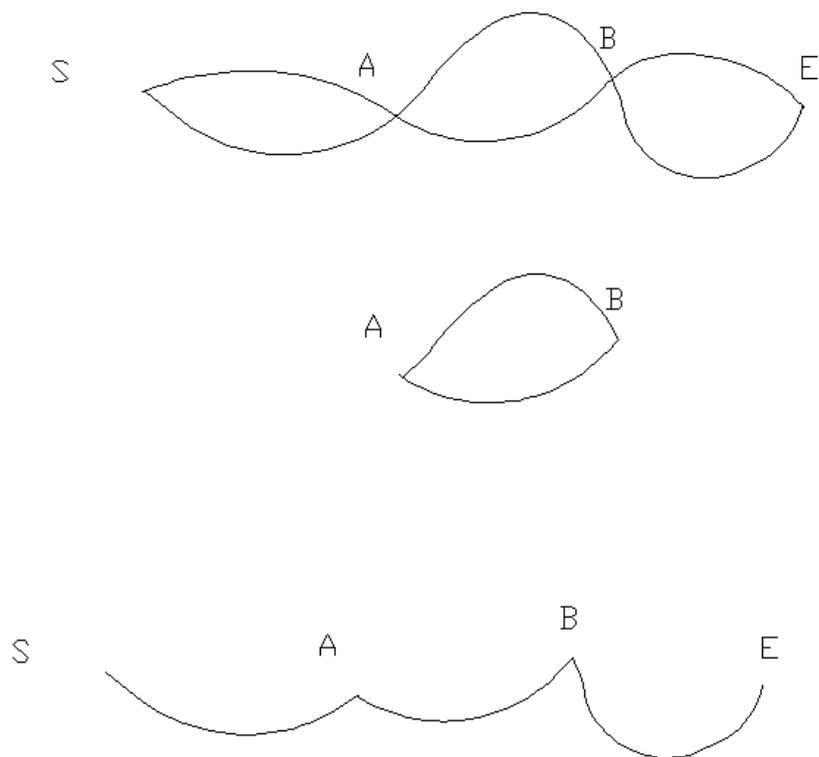


Fig.3 dual-core impact strategy

When there is only one intersection between the head path and other paths except the starting point and the ending point, the wolf influence strategy does not function.

In order to enhance the diversity of the algorithm, roulette mechanism is also applied in the wolf impact strategy. Different rank members belong to different roulette thresholds: elimination will be definitely affected by dual cores; ordinary may be greatly affected while elite as a candidate for dual cores, the probability of being affected is relatively low.

The application of the strategy of the dual cores affects the communication between cores and other rank members in the population, following the natural law of the survival of the fittest, giving the better individuals the free development space and forcing the behavior of the weaker individuals to make the whole population develop better.

4.7 Dynamic pheromone updating strategy

The information value of ants of different ranks is different.

In order to effectively utilize the pheromones of elite individuals, we can reduce the interference of weak individuals.

In the early stage of pheromone updating, with the less pheromone on the path, the search path of individuals will be more affected by the heuristic information, resulting in too many members of the elimination and almost no elite class. In the later period of the pheromone updating, the pheromone on the better path tends to saturate, making the individuals difficult to fall into the dead zone, at this time, almost all the members of the whole population belong to the ordinary and elite class. The more they develop, the more members will be in the elite class.

In order to ensure that the importance of the hierarchy can be smoothly embodied in the

whole process of the algorithm and the guidance function of the advanced class can be played steadily, while adopting a hierarchical dynamic pheromone updating strategy, the algorithm joins the normalization process in this algorithm. The pheromone of the path segment of the individual is given by the following equation:

$$\tau(i, j) = \eta \times rand(0, 1) \times \exp(\tau_{\max}, i(i, j), 1) + (1 - \eta) \times rand(-1, 1) \times \exp(\tau_{ord}, i(i, j), 1)$$

Where $\tau(i, j)$ is current individuals pheromone; η is Pheromone utilization rate;

$rand(0, 1)$ is random number between 0 and 1; $rand(-1, 1)$ is random number between -1

and 1, τ_{\max} is the maximum pheromone of rand population and τ_{ord} is the ordinary pheromone.

The first half of above equation enhances the part optimization ability of the individuals while second half enhances the global search ability of the individuals. The equation balances the global search ability and local optimization ability of the individuals, which not only embodies the leadership ability of individuals, but also keeps the close communication between the individuals.

The hierarchical pheromone updating strategy reflects the influence of different classes of individuals. The experience of the outstanding individuals in the current iteration can have a greater role in the path selection of the next iteration, and the experience of the weak individual is not considered because of the less reference value.

This updating strategy embodies the guidance function of the elite individuals and improves the convergence of the algorithm. At the same time, because it depends on the above dynamic classification operator, it will be adaptive because of the change of iteration, avoiding the imbalance of algorithm.

5. Experimental results

To demonstrate the result of the algorithm, this paper compares the algorithm with the ant algorithm in 20*20 environment.

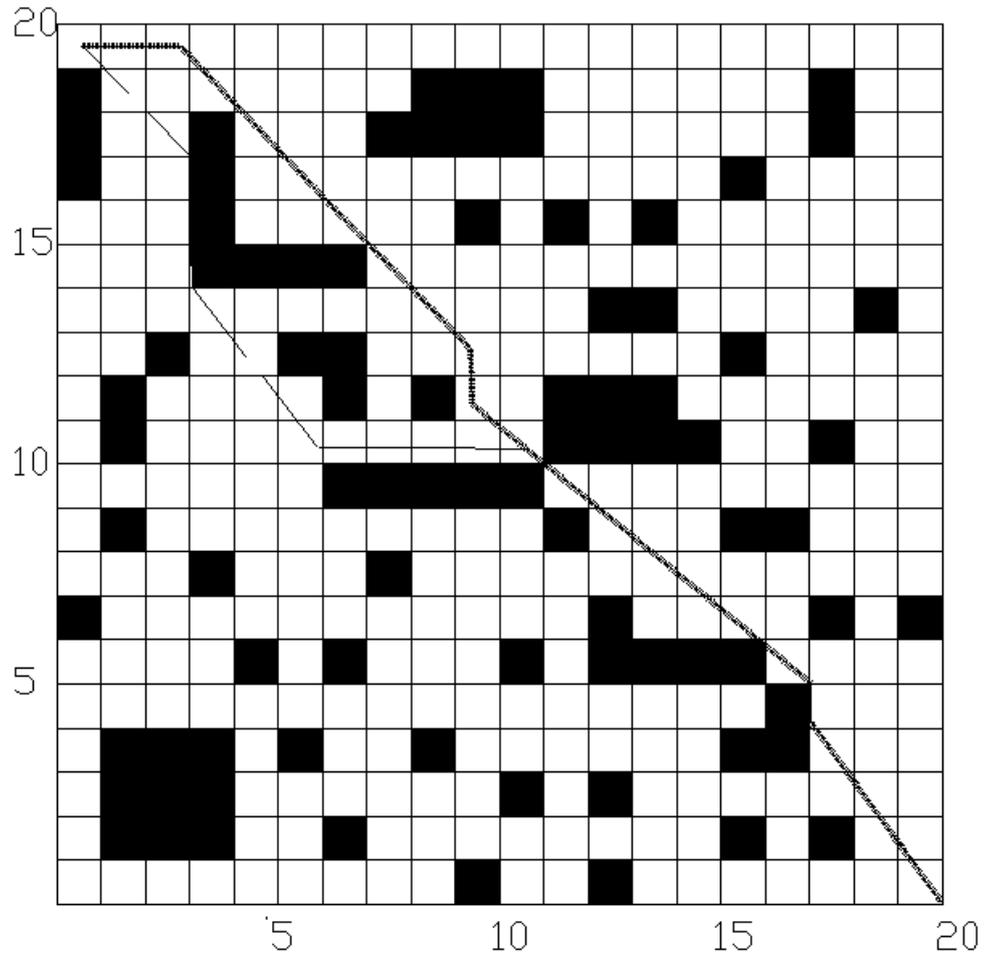


Fig.4 Path comparison

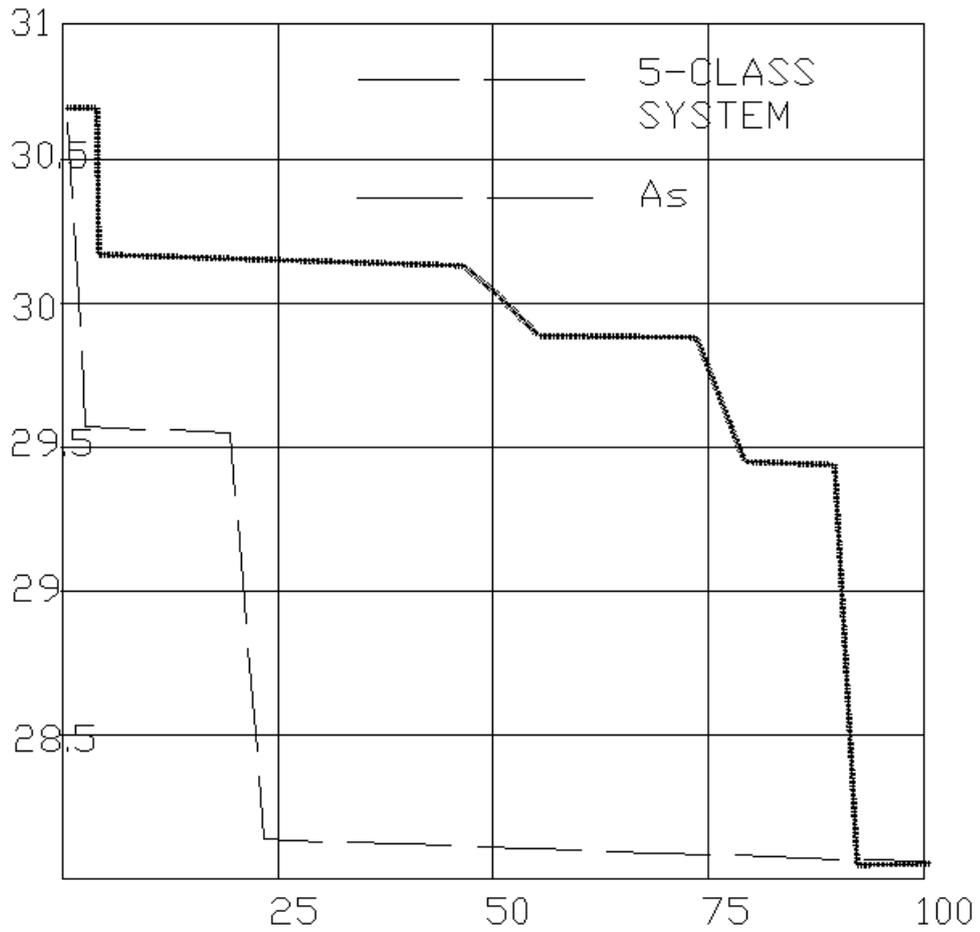


Fig.5 iteration

From Figure 4 and Figure 5, it is concluded that the algorithm converges faster and finds better solutions than other algorithms.

The comparison between AS and 5-class system

optimum solution	algorithm	optimal value	worst value	average value	Average iteration
28.6274	5-class system	28.6274	29.4558	29.2416	7.1
28.6274	AS	28.6274	29.799	29.4759	38.9

The small wave basis ANN algorithm and 5-class decision factor AI algorithm is introduced to estimate the LOC OF LiFePO₄ battery.

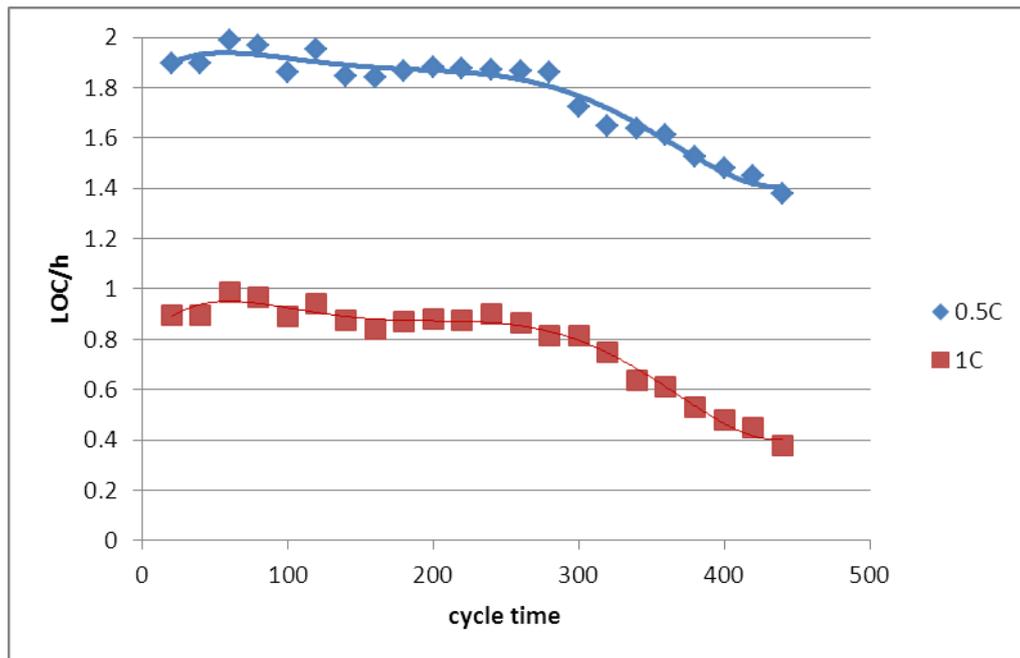


Fig.6 LOC curve

The blue diamonds are the LOC values at current rate of 0.5C; while the red squares are the maximum voltage values at current rate of 1C. The blue curve and red curve are obtained by 5-class AI. The LOC model slightly deviates from actual data at cycle time from 50-200. Cycle time reaches 50-200, the capacity gets up to peak value that leads to LOC curve above.

Ethical approval

Written informed consent for publication of this paper was obtained from Foshan Polytechnic, Zhongshan Polytechnic, Shenzhen Polytechnic and all authors.

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Conflict of interest

The authors declare that there is no conflict of interests regarding the publication of this article

Informed Consent

For the manuscript that include details, images, or videos relating to individual participants, informed consent for the publication of these is obtained from the participants

Authorship contributions

Study conception and design: Xuepeng Liu

Acquisition of data: Dongmei Zhao

Analysis and interpretation of data: Yihang Peng

Drafting of manuscript and Critical revision: Jianping Li

Reference:

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