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MULTI-OBJECTIVE OPTIMIZATION ALGORITHM OF CROSS-BORDER E-COMMERCE SOCIAL TRAFFIC NETWORK BASED ON IMPROVED PARTICLE SWARM OPTIMIZATION

WENJIN JIN*AND YINGYU LI

Abstract. The optimization algorithm known as Particle Swarm Optimization (PSO) is based on swarm intelligence and was created by modeling the foraging behavior of bird flocks. This study using the generalized regression neural network to improve particle swarm optimization (PSO) algorithm, proposed a target for cross-border electricity social network optimization algorithm PSO-PNNG, the simulation experiment in multiple real social network data environment and algorithm comparison, and the basic operation of genetic algorithm into the particle swarm algorithm, enhance the particle swarm optimization algorithm's performance, speed up the convergence speed. In this study, three social network datasets obtained by real reptiles were used to solve the proposed PSO-PNNG algorithm in a real social network data environment. The findings of the experiment indicate that the suggested multi-objective optimization algorithm for cross-border e-commerce social traffic network based on improved PSO has higher efficiency and accuracy than the traditional method.

Key words: Improved particle swarm optimization; Cross-border e-commerce; Social networks; Multi-objective optimization

1. Introduction. PSO works with members of a group to collaborate and share knowledge in order to find the best answer, and is widely used. due to easy coding, fast convergence, and easy parallelization [1]. The particle swarm algorithm, with its simplicity and efficiency, is effectively used to solve a variety of challenging optimization issues [2]. In real life, we often encounter a variety of complex multi-objective optimization problems, which are often difficult to solve through the traditional optimization methods. The multi-objective particle swarm algorithm, as an effective algorithm, can help us to solve such problems [3]. The challenge of determining the best solution when there are several competing goals is known as multi-objective optimization. Multi-objective optimization problems are often expressed as mathematical programming problems where there are two or more objective functions rather than a single objective function. In this case, we look for solutions that trade off between these targets, rather than a single optimal solution [4].

The integration of generalized regression neural network (GRNN) and particle swarm optimization (PSO) can significantly enhance its global search and best approximation ability through parameter optimization, combination of global search and local search, and dynamic adjustment of network structure. Parameter optimization refers to the fact that the performance of GRNN is significantly affected by its internal parameters (such as smoothing factors), and the PSO algorithm can be used to optimize these parameters to improve the global approximation ability of GRNN. The PSO optimizes the performance of the GRNN by constantly adjusting the velocity and position of the particles to find the optimal combination of parameters. The combination of global search and local search means that the PSO algorithm is a global optimization algorithm, which can find the best solution widely in the search space. GRNN is a local approximation method, which approximates in a local region of the input space. By combining the global search ability of PSO with the local approximation ability of GRNN, the best approximation function can be found in the global scope and fine-tuned in the local region to improve the approximation accuracy. Dynamic adjustment of network structure means that the PSO algorithm can also be used to dynamically adjust the network structure of GRNN, such as the number of hidden layer neurons. By optimizing the network structure, the global approximation ability and adaptability of GRNN can be further improved. The structure of neural network and its interaction with PSO are reflected in the network structure adjustment. PSO can be used to optimize the network structure of GRNN, for exam-

*School of Entrepreneurship, Yiwu Industrial and Commercial College, Yiwu Zhejiang 322000, China; School of International Economics and Trade, Lanzhou University of Finance and Economics, Lanzhou Gansu 730000, China

ple, the optimal number of hidden layer neurons can be determined by PSO, or the most suitable radial basis function can be selected. PSO searches different network configurations to find the network structure with the best performance.

As an important form of trade digitalization, the rapid development of new generation digital technologies like big data, cloud computing, and other technologies such as internet, blockchain, and 5G has provided cross-border e-commerce with a strong [5, 6, 7] technological base for its growth. At present, cross-border e-commerce has entered a new stage of industrial digitalization. Based on the new generation of digital technology, cross-border e-commerce uses a variety of business models to digitally transform commodity information flow, logistics and capital flow, thereby effectively improving the logistics efficiency, payment security, marketing conversion rate and the quality of production and operation decision-making of cross-border e-commerce, and promoting the digital development of cross-border e-commerce industry. Improve the operational efficiency of the cross-border e-commerce ecosystem. In the context of the rapid development of the global digital economy, cross-border e-commerce enterprises should focus on digitalization, give full play to the potential of digital elements, and accelerate their development and transformation [8].

The rise of social networks has changed People's Daily life style. People can easily express their opinions and emotions with the help of social media, and establish a wide range of social relationships [9] through social platforms. Related research on social networks can not only excavate the structural characteristics of the crowd in social networks, but also analyze and predict the flow direction of information transmission on the network and the possible consequences of information transmission. Therefore, research on social networks has important theoretical research significance and practical application value. For viral marketing of social networks, Influence Maximization (IM) aims to find and activate the influence of several user nodes with high influence from social networks, and make use of the word-of-mouth characteristics of social users to trigger the chain transmission of influence among users, so as to maximize the spread of influence [10]. Thanks to the advancements in 5G and Internet of Things technology in recent years, location-based advertising marketing has shown great commercial potential. Influence maximization in social networks has become an important research branch in the field of influence maximization. In contrast to the conventional influence maximization issue, which maximizes propagation in the whole picture of social network, influence maximization problem considers various characteristics and attributes of users in the physical world, so that influence [11] can achieve the best propagation effect among some location-related user groups.

In the fierce competition of e-commerce, it is very important to assist users to explore their needs. Many enterprises use efficient personalized recommendation technology to turn the potential demand of visitors into the real consumption of purchasers, and then improve business profits. Known as the "king of recommendation system", at least one fifth of the items sold in Amazon Mall come from the recommendation system [12]. Netflix claims that about 60% of movies and videos are discovered through its recommendation system; YouTube designed an experiment to compare click-through rates between recommended lists and popular lists, and found that personalized items were twice as likely to be viewed as popular items. Social networks have the characteristics of instant consultation and sharing, open media, realistic user interaction and wide coverage. They are the key hubs linking real life, virtual environment and physical communication. They penetrate into all aspects of human life in an all-round way and promote the transformation and upgrading of business models in the e-commerce industry. It is also hailed by the Internet industry as the next "treasure" after the invention of search engine.

The study uses a particle swarm optimization algorithm and improves by introducing a generalized regression neural network. This improvement may improve the performance and adaptability of the algorithm. At the same time, integrating the basic operation of the genetic algorithm into the particle swarm algorithm can further enhance its performance and convergence speed. These methods are all feasible and are widely used in the optimization field. Furthermore, this paper is also introduces the research significance and practical application value of social network. Through the relevant research on social network, we can not only mine the structural characteristics of people in social network, but also analyze and predict the direction of information transmission on the network and the possible consequences of information transmission. The improved PSO-PNNG multi-objective recommendation optimization technique for cross-border e-commerce social traffic networks is proposed in this research based on the improved particle swarm algorithm (PSO), and conducts simulation experiments and algorithm comparison in multiple real social network data environments. The experimental results show that the proposed multi-objective optimization algorithm for cross-border e-commerce social traffic network based on improved PSO has higher efficiency and accuracy than the traditional method.

2. Literature Review. The optimization algorithm is a method for finding the optimal solution, which aims to find the optimal solution to solve the given problem while satisfying specific constraints. The optimization algorithm has been well studied in the literature, and there are a large number of methods. The original PSO was specially developed to solve the problem of continuous value optimization. Although the original PSO algorithm has been widely used in various optimization problems, the PSO algorithm cannot directly solve discrete optimization problems [13]. However, the update strategy of the traditional PSO algorithm is to update the position and speed of particles by learning global optimal particles, which can easily lead to a decrease in population diversity, making it easy to fall into local optimal solutions or premature convergence [14]. The performance of the PSO algorithm is sensitive to the control parameter values used, and it is difficult to adjust the parameters. The calculation amount of adjusting the control parameters for the current problem is very high [15]. In addition, PSO algorithms may need more iterations when looking for high-quality solutions, resulting in slower convergence. When dealing with some complex problems such as nonlinear and non-stationary, the performance of the PSO algorithm may be affected to a certain extent. Therefore, to improve the traditional PSO algorithm, the generalized neural network has strong pattern recognition and local search ability, and can effectively find the local optimal solution to the problem. Genetic algorithms have global search capabilities and can find high-quality solutions on a large scale. Combining the two can give full play to their respective advantages, accelerate the convergence speed of the particle swarm algorithm, and improve the overall search efficiency of the algorithm. Therefore, an improved PSO-PNNG optimization algorithm is very important to improve the efficiency and performance of the particle swarm optimization algorithm.

In comparison with other algorithms, ten particle swarm optimization and ten differential evolution variants were selected for comparison on numerous single-objective numerical benchmarks and 22 realistic problems. On average, the differential evolution algorithm is significantly better than the PSO algorithm and is used at two to three times the frequency of the differential evolution algorithm [16]. Particle swarm optimization (PSO) is a simple and effective optimization method, which has been applied in many fields. However, the particle swarm algorithm has defects such as early convergence and poor population diversity [17], so the improved particle swarm optimization algorithm is proposed. For example, combine the particle swarm algorithm and the genetic algorithm (GA), set the dynamic inertia weight, increase the sigmoid function to improve the crossover and mutation probability of the genetic algorithm, and change the selection method. The results show that the improved particle swarm algorithm solves the better routing results, with faster speed and higher stability [18]. In order to overcome these shortcomings of PSO, a multi-based learning PSO algorithm (MLPSO) is also proposed. In MLPSO, the multi-sample selection strategy (MSS) and the adaptive sample crossover strategy (ASC) are used to select the appropriate learning sample for the whole. Experimental results show that MLPSO outperforms MLPSO over 7 competitive PSO variants and 19 metaheuristics in most functions [19]. In addition, in order to solve the improved particle swarm algorithm (PSO) limited by the robot topology, strange position and back solution accuracy, some scholars are proposed to solve the inverse problem of the robot. The algorithm initializes the particle population based on the joint angle limit. The results show that the improved PSO has higher convergence accuracy and faster convergence rate than the other algorithms, and the proposed has is generality [20].

As a new trade model, cross-border e-commerce has been emerging for a short time, but it is developing rapidly. The research on it is booming all over the world, and it is fully recognized that its development brings positive impetus [16] to promote the development of the world market. Previous studies have highlighted the positive impact that cross-border e-commerce has already had on the economy and its potential growth. These impacts include challenges and opportunities for supply and demand, increased price competition, the positive impact of improving efficiency in the retail sector and production in other sectors, and promoting the benefits of individual and household consumers and Labour productivity and GDP growth [17]. Some studies have suggested that the development of cross-border e-commerce brings many benefits, Such as access to a diverse range of sellers and products from all over the world, reduced information asymmetry, reduced search costs, adequate comparison in the selection of goods, open and transparent competition among sellers, greater time savings, and most importantly, it enables individual consumers to share their comments and experiences through shopping platforms and social media [18].

China can form a brand theory with global influence in the reconstruction research of brand theory in the digital age. In the era of digital economy, the traditional classic brand theory cannot explain the brand practice under the environment of digital media, and it is urgent to reconstruct, and the global business community urgently needs new brand theory guidance. Some scholars believe that the essence of communication for brands in the digital era has not changed, and traditional creative experiences are still valid. In the digital platform, a series of new communication methods have emerged, and consumers have to be placed in the center position, and word-of-mouth has become more important [19].

While accuracy is indeed critical to a recommendation system, a good "user-centric" recommendation system should not be limited to accuracy. Many users' consumption preferences are habitual (stereotyped: they often consume a certain type of item or consume it in a certain way) and the items they buy are mostly popular items [20]. In order to make predictions more accurate, the system tends to recommend similar items that better fit the user's history. Or popular items that are more likely to be purchased. The reason for this dilemma: In improving the accuracy of the system, it reduces the variety and novelty. It can be seen that when designing a social network recommendation system, multiple goals should be considered: not only to ensure satisfactory accuracy, but also to maximize the variety and novelty. Multiple recommendation of long-tail items is a necessary condition [21] to increase the diversity and novelty of the system. At present, the optimization routing algorithms in other fields have been quite perfect, and related technologies have been widely used, but these optimization routing algorithms can not be directly applied to social networks [22]. The specific form of the multi-objective optimization problem in the recommended algorithm is to find an optimal collection of items under the condition of meeting the constraints of user satisfaction and diversity. The goal of optimizing the cross-border e-commerce social traffic network is to increase user engagement, user retention, and conversion rates of cross-border e-commerce platforms, thereby increasing sales and profits. The variables that need to be optimized mainly include content quality, interactive activities, social functions, personalized recommendations, and user experience, etc. This paper solves the multi-objective optimization problem of cross-border e-commerce social traffic networks through improved particle swarm optimization algorithms. The purpose is to enable the recommendation system of cross-border e-commerce platforms not only achieve the accuracy of recommendations, but also take into account the novelty and diversity of recommendations at the same time, so that the recommendation algorithm is not limited to stereotypical data such as users' historical purchases, but also needs to accurately mine users' preferences and recommend more diverse results to users, so as to promote the development of cross-border e-commerce platform social networks.

3. Model Construction. A complex network diagram can be represented as $G(V, E)$, where, $V = \{v_i \mid i = 0, \ldots, n\}$, $E = \{e_{ji} = \{v_i, v_j\} \mid v_i, v_j \in V\}$, N is the number of nodes in $|V| = N$, and e_{ij} is the connections between v_i, v_j edges. In most literature, graphs use an adjacency matrix $A = [a_{ij}]_{V\times V} \cdot a_{ij} = 1$ to represent the v_i, v_j where an edge exists between nodes, otherwise $a_{ij} = 0$. This study considers a social network represented by a directed random graph $G = (V, E, \omega)$ with $|V| = n$ nodes and $|(u, \nu) \in E| = m$ weighted edges. Each edge is associated with the right of infection $\omega \in [0, 1]$, indicating the likelihood of infecting u node once it is infected ν. Suppose a group of suspicious nodes V_I in a social network is observed that may be infected by information, but it is not clear which specific nodes are infected. Instead, the probability of a node ν can be given by probability $p(\nu)$. In a normal social network, this probability can be determined by analyzing the text content to determine the likelihood that the information will be transmitted. Finding a collection of nodes or edges whose removal will result in the biggest impact of the infected node aborting is the aim of a social network multi-objective optimization problem. It is also assumed that the candidate nodes or edges of a subset C can be removed from the graph, so the subset C can be determined according to the current situation. If you want to include the multi-target information of the social network more quickly, the subset C can include nodes from highly suspicious or even external nodes V_I. If you want to maximize the influence of the subset, then the subset C can contain edges associated with suspicious nodes in V_I or C.

Given $G = (V, E)$ and a seed set S, the influence propagation of the set S can be expressed as $I(\cdot)$, the expected number of infected nodes at the end of the propagation process, where the expected value represents the randomness of all thresholds θ_v. One of the existing classical problems is the influence maximization problem, which requires the degree of maximization $I(\cdot)$ of a seed set containing a number of k nodes. In the actual context of social networks, the infection weight $w(u,v)$ between nodes u and nodes v can be estimated by the interaction frequency between nodes u and nodes v. The probability distribution of possible seed sets is defined using $V_I = (V_I, p)$ representing the suspicious node set V_I and its probability as the source node. And the probability of a particular seed set $X \subset V_I$ can be given by equation (3.1).

$$P(X) = \prod_{u,v \in X, V_I/X} p(u) * (1 - p(v)) \tag{3.1}$$

The expected propagation influence of V_I can be defined by considering the seed set X as shown in Equation (3.2). $I(\cdot)$ Representing the influence spread of the seed set, this formula can fully represent the expected spread impact. Because the goal of the algorithm is to remove k nodes or edges from the social network to minimize the transmission influence of infected nodes V in the remaining network G' and maximize the influence of $I(G) - I(G')$. When it is a group of nodes S, all edges adjacent to it are also removed from the graph. Therefore, two social network multi-objective optimization problems can be formulated as follows.

$$I(V) = \sum I(\cdot) * P(X) \tag{3.2}$$

Edge-based transmission control, that is, the probability of a given $G = (V, E, w)$, suspicious node being infected is $V_I = (V_I, p)$, candidate subset C and budget $k \in [1, C]$, edge-based transmission control problem requires the edge set $T^*(\cdot)$ shown in equation (3.3) to maximize the blocking influence $I(G) - I(G')$. The purpose of formula (3.3) is to describe the goal of the edge-based propagation control problem, that is, to maximize the propagation impact of blocking the network by selecting the set of some edges.

$$T^*(\cdot) = \underset{T_k \subseteq C, |T_k| = k}{\arg\max} \{I(G) - I(G')\}. \tag{3.3}$$

For node-based propagation control, given a random graph $G = (V, E, w)$, the probability of suspicious nodes and their infection is V_I, a candidate set C and budget $k \in [1, C]$, and node-based propagation control problems require that the knode-set S^* can maximize the influence $I(S_k, V_I)$, while the multi-objective optimization problems of social networks based on edges and nodes are NP-hard problems. The economic scheduling of the social network model takes the lowest operating cost of the whole network as the objective function, schedules according to the coordination equation method and the equal incremental rate method, comprehensively considers the cost of multi-objective optimization and the loss generated, and maximizes the overall benefit of the whole network by sacrificing local benefits, which reflects the optimization of the entire social network cost. The loss of the $EC(P_G)$ multi-objective optimization model of the social network can be defined as formula (3.4). where, EC represents multi-objective economic cost, P_G represents the possibility of partial benefit loss. The purpose of formula (3.4) is to define the loss of the multi-objective optimization model of social networks, that is, $EC(P_G)$, which is used to measure costs and losses in the network. The purpose is to comprehensively consider costs and losses in the process of economic scheduling, so as to achieve the goal of the lowest operating cost of the whole network.

$$EC(P_1, \ldots, P_D) = \sum_{d=1}^{D} 10^{-2}(\alpha_d + \beta_d P_{Gd} + \gamma_d P_{Gd}^2) + \xi_d \exp(\lambda_d P_{Gd}) \tag{3.4}$$

Considering that the multi-objective optimization of social networks is a multi-objective problem, this paper will convert the multi-objective optimization problem proposed in this paper into a single objective problem, as shown in Formula (3.5). By converting into a single-objective problem, a single-objective optimization algorithm can be used to solve and simplify the complexity of the problem. The purpose is to optimize the scheduling of social networks more conveniently to achieve the best balance of multiple goals.

$$\begin{aligned} TC(\cdot) = u * \sum_{d=1}^{D} FC_d(P_{Gd}) + h * (1 - u) * \sum_{d=1}^{D} EC_d(P_{Gd}) + P_L \\ + abs\left(\sum_{d=1}^{D} P_{Gi} - P_D - P_L\right) \end{aligned} \tag{3.5}$$

This study assumes that there are Nindividual users n in a group of users who can be connected through a social network. Users i have a positive scalar value of public opinion, modeled as a state $x_i(t) \in R$ of t time, and users interact with their neighbors through the social network and evolve their public opinion over time. The weighted edges E of the network graph Gare used to model the social interactions, and the edge sets are used to model the interactions between users. This study assumes that the graph G is strongly connected, and in the absence of external control inputs, the dynamics of public opinion (state) at each node i in the network are controlled by changes in the following Friedkin-Johnsen model as shown in Equation (3.6).

$$x_i(t+1) = q_i + \sum_{j:(i,j)\in E} a_{ij}(x_j(t) - q_j) + a_{ii}(x_i(t) - q_i) \tag{3.6}$$

where, $q_i \geqslant 0$ denotes the static cognition of the user i, $0 \leqslant a_{ij} < 1$ simulates the intensity of the influence of the userj's opinions on the user, and a_{ii} simulates the stabilityi of the user i. This istudy assumes that $\sum_{j=1}^{n} a_{ij} < 1$ for all i, that is, the weight matrix $A = [[a_{ij}]]$ is subrandom. Under this assumption, at any given time, each user's opinion can be divided into two components: a fixed ontology view and an additional disturbance resulting from interactions with neighboring nodes. In the absence of external input, all users revert to their own opinions. In the incentive scenario of this study, it is considered to be the better model, so the vector form can be written as shown in equation (3.7).

$$x(t+1) = Ax(t) + (I_n - A)q \tag{3.7}$$

Where, here $x(t)$ is the column vector with the first componenti, the $x_i(t)$ column vector representing the static view, and the identity matrix q. I_n Can be checked $x(t) \to q$ to satisfy without input. There are several mtarget sources, each of which can precisely inject control inputs into the node. This indicates that the control input is sent to the node by the target source. Each target source is able to map the control inputs to the node, meaning that the control input is oriented. When the target source j is connected to the node i and $\sum_i b_{ij} = 1$, the matrix $B \in R^{n\times m}$ maps the target source to the target node with $b_{ij} = 1$. And this study considers that it can be any real number, making it accept the values in the interval can provide additional $\{0, 1\}$ results. Moreover, the weighted minimum of the penalty function of social network loss, node fluctuation and each node exceeding the limit is defined as the objective function, P_{loss}^{new} represents the likelihood of new social network losses, while P_{loss}^{old} represents the likelihood of previous social network losses, as shown in equation (3.8).

The purpose is to provide an indicator to comprehensively evaluate social network optimization to guide the search process of the optimization algorithm.

$$\min F = \beta_1 \sum_{j\in\Omega^N} \frac{P_{loss}^{new}}{P_{loss}^{old}} + \beta_2 AU + \beta_3 \sum_{j\in\Omega^V} CF\left(\frac{\Delta V_j}{V_{j,\max} - V_{j,\min}}\right)^2 \tag{3.8}$$

In the continuous iterative optimization process of standard particle swarm optimization algorithm, the inertia weight needs to change with the change of particle fitness value, so as to better balance the particle search speed and improve the overall optimization ability of particles. Therefore, the value of inertia weight ω as a fixed constant is not conducive to the optimization of the algorithm, and real-time adaptive inertia weight ω is more helpful to solve the reactive power optimization problem. For the inertia weight coefficient, this study proposed the adaptive inertia weight, as shown in equation (3.9).

$$\omega = \omega_{\min} + (\omega_{\max} - \omega_{\min}) \exp\left(\frac{f_{\min}^n - f^n}{f_{average}^n - f_{\min}^n}\right) \tag{3.9}$$

In social networks, the connection between users is generally represented by constructing the relationship diagram, in which each user can be represented by the node $\nu_i \in V$, and the interaction class between users is represented by the edge $(\nu_i, \nu_j) \in E$. The community structure in social networks usually means that user nodes can be divided into subsets $C = \{C_1, C_2, \ldots, C_k\}$, so that nodes C_j in the same subset are closely linked and the connections between subgroups relatively sparse. Existing research focuses on disjoint community structures and makes each node belong to only one community. In social networks, users' forwarding, collection and comment can be identified as positive responses. Therefore, the set of social network users can be defined as $U = (a_1, a_2, a_3, \ldots, a_n)$, and the set of social network information is $I = (i_1, i_2, i_3, \ldots, i_k)$. Order $I(\cdot)$ represents the degree of interest $\frac{\overline{Luj}}{\overline{Lu}}$ of the user u to the user in the item attribute set A, $\overline{Luj}$ is the average of all scores of the user u subattribute j, $\overline{Luj}$ is the average of all scoring items of the user u, so there are several set item sub-attributes, and the similarity of the user's preference for the item sub-attributes is shown in Eq. (3.10).

$$sim_P(u,v) = \frac{\sum_{j=1}^{n}(Puj-\overline{Pu})(Pvj-\overline{Pv})}{\sqrt{\sum_{j=1}^{n}(Puj-\overline{pu})^2}\sqrt{\sum_{j=1}^{n}(Pvj-\overline{Pv})^2}} \tag{3.10}$$

4. Algorithm design.

4.1. Algorithm framework. Particle swarm optimization algorithm (PSO) is an intelligent optimization algorithm inspired by bird foraging behavior, which is commonly used to solve various optimization problems. The fitness function determines the fitness value of the particle, and the fitness value of the particle is the standard used to judge the quality of the particle. There are interactions between the particles in the particle swarm optimization algorithm. Particles update their speed and position by sharing information to find the globally optimal solution. Each particle remembers the best position in its trajectory, and uses it to update its speed and direction. Each particle in the particle swarm can determine its next search track according to its current position and the information sharing mechanism between particles, and judge the merits of particles by the fitness value of particles, so as to iteratively find the optimal solution and finally find the optimal solution. The optimal solution is usually the extremum solution with the maximum or minimum fitness function value.

Determining the global optimal location within the PSO framework is critical because it represents the most ideal solution to the current optimization problem. To achieve this, the algorithm iteratively updates the position of the particle based on its speed, which is adjusted for both the personal best and the global best position. Over time, if the parameters of the algorithm are set properly, the particle swarm will converge to a global optimal solution. Convergence conditions are a set of criteria that determine when an algorithm finds a satisfactory solution and can be terminated. These conditions can be based on the number of iterations, changes in the global optimal position in successive iterations, or predetermined thresholds for the value of the objective function.

The particle adjusts its motion direction and speed in real time through the trajectory. The current position of the particle, the best position of the particle history and the best position of the population particle history are important factors affecting the trajectory of the particle. Initialize a population of particles in a multi-dimensional search space, the number of particles is set to n, the position information of the particles in the population is expressed as $X = (X_1, X_2, X_3, \ldots, X_n)$, the position information of the i th particle can be expressed as X_i, and the velocity information of the i th particle d dimensional space is also a d dimensional vector $V_i = (V_{i1}, V_{i2}, \ldots, V_{ij}, \ldots, V_{id})$. Due to the ability of memory, the particles can remember the best position in their running trajectory and obtain the global optimal solution P_{best} at the current moment with P_{opt}. The velocity and position of the basic particle swarm algorithm can be expressed as shown in Eq. (4.1) and Eq. (4.2).

$$V_{id}(t+1) = V_{id}(t) + c_1r_1[P_{bestd}(t) - X_{id}(t)] + c_2r_2[P_{optd}(t) - X_{id}(t)] \tag{4.1}$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t) + c_1r_1[P_{bestd}(t) - X_{id}(t)] + c_2r_2[P_{optd}(t) - X_{id}(t)] \tag{4.2}$$

where t represents the moment; V_{id} and X_{id} represent the speed and position of particle i on dimension d, respectively; c_1 and c_2 represent individual and social learning factors, respectively; P_{bestd} and P_{optd} represent the individual historical best position and the global optimal solution of the particle i on dimension d; r_1 and r_2 are the random number between $[0, 1]$.

The steps of the classical PSO are as follows. First, parameters such as the population size, maximum number of iterations are initialized and the individual optima and global optima are determined by calculating the particle fitness values. Secondly, the velocity and position of the particles are updated, and the fitness value of the updated particles is calculated, and their fitness value is compared to the individual optimal value P_{best}, If better, P_{best} is updated to the current value and the current value is updated to the individual optimal value. Otherwise continue iterate and continue comparing. The updated individual optima are compared to the global optimum P_{opt}, and if better, P_{opt} is updated to the current value and the particle current value is updated to the global optimum. Otherwise continue iterate and continue comparing. Finally, the fitness value of the updated particle is terminated if the maximum number of iterations is satisfied.

In addition, the known particle fitness value will affect the trend of inertia weight ω, commonly used particle group algorithm is in the process of constant iterative optimization, inertial weight ω need as the particle fitness value changes, so as to better balance the particle search speed and improve the particle overall optimal ability.Therefore, the value of inertial weight ω as fixed constant is not conducive for the algorithm, and the real-time adaptive inertial weight ω is more helpful to solve the reactive power optimization problem. For the inertial weight coefficient, in this paper, the adaptive inertial weight $\omega(\cdot)$ is proposed as shown in Eq. (4.3).

$$\omega(\cdot) = \omega_{\min} + (\omega_{\max} - \omega_{\min}) \exp\left(\frac{f_{\min}^n - f^n}{f_{average}^n - f_{\min}^n}\right) \tag{4.3}$$

where $\omega_{\min}$ and $\omega_{\max}$ are the minimum and maximum values of the inertial weight, respectively; $f_{average}^n$ is the average fitness of all particles in the n iteration; f^n is the fitness of the particles at the n iteration; and $f_{\min}^n$ is the minimum fitness of all particles at the n iteration. By comparing the adaptive inertial weight $\omega(\cdot)$ with the original inertial weight ω, it can be seen that the adaptive inertial weight $\omega(\cdot)$ is more sensitive to the changes in particle fitness value compared to the original inertial weight ω. This means that the proposed algorithm can better balance the particle search speed and improve the particle overall optimal ability, making it more suitable for solving the reactive power optimization problem.

4.2. Algorithm Improvement. In order to improve the performance of the algorithm, the author improved the PSO algorithm and introduced genetic algorithm and neural network. Genetic algorithm is a kind of optimization algorithm based on natural selection and genetic principle, which can be used to solve various complex optimization problems. A neural network is a computational model that simulates the human brain's nervous system and can be used for learning and prediction. By introducing genetic algorithm and neural network into PSO algorithm, PSO-PNNG optimization algorithm is proposed. The crossover and mutation operation of genetic algorithm and the learning and adaptation ability of neural network are introduced in the process of particle swarm optimization, which improves the search efficiency and convergence speed of the algorithm. The effect of algorithm selection and adjustment on algorithm performance is that algorithm selection and adjustment have an important effect on algorithm performance. Selecting the appropriate algorithm can improve the efficiency and accuracy of solving the problem, and adjusting the parameters of the algorithm can further optimize the performance of the algorithm. In this study, by improving the PSO algorithm, the author introduced genetic algorithm and neural network to improve the search efficiency and convergence speed of the algorithm, so that the algorithm can better adapt to the multi-objective optimization problem of cross-border e-commerce social networks.

In this study, generalized regression neural network is used to improve the particle swarm optimization algorithm. Integration of generalized regression networks into particle swarm optimization algorithms requires initialization of a population of particles, each particle representing a candidate solution. For each particle, its fitness value is calculated according to the generalized regression neural network algorithm, which can be a function of the prediction error. The global optimal solution is updated according to the fitness values of all the particles. According to the current position, velocity and global optimal solution of the particle, using the formula of the particle swarm optimization algorithm, the updated position and velocity will affect the parameters of the generalized regression neural network. Then repeat the calculated fitness step to update the particle position and speed step until the stop condition is reached. By combining the generalized regression neural network algorithm with the particle swarm optimization algorithm, the global search capability of the PSO can be used to optimize the parameters and thus improve the prediction performance. Define a new particle representation and represent each particle as a parameter of a generalized neural network. In the optimization process of the particle swarm algorithm, the generalized neural network parameters of each particle are updated. Use a generalized neural network to predict or classify to evaluate the adaptability of each particle. Its principle is based on the local response of neurons to the outside world, and it has the advantages of global approximation and best approximation. Similar to the BP neural network, it consists of a three-layer forward network of input, hidden and output layers. Where the input layer transmits the input signal to the hidden layer, and the number of nodes in the hidden layer is equal to the input vector dimension of the sample. The node functions of the hidden layer use radial Gaussian functions, and the nodes of the output layer are combined using specific linear functions.The basic principle is described below.

Let the j-dimensional vector, $x = [x_1, x_2, \ldots, x_j]^T$ be the input vector of the process, the corresponding output vector be y, and the joint probability density function of random variables x and y be $f(x, y)$. Since the theoretical basis of GRNN is a non-linear regression analysis, the regression is performed by calculating the conditional mathematical expectation of the corresponding y, given the value of x. GRNN estimates the sum of the joint probability density function, to build an estimated probability model. By training the input-output set, the probability density function estimator is constructed using the non-parametric density estimation method. For a given input vector x, assuming that the estimated function is continuous and smooth, the expected value family of the estimated y is expressed as shown in Eq. (4.4), and the continuous probability density function can be defined as shown in Eq. (4.5).

$$E[y|x] = \frac{\int_{-\infty}^{\infty} v f(x,v)\mathrm{d}v}{\int_{-\infty}^{+\infty} f(x,y)\mathrm{d}y} \tag{4.4}$$

$$f(x,y) = \frac{\sum_{i=1}^{k} \exp\left[\frac{(x-x_i)^T(x-x_i)}{2\sigma^2} * \frac{(y-y_i)^2}{2\sigma^2}\right]}{(2\pi)^{\frac{p+1}{2}}\sigma^{(p+1)}k} \tag{4.5}$$

where x_i, y_i is the i th sample value of the random variables x and y, respectively, σ is the smoothing parameter, p is the dimension of the random variable x, and k is the number of samples. First, the sample is input to the input layer, the number of nodes in the input layer is equal to the dimension p of the input vector, and then the elements of the input vector are transmitted to the mode layer, and its transfer function can be defined as shown in Eq. (4.6).

$$t_i = \exp\left(-\frac{D_i^2}{2\sigma^2}\right) \tag{4.6}$$

The sum layer has two types of nodes. The first type contains only one neuron, which arithmetic sums the output of all neurons in the pattern layer. The connection weight of each neuron between the neurons in the pattern layer and the neuron is 1, and its transfer function is $s_D = \sum_{i=1}^{n} P_i$; The second type contains remaining nodes that weighted sum the output of neurons in all pattern layers, the transfer function of the summing neuron j is $s_j = \sum_{i=1}^{n} y_{ij} P_i$. Where, y_{ij} is the connection weight between the i th neuron in the pattern layer and the j th summation neuron in the summation layer is the j th element in the i th output sample Y_i.

And use the basic operation of the genetic algorithm to improve the performance of the particle swarm algorithm to accelerate the convergence rate. In the process of optimizing the particle swarm algorithm, the operation of the genetic algorithm is introduced, and the genetic algorithm is used to evolve the particles in the particle swarm algorithm to generate new particles. Add the generated new particles to the particle swarm algorithm to update the state of the particle swarm. First randomly initiate N subgroups and remember them as GA_i, $i = 1, 2, \ldots, N$. Each subgroup runs its own genetic algorithm independently. After a certain number of generations, the optimal individual is taken out of the elite group in the upper layer and denoted as the particle group. The particle group algorithm is used to evolve the elite group. After a certain algebra, the stopping criterion is satisfied. If so, the output result and the algorithm stops. Otherwise, each genetic subgroup randomly obtains the individual extremums of k particles from the upper elite group, randomly replacing its own k individuals. N subgroup resumes the genetic algorithm operation and cycles until the stopping criterion is met. Classical genetic algorithms can converge to the global optimal solution as long as they contain the historical optimal solution in each generation of the population, whether before or after the operator, which is called the optimal retention strategy. In this paper, the genetic algorithm of evolving the underlying subgroup adopts the optimal retention strategy, finds the historical optimal solution before selecting the operator, and randomly replaces anyone in the current population if it is not in the current population. Thus the genetic algorithm used by the underlying subgroup has a global convergence. In particle swarm optimization, assuming that $p_{ib}(t)$ and $p_{gb}(t)$ remain unchanged in evolution, the $x_i(t)$ of the particle swarm algorithm converges to

$p_{ib}(t)$, φ represents the velocity of the particles and the weighted center of $p_{gb}(t)$ is shown in Eq. (4.7).

$$x_i(t) \to \frac{\varphi_1 p_{ib}(t) + \varphi_2 p_{gb}(t)}{\varphi} \tag{4.7}$$

Consider that the global optimal position is p_{gbest}, because the genetic algorithm of the underlying subgroup has global convergence. When the underlying subgroup converges to the global optimal solution, all the particles in the upper elite group will be in the global optimal position, and the individual extreme values are the same and remain unchanged in the evolutionary process, both are p_{gbest}. Therefore, when the underlying subgroup evolves with a genetic algorithm with optimal retention strategy, the upper particle group optimization has global convergence as long as ω, c_1 and c_2 satisfying Eq. (3.3) select the algorithm.

Algorithm 1 Improved particle swarm optimization (PSO) which fuses genetic algorithm and neural network

Require: s, $T(t)$, $D(t)$, $I(t)$
Ensure: $p_{ib}(t)$, p_{gbest}, F_{best}
Remember individual as $x_i (i = 0, 1, \ldots, n-1)$
Use the unbiased league selection method to select n individuals in the middle generation
if $f_i \leqslant f_k \to x'_i = x_i$ **then**
    Complete crossover of intermediate generation individuals (with 100% probability of crossover) to generate new generation individuals
    $x_i = rand1 * x'_i + (1 - rand2) * x'_{i+1}$
end if
Using non-consistent variation, each one-dimensional component of all individuals is mutated by probability P_m
if $rand \leqslant 5 \to x_j = x_i + \Delta(t, U^j_{\max} - x_j)$ **then**
    Calculate the fitness value of the individual
    Find the best individual in the current generation, update the historical best individual and its fitness value $I_{best} F_{best}$
end if
Return $p_{ib}(t)$, p_{gbest}, F_{best}

The steps of this algorithm are: initialize the particle swarm and calculate the adaptability value of each particle; select particles according to the adaptability value to form the intermediate generation; use inconsistent variation to mutate each particle of the intermediate generation, completely cross the particles of the intermediate generation, and generate a new generation of particles; then calculate the adaptation of the new generation of particles. Degree value, and update the best particle and adaptability value in history. Repeat the above steps until the stop condition is reached. The algorithm combines particle swarm optimization, genetic algorithm and neural network, and continuously optimizes the particle swarm through selection, crossover, mutation and other operations to find the optimal solution.

This study assumes that all individuals adopt the same information search strategy $s = S$, combined with Algorithm 1, considering the presence of smaller scale individual ε will transform the overall search strategy $S = S + \delta S$. In order to ensure that the GPU parallel get global optimal evolution algorithm in algorithm 2, by expanding the participant strategy space, improve the traditional evolution game, the computing complexity, in the rough set attribute evolution game each evolutionary population should adopt the population evolution law and behavior pattern of real game problem collaborative mechanism, enhance the global information exchange and local depth search balance, and how to determine the cooperative evolution strategy to make their utility can achieve their optimal solution set, so as to stabilize the global optimal solution set.

The input of the algorithm includes the problems to be optimized and related parameters, and the output is the optimized solution. The steps of the algorithm are: initialize the policy set and randomly select nodes with the policy set; use the policy set to select the edge according to the active edge LT model; if the edge is selected, the parallel probability is obtained according to the policy set; if the node is searched for by loop, it will be defined. The algorithm uses GPU for parallel computing, optimizes problems by selecting nodes and edges, and obtaining parallel probability according to the policy set.

Algorithm 2 GPU parallel optimal evolution algorithm

Require: s, $T(t)$, $D(t)$, $I(t)$
Ensure: $E^E(v)$, $E^o(v)$
Initializes the policy sets $\leftarrow \varnothing$
Select nodes uniformly at random using the policy setsv
Select edges according to live-edge LT model using policy set $s(u, v) \in E$
if select edge $(u, v) \in E$ **then**
  if edge $u \in V$ **then**
    Parallel probability obtained using the policy set $sE^E(v)$, $E^o(v)$
    else if loop search node then u, v
    Define $v = u$
  end if
end if
$E^E(v)$, $E^o(v)$

In addition, since the proposed algorithm is obtained by the GPU technology integrated evolutionary search and the optimal search strategy in parallel, the two strategies can complement each other in the control of information in the directed graph and the undirected graph, effectively improving the adaptability of the algorithm. Finally, the improved Particle Swarm Optimization Parallel of Neural Network and Genetic algorithm (PSO-PNNG) is formed, which integrates neural network and genetic algorithm.

5. Numerical examples.

5.1. Experimental design and data description. For reference [24, 25], Python software was used in this study, and nearly 30 user nodes of "opinion leaders" were taken as the initial node. User data sets of Facebook, Instagram and Twitter were captured as the basic data of the experimental simulation. Specifically, the capture time is from May 2, 2023 to October 24, 2023, and the data sample is shown in Table 1. These data sets contain a large amount of user information, such as user ID, user name, gender, age, geographic location, friend list, post content, etc. The research team uses the Tensorflow 1.5.1 framework to implement the proposed PSO-PNNG algorithm in this paper and compare the related algorithms. Before the experiment, all data were saved in CSV format in MySQL database for pre-processing, including removing noise data, processing missing values and outliers. For each social network dataset, the Rapidminer data mining tool is used to randomly extract 10% of user rating data as a test set, and the remaining 90% of user data as a training set. The experimental process was carried out in a grouping way, and the data was divided into 10 groups, and the cross-validation method was adopted, that is, the data set was divided into 10 equal parts, and one group of data was selected as the test set each time, and the other groups were selected as the training set. Finally, take the average value. In this study, 30 users with strong influence and their friends list are selected as the initial nodes of the social network to generate a complex social network. In order to verify the effectiveness and robustness of the proposed PSO-PNG algorithm, a comprehensive experiment was carried out in this study, and Numpy, Scipy, Pandas, Matplotlib and Theano packages were used to implement the proposed PSO-PNNG cross-border e-commerce multi-objective optimization algorithm. The algorithm aims to increase the traffic and conversion rate of cross-border e-commerce by optimizing the interaction and information dissemination between users. All experiments were conducted on Windows 10 servers with Intel Xeon processors (3.4 GHz) and 32 GB of RAM. The experimental results show that the PSO-PNG algorithm proposed in this paper has a good effect and application prospect in the AC network of cross-border e-commerce companies. The algorithm can effectively predict the interaction and information transmission between users, and provide more accurate marketing strategies and advertising programs for cross-border e-commerce. Since the results of the social network multiobjective optimization approach may vary from run to run, the evaluation results of the algorithm presented here are based on the average of Monte Carlo simulations over 1000 iterations with an operating standard deviation of 1.839.

In this study, the Closeness Centrality, Degree Centrality (DC), Intermediate Centrality (IC) and closeness

Table 5.1: Social network data set

Network serial number	Social network name	Type	Number of nodes	Number of node boundaries	Average degree	Average path of nodes	Clustering coefficient
1	Instagram	Directed	43571	824058	55.13	5.46	0.569
2	Facebook	Directed	55758	614516	63.37	6.47	0.615
3	Twitter	Directed	54537	675961	56.84	5.30	0.536

centrality of the proposed multi-objective optimization algorithm of cross-border e-commerce social transportation network based on PSO-PNNG are studied. CNC, Ant Colony Optimization (ACO), Swarm Optimization (SWO), K-Shell Centrality (K-Shell Centrality, ACO) KSC) and benchmarked algorithms such as Weighted K-Shell Degree Neighborhood (WKS-DN). Recommendation problems in social networks are often viewed as binary classification tasks, whereas In the binary classification task of evaluating the confusion matrix, there are two categories. For both categories, True Positives (TP) represent the number of correctly predicted links, and True Negatives (TN) indicate the number of correctly predicted unlinks. While False Positives (FP) represent the number of mispredicted links, and False Negatives (FN) indicate the number of mispredicted unlinks. Based on this, the evaluation indicators such as accuracy, accuracy rate, recall rate and F-measure used in this study can be expressed as shown in equations (5.1) – (5.4) respectively. In addition, combined with the literature, two precision functions are used: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Equations (5.5) and (5.6) illustrate the particular computation techniques respectively.

$$Precision = \frac{TP}{TP+FP} \tag{5.1}$$

$$Accuracy = \frac{TP+TN}{P+N} \tag{5.2}$$

$$Recall = \frac{TP}{TP+FN} \tag{5.3}$$

$$F - measure = \frac{2*precision*recall}{precision+recall} \tag{5.4}$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |f_i - y_i| \tag{5.5}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (observed_t - predicted_i)^2} \tag{5.6}$$

Since the PSO-PNNG cross-border e-commerce social network multi-objective optimization algorithm defined in this paper is usually used in large-scale social network graphs. Therefore, the coloring finger of G paints each vertex with one color so that the color of any adjacent vertex is different, if the vertex of G can be colored with k colors, i. e., G is k point colorable; If G is k point coloring, but not $k-1$ point coloring, G is called k color map, k is the number of G colors, recorded as $x(G)$, which is the minimum value of k that colors G. Based on this, the greedy ant colony graph coloring solution technique (GAC-GC) uses the color allocation among the vertices of the network graph.

The introduction of graph shading in the optimization algorithm can help the algorithm better deal with constraints and optimize goals. By assigning nodes to different colors, constraints or optimization targets can be converted into node color restrictions. In this way, the algorithm can better handle constraints and optimize targets, thus improving the efficiency and accuracy of the algorithm. This method is essentially a

Algorithm 3 The concrete steps of the social network graph coloring algorithm used

Require: Graph $G = (V, E)$, S, A, P, τ, k
Ensure: Upper and lower bounds $B(+)/B(-)$

1: Settings $B(\cdot) \leftarrow \varnothing$
2: Calculate the upper and lower bounds with the improved Greedy algorithm $B(+)/B(-)$
3: **while** $G(\cdot) = \sum x_{ik} * x_{jk} = 0$, x_{ik}, $x_{jk} \in \{0, 1\}$ **do**
4:     **if** there is no solution then make a lower bound $B(-) = B(-) + 1$ **then**
5:         Calculate the upper bound $B(+)$
6:     **end if**
7:     $B(-)! = B(+)$
8: **end while**

Table 5.2: Area values under the curve of various social network data sets in different methods

Level of cross validation	Data set name	Optimization method			
		DC	IC	CNC	ACO
2-fold	Instagram	0.160	0.241	0.274	0.362
	Facebook	0.175	0.253	0.222	0.330
	Twitter	0.135	0.273	0.262	0.424
4-fold	Instagram	0.136	0.328	0.283	0.373
	Facebook	0.153	0.262	0.264	0.350
	Twitter	0.133	0.224	0.240	0.336
10-fold	Instagram	0.165	0.267	0.262	0.362
	Facebook	0.181	0.262	0.274	0.344
	Twitter	0.137	0.266	0.222	0.352
Cross verification rating	Data set name	Optimization method			
		SWO	KSC	WKS-DN	PSO-PNNG
2-fold	Instagram	0.460	0.460	0.550	**0.917**
	Facebook	0.451	0.514	0.503	**0.871**
	Twitter	0.346	0.451	0.520	**0.882**
4-fold	Instagram	0.457	0.536	0.552	**0.881**
	Facebook	0.441	0.460	0.535	**0.833**
	Twitter	0.445	0.450	0.546	**0.851**
10-fold	Instagram	0.451	0.502	0.545	**0.838**
	Facebook	0.432	0.460	0.529	**0.923**
	Twitter	0.424	0.431	0.566	**0.875**

Note: The values shown in bold all indicate that their corresponding algorithms perform well.

linear decomposition of the graph for color. To make the proposed solution algorithm suitable for large-scale graphs, a hybrid technique based on decomposition and heuristic methods is proposed, specifically as shown in Algorithm 3.

The input of this algorithm is a social network graphic, and the output is the upper and lower bounds of the graph. The steps of the algorithm are: initialize the settings; use an improved greedy algorithm to calculate the upper and lower bounds; when there is no solution, calculate the lower bound and then calculate the upper bound. The algorithm optimizes the coloring problem of social network graphics by calculating the upper and lower bounds.

Table 5.3: Average accuracy values of each social network data set in different methods

Level of cross validation	Data set name	Optimization method			
		DC	IC	CNC	ACO
2-fold	Instagram	0.155	0.221	0.406	0.382
	Facebook	0.158	0.207	0.383	0.395
	Twitter	0.150	0.238	0.372	0.395
4-fold	Instagram	0.161	0.219	0.384	0.385
	Facebook	0.159	0.230	0.394	0.408
	Twitter	0.149	0.245	0.371	0.372
10-fold	Instagram	0.179	0.231	0.385	0.463
	Facebook	0.157	0.219	0.399	0.395
	Twitter	0.171	0.214	0.372	0.420
Cross verification rating	Data set name	Optimization method			
		SWO	KSC	WKS-DN	PSO-PNNG
2-fold	Instagram	0.514	0.546	0.561	**0.749**
	Facebook	0.461	0.622	0.545	**0.787**
	Twitter	0.442	0.612	0.556	**0.877**
4-fold	Instagram	0.507	0.581	0.567	**0.796**
	Facebook	0.450	0.566	0.545	**0.808**
	Twitter	0.497	0.553	0.565	**0.917**
10-fold	Instagram	0.507	0.559	0.566	**0.913**
	Facebook	0.450	0.545	0.545	**0.864**
	Twitter	0.461	0.592	0.528	**0.882**

Note: The values shown in bold all indicate that their corresponding algorithms perform well

5.2. Experimental results. Table 5.2 reports the results of the area under the curve of the PSO-PNNG cross-border e-commerce social traffic network multi-objective optimization algorithm and other benchmark methods in the real social network data set. In this study, it is found that the multi-objective optimization algorithm of cross-border e-commerce social traffic network proposed in this paper has better experimental results in real social network data sets.

Table 5.3 displays the average accuracy results of the multi-objective optimization algorithm of cross-border e-commerce social transportation network and other benchmark algorithms in the real social network data set. The findings demonstrate that, across all genuine social network data sets, the multi-objective optimization method of the cross-border e-commerce social transportation network put forth in this research has a high average accuracy value.

Two measures of accuracy are used: mean absolute error (MAE) and root mean square error (RMSE). Table 5.4 lists the MAE and RMSE values of the proposed PSO-PNNG multi-objective optimization algorithm and other benchmark algorithms on different real social network datasets. The higher the MAE and RMSE values, the lower the accuracy of the prediction optimization algorithm. Table 5.5 shows that the suggested PSO-PNNG multi-objective optimization algorithm for cross-border e-commerce social traffic network outperforms the other approaches in general.

This is because the PSO-PNNG cross-border e-commerce social network multi-objective optimization algorithm has the ability to respond quickly and optimize social networks in real time to a certain extent, and can also minimize the overall loss of calculation.

6. Conclusions. With the deepening of global economic integration, international trade and logistics activities show a trend of rapid growth. This study on the basis of cross-border electricity social network research, based on the improved particle swarm algorithm (PSO), put forward a kind of cross-border electricity social traffic network improvement PSO-PNNG multi-target recommended optimization algorithm, and in the environment of multiple real social network data simulation experiment and algorithm comparison, we found that

Table 5.4: Comparison results of precision functions of various social network datasets in different methods

	Indicators	DC	IC	CNC	ACO
Actual value	MAE	0.087	0.085	0.073	0.066
	RMSE	0.087	0.089	0.075	0.071
Optimal value	MAE	0.085	0.082	0.071	0.064
	RMSE	0.086	0.084	0.074	0.065
	Indicators	SWO	KSC	WKS-DN	PSO-PNNG
Actual value	MAE	0.610	0.577	0.599	**0.359**
	RMSE	0.620	0.632	0.620	**0.394**
Optimal value	MAE	0.578	0.573	0.579	**0.335**
	RMSE	0.591	0.578	0.587	**0.347**

Note: The bold indicates that this algorithm is relatively optimal under this parameter condition.

Table 5.5: Results of algorithm running time comparison in different social network datasets

Data set Name	DC	IC	CNC	ACO
Instagram	2252.759	762.460	457.739	789.786
Facebook	3017.693	1003.585	910.585	1032.070
Twitter	6966.902	737.816	643.959	959.974
Data set name	SWO	KSC	WKS-DN	PSO-PNNG
Instagram	1537.104	261.794	470.142	130.074
Facebook	1720.321	335.864	844.879	154.219
Twitter	1328.834	268.177	639.295	136.027

Note: The values shown in bold all indicate that the corresponding algorithm performs well.

the algorithm on multiple real social network data set has shown excellent performance. The experimental findings demonstrate that the PSO-PNNG multi-objective optimization algorithm, which is based on an enhanced PSO optimization algorithm, outperforms traditional techniques in terms of accuracy and efficiency. At the same time, the algorithm can respond quickly and achieve multi-objective optimization, effectively reduce computational losses, and can help enterprises improve the operational efficiency of cross-border e-commerce social networks. In the future, we can further explore the characteristics of social network data in order to continuously improve the optimization effect.

REFERENCES

[1] M. S. Salman, I. M. Almanjahie, A. Yasin, and A. N. Cheema, *Bn-gepso: Learning bayesian network structure using generalized particle swarm optimization.*, Computers, Materials & Continua, 75 (2023), pp. 4217–4229.

[2] S. Chansamorn and W. Somgiat, *Improved particle swarm optimization using evolutionary algorithm*, in 2022 19th International Joint Conference on Computer Science and Software Engineering (JCSSE), IEEE, 2022, pp. 1–5.

[3] X. Zheng, B. Nie, J. Chen, Y. Du, Y. Zhang, and H. Jin, *An improved particle swarm optimization combined with double-chaos search*, Mathematical Biosciences and Engineering, 20 (2023), pp. 15737–15764.

[4] X. Shu, Y. Liu, J. Liu, M. Yang, and Q. Zhang, *Multi-objective particle swarm optimization with dynamic population size*, Journal of Computational Design and Engineering, 10 (2023), pp. 446–467.

[5] J. Fan, W. Huang, Q. Jiang, and Q. Fan, *A zoning search-based multimodal multi-objective brain storm optimization algorithm for multimodal multi-objective optimization*, Algorithms, 16 (2023), p. 350.

[6] P. Zhang, H. Lin, B. Yao, and D. Lu, *Level-aware collective spatial keyword queries*, Information Sciences, 378 (2017), pp. 194–214.

[7] A. Liu, M. Osewe, Y. Shi, X. Zhen, and Y. Wu, *Cross-border e-commerce development and challenges in china: A systematic literature review*, Journal of theoretical and applied electronic commerce research, 17 (2021), pp. 69–88.

[8] A. Cary, O. Wolfson, and N. Rishe, *Efficient and scalable method for processing top-k spatial boolean queries*, in International Conference on Scientific and Statistical Database Management, Springer, 2010, pp. 87–95.

[9] D. Dang-Pham, A.-P. Hoang, D.-T. Vo, and K. Kautz, *Digital kaizen: An approach to digital transformation*, Australasian

Journal of Information Systems, 26 (2022).
[10] Z. Qian, J. Xu, K. Zheng, P. Zhao, and X. Zhou, *Semantic-aware top-k spatial keyword queries*, World Wide Web, 21 (2018), pp. 573–594.
[11] M. Chen, S. Wang, and J. Zhang, *A multi-factorial evolutionary algorithm concerning diversity information for solving the multitasking robust influence maximization problem on networks*, Connection Science, 35 (2023), p. 2275534.
[12] L. Vega, A. Mendez-Vazquez, and A. López-Cuevas, *Probabilistic reasoning system for social influence analysis in online social networks*, Social Network Analysis and Mining, 11 (2021), p. 1.
[13] Van Zyl J-P, Engelbrecht AP. *Set-Based Particle Swarm Optimisation*[J]. A Review. Mathematics, 2023, 11(13): 2980.
[14] Garcia-Collart, T. *Speak up! brands' responsiveness matters: consumer reactions to brand communications in the early stages of a crisis*[J]. Journal of Product & Brand Management, 2023.
[15] Nasim Mousavi, Panagiotis Adamopoulos, Jesse Bockstedt. *The Decoy Effect and Recommendation Systems*[J]. Information Systems Research, 2023, 34(4): 1533–1553.
[16] Piotrowski A P, Napiorkowski J J, Piotrowska A E. *Particle swarm optimization or differential evolution—A comparison*[J]. Engineering Applications of Artificial Intelligence, 2023, 121: 106008.
[17] Yang X, Li H, Huang Y. *An adaptive dynamic multi-swarm particle swarm optimization with stagnation detection and spatial exclusion for solving continuous optimization problems*[J]. Engineering Applications of Artificial Intelligence, 2023, 123: 106215.
[18] Deng L, Chen H, Zhang X, et al. *Three-dimensional path planning of UAV based on improved particle swarm optimization*[J]. Mathematics, 2023, 11(9): 1987.
[19] Yang X, Li H. *Multi-sample learning particle swarm optimization with adaptive crossover operation*[J]. Mathematics and Computers in Simulation, 2023, 208: 246–282.
[20] Zhang S, Li A, Ren J, et al. *Kinematics inverse solution of assembly robot based on improved particle swarm optimization*[J]. Robotica, 2024: 1–13.
[21] N. A. El-Hefnawy, O. A. Raouf, and H. Askr, *Dynamic routing optimization algorithm for software defined networking.*, Computers, Materials & Continua, 70 (2022), p. 1349–1362.
[22] T. Jastrzab, M. Myller, L. Tulczyjew, M. Blocho, W. Ryczko, M. Kawulok, and J. Nalepa, *Particle swarm optimization configures the route minimization algorithm*, in International Conference on Computational Science, Springer, 2022, pp. 80–87.
[23] B. Y. Hayden, *Time discounting and time preference in animals: a critical review*, Psychonomic bulletin & review, 23 (2016), pp. 39–53.
[24] B. K. Kim and G. Zauberman, *Psychological time and intertemporal preference*, Current Opinion in Psychology, 26 (2019), pp. 90–93.
[25] A. M. Aytekin and T. Aytekin, *Real-time recommendation with locality sensitive hashing*, Journal of Intelligent Information Systems, 53 (2019), pp. 1–26.
[26] S. Li, A. Karatzoglou, and C. Gentile, *Collaborative filtering bandits*, in Proceedings of the 39th International ACM SIGIR conference on Research and Development in Information Retrieval, 2016, pp. 539–548.

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