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In-depth Analysis of Chinese Traditional Music Overseas Communication Path Based on Multi-objective Optimization Algorithm

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ABSTRACT

This paper combines the multifactorial influence of the actual situation, adds the objectives of user interest preference and traditional music overseas communication budget into the influence maximization model, and constructs the Multi-Objective Influence Maximization Model (MOIM) of Chinese traditional music overseas communication to deal with the problem of objective inconsistency in the process of music communication. After that, the seed node selection algorithm of MOEA/D based on decomposition strategy is proposed to improve the search optimization strategy of seeds in the MOIM model. The cross-variance operator designed in the algorithm optimizes the set of solutions generated by the chromosome in the iterative process and finally obtains the Pareto non-dominated solution. The results show that the distribution of Pareto optimal solutions for each graph in the three datasets of TFM, TCC and TCO is very uniform when T=300, and the distribution of Pareto optimal solutions is more uniform with the increase of the number of iterations. The more influential nodes in the multi-objective optimization model of this paper, the higher the cost. The influence and cost of the seed set need to be considered in the overseas dissemination of music, and the seed set should be selected to maximize the influence within the budget. When the network structure and user behavior conform to different characteristics, the MOEA/D model can also get the corresponding undominated solution.The MOEA/D model integrally optimizes the influence index and cost index, so it provides a more flexible set of decision-making solutions for the overseas dissemination of Chinese traditional music.

Keywords: user interest preference, influence maximization, MOEA/D, node selection algorithm, cross-variance operator

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1. Introduction

With China receiving more and more international attention, more and more people are interested in the long history, rich connotation and unique flavor of Chinese traditional culture. As an important part of Chinese traditional culture, Chinese traditional music is one of the oldest and richest music in the world, with a long history and unique cultural connotation. With the rise of China's economy and the increasing cultural exchanges, Chinese traditional music has gradually become an important part of the world's cultural exchanges [1-2].

The overseas dissemination path of Chinese traditional music mainly has the following aspects: the rise of cultural industry: with the development of China's economy, the cultural industry has become an important part of supporting economic growth. The music industry, as one of the important fields of cultural industry, has received strong support and investment from the government. Secondly, the change of market demand: with the improvement of Chinese people's living standard and the increase of demand for art, people's demand for music has also changed. In addition to traditional forms of music, more and more people are paying attention to modern forms of music such as pop music and rock music. This change in market demand has played a positive role in the international dissemination of Chinese traditional music [3-6]. Third, the promotion of technological development: with the development of the Internet and digital technology, the way of music dissemination has been greatly changed. Streaming media platforms such as music apps and online music platforms have made it possible for Chinese music to spread to the world through the Internet. This technological development breaks the limitation of traditional music dissemination and promotes the international dissemination of Chinese traditional music [7-8].

Taking zheng music as an example, literature [9] examines the origin and development of zheng music as well as the history, current situation, and challenges of its overseas dissemination, so as to analyze the overseas dissemination of Chinese folk music and put forward favorable suggestions. Literature [10] introduces narrative theory into the cross-cultural communication of Chinese traditional music, dividing its overseas narratives into multiple paradigms. And based on the analysis of narrative subject and discourse, it puts forward suggestions to reconstruct the cross-cultural narrative system of Chinese traditional music. Literature [11] analyzed the international dissemination of Chinese music based on the spatial and temporal context of the old and new Silk Road. The empirical method of questionnaire survey was used to investigate 175 respondents, and the results showed that most of the respondents were greatly influenced by Chinese music, and emphasized that foreign exchange is conducive to the promotion of Chinese music. Literature [12] examines the phenomenon of Chinese music and culture being maliciously targeted in the U.S. By combining the ways in which Chinese music and culture have been disseminated both at home and abroad, it explores the overseas dissemination of Chinese music as well as attempts to create a unity of history and humanities in overseas dissemination. Literature [13] explores the development trend of Chinese folk music in this century, elucidating the important role of centralized control, which not only realizes a new vision of musical traditions of different ethnic groups and regions, but also makes it a multifaceted and unified heritage with a thousand-year history. Literature [14] reveals the impact that Cantonese music has had on music education in Malaysia. Interviews and comparative studies have shown that Cantonese music has had a positive impact on music education in Malaysia by expanding the scope of music education in Malaysia and enriching the methods and forms of music education. Literature [15] reveals the historical status of Chinese folk songs and points out that the "Belt and Road" initiative brings opportunities for the inheritance and development of Chinese folk songs. It emphasizes that the development of diversified communication strategies and the integration of excellent musical elements are important ways to realize the development of Chinese folk songs. Literature [16] aims to discuss the inheritance and development of modern Chinese zheng music. Interview method and observation method are used. An obvious evolution of modern Chinese zheng music composition was mentioned, and the evolution process was systematically introduced, emphasizing the important role played by zheng musicians in this process. Literature [17] aims to explore effective strategies to enhance the dissemination and preservation of "Xintianyou" folk songs in northern Shaanxi. Interviews and questionnaires were applied and different groups were surveyed. The results reveal that the dissemination and preservation of Xintianyou are affected by social and cultural changes, and emphasize the importance of strengthening measures of innovation, protection and dissemination. Literature [18] takes the new development direction of Han Dynasty music as the theme and discusses the inheritance direction of traditional music in terms of performance forms and aesthetic concepts, which provides a new way of thinking for the development of Chinese traditional music. Literature [19] examines the intricate tapestry of traditional music culture in Anhui, by emphasizing the historical importance of traditional music in Anhui and revealing the many challenges facing its inheritance and development, including low awareness and inheritance gaps. Literature [20] indicates that the integration of the Internet into traditional music is an inevitable trend of the times, and outlines the opportunities and challenges that the Internet brings to the development of traditional music, as well as the development path of traditional music. Literature [21] emphasized the important position of Chinese traditional music in Chinese traditional culture and human civilization, and pointed out that Chinese traditional music is facing serious challenges. And by exploring the modern inheritance of Chinese traditional music, the related contents are discussed to provide reference for related people.

In this paper, we first outline the graph structure of networks, the main topological properties of social networks, and give two typical influence propagation models, the independent cascade model and the linear threshold model, as well as the definition of the influence maximization problem. Then the concepts of group intelligent optimization solution algorithm and multi-objective optimization problem are presented. After that, a Monte Carlo sampling method and its parallelized optimization design are used to obtain a reliable subset of each user and select the more influential users as a candidate seed set. Then, a seed node selection algorithm based on the decomposition strategy of MOEA/D is proposed to combine and optimize the candidate seed sets. The cross-variance operator is designed to optimize the chromosomes during the iterative evolution process, and finally the Pareto non-dominated solution is computed.

2. Multi-objective optimization algorithm model based on communication influence

In this paper, the depth of Chinese traditional music's overseas communication path can be replaced by the network influence introduced in the methodology of this paper.

2.1. Maximizing social network influence with multiple target groups

2.1.1. Graph structure of social networks. A social network is a social structure resulting from interactions between individuals or organizations. When modeling a social network structure, individuals or organizations are usually considered as social network nodes, and social relationships are considered as connecting edges between nodes, thus forming a graph model. A general definition of a graph is given below.

Definition 1: An ordered binary (V,E) is called a graph, denoted as $G=(V,E)$, where V denotes the set of nodes of the network and E denotes the set of edges of the network.

Definition 2: For graph $G=(V,E)$, a graph G is said to be undirected if the interrelationships between nodes have no direction. That is, if there exists a connected edge from nodes u to v, then from nodes v to u are also connected.

Definition 3: A graph G is said to be a directed network if for graph $G=(V,E)$, the set of edges E satisfies: $\exists(u,v)\in G \mid (v,u)\notin G$.

Definition 4: For graph $G=(V,E,W)$, where V is the set of nodes, E is the set of edges, and W is the matrix $V\times V$ consisting of the weights of the edges, the graph G is said to be a weighted graph. If the edges $(u,v)\in G$, whose weights are w and $w>0$, are $W_{uv}=w$.

2.1.2. Topological statistical description:

1) Degree, average degree and degree distribution. Degree: the degree k_i of node i in an undirected network [22] $G=(V,E)$ is defined as the number of edges directly connected to node i. Let the adjacency matrix of network G be $A=(a_{ij})_{N\times N}$, then:

$$k_i=\sum_{j=1}^{N}a_{ij}=\sum_{i=1}^{N}a_{ji} \tag{1}$$

The following relationship exists between the total number of edges M and the degree of a node in an undirected network:

$$M=\frac{1}{2}\sum_{i=1}^{N}k_i \tag{2}$$

Average Degree: the average of the degrees of all nodes in the network, denoted by $\langle k\rangle$:

$$\langle k\rangle=\frac{1}{N}\sum_{i=1}^{N}k_i=\frac{2M}{N} \tag{3}$$

In directed networks [23], the degree of a node is categorized into in-degree and out-degree. The in-degree k_i^{in} of node i represents the number of connected edges pointing from other nodes to node i and the out-degree k_i^{out} represents the number of connected edges pointing from node i to other nodes. The degree of node i can be expressed as:

$$k_i=k_i^{in}+k_i^{out} \tag{4}$$

The relationship between the total number of edges M and the degree of a node in an undirected network is as follows:

$$M=\sum_{i=1}^{N}k_i^{in}=\sum_{i=1}^{N}k_i^{out} \tag{5}$$

For example, in the World Wide Web, the out-degree k_i^{out} of a web page is the number of other web pages to which the page links, and the in-degree k_i^{in} is the number of other web pages linking to it.

The average degree of in-degree and out-degree of a directed network node is the same, and is related to the total number of connected edges M as follows:

$$\langle k_t^{in}\rangle=\langle k_t^{out}\rangle==\frac{M}{N} \tag{6}$$

Degree distribution: the probability of randomly selecting a node with degree k in an undirected network, whose probability distribution is described as follows:

$$P_k=\frac{\lambda^k e^{-\lambda}}{k!} \tag{7}$$

2) Clustering coefficient. Clustering coefficient: a coefficient that measures the degree of closeness between nodes in a network. For a node i with degree k_i, it means that it has k_i nodes directly

connected to it. Node i has k_i neighboring nodes that may be fully or partially connected to each other. Assuming that E_i represents the actual number of edges between k_i neighboring nodes, the clustering coefficient C_i of node i is defined as:

$$C_i = \frac{2E_i}{k_i\left(k_i - 1\right)} \tag{8}$$

When $k_i = 0$ or $k_i = 1$, the clustering coefficient $C_i = 0$.

The clustering coefficient of the whole network is denoted by C, which is the average of the clustering coefficients of all nodes in the network:

$$C = \frac{1}{N}\sum_{i=1}^{N} C_i \tag{9}$$

Obviously $0 \le C \le 1$. The larger C is, the more tightly connected the network is; C tends to 0, indicating that the network is more loosely connected.

2.1.3. Influencer communication model. The independent cascade (IC) model [24] is a probabilistic model. In the IC model, the activated node u in Fig. G tries to activate its neighboring nodes in the inactive state once with the probability of influence $p(u,v)$ and these attempted activation events are independent of each other.

The dynamic propagation of information in the IC model proceeds as follows:(1) Given an initial set of nodes S in the active state, any node u that is activated at the moment of t has the ability to try to activate once for each of its neighboring nodes in the inactive state. The probability of a successful attempt is $p(u,v)$, called the probability of influence. The higher the influence probability, the more likely node v is to be influenced. (2) If node v has more than one neighbor node that has been activated at moment t, then these nodes will try to activate node v in any order at moment $t+1$. If node v is successfully activated at moment $t+1$, node v transitions to active state. (3) At moment $t+1$, the activated node v will try to activate its neighbor nodes in inactive state in the above manner. The above process is repeated until no more new active nodes are generated.

The Linear Threshold Model [25] (LT) is a value accumulation model that describes the situation where multiple individuals collaboratively influence another individual. In the LT model, each directed edge (u,v) has a corresponding influence weight $w(u,v) \in (0,1)$, and the influence weight reflects the weight of node u's influence among all incoming neighbors of node v. Each node has an influence threshold $\theta_v \in [0,1]$ and this threshold, once determined, does not change during propagation. Threshold θ_v indicates how easy or difficult it is for node v to accept the influence of a new entity; a smaller θ_v indicates that it is easier for node v to accept the new entity, and a larger θ_v indicates that it is harder for that node v to accept the new entity. Node v can be activated only if the node v's activated neighbor node has more influence on it than θ_v. Then there are:

$$\sum_{u \in N^-(v) \cap S_{t-1}} w(u,v) \ge \theta_v \tag{10}$$

where $N^-(v)$ denotes the set of all incoming neighbors of node v and S_{t-1} is the set of active nodes at moment $\mathrm{t}-1$.

2.1.4. The problem of maximizing impact. Definition 5: For a given directed network $G = \left(V, E\right)$ and a positive integer k, the influence maximization problem is defined as selecting a seed set S^* of nodes from the network G with at most k points such that the influence spread of this seed set is $\sigma(S)$ maximized under a restricted influence spreading model, i.e:

$$S^* = \underset{S \subseteq V, |S| \leq k}{\arg\max}\, \sigma(S) \tag{11}$$

The influence maximization problem is a mathematical description of viral marketing.

2.1.5. Multi-objective optimization problems. Multi-objective optimization problems [26] are also known as multi-criteria decision making or vector optimization problems. Without loss of generality, a multi-objective optimization problem with n decision variable and m objective functions can be expressed as:

$$\begin{aligned}
&\min y = F(x) = \left(f_1(x), f_2(x), \cdots f_m(x)\right) \\
&subjectto: g_i(x) \leq 0, i = 1, 2, \ldots q \\
&h_j(x) = 0, j = 1, 2, \cdots, p \\
&x = \left(x_1, x_2, \cdots, x_n\right) \in X \subset R^n \\
&y = \left(y_1, y_2, \cdots, y_m\right) \in Y \subset R^m
\end{aligned} \tag{12}$$

In the above equation, $x = \left(x_1, x_2, \cdots, x_n\right) \in X \subset R^n$ is called the decision vector, $x_i (i = 1, 2, \cdots, n)$ is called the decision variable, X is the n-dimensional decision space; $y = \left(y_1, y_2, \cdots, y_m\right) \in Y \subset R^m$ is called the objective vector, Y is the m-dimensional objective space; the objective function F defines the mapping function and the m sub-objectives that need to be optimized at the same time; $g_i(x) \leq 0$, $\left(i = 1, 2, \ldots q\right)$ defines the q inequality constraints; $h_j(x) = 0$, $\left(j = 1, 2, \cdots, p\right)$ defines the p equality constraints, and m is the number of sub-objectives of the optimization problem. In multi-objective optimization, the sub-objective functions can generally be transformed into a uniform minimization or maximization objective function, which can be done using the following simple approach:

$$\max f_i(x) = -\min\left(-f_i(x)\right) \tag{13}$$

Similarly, the inequality constraints $g_i(x) \leq 0$, $i = 1, 2, \ldots q$ can be transformed into the following form:

$$-g_i(x) \geq 0, i = 1, 2, \ldots q \tag{14}$$

Therefore, any MOP problem with different expressions can be transformed into a unified expression that unifies the problem of minimizing the total objective function, i.e., $\min y = F(x) = \left(f_1(x), f_2(x), \cdots f_m(x)\right)$.

Definition 6: For $x \in X$, x is called a feasible solution if constraints $g_i(x) \leq 0$, $\left(i = 1, 2, \ldots q\right)$ and $h_j(x) = 0$, $\left(j = 1, 2, \cdots, p\right)$ are satisfied. The set of all feasible solutions forms the set of feasible solutions, denoted $X_f \left(X_f \subseteq X\right)$.

Definition 7: Let $x_1, x_2 \in X_f$, say x_1 Pareto dominates x_2, denoted $x_1 < x_2$, if and only if the following equation holds. i.e:

$$v_i = 1, 2, \ldots m : f_i\left(x_1\right) \leq f_i\left(x_2\right) \wedge \exists j = 1, 2, \ldots m : f_j\left(x_1\right) \leq f_j\left(x_2\right) \tag{15}$$

Definition 8: If $x^* \in X_f$ is called a Pareto optimal solution if and only if the following conditions are satisfied:

$$\neg \exists x \in X_f : x < x^* \tag{16}$$

Pareto optimal solutions are also known as non-inferior or efficient solutions.

Definition 9: A Pareto front is the projection of the set of Pareto optimal solutions into the objective space, denoted $PF\left(PF=\{F(x) \mid x \in PS\}\right)$.

2.2. *Influence modeling*

2.2.1. Information proliferation impact objectives. In the probabilistic information diffusion model of social networks, a reliable subset R_u of users u is defined as a set of information that can diffuse from u to reach a child user with high probability. Assuming S is a candidate set of seed nodes, the influence scale S^* can be modeled by:

$$S^* = \arg\max_u \sum_{u=1}^{N} x_u \left(\sum_{v \in R_u} y_{uv} \right) \tag{17}$$

where y_{uv} and x_u denote whether user v is a control variable in the reliable subset of users u and whether user u is a selected seed user, respectively:

$$y_{uv} = \begin{cases} 1 & v \in R_u \\ 0 & \text{Otherwise} \end{cases}, x_u = \begin{cases} 1 & u \in S \\ 0 & \text{Otherwise} \end{cases} \tag{18}$$

The influence scale objective means that the MOIM model aims to select seed users to maximize the scale of influence propagation.

2.2.2. Audience Interest Preference Targets. Maximizing interest preference is to maximize the total value of interest preference in traditional Chinese music for all listeners that can be influenced by using the influence of multiple candidate seed listeners. In this paper, in order to model the total interest of the candidate seed set, the first objective function is extended by introducing the interest value of each listener as shown in the following equation:

$$I^* = \arg\max_u \sum_{u=1}^{N} x_u \left(\sum_{v \in R_u} r_{uv} \right) \tag{19}$$

$$r_{uv} = \begin{cases} 1 & v \in R_u and r_v > \varepsilon \\ 0 & \text{Otherwise} \end{cases} \tag{20}$$

where r_{uv} denotes the interest preference of the sub-users v affected by the seed user u for the given product r_v and constrains r_v to be greater than an interest threshold indicating that the affected v have a high interest in the product. Similarly, if user v is repeatedly influenced by multiple candidate seed nodes, we set $\sum_{u \in S} r_{uv} = 1$. The interest preference goal implies that the sub-users influenced by the candidate seeds are not always interested in the information, and we should disseminate the information to those users who are interested in it.

2.2.3. Dissemination of budgetary objectives. Cost constraints are an important factor to consider in marketing strategy campaigns for traditional Chinese music. On social networks, the more influential the audience, the more expensive it is for advertisers to hire them to spread their message. Under budget constraints, high-influence listeners who have the largest possible number of listeners they can influence and who may be interested are flexibly selected to promote and publicize the message for Chinese traditional music and to increase the popularity of Chinese traditional music. Therefore, the third objective of the MOIM model is that traditional Chinese music should be constrained by a certain budget cost when planning information diffusion activities.

The budget is the total cost of the company's plan to promote its product promotional messages in social networks. Assuming that constant c_u refers to the cost that the company has to pay to user u when he is hired to disseminate the message, the cost objective function can be modeled as:

$$C^* = \arg\min_u \sum_{u=1}^{N} x_u * c_u \tag{21}$$

This means that our goal is to minimize expenses in the pursuit of maximizing impact and to ensure that the company obtains higher revenues.

When disseminating information, managers often pre-set the size of the budget and the size of the number of seed users, and select an appropriate number of seed users to promote promotional information, which ensures greater impact dissemination and also controls the cost of information dissemination. Therefore, these three objectives are constrained by both:

$$\sum_{u=1}^{N} x_u * c_u \le budget \tag{22}$$

$$\sum_{u=1}^{N} x_u = H \tag{23}$$

This paper takes the social network influence maximization problem as the research direction, and combines the network users' own interest preference attributes and marketing budgets, etc., and proposes a multi-objective influence maximization (MOIM) model that integrates influence maximization, interest preference maximization and enterprise cost minimization, and the mathematical model of MOIM is shown as follows:

Objective one: $S^* = \arg\max_u \sum_{u=1}^{N} x_u \left(\sum_{v \in R_u} y_{uv} \right)$

Objective two: $I^* = \arg\max_u \sum_{u=1}^{N} x_u \left(\sum_{v \in R_u} r_{uv} \right)$

Objective three: $C^* = \arg\min_u \sum_{u=1}^{N} x_u * c_u$

$$s.t y_{uv} = \begin{cases} 1 & v \in R_u \\ 0 & \text{Otherwise} \end{cases}, x_u = \begin{cases} 1 & u \in S \\ 0 & \text{Otherwise} \end{cases} \tag{24}$$

$$\begin{gathered} r_{uv} = \begin{cases} 1 & v \in R_u and r_v > \varepsilon \\ 0 & \text{Otherwise} \end{cases} \\ \sum_{u=1}^{N} x_u * c_u \le budget, \sum_{u=1}^{N} x_u = H \end{gathered} \tag{25}$$

2.3. Node influence calculation based on Monte Carlo sampling

In this paper, we use a parallelized algorithm for Monte Carlo sampling to obtain a reliable subset of each listener and the corresponding total interest and propose a multi-objective optimization algorithm based on diffusion influence (MOEA/D) to search for a Pareto-optimal solution of the model. In this paper, Monte Carlo sampling method is used to compute the reliable subset R_u, the total interest value I_u and the diffusion cost c_u of user u. The reliable subset R_u sampled from G indicates that the information disseminated from u can be received directly and indirectly by its connectors with high probability. In order to ensure that information diffused by user u is obtained by R_u with high probability, we set the probability threshold $\eta \in [0,1]$ to ensure that only edges with probability greater than η will be sampled during the sampling process. At the same time, we set the shortest path threshold dis to limit the magnitude of information dissipation during the information transfer process. We utilize *R*u and the computational formula to obtain the influence size, total interest preference value, and hiring cost of each node, and then filter the candidate seed set based on the influence.

The algorithm transforms the directed probability graph into a N st order matrix representing the social relationships between users and the probability of passing from each user to his/her followers. We obtain the set $D=\left(D_1,D_2,\ldots,D_N\right)$ of deterministic subgraphs of all users from the directed probability graph G. Then for each user's subgraph D_u, we compute a reliable subset $-R_u$ reachable from user u. Each user u has its own attribute interest value for a specific product r_u. We compute the number of subusers that u can influence based on R_u formalized as the influence size σ_u and the cumulative total interest preference value of the interest level of all the subusers that can be influenced I_u, and compute the cost value using the user's influence value and the cost function c_u. Finally, we select high-influence users as a candidate seed set S as input for subsequent work.

2.4. MOEA/D based seed node selection algorithm

2.4.1. Algorithmic framework. The influence maximization problem is defined as a multi-objective problem with user interest preferences and corporate budget. Multi-objective optimization algorithms are commonly used to solve multi-objective problems, most of the multi-objective optimization algorithms view the multi-objective problem as a whole, and each of the solutions obtained is independent of each other without any connection.The algorithmic flow of MOEA/D is illustrated in Fig. 1.

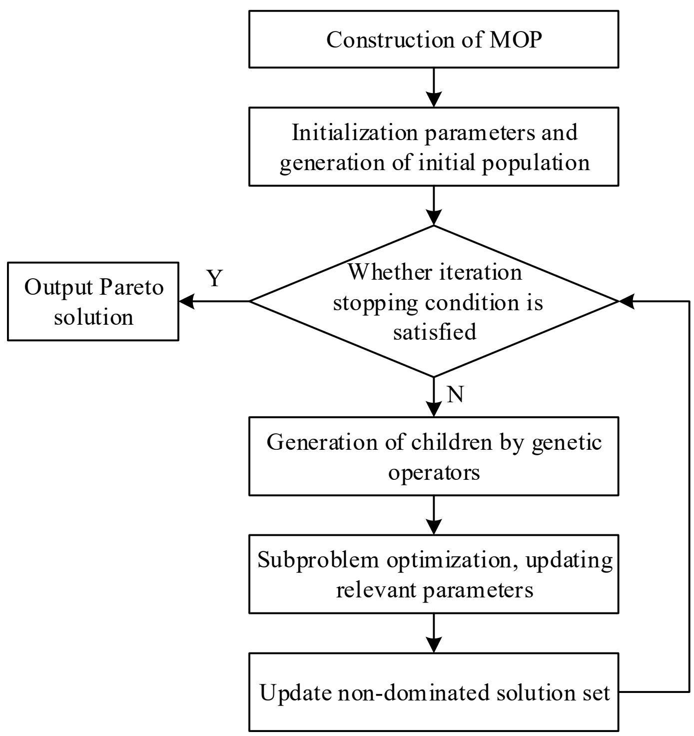


Fig. 1. MOEA/D algorithm process

2.4.2. Seed node selection algorithm. In this section, a high-impact seed node selection algorithm is designed using the MOEA/D framework, with a view to searching for combinations to optimize a high-quality seed set that meets the actual needs of the enterprise. The objective function and reference point of the jth subproblem can be expressed as:

$$g\left(x \mid \lambda^j, z^*\right)=\max_{1\le n\le m}\left\{\lambda_n^j\left|f_n(x)-z_n^*\right|, x\in U\right\} \tag{26}$$

$$z_n^* = \max\left\{ f_n(x) \mid x \in U \right\} \tag{27}$$

where $m=3$, the objective function f_1, f_2, f_3 corresponds to the scale objective, the interest objective and the cost objective, respectively. The corresponding optimal solution z_i^* in $Z^* = \left\{ z_i^*, z_2^*, z_3^* \right\}$ is the best value found so far for objective f_i. For each neighbor $d \in B(i)$, if $g\left(j \mid \lambda^d, z^* \right) < g\left(x^d \mid \lambda^d, z^* \right)$, we update the corresponding chromosome and objective values, $x^d = j$ and $FC^d = F(j)$, where FC^d is the value of chromosome F for x^d. After we solve all subproblems, if the new solution is not dominated by the set of solutions in the set of Pareto-optimal solutions PS, we add it to PS and remove those known solutions in PS that are dominated by the new solution.

2.4.3. Genetic operators. The genetic operator operations designed in this paper for searching new solutions to the MOIM model consist mainly of crossover and mutation, and the genetic operator is designed to ensure that quality solutions are obtained faster during the evolution of the population. Among them, crossover operation is the process of crossover interchanging some or some genes (user numbers) on two given parent chromosomes with some efficient strategy to produce new feasible offspring solutions, and the new offspring have to satisfy the given cost constraints; and mutation operation is the process of individual chromosomes' own some or some gene positions (user numbers) are changed with some mutation probabilities to form new solutions. Both operations result in a new solution, and if the new solution is not a quality solution, it can be generated in some way.

3. Results of Overseas Dissemination of Chinese Traditional Music under MOEA/D Algorithm

3.1. Analysis of optimal solution distribution results for multi-objective evolutionary process

3.1.1. Experimental data acquisition and processing. In order to ensure the real validity as well as the universality of the experiments, three real and effective cooperative network datasets are selected in this paper to validate the proposed method, and the three datasets are: traditional folk music (TFM), traditional classical compositions (TCC) and traditional classical opera (TCO). These three datasets are physical cooperative networks, in which the nodes of the networks are real names, so we identify the nodes in the network by their attribute information with the ID of the network, refer the same author nodes to the same entity, and construct a multilayer network by connecting them through the same entity on these three single-layer networks. The statistical information of the dataset is shown in Table 1.

Table 1. Data set statistics

Data set	Node number	Side number	Average degree	Average clustering coefficient
Traditional folk music(TFM)	1613	2754	3.673	0.3322
Traditional classical comedy(TCC)	8155	15543	3.654	0.2342
Traditional classical opera(TCO)	16358	120593	14.471	0.7392

The analysis of influence maximization in multilayer networks needs to consider the connection relationship between entities on different networks and the entity identification problem, although there have been some research results solving the entity-to-entity connection in multilayer networks, we will use the dataset corresponding to Chinese traditional music to ensure the accuracy. For constructing a multilayer network, this can be accomplished through multiple cooperative networks.

Specifically, the interlayer connection of a multilayer network dataset TFM-TCC can only be established by the same entities in both TFM and TCC networks. For example, if entity a exists in both TFM and TCC networks, then a multilayer network can be constructed by establishing a connection between entity a in the TFM network and entity a in the TCC network. Using the same approach, two other multilayer network datasets, TFM-TCO and TCC-TCO, can be obtained, where there are 89 co-authors of the TFM and TCC networks, 90 co-authors of the TFM and TCO networks, and 1290 co-authors of the TCC and TCO networks. In this paper, we analyze and study the influence maximization problem in multilayer networks, in order to facilitate the calculation, we map the multilayer networks into projection networks and take the maximum value of the weights on the edges in the multilayer networks, in addition, in order to more accurately reveal the process of information dissemination, we extract the maximum connectivity subgraph from each data set to study the influence maximization problem.

3.1.2. Multi-objective evolutionary processes. Since MOEA/D is a multi-objective evolutionary algorithm, the result we obtain is a set of non-dominated solutions. In order to reveal the evolution of the nondominated solutions, we will show it through the distribution of the solutions with different number of iterations. First, Figures 2, 3, and 4 show the Pareto optimal solution for each graph obtained by MOEA/D on the TFM-TCC, TCC-TCO, and TFM-TCO datasets, respectively, for K = 50, where the number of iterations, T, is set to be 300. The horizontal coordinates denote the centrality of the set of seeds $f^C(x)$, and the vertical coordinates denote the accessibility of the set of seeds $f^A(x)$. It can be clearly seen that the final Pareto front is almost uniformly distributed on these three datasets, which indicates that MOEA/D has good performance.

Furthermore, this paper finds that $f^C(x)$ and $f^A(x)$ are actually conflicting objective functions, as they are mutually constraining. The former collects as many closely related entities as possible, while the latter gathers together as many influential entities as possible. Multi-objective optimization, on the other hand, is an effective way to balance these two objectives. It is obvious from Fig. 2 that the distribution of Pareto optimal solutions in each graph is very uniform, and the PF is almost unchanged when T reaches 300, which implies that the genetic operator we designed solves the shortcomings of the existing algorithms. As can be seen from Fig. 3, when T = 300, the Pareto optimal solution forms a frontier surface and the Pareto frontier obtained by MOEA/D moves in the direction of larger $f^C(x)$ and $f^A(x)$. Figure 3 shows the distribution of Pareto optimal solutions when iteration T is 300. It can be clearly seen that although these solutions almost form a PF, their distribution is relatively discrete. As the number of iterations increases, the distribution of Pareto optimal solutions is more uniform.

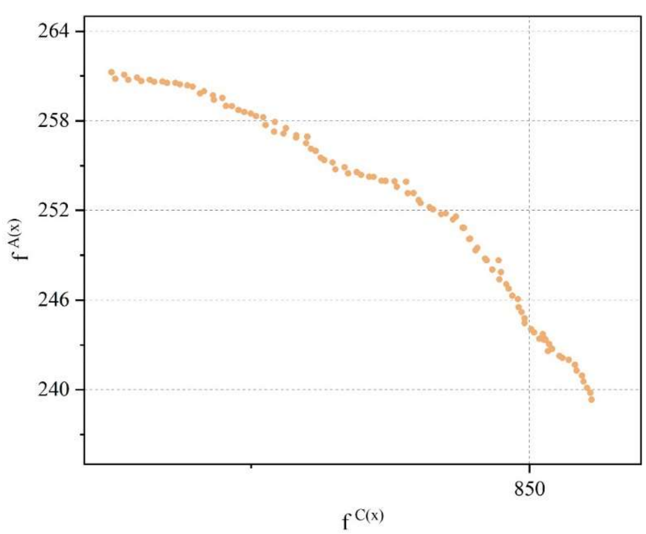


Fig. 2. The evolution of pareto optimal solution in TFM-TCC data set

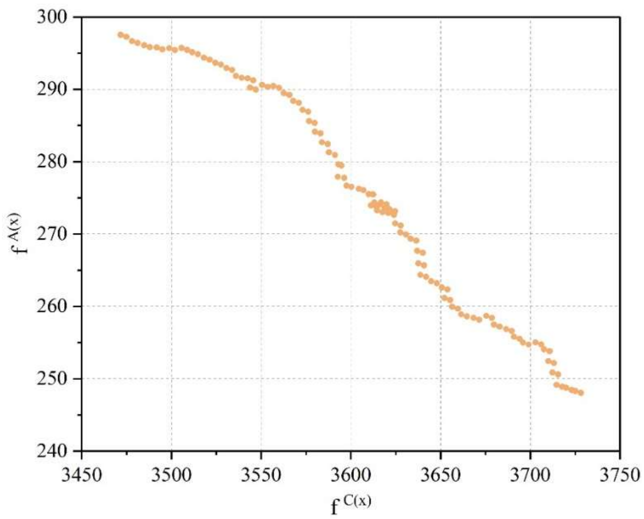


Fig. 3. The evolution of pareto optimal solutions in the TCC-TCO data set

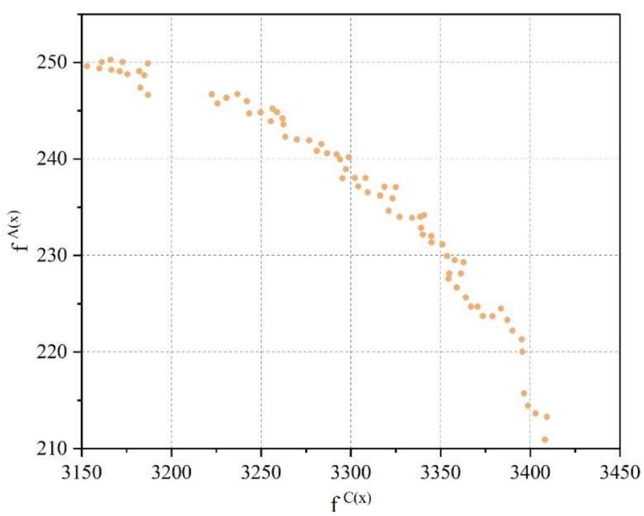


Fig. 4. The evolution of pareto optimal solutions in the TFM-TCO data set

3.2. Impact of Model Parameters on the Diffusion of Traditional Music

In the following, this paper selects traditional classical opera music as the research object and investigates its communication path (communication influence).

3.2.1. Non-dominated solution distribution results. The final non-dominated solution distribution results of the experiment are shown in Fig. 5. The multi-objective optimization model in this paper has conflicting objectives: influence and cost, and the more influential the node, the higher the cost.

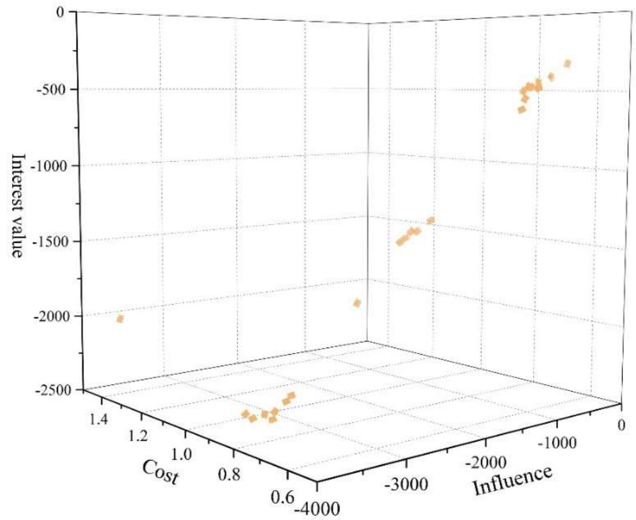


Fig. 5. Final non-dominant solution distribution results

In order to look at these two objectives in more detail, the Pareto fronts of each set of elite solutions are shown in two perspectives: cost and influence, which can be used to improve the flexibility of the decision-making for the selection of social marketing seed collections. The projection of the experimental results on the influence and cost axes is shown in Figure 6. The experimental results show that cost minimization and influence maximization are two contradictory goals, and when enterprises select seed user sets in music distribution overseas, they should consider not only the influence of the seed set but also the cost of the seed set, and the seed set should be selected to maximize the influence within the budget.

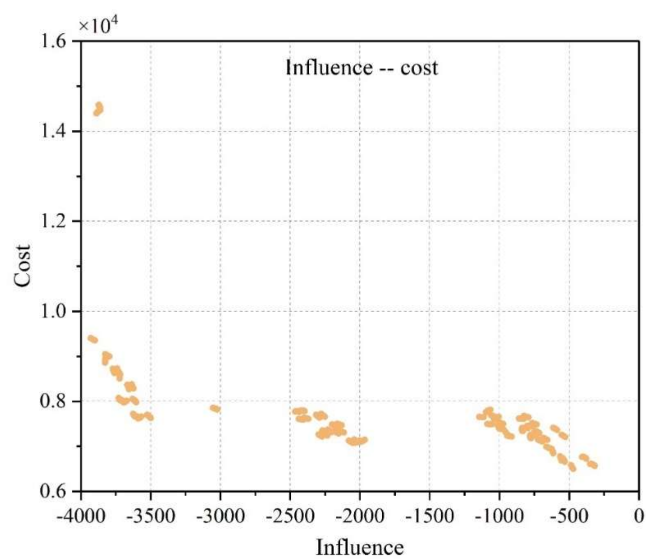
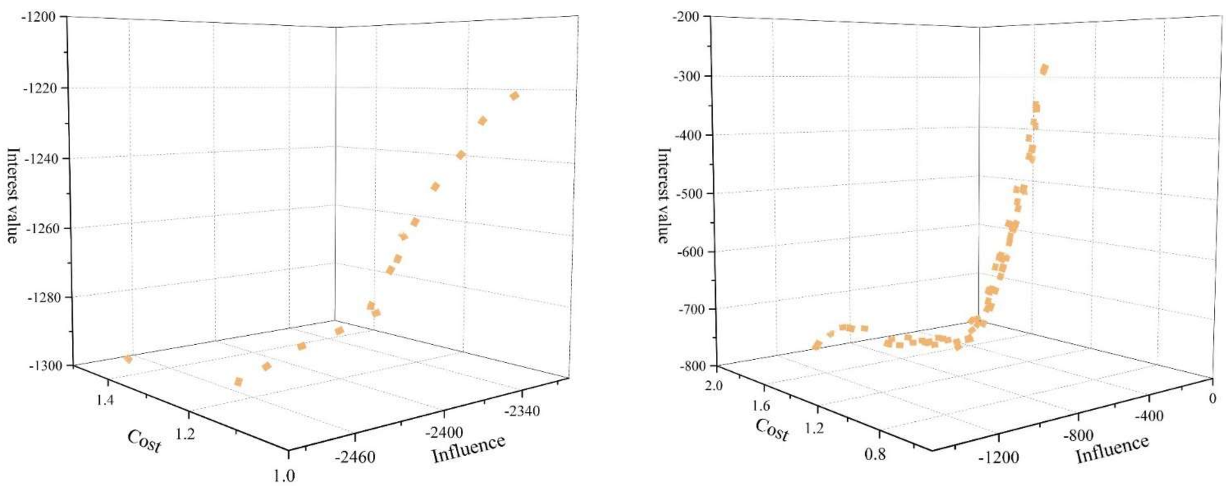


Fig. 6. The projection of influence and cost axes

3.2.2. Relationship between model parameters and network influence. Next, the paper further explains the parameter settings in the model and validates them with experiments. In this paper, parameters δ, τ and λ in the influence maximization multi-objective optimization model have an impact on the effectiveness of the model. In order to verify the robustness of the proposed model, this paper performs sensitivity analysis on parameters δ, τ and λ. Parameter λ affects the ease with which the network nodes are activated. The larger λ is, the higher the threshold is and the more difficult it is for a node to be activated. Conversely, the smaller λ and the lower the threshold, the easier it is for a node to be activated. δ and τ affect the cost of seed node selection. The larger δ and τ are, the larger the cost and the lower the number of seed nodes that can be selected with the same budget; the smaller δ and τ are, the smaller the cost and the higher the number of seeds that can be selected.

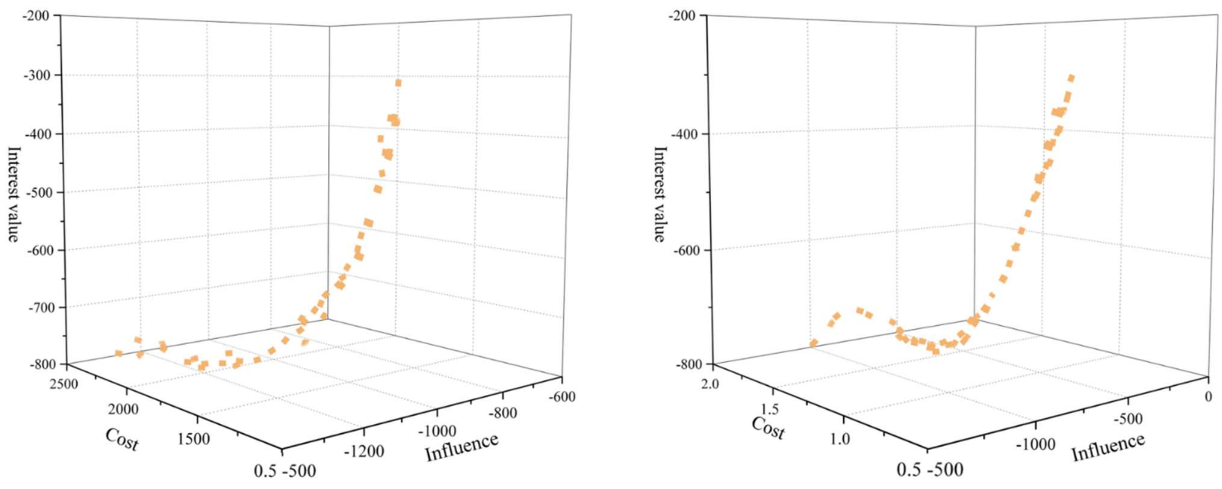
The sensitivity analysis results of the model parameters in the traditional Chinese classical opera music dataset are shown in Fig. 7, where (a) and (b) are the sensitivity analysis results of the parameters under the conditions of δ=150, τ =1/40, λ=0.2 and δ=150, τ =1/40, λ=0.5, respectively. From the Pareto front surface in the figure, it can be seen that the lower the value of λ, the greater the spread and interest, and the lower the cost of seed integration, with δ and τ fixed. Conversely, the lower the value of λ, the smaller the spread and interest, and the higher the seed integration cost. In addition, when λ is small, the number of non-dominated solutions is small and the Pareto front is sparse.



(a) δ=150, τ =1/40, λ=0.2 (b) δ=150, τ =1/40, λ=0.5

Fig. 7. The sensitivity analysis of model parameter λ

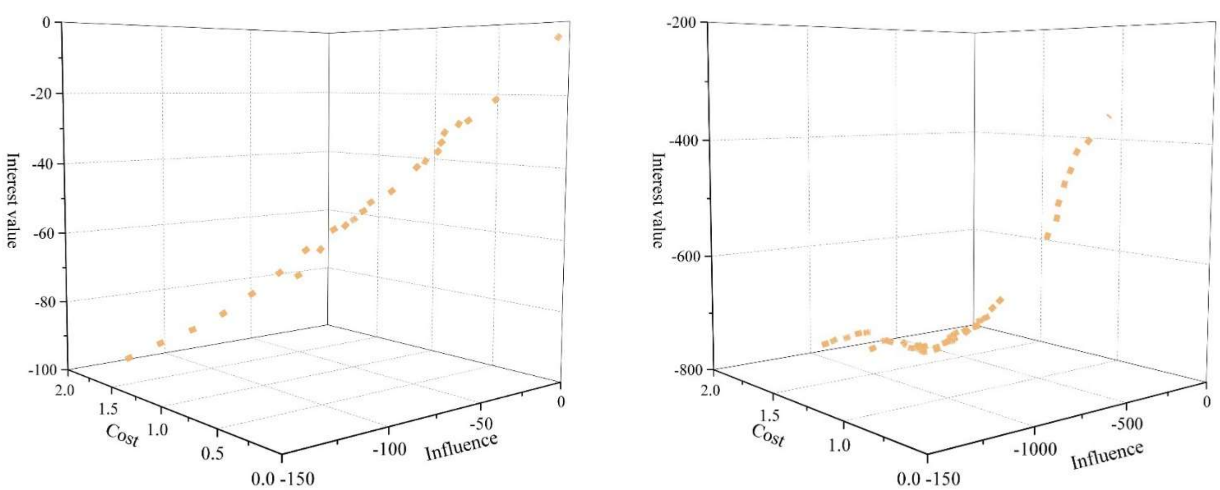
The results of the sensitivity analysis of model parameter δ are shown in Fig. 8, where (a) and (b) are the results of the sensitivity analysis of the parameters under the conditions of δ=50, τ =1/40, λ=0.5 and δ=150, τ =1/40, λ=0.5, respectively. As can be seen from the figure, under the condition of τ and λ being fixed, the larger the value of δ, the smaller the spreading range and interest, and the higher the seed integration cost. The smaller the value of δ, the larger the range of spread and interest, and the higher the cost of seed integration. In addition, the number of non-dominated solutions is low when δ is small or large, and the Pareto front is sparse when δ is large.



(a) δ=50, τ =1/40, λ=0.5 (b) δ=150, τ =1/40, λ=0.5

Fig. 8. The sensitivity analysis of model parameter δ

The sensitivity analysis results of model parameter τ are shown in Fig. 9, where (a) and (b) are the sensitivity analysis results of parameters under the conditions of δ=150, τ =1/25, λ=0.5 and δ =150, τ =1/40, λ=0.5, respectively. It can be seen that, under the condition of δ and λ being fixed, the larger τ is, the smaller the spreading range and the degree of interest are, and the higher the seed integration cost is; the smaller τ is, the larger the spreading range and the degree of interest are, and the lower the seed integration cost is. In addition, when τ is larger or smaller, the Pareto front is sparse.



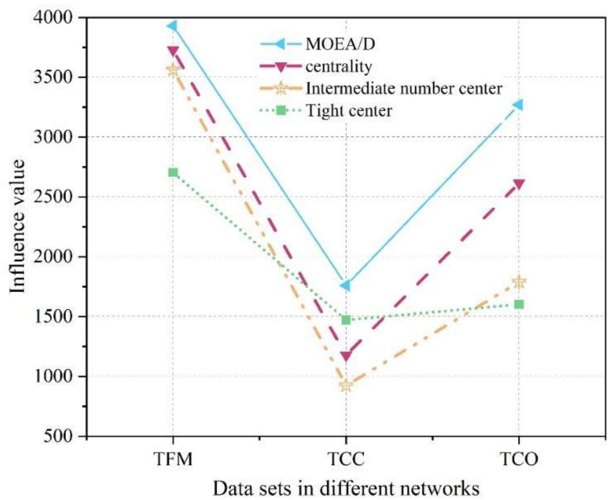
(a) δ=150, τ =1/25, λ=0.5 (b) δ=150, τ =1/40, λ=0.5

Fig. 9. The sensitivity analysis of model parameter τ

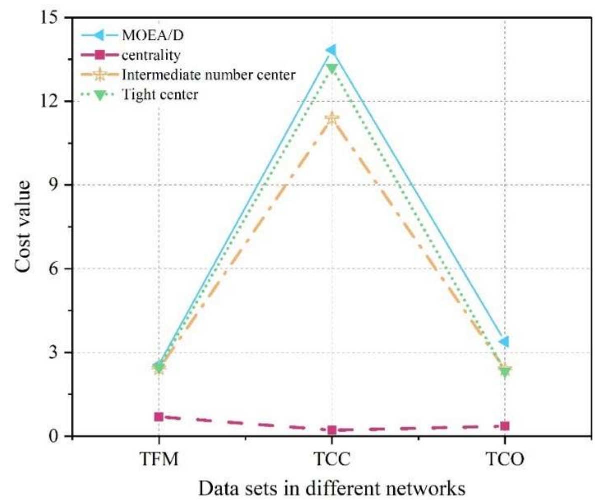
The sensitivity analysis of parameters δ and τ shows that the cost of disseminating information is different for different users, and usually the higher the cost, the fewer the number of selectable users. Therefore, when selecting seed users to disseminate information, not only the influence factor of users should be considered, but also the cost factor of users to disseminate information. The results of the above sensitivity analysis show that when the network structure and user behavior conform to different characteristics, the proposed model can all obtain the corresponding undominated solutions.

3.3. Comparative results of population target values of different methods

In order to compare the advantages and disadvantages of the method proposed in this paper with the classical algorithms of degree centrality, tight centrality and median centrality, this paper designs comparison experiments for the three networks respectively. Setting the size of the seed set as 200, this paper finds out the 200 nodes with the largest influence using the three classical algorithms, calculates the influence index and cost index of the nodes, and compares them with the optimal influence index and cost index of the 200 nodes found by the methods in this paper. The results of the experimental comparison of different methods are shown in Fig. 10, (a) and (b) are the influence indicators and cost indicators, respectively. Compared with the classical algorithm, the model proposed in this paper can always find the seed set with better metrics. Since the method in this paper optimizes the influence and cost indicators comprehensively, it can provide a more flexible set of decision-making solutions for the overseas dissemination of Chinese traditional music.



(a)Influence index



(b)Cost indicator

Fig. 10. Comparison results of different methods

4. Conclusions and directions for future research

4.1. Conclusion

In this paper, considering the scale of information diffusion, user interest preference and music dissemination budget, we take the influence maximization model as a multi-objective optimization problem and propose a multi-objective optimization (MOIM) model for the overseas dissemination path of Chinese traditional music, which utilizes Monte Carlo sampling to compute high-influence users. Then a seed selection algorithm based on multi-objective evolutionary algorithm with decomposition strategy (MOEA/D) is proposed to combine the optimization seeds to solve the MOIM model. The results show that the final Pareto front is almost uniformly distributed on the three datasets of "TFM-TCC, TCC-TCO and TFM-TCO", and all of them obtain the Pareto optimal solution, and the MOEA/D model performs well. Simulation experiments on user interest values and costs based on three real social networks prove that the model can effectively balance different objectives. The sensitivity experimental analysis shows that the model exhibits good robustness and effectiveness on parameter variations.

4.2. Directions for future research

For future research, since real social network platforms usually contain a large number of users and numerous linking relationships, one possibility is to design some strategies to improve the efficiency of the model. An important assumption in the proposed model is that we already know the user interest values and diffusion probabilities. Another possibility for the future is to evaluate the interest value of each user in Chinese traditional music and the probability of overseas diffusion among users by using real social network data and integrate the information into the proposed model. User-generated content and interaction information in social media provide us with the potential to handle this task.

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