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A Novel Many-Objective Recommendation Algorithm for Multistakeholders

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ABSTRACT Most traditional recommender systems focus specifically on increasing consumer satisfaction by providing a list of relevant content to consumers. However, the perspectives of other multisided marketplace stakeholders are also equally important, i.e., the exposure for suppliers or providers and profit for the platform. The suppliers want their products to be presented to users, and the objective of the platform is to maximize their profit. Nevertheless, because consumers' preferences and the objectives of providers as well as the platform may conflict with each other, it degrades the utility of the recommendation methods by only considering users' views. Therefore, in this work, we use a many-objective optimization method to maintain a tradeoff among five objectives for three stakeholders and obtain multiple Pareto front solutions in a single run. We first combine customer lifetime value and user purchase preference to create a new similarity model (Sim_RFMP) to increase the recommendation accuracy of the recommendation list. Furthermore, we propose a many-objective model (NBHXMAOEA) for multistakeholder recommendation. In NBHXMAOEA, we present a novel N-block heuristic crossover operator (NBHX) that recombines blocks of chromosomes based on heuristics. Through extensive experiments, the results demonstrate that our proposed NBHXMAOEA achieves superior performance in terms of average accuracy, diversity, novelty, provider coverage, and platform profit to its competing methods.

INDEX TERMS Many-objective, recommender systems, similarity model, stakeholders.

I. INTRODUCTION

Recommender systems (RS) have been successfully applied to assist decision making by producing a list of items tailored to user preferences and tastes, supporting e-commerce, social media, and other applications where the content volume would otherwise be overwhelming for users [1], [2]. They have become indispensable tools of the Internet age. Traditional RS produces recommendations to satisfy the needs and interests of end users [3], [4]. It is entirely appropriate to maintain customers or viewers high loyalty and retention. However, the recommendation recipient may not be the only party in the recommendation outcome.

Sole focus on the preference of end users hampers the utility for other parties, for example, providers or sellers. They would not use RSs if they believed such systems were not profitable for them. What is needed is a shift in focus, considering not only the customers' considerations but also the perspectives and utilities of multiple stakeholders. Other stakeholders such as the platform whose perspective differs from those of customers, also need to be considered. Therefore, an appropriate balance between the needs of consumers, providers and platforms is required.

Although the provider and system are two crucial participants in recommender systems, very little focus has been given on the utility of multiple stakeholders, e.g., exposure of items and profit or revenue of products, which represent the perspectives of providers and the system, respectively. The entire space multitask model (ESMM) is one of the few works that considers both click-through rate (CTR), click conversion rate (CVR), and gross merchandise volume (GMV) value simultaneously for multiple stakeholders [5]. In online commerce, optimization of CVR or CTR is considered synonymous with optimizing for consumer relevance [6]. GMV is the total amount of revenue users spent on the recommended items. This metric evaluates the willingness of users to purchase in RS and raising GMV can better benefit system revenue. In [4], a recent learning-to-rank approach is adopted

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for GMV maximization, where CTR and CVR are predictions from the two separate models. Additionally, the ranking differences between relevance and revenue are addressed by a multitask learning technique, which trains both CTR and CVR models [7]. The two models share the same user, item embedding, and similar neural network structures, and the ranking model is also price*CTR*CVR.

However, the classic economic approach to optimizing profit by computing and optimizing expected conversion rate times expected profit per conversion would generally not give the optimal solution in real-world situations. One significant reason is that specific conversion values for recommendations are difficult to predict accurately; thus, the product of conversion rate and profit may introduce error into the solution, and the two indicators cannot be optimized concurrently. In addition, CTR and GMV are two important objectives that are not entirely consistent. A CTR-optimal or GMV-optimal recommendation can be rather suboptimal or even poor in terms of the other objective [8].

When considering different stakeholder perspectives, there will be more goals and tasks, and they may conflict with each other. In recommendation systems, precision, recall, and F1 score are the most commonly used matrices of accuracy measurement, and the recommendation accuracy is crucial to users. To validate the inconsistency between different objectives, we obtain several user recommendations generated by the traditional collaborative filtering algorithm. Fig. 1 illustrates the accuracy and GMV value of different recommendation solutions. Each point represents a solution for all users. According to the trends reflected in Fig. 1, the three accuracy matrices, precision, recall, and F1, score show a negative correlation with the gross merchandise volume value. When the GMV value gradually increases, precision, recall, and F1 decrease.

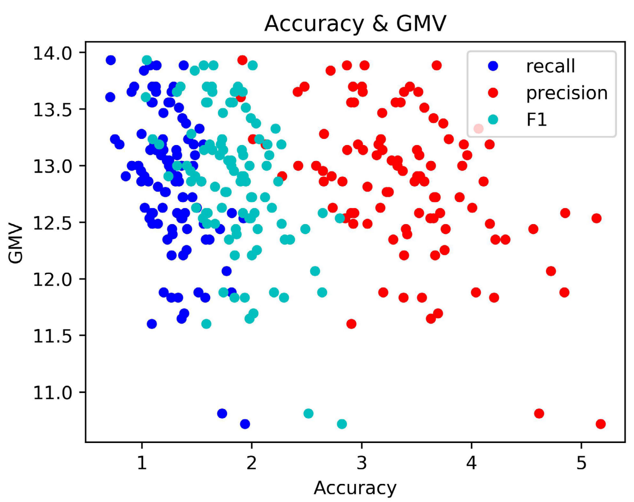

FIGURE 1. Distribution of accuracy and GMV value. The Pearson Correlation Coefficient is −0.50519521.

Obviously, using one formula to express the conflicting objectives is inaccurate. Therefore, we formulate the multiple stakeholder recommendation problem as a many-objective optimization problem, which can simultaneously optimize the recommendation accuracy, diversity, novelty, coverage, and profit.

Additionally, traditional collaborative filtering algorithms commonly adopt similarity metrics, e.g., cosine, Jaccard, Pearson correlation, to recommend the items consumers are most likely to choose [9], [10]. However, these correlation coefficients only consider the ratings of the items purchased by users and do not consider more specific RS information.

To address the above problems, we propose a many-objective algorithm, NBHXMAOEA, which consists of three phases for many-objective optimization. First, the traditional user-based collaborative filtering (UCF) algorithm with our new sim_RFMP similarity model is used to generate a recommendation list for all users. Second, many-objective optimization is used to filter the recommendations by reranking the recommendation list. Specifically, we adopt five conflicting objective functions: accuracy, diversity, and novelty are indicators to quantify the fitness of recommendation solutions for users, the coverage indicator is for providers and the profit indicator is for the platform. These objective functions reflect the needs of multiple stakeholders in different aspects. Furthermore, we propose the N-block heuristic crossover algorithm NBHX, which optimizes five conflicting objective functions and obtains a set of optimal recommendation solutions.

Our contributions to this work can be summarized as follows:

1) We propose a nonlinear similarity model sim_RFMP to evaluate the similarities between users.
2) We formulate a novel many-objective recommendation algorithm, NBHXMAOEA, which is used to obtain tradeoff solutions for multiple stakeholders simultaneously considering accuracy, diversity, novelty, coverage, and profit.
3) A new N-block heuristic crossover operator NBHX is proposed that considers the recommendation list features.
4) The NBHXMAOEA algorithm, which combines NBHX with sim_RFMP, obtains superior results in terms of diversity, novelty, coverage, and profit, sacrificing a certain degree of accuracy.

The remainder of this article is organized as follows. In Section II, we briefly introduce the related work. In Section III, we introduce the proposed framework NBHXMAOEA. Then, we describe the experimental settings and report the experimental results in Section IV. Finally, we conclude our work in Section V.

II. RELATED WORK

In this section, we introduce the multistakeholder recommender systems, many-objective optimization, genetic algorithms, customer lifetime value, and top-k recommendation strategies.

A. MULTISTAKEHOLDER RECOMMENDER SYSTEMS

Recommender systems that balance the interests of several parties are called multistakeholder recommender systems (MSRS) [11]. The multistakeholder recommendation is an extension of recent efforts to expand the considerations involved in RS evaluation beyond simple accuracy measurements. Prior research has examined specific cases of such concerns in the category of reciprocal recommendations, such as applications in online dating [12], recruitment [13], education [14], advertising [15], and scientific collaboration [16].

In dating scenarios, both the user and the item models represent people, and a date is successful when each side is satisfied [17]. Therefore, it is necessary to consider the utilities of two parties to produce accurate recommendations. In the advertising area, a display ad in a real-time display advertising context depends not only on whether the ad is of interest to the user but, because advertisers pay for each impression, it also matters if the user is of interest to the advertiser. In that case, an advertisement should be recommended to target users who have the possibility to purchase. Similar ideas have appeared in work on group recommender systems where the goal is to find recommendations that can maximize the utility of users in each group [18].

Although extraordinary successes have been achieved by considering different sides, far from being two-sided recommendations, RS families should be broadened to include the perspectives and utilities of multiple stakeholders. When recommendation accounts for the needs of more than just the two transacting parties, the reciprocal recommendation systems are extended to multistakeholder recommender systems (MSRS).

Different recommendation scenarios can be distinguished by differing configurations of interests among the stakeholders. In online marketplaces, we can consider three primary categories:

1) Consumers or users who receive the recommendations. They are the individuals whose choice or search problems bring them to the platform and whose input and purchasing decisions ultimately determine the success of the recommendation systems.
2) The providers or sellers, those entities that supply goods and services for sale or otherwise stand behind the recommended objects, and possibly gain utility from the consumer's choice.
3) The platform or system creates the RS to match consumers with providers via its recommendation algorithms and has some means of gaining benefit from successfully doing so. The platform may be a retailer, e-commerce site, broker, or other venues where consumers seek recommendations.

Building an MSRS will introduce a unique set of challenges, as each side of the marketplace has intrinsic and distinct values that the model needs to consider. However, it is difficult to optimize multiple objectives simultaneously, where the core difficulty lies in the conflicts between different objectives.

B. MANY-OBJECTIVE OPTIMIZATION

In general, a many-objective optimization algorithm is used to solve the optimization problem of four or more conflicting objective functions [19]. The many-objective problem can be formalized as follows:

$$Minimize/\mathrm{Maximize}\{f_1(x),f_2(x),f_3(x),\ldots,f_m(x)\}$$

which is subject to:

$$\begin{aligned} &g_i(x) \leq 0, \quad i = 1,2,3,\ldots q \\ &h_i(x) = 0, \quad i = 1,2,3,\ldots p \\ &x = [x_1, x_2,\ldots,x_s], \quad s \geq 1 \\ &x_L \leq x_i \leq x_U, \quad i = 1,2,\ldots,s \end{aligned} \tag{1}$$

where x is the s-dimensional decision vector, $f_i(x)$ is the ith objective function, and m is the number of objective functions. When the value of m is larger than 3, (1) is called the many-objective optimization problem, which attempts to minimize or maximize all the objectives. $g_i(x)$ and $h_i(x)$ are inequality and equality constraints, and x_L and x_U are the lower and upper bounds of decision variables.

Any solution that meets the requirements above is defined as a feasible solution [20]. A solution is considered as a Pareto-optimal solution to many objectives in the sense that no objective can be further improved without hurting the other one. The set of all Pareto-optimal solutions is called the Pareto-optimal solution set, and the set of objective vectors corresponding to all Pareto-optimal solutions is called the Pareto front. Many-objective optimization aims to find a set of Pareto-optimal solutions that approximate the Pareto-optimal front.

Most real-world problems, such as recommender systems, involve multiple conflicting objective functions. It is not possible to obtain a single optimum solution to such problems [21]. Instead, we aim to obtain a set of tradeoff solutions where no solution is dominated by the others. All these solutions are known as nondominated solutions [22].

C. GENETIC ALGORITHMS

Genetic algorithms (GAs) [23] are a subset of evolutionary algorithms [24], that have emerged as flexible and efficient metaheuristic methods for solving optimization problems and achieving a high level of problem-solving efficacy in most research domains, e.g., aircraft design [25], battery systems [26], resource allocation [27], job-shop scheduling [28], virtual machine placement [29], cloud task scheduling [30], quadratic assignment [31], and vehicle routing [32].

Several works have ascertained that the GA is more suitable for solving complex and constrained optimization problems in the area of machine learning and data mining [33], [34]. Kim *et al.* [35] devised a novel genetic algorithm based on deep reinforcement learning and used it to solve long initial learning times and an overwhelming number of branching factors. Nagar *et al.* [36] adopted a genetic algorithm for efficient feature selection to reduce the dataset dimensions and enhance the classifier pace of a k-nearest-neighbors technique, which was employed for diagnosing the stage of patients' disease. Sayantari and Bhattacharya [37] employed a probabilistic cellular automata-based method to model the infection dynamics for a significant number of different countries. The cellular automata method provides an excellent platform for accurate data-driven modeling of infection spread, with a sequential genetic algorithm for efficiently estimating the parameters of the dynamics. They attempted to understand and interpret COVID-19 data using optimized cellular automata through a genetic algorithm.

GAs are the most commonly used algorithms for solving multiobjective and many-objective problems due to their superior performance and strong universality [38]. They use selection, crossover, and mutation operators to effectively manage the searching system strategy. GAs are implemented in computer simulations in which a population of candidate solutions is generated randomly, and each solution is encoded in a string named chromosome [39]. The crossover of multiple parents produces offspring by swapping genes of the chromosomes. The mutation is performed by flipping some genes of a chromosome, which generates new solutions. In GA, the crossover operator provides exploration capability that directs solutions to the optimum search space. Similarly, the mutations better exploit the optimum search space. The newly generated solutions combined with the original solutions in each generation are evaluated by their fitness, which is linked to the objective function of the optimization problem. The new solutions are selected according to their fitness by different strategies, e.g., decomposition-based approaches (MOEA/DD [40], RVEA [41]), diversity-based selection (SPEA2+SDE [42], NSGA-III [43]), preference-based approaches (PICEAg [44], Two_Arch2 [45]), and approaches that modify the traditional dominance relation (GrEA [46], VaEA [47]). The process of selection, crossover and mutation iterates until the termination condition is satisfied, e.g., the maximum number of iterations or a satisfactory fitness level.

D. CUSTOMER LIFETIME VALUE

Traditional collaborative filtering algorithms commonly adopt similarity metrics, e.g., cosine, Jaccard, and Pearson correlation, to recommend the top n items for use [48]. However, these correlation coefficients only consider the ratings of the items purchased by users and do not consider more information, e.g., user purchasing characteristics.

Although various approaches for making recommendations have been presented, few consider customer lifetime value (CLV) and the effect on product recommendations. CLV is typically used to identify profitable customers and to develop strategies to target customers [49]. In fiercely competitive environments, identifying the CLV or loyalty ranking of users is important for user retention. Additionally, the effect of CLV on recommendations should be investigated to develop more effective marketing strategies [50].

The magnitude of CLV is determined by three main components: recency, frequency, and monetary value [51].

1) R(Recency): represents the age of the customer when they made their most recent purchases. It is equal to the duration between a customer's first purchase and their latest purchase.
2) F(Frequency): the number of purchases within a certain period; higher frequency indicates higher user loyalty.
3) M(Monetary value): the average amount of money spent during a certain period, a higher value indicates that the company should focus more on that customer.

Generally, CLV is adopted to group consumers into segments if their CLV estimates are similar and to incorporate the consumer's segment assignment in the recommendation process.

Two main explorations for making recommendations have been successfully conducted: the former proposes two hybrid methods for recommending products [52]. These two methods incorporate the advantages of the weighted RFM-based (WRFM-based) method and the preference-based CF method. The core concept of the WRFM-based method is to group customers based on weighted RFM, and then extract recommendation rules from each customer group. The first hybrid method groups customers separately based on CLV and purchase preferences. Recommendation rules extracted from high loyalty CLV clusters are recommended to users in the same cluster, and recommendation rules extracted from the preference-based CF method are used to recommend products to less loyal customers. The second hybrid method groups customers by considering both CLV and purchase preferences and then extracts recommendation rules from each group to support recommendations [53].

E. TOP-K RECOMMENDATION STRATEGIES

The traditional recommendation system evaluates the ratings of unknown items based on the user's experiences, and then the top-k high rating items are selected to recommend [54]. The item rating evaluation is the basic step for a recommendation algorithm. In this section, we briefly introduce the user-based collaborative filtering algorithm, item-based collaborative filtering algorithm, and two hybrid weighted RFM rating methods [55], [56].

The user-based collaborative filtering algorithm (UCF) is used to find similarity neighbors and then predict the item ratings for each user according to the most similar neighbors. After the item rating evaluation, the top-k high rating items are recommended to each user.

The item-based collaborative filtering algorithm (ICF), which predicts a user's preference and recommends items similar to those preferred by the target user, is the most popular and widely used recommendation algorithm in real applications. The top-k recommendation process is the same as that of UCF.

The WRFM-based algorithm considers both customer lifetime value and the similarities of customer preferences. It consists of two different models, WRFM_H1 and

WRFM_H2. The former WRFM_H1 is proposed to group customers separately based on CLV and purchase preferences. Then, recommendation rules extracted from the WRFM model are used to recommend products to loyal customers; recommendation rules extracted from the preference-based CF method are used to recommend products to less loyal customers. While the WRFM_H2 method groups customers by considering both CLV and purchase preferences, hybrid2 is a linear combination of the two methods. The two hybrid models recommend top-k products to each user according to the association rules selected by user purchase history.

III. THE PROPOSED MANY-OBJECTIVE RECOMMENDATION FRAMEWORK

In this section, we first introduce the framework of our proposed many-objective recommendation algorithm NBHXMAOEA. Second, we explain how our similarity model sim_RFMP works. Third, we formulate five objective functions for different parties of the recommender systems. The details are depicted in the following subsections.

A. THE FRAMEWORK OF NBHXMAOEA

Recently, several many-objective optimization algorithms have been applied to recommender systems. The motivation of the many-objective optimization for recommendation is to formulate the recommendation to be a many-objective optimization problem and solve it. Many objectives typically refer to the optimization problems with more than three objectives [22]. To solve the conflict between different objectives of the recommendation, we design an N-block heuristics many-objective evolutionary algorithm NBHXMAOEA, which is suitable for the recommendation systems. The working process of NBHXMAOEA is shown in Fig. 2. The primary processes can be described as follows.

Step 1: Data preparation and processing. The original data of recommender systems exist in different forms and these data should be converted into uniform formats before calculation. In NBHXMAOEA, we process the user purchase history data into two forms, the RFM matrix and the user-item rating matrix, which are then used to calculate user similarities.

Step 2: User similarity calculation. In this stage, we employ three new user similarity models for the calculation of recency, frequency, and monetary value. The three models are then combined with the preference-based similarity model, the two models are multiplied, and finally, the novel RFM similarity model sim_RFMP is generated.

Step 3: Item rating evaluation and recommendation generation. The traditional user-based collaborative filtering algorithm selects the most similar users and recommends the top-k items from these neighbors to the target user. We follow the basic flow of the classical collaborative filtering algorithm. Nevertheless, the most similar user calculations are performed in step 2.

Step 4: Many-objective evolutionary algorithm for multistakeholder recommendation. This stage is based on the

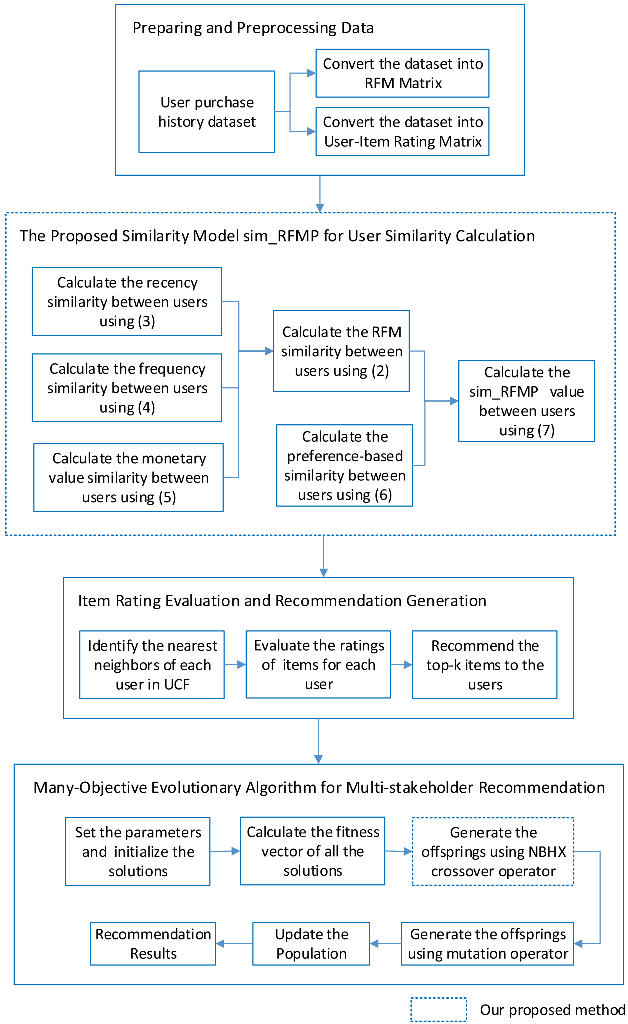

FIGURE 2. The proposed NBHXMAOEA framework.

recommendation list generated by step 3. Recommendations in step 3 only consider the accuracy of the recommended items, while in this step, we simultaneously optimize five goals for three different groups.

In this stage, many-objective evolution optimization is employed to generate optimal solutions based on genetic algorithms, which utilize selection, crossover, and mutation operators to effectively manage the searching strategy. The complete procedure of the many-objective evolution algorithm for multistakeholder recommendation is depicted in Algorithm 1.

First, a set of solutions are randomly generated, and parameters are initialized, e.g., population size, the maximum number of generations, variable dimension, type of encoding, number of parents, probability of crossover, and probability of mutation. After all of the parameters are set, the iteration of evolution begins. In each iteration, the fitness value of the generated population is calculated first. Then, new solutions are produced through the operations of crossover and mutation on the original solution. In NBHXMAOEA, we use our proposed N-block heuristic crossover operator

Algorithm 1 Many-Objective Evolutionary Algorithm for Multistakeholder Recommendation

Input: population size N, the maximum number of generations gen, variable dimension dim, type of encoding etype, number of parents np, probability of crossover px, probability of mutation pm, and length of recommendation lists K.
Output: Recommendation lists
1. **Initialization**: randomly generate an initial population Pop
2. **While** the termination criteria are not satisfied
3. Calculate the fitness value of Pop
4. Off ← Generate new solutions through the operations of crossover and mutation by Pop
/∗ Off is the offspring chromosomes, ∗/
5 Calculate the fitness value of Off
6. Combine the newly generated solutions and the original solutions as Pcob
Pcob ← Off ∪ Pop
7. P← Select N fittest solutions from Pcob to P
8. **end while**
9. Top-K recommendation←P

NBHX, and the mutation operator is one-point mutation. The newly generated solutions and the original solutions are combined. Then, the selection procedure begins, and we adopt the NSGA-III algorithm as the nondominated solution selection method [57], which is designed typically for solving many-objective problems and can effectively maintain the convergence and diversity of the solution; therefore, the solution is close to the optimal solution. In this process, the best N solutions are selected from the combined 2N solutions; therefore, the population is updated. The evolutionary process is repeated until the termination criteria are satisfied, and the final solutions are the recommendation results for the input users. Each solution is the order of the items in the list of all users. Finally, the recommendation algorithm decodes the order of the items in the recommendation list into product names and then recommends them to each corresponding user.

B. THE SIMILARITY MODEL

In this section, a novel similarity measurement sim_RFMP is proposed to calculate the distance between users. The sim_RFMP similarity is formulated by combining RFM similarity and user preference. The RFM similarity between users is defined as follows:

$$Sim\_RFM(u, v)=Sim\_R(u, v)^{*}Sim\_F(u, v)^{*}Sim\_M(u, v) \tag{2}$$

which is made up of three parts multiplied by each other. The first part is the recency similarity Sim_R(u,v) between two users, the second part, Sim_F(u,v), represents the frequency similarity of two users and the third, Sim_M(u,v), is for monetary value similarity. The recency, frequency and monetary value similarities are calculated by (3), (4), and (5), respectively.

$$Sim\_R(u, v) = \frac{1}{1+\exp(\alpha^{*}|u_r - v_r|)} \tag{3}$$

$$Sim\_M(u, v) = \frac{1}{\exp(|u_m - v_m|)} \tag{4}$$

$$Sim\_F(u, v) = \frac{1}{1+\exp(|u_f - v_f|)} \tag{5}$$

where u_r and v_r are the normalized recency values of users u and v, u_f and v_f are the normalized frequency values of users u and v, and u_m and v_m are the normalized monetary values. |u| represents the absolute value of u. Parameter α is a constant. In this case, $\alpha = 10$.

In traditional recommender systems, several methods are proposed to compute user preference-based similarity, e.g., Pearson and cosine. In this article, the preference similarity between user u and user v is computed by the cosine metric, as shown in (6).

Then, the similarity between two users u and v can be calculated in (7)

$$Sim\_P(u, v) = \frac{\sum_{i\in I}(r_{u,i}-r_u)(r_{v,i}-r_v)}{\sqrt{\sum_{i\in I}(r_{u,i}-r_u)^2}\sqrt{\sum_{i\in I}(r_{v,i}-r_v)^2}} \tag{6}$$

$$Sim\_RFMP(u, v) = Sim\_RFM(u, v)^{*}Sim\_P(u, v) \tag{7}$$

C. THE PROPOSED CROSSOVER OPERATOR (NBHX)

The crossover operator plays an important role in genetic algorithms and is used to inherit genes from offspring. Traditional crossover operators include one-point crossover [58], two-point crossover, partially mapped crossover [59], order crossover, and cycle crossover [60]. However, these crossover operators do not work well for recommendation systems because they do not consider the features of the recommendation list. Therefore, we design a novel N-block heuristic crossover operator NBHX, which takes the feature of the recommendation list and can perform well in solving the combinational optimization problem of the recommendation list.

The primary steps of the proposed crossover NBHX are as follows:

Step 1: Obtain the initial block crossover probability pxb, heuristic crossover probability pxh, and reference set R. The reference set is generated by selecting M chromosomes of the best objectives in the evolutionary process. Here, M is the number of objective functions.

Step 2: Select two chromosomes randomly as parent solutions named P1 and P2. The two chromosomes are divided into N blocks, and the positions of the cut points in the two chromosomes are the same. The parameter R is equal to the variable dimension divided by the length of a recommendation list.

Step 3: For each block of a chromosome, generate a random number a ∈ 0, 1. If a is smaller than pxb, then perform the block crossover operation; if the generated random value a is between pxb and pxh, the heuristic crossover operation is performed; otherwise, the two blocks in P1 and P2 remain the same and turn to the next block.

Step 4: In the block crossover operation, the two blocks of genes are exchanged from P1 and P2 and fill in the same positions of offspring O1 and O2. In the heuristic crossover operation, two chromosomes R1 and R2 are selected randomly from the reference set R, and the genes of the same block position of the two reference chromosomes are filled into the corresponding positions of O1 and O2.

Step 5: Repeat step 2-step 4 until a sufficient number of offspring chromosomes are generated.

The complete procedure of NBHX is depicted in Algorithm 2.

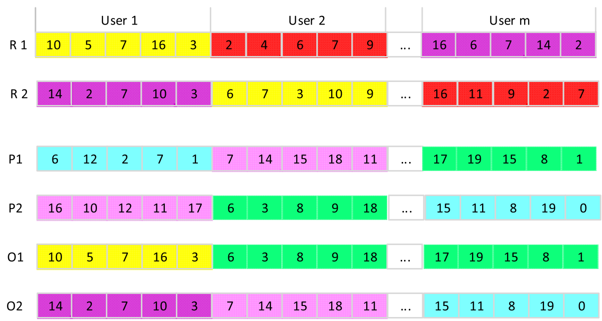

FIGURE 3. Illustration of offspring generation by NBHX operator.

For an illustration, consider the case depicted in Fig. 3, where R1 and R2 represent reference chromosomes, P1 and P2 represent parent chromosomes, and O1 and O2 represent offspring chromosomes. In our experiments, each chromosome represents a recommendation result for all users. We use $X = \{x1, x2\ldots, xn\}$ to depict a chromosome, and xi is the gene in the chromosome. The length of the chromosome is equal to the number of users multiplied by the length of a recommendation list. Therefore, each solution includes several recommendation lists, each of which is recommended to a user. Each gene represents the order of an item in a user's recommendation list, and thus, an item can only appear once.

Note that our proposed N-block heuristic crossover operator and multipoint crossover operator are essentially different. Traditional multipoint crossover [61] includes two forms: n-point crossover and uniform crossover. The n-point crossover has cut points greater than two, and these cut points are randomly generated. All of the genes between two points are exchanged of parent chromosomes with the same fixed length. In uniform crossover [62], [63], for each position of a selected chromosome, a random decision is made on whether swapping should be done or not. Unlike the multipoint crossover operator, in block crossover, some blocks (segments) of elements are considered instead of the single elements [64]. Block crossover is composed of multiple blocks, each of which consists of a gene section. N-block crossover can be divided into N gene segments, each of

Algorithm 2 N-Block Heuristic Crossover (NBHX)

Input: current population Pop, block crossover probability pxb, heuristic crossover probability pxh, reference set R
Output: Offspring Off
1. **for** i=1 to P/2 /*P is population size */
2. select two chromosomes randomly from Pop as P1 and P2 /*P1 is the first parent chromosome, P2 is the second parent chromosome*/
3. **for** j=1 to N/*N is the number of blocks */
4. generate a random number a ∈0, 1
5. **if** a<pxb then
6. O1(block j)← P2(block j), O2(block j)← P1(block j) /*O1 is the first offspring chromosome, O2 is the second offspring chromosome*/
7. **else if** a>=pxb and a< pxh then
8. select two chromosomes randomly from R as R1 and R2 /*R1 is the first reference chromosome, R2 is the second reference chromosome*/
9. O1(block j)← R1(block j), O2(block j)← R2(block j)
10. **else**
11. O1(block j)← P1(block j),
12. O2(block j)← P2(block j)
13. **end if**
14. Off ← Off ∪ (O1, O2)
13. **end for**
14. **end for**

which (blocks) is a whole and cannot be separated by the cut points, which is different from multipoint crossover where the cut positions are random.

In our work, it is reasonable to choose N-block crossover instead of multipoint crossover because a chromosome is composed of a fixed-length recommendation list of multiple users, and the number in each list corresponds to a gene. The block size can be set according to the length of the user list, and the block size is fixed in the top-k recommendation, which is very convenient for crossover operation. The position of cut points in multipoint crossover is random, which is likely to cause disorder in the process of crossover. If multipoint crossover is used, a repair procedure is required, which is relatively complicated. Our NBHX operator based on block crossover does not require a repair process. Taking two chromosomes as an example, chromosome 1 is [1, 5, 7, 9, 6, 12, 2, 1, 5, 4, 3, 7, 8, 1, 2], and chromosome 2 is [5, 7, 4, 1, 2, 10, 6, 1, 3, 7, 4, 3, 2, 8, 9]. Assume this is a top-5 recommendation from three users, and the number of cut points is 2. In block crossover, the cut points are between 6 and 12, 4 and 3 of chromosomes 1, 2 and 10, and 7 and 4 in chromosome 2. We can exchange the blocks between two chromosomes and obtain their offspring, which are [1, 5, 7, 9, 6, 10, 6, 1, 3, 7, 3, 7, 8, 1, 2] and [5, 7, 4, 1, 2, 12, 2, 1, 5, 4, 4, 3, 2, 8, 9].

If we use multipoint crossover, suppose that the randomly generated cut points are 3 and 13, the genes 7, 9, 6, 12, 2, 1, 5, 4, 3, 7, 8 in chromosome 1 and 4, 1, 2, 10, 6, 1, 3, 7, 4, 3, 2 in chromosome 2 are exchanged, they are [1, 5, 4, 1, 2, 10, 6, 1, 3, 7, 4, 3, 2, 1, 2](off1) and [5, 7, 7, 9, 6, 12, 2, 1, 5, 4, 3, 7, 8, 8, 9](off2). We can see that off1 has two 1s for the first user and two 2s for the third user; similarly, off2 has two 7s and two 8s for the same user. However, this situation is unreasonable because each gene represents an item. For a user, the same product cannot appear multiple times in the list of the same user.

To explain the features of chromosome encoding more clearly, we give an example of the structure of a solution with chromosome encoding in Fig. 3. As shown in Fig. 3, each solution consists of 3 recommendation lists, each of which is a block to a user. Here, we make a recommendation list for top-k items, where k=5. The genes in a chromosome indicate the order of the recommendation list, e.g., the genes in R1 for User 1 are 10, 5, 7, 16, and 3 represent the 10^{th}, 5^{th}, 7^{th}, 16^{th}, and 3^{rd} items in the recommendation list of User 1.

We selected two chromosomes randomly from the whole population as parent chromosomes named P1 and P2. For each block in P1 and P2, a random number a is generated between 0 and 1; if the value of a is smaller than the probability of block crossover, then fill the block of P1 in the corresponding position of offspring O1 and fill the block of P2 in the corresponding position of offspring O2. If the value of a is larger than the probability of block crossover pxb yet smaller than the probability of heuristic crossover pxh (pxh is larger than pxb), then two chromosomes are selected from the reference set as R1 and R2, followed by filling the R1 block in the corresponding position of offspring O1, and the R2 block is filled in the corresponding position of offspring O2. Otherwise, if the random number a is larger than pxh, we fill the P1 block to the same position as O1 and fill the P2 block to the same position as O2.

Without loss of generalization, we let the values of an equal 0.65, 0.15, and 0.90 for User 1, User 2, and User m, respectively. The probability of block crossover is pxb=0.3, and the probability of heuristic crossover is pxh=0.8. For User 1, a=0.65, which is smaller than pxh and larger than pxb; thus, we fill the first block of O1 with the first block in R1, that is, {10, 5, 7, 16, 3}, and filled O2 with {14, 2, 7, 10, 3}, which is the first R2 block. For User 1, the random value a is 0.15, which is smaller than pxb; therefore, we fill the second block of O1 with the corresponding P2 block, which is {6, 3, 8, 9, 18}, and the second O2 block is filled with the corresponding P1 block, that is, {7, 14, 15, 18, 11}. For the remaining blocks, we conduct the same operation. We will give a brief description of the operation to User m. The random number generated for User m is 0.9, which means we copy the last P1 block to O1, the last P2 block to O2. Then, the final results of O1 and O2 are shown in Fig. 3.

D. MANY-OBJECTIVE OPTIMIZATION

In this subsection, we use evaluation indicators as the optimization objectives, including accuracy, diversity, novelty, coverage, and the gross merchandise volume value. The objectives in the proposed NBHXMAOEA model can be divided into three categories for different stakeholders: the user, provider, and platform. Accuracy is used to evaluate whether the recommendation list satisfies the user's interests, and diversity and novelty denote the difference between items and the degree of unpopularity in the recommendation list. They aim to increase the variety of user lists. Provider coverage reflects the percentage of suppliers whose products are exposed in the recommended list. To obtain a more reasonable recommendation list for the interest of the platform, we introduce the GMV value, which is the sum of the average value of items in the recommended list for each user.

Precision and recall metrics are extensively used to measure the quality of recommendation. Precision indicates the proportion of the items that the user truly needs to the total recommended items. The precision function can be formulated as follows.

$$\Pr ecision = \frac{N_{\text{correct}}}{N_{recommend}} \tag{8}$$

Recall describes the probability of a relevant item selected in a recommendation list. The recall function can be formulated as follows.

$$Recall = \frac{N_{correct}}{N_{relevant}} \tag{9}$$

where N_{correct} represents the number of items that are recommended to a user, and the user truly likes, $N_{\text{recommend}}$ represents the total number of items that are recommended to a user, and N_{relevant} is the total number of items the user likes.

The F1 metric can be used to balance the tradeoff between precision and recall. In our work, accuracy is evaluated by the F1 metric, which is given by (10).

$$F1 = \frac{2^{*} \Pr ecision^{*} Recall}{\Pr ecision + Recall} \tag{10}$$

In addition, users generally require different kinds of recommendations. In this article, the diversity and novelty of recommendations are optimized to provide users with diverse recommendations. The objective of diversity is calculated by the similarity between the items in the recommendation list and is defined as:

$$div_{RS} = \frac{1}{K(K-1)} \sum_{p \in L} \sum_{q \in L, p \neq q} 1 - Sim(p, q) \tag{11}$$

where L is a recommendation list recommended to a user, K is the length of a recommendation list, Sim(p, q) is the similarity between p and q, and its calculation formula is shown in (6).

Novelty is used to evaluate the degree to which nonpopular items are purchased [65]. The novelty is defined as:

$$novelty_{RS} = \frac{1}{MK} \sum_{u=1}^{M} \sum_{i=1}^{K} \log_2(\frac{M}{d_i + 1}) \tag{12}$$

where M is the total number of users in a recommender system and d_i is the number of users who truly like item i.

Coverage is the proportion of recommended items in the whole system. In our work, we calculate the degree of the providers of the recommended items. The provider coverage is defined as follows:

$$coverage_{provider} = \frac{N_{provider}}{N_{total}} \tag{13}$$

where $N_{provider}$ is the number of different providers that can be recommended by this system and N_{total} is the total number of providers in the whole system.

As mentioned previously, the objective of the platform is to maximize profit. In this article, we use GMV (gross merchandise volume) as the 5th objective. The GMV value is defined as follows.

$$GMV = \frac{1}{K}\sum_{u=1}^{M}\sum_{i=1}^{K} P_i \tag{14}$$

IV. EXPERIMENTS

In the following section, we first describe the parameter settings and evaluation measures and then introduce the experimental dataset and the comparison algorithms. The performances of the different algorithms are further tested and discussed in detail.

A. PARAMETER SETTINGS AND EVALUATION MEASURES

To judge the efficacy of our proposed algorithm with existing state-of-the-art algorithms, 20 independent runs of experiments are performed on a PC with 2.40 GHz Intel Core i7-8700T CPU and Windows 10 SP1 64-bit operating system with 32 GB RAM in the windows environment, and the Anaconda platform is used for simulation. One of the crucial issues is the setting of parameters during simulation. Therefore, in this section, the detailed parameter settings are given. We set the parameters the same as those of the comparison algorithms. Note that the probability of heuristic crossover and the probability of block crossover are only used in our proposed NBHX operator. The parameter settings for the experiments are listed in Table 1.

To evaluate the performance of a recommendation list, we adopt five widely used metrics, precision, recall, diversity, novelty, coverage, and GMV value, which are also the optimization objectives.

B. EXPERIMENTAL DATASET

We performed experiments on a real word dataset named ODTS, which contains sufficient user transaction data gathered from an online delicacy takeout service app from January to December 2016. The dataset contains sufficient information, such as the basic information of a transaction, product features, and provider features. The dataset consists of 430,991 transaction records of 4,036 users and 15,438 products. We filtered them such that only users with at least 80 interactions and products with at least 100 interactions were retained. We evaluated the performance of the proposed algorithm on the combination of 75% as the training set and 25% as the test set.

TABLE 1. Parameter settings.

Parameter	Meaning	Value
K	The length of a recommendation list	10
n	The number of neighbors	100
P	The number of population	40
M	The number of optimization objectives	5
pxh	The probability of heuristic crossover	0.8
pxb	The probability of block crossover	0.3
pm	The probability of mutation	0.1
Gen	The maximum number of generations	20
np	The number of parents in crossover	2
rp	The reference points	56
N	The number of blocks	4036
d	The variable dimension	40360

C. COMPARISON ALGORITHMS

To compare the performance of our proposed algorithm, we selected UCF [66], ICF [56], WRFM_h1, and WRFM_h2 [52] with Pearson similarity as the comparison algorithms for evaluating the top-k item recommendation. For the many-objective evolutionary algorithm MaOEA, we employed the NSGA-III algorithm as a nondominated solution selection method [43], which is designed typically for solving many-objective problems and can effectively maintain the convergence and diversity of the solution. Partially mapped crossover and a one-point mutation operator were used for generating new offspring.

The following competing algorithms were formed.

1) **UCF + sim_Pearson(UCF_P).** This algorithm uses the UCF algorithm with Pearson similarity to generate the top-k item list.
2) **ICF + sim_Pearson(ICF_P).** This algorithm uses the ICF algorithm with Pearson similarity to generate the top-k item list.
3) **WRFM_H1 + sim_Pearson(WRFMH1_P).** This algorithm uses the weighted RFM-based method and preference-based CF method to group users into different clusters. Then, association rules are used to recommend items to the users from the clusters to which the users belong.
4) **WRFM_H2 + sim_Pearson(WRFMH2_P).** This algorithm uses the linear combination of the weighted RFM-based method and preference-based CF method to group users into different clusters. Then, association rules are used to recommend items to the users from the clusters to which the users belong.
5) **UCF + sim_RFMP(UCF_RFMP).** This algorithm uses the UCF algorithm with our proposed sim_RFMP similarity to recommend items to users.
6) **MaOEA + UCF_P(MaUCF_P).** This algorithm uses UCF_P to generate a recommendation list. Then, the standard many-objective optimization algorithm

(MaOEA) is used to obtain the Pareto-optimal solutions for the users.

7) **MaOEA + ICF_P(MaICF_P).** This algorithm uses the ICF_p to generate a recommendation list. Then, the standard many-objective optimization algorithm (MaOEA) is used to obtain the Pareto-optimal solutions for the users.
8) **MaOEA + WRFMH1_P(MaH1_P).** This algorithm uses the WRFMH1_P algorithm, which generates a list of recommendations for each user. Then, the standard many-objective optimization algorithm (MaOEA) is used to obtain the Pareto-optimal solutions for the users.
9) **MaOEA + WRFMH2_P(MaH2_P).** This algorithm uses the WRFMH2_P algorithm, which generates a list of recommendations for each user. Then, the standard many-objective optimization algorithm (MaOEA) is used to obtain the Pareto-optimal solutions for the users.
10) **MaOEA + UCF_RFMP(MaUCF_RFMP).** This algorithm uses the UCF_RFMP algorithm, which generates a list of recommendations for each user. Then, the standard many-objective optimization algorithm (MaOEA) is used to obtain the Pareto-optimal solutions for the users.
11) **NBHXMAOEA + UCF_P(NBHXUCF_P).** This algorithm uses UCF_P to generate a recommendation list. Then, the novel many-objective optimization algorithm NBHXMAOEA is used to obtain the Pareto-optimal solutions for the users.
12) **NBHXMAOEA + ICF_P(NBHXICF_P).** This algorithm uses the ICF_P to generate a recommendation list. Then, the novel many-objective optimization algorithm NBHXMAOEA is used to obtain the Pareto-optimal solutions for the users.
13) **NBHXMAOEA + WRFMH1_P(NBHXH1_P).** This algorithm uses WRFMH1_P to generate a recommendation list. Then, the novel many-objective optimization algorithm NBHXMAOEA is used to obtain the Pareto-optimal solutions for the users.
14) **NBHXMAOEA + WRFMH2_P (NBHXH2_P).** This algorithm uses WRFMH2_P to generate a recommendation list. Then, the novel many-objective optimization algorithm NBHXMAOEA is used to obtain the Pareto-optimal solutions for the users.
15) **NBHXMAOEA + UCF_RFMP(NBHXUCF_RFMP).** This algorithm uses the UCF_RFMP to generate a recommendation list. Then, the novel many-objective optimization algorithm NBHXMAOEA is used to obtain the Pareto-optimal solutions for the users.

D. EXPERIMENTAL RESULTS

To justify the effectiveness of our methods, the experiments were conducted as follows.

1) To test the effectiveness of the novel sim_RFMP model in recommending the top-k items, we compared UCF_RFMP with UCF_P, ICF_P, WRFMH1_P, and WRFMH2_P.
2) To test the search capability of our proposed NBHX in the whole population and the Pareto front (PF) in the objective space, we compared NBHXUCF_P, NBHXICF_P, NBHXH1_P, NBHXH2_P, NBHXUCF_RFMP with MaUCF_P, MaICF_P, MaH1_P, MaH2_P, and MaUCF_RFMP.
3) To test the performance of our proposed NBHXMAOEA model, which combines the sim_RFMP model and NBHX algorithm, we compared the average accuracy, diversity, novelty, coverage, and gross merchandise volume value for all the users in each competing algorithm.
4) Finally, we selected 10 random users in the test dataset for comparing the accuracy, diversity, novelty, coverage, and gross merchandise volume value on different algorithms.

TABLE 2. Recommendation accuracy of different algorithms.

Method	Precision	Recall	F1
WRFMH1_P	10.127	1.233	2.198
WRFMH2_P	**11.170**	1.039	1.902
UCF_P	7.996	2.995	4.358
ICF_P	7.919	2.966	4.316
UCF_RFMP	10.102	**3.784**	**5.506**

1) COMPARISON OF ACCURACY OF PEARSON SIMILARITY AND SIM_RFMP SIMILARITY

Table 2 illustrates the results of the recommendation accuracy of the five methods. The best result for each matrix is shown in bold. We can see that our proposed UCF_RFMP model achieves the best performance in recall and F1 score, and only WRFMH2_P slightly outperforms it in terms of precision. The reason for this phenomenon is that the recommendation results of WRFM_H1 are based on association rules. Due to the sparsity of the dataset, not enough rules are generated to meet the support and confidence thresholds. Therefore, when WRFM_H1 generates recommendation lists for users, there is a possibility that a sufficient number of K items were not generated. In addition, the products generated by association rules are popular items and are more likely to be purchased by users. As a result, these factors lead to a higher accuracy score of WRFM_H1, but this does not mean that WRFM_H1 has a better recommendation effect. We can obtain verification from the recall and F1 score of WRFM_H1, both of which obtain the worst results. This situation also exists in WRFM_H2, whose recommendation method is very similar to that of WRFM_H1. Recommendations based on association rules limit their performance on sparse datasets.

Compared with the WRFM_H1 and WRFM_H2 models, the superiority of UCF_P and ICF_P is remarkable. Both of them obtain relatively good results on accuracy, recall, and F1 score. However, our proposed UCF_RFMP model achieves the best overall performance compared to the state-of-the-art models, as demonstrated in Table 2.

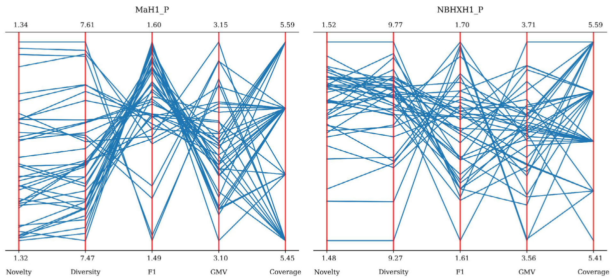

FIGURE 4. Parallel coordinates of non-dominated fronts obtained by MaH1_P and NBHXH1_P on the 5 objectives.

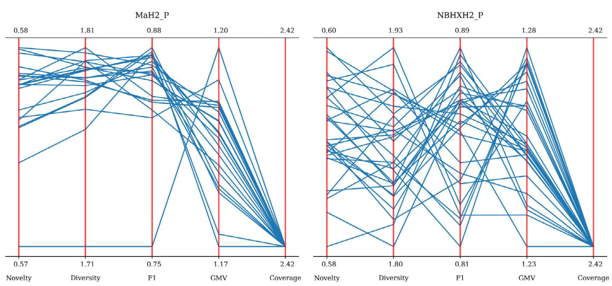

FIGURE 5. Parallel coordinates of non-dominated fronts obtained by MaH2_P and NBHXH2_P on the 5 objectives.

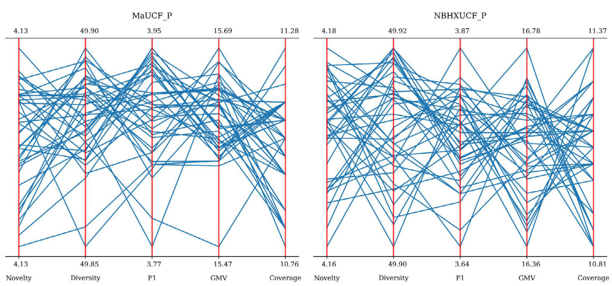

FIGURE 6. Parallel coordinates of non-dominated fronts obtained by MaUCF_P and NBHXUCF_P on the 5 objectives.

2) COMPARISON OF THE WHOLE POPULATION AND THE PARETO FRONT

To show that our proposed NBHX algorithm has advantages in solving many-objective optimization problems, we compare five MaOEA algorithms with their corresponding NBHXMAOEA. Figs. 4 - 8 show the parallel coordinates of nondominated fronts obtained by 10 many-objective optimization algorithms. It is easy to see that the five objectives

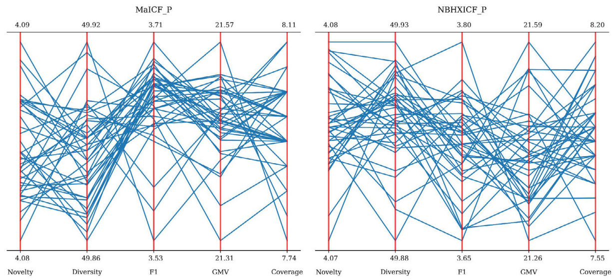

FIGURE 7. Parallel coordinates of non-dominated fronts obtained by MaICF_P and NBHXICF_P on the 5 objectives.

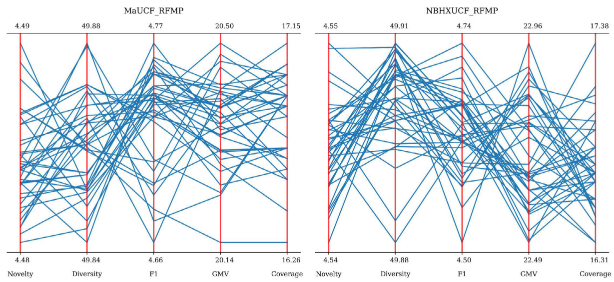

FIGURE 8. Parallel coordinates of non-dominated fronts obtained by MaUCF_RFMP and NBHXUCF_RFMP on the 5 objectives.

have different degrees of conflict. Take Fig. 4 for example; the optimization results obtained by using MaH1_P and NBHXH1_P produce between the objectives of F1 score and diversity. As the accuracy increases, the recommendation list tends to present items that users clearly prefer, which often have similar characteristics, resulting in a reduction in the diversity of items. We can also observe that there is a significant positive correlation between diversity and novelty, which also suggests that there is a conflict in F1 score and novelty. Compared with novelty, the conflict between F1 and GMV is more obvious, and the two metrics are completely opposite optimization objectives.

From these five figures, we can observe that the effect of NBHXMAOEA is generally better than that of MaOEA on both convergence and diversity. NBHXMAOEA can cover more solution space than MaOEA on five recommendation algorithms. According to Fig. 5, NBHXH1_P significantly improves convergence and distribution on novelty, diversity, accuracy, and GMV value. Compared with MaH2_P, NBHXH1_P improves the imbalanced distribution, and the nondominant solutions in NBHXH1_P are more uniform. NBHXH1_P has a better objective space. Figs. 6 - 8 illustrate that NBHXUCF_P, NBHXICF_P, and NBHXUCF_RFMP have better distribution breadth and uniformity of the optimal solution set compared with MaUCF_P, MaICF_P, and MaUCF_RFMP. It is worth noting that NBHXUCF_RFMP can significantly improve the metrics of coverage, novelty, and GMV value, which are obviously better than those obtained by the other nine many-objective optimization algorithms, only sacrificing a certain degree of accuracy.

TABLE 3. Accuracy of recommendation list for competing algorithms for 10 sample users.

ALGORITHM		User 1	User 2	User 3	User 4	User 5	User 6	User 7	User 8	User 9	User 10
WRFMH1_P		10.000	6.900	5.882	0.000	12.121	0.000	4.255	11.429	6.667	7.843
WRFMH2_P		5.000	6.900	0.000	0.000	6.061	0.000	4.255	5.714	6.667	7.843
UCF_P		**15.000**	6.900	5.882	5.882	6.061	0.000	4.255	5.714	13.333	7.843
ICF_P		10.000	0.000	5.882	5.882	6.061	0.000	0.000	11.429	6.667	11.764
UCF_RFMP		5.000	**20.690**	**11.765**	5.882	12.121	**4.444**	**17.021**	**17.143**	**20.000**	7.843
	Max	5.000	0.000	5.882	0.000	18.182	0.000	0.000	5.714	6.667	11.765
MaH1_P	Min	0.000	0.000	0.000	0.000	18.182	0.000	0.000	5.714	6.667	7.843
	Mean	1.750	0.000	2.500	0.000	18.182	0.000	0.000	5.714	6.667	8.039
	Max	0.000	0.000	0.000	0.000	6.060	0.000	4.255	0.000	0.000	0.000
MaH2_P	Min	0.000	0.000	0.000	0.000	6.060	0.000	4.255	0.000	0.000	0.000
	Mean	0.000	0.000	0.000	0.000	6.060	0.000	4.255	0.000	0.000	0.000
	Max	**15.000**	6.897	5.882	**17.647**	18.182	0.000	8.511	11.429	6.667	**15.686**
MaUCF_P	Min	5.000	0.000	5.882	5.882	6.061	0.000	4.255	0.000	0.000	11.765
	Mean	6.000	2.414	5.882	13.971	6.364	0.000	6.809	8.571	6.500	11.863
	Max	15.000	6.897	5.882	11.765	**24.242**	0.000	0.000	11.429	6.667	11.764
MaICF_P	Min	0.000	0.000	0.000	0.000	12.121	0.000	0.000	0.000	0.000	7.843
	Mean	5.625	1.034	4.559	1.618	18.182	0.000	0.000	1.143	3.167	8.137
	Max	**15.000**	**20.690**	5.882	5.882	12.182	0.000	8.511	11.429	**20.000**	**15.686**
MaUCF_RFMP	Min	0.000	6.897	5.882	0.000	6.061	0.000	8.511	11.429	0.000	11.765
	Mean	8.25	13.793	5.882	2.941	7.273	0.000	8.511	11.429	2.000	14.314
	Max	10.000	6.897	5.882	0.000	12.121	0.000	4.255	11.428	6.667	7.843
NBHXH1_P	Min	0.000	0.000	0.000	0.000	6.061	0.000	0.000	0.000	0.000	0.000
	Mean	4.750	2.414	5.294	0.000	11.061	0.000	2.021	6.857	3.500	4.216
	Max	5.000	6.897	0.000	0.000	6.061	0.000	4.255	5.714	6.667	3.922
NBHXH2_P	Min	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Mean	2.125	5.172	0.000	0.000	3.788	0.000	3.617	3.000	0.500	2.451
	Max	**15.000**	6.897	5.882	11.765	**24.242**	0.000	8.511	**17.143**	13.333	**15.686**
NBHXUCF_P	Min	5.000	0.000	0.000	0.000	6.061	0.000	0.000	0.000	0.000	9.322
	Mean	8.250	6.724	2.794	5.882	10.910	0.000	4.043	7.429	4.167	10.294
	Max	**15.000**	6.897	5.882	5.882	**24.242**	0.000	0.000	11.429	6.667	11.765
NBHXICF_P	Min	5.000	0.000	0.000	5.882	6.061	0.000	0.000	5.714	0.000	7.843
	Mean	9.250	1.379	3.824	5.882	20.000	0.000	0.000	9.571	0.833	8.039
	Max	**15.000**	**20.690**	**11.765**	5.882	18.182	**4.444**	**17.021**	**17.143**	**20.000**	**15.686**
NBHXUCF_RFMP	Min	**5.000**	6.897	0.000	0.000	6.061	4.444	4.255	0.000	0.000	7.843
	Mean	7.500	9.655	7.647	1.176	12.424	4.444	10.319	11.857	7.500	9.314

In summary, compared with the classical many-objective evolutionary algorithm MaOEA, our novel NBHXMAOEA algorithm shows good competitiveness. Integrated with the five recommendation algorithms, NBHXMAOEA achieves a superior performance, which obtains most of the optimal objective values, and the nondominated solutions also maintain an excellent distribution.

3) OVERALL PERFORMANCE COMPARISON OF NBHXMAOEA CONCERNING STATE-OF-ART ALGORITHMS

In this section, we present the overall comparison of the NBHXMAOEA algorithm concerning the state-of-the-art algorithms in terms of accuracy, diversity, novelty, coverage, and GMV value. Regarding accuracy in Fig. 9, the UCF_RFMP algorithm, which is based on sim_RFMP, obtains much superior performance compared to WRFMH1_P, WRFMH2_P, UCF_P, and ICF_P, which is based on Pearson similarity. Similarly, the two many-objective optimizing algorithms MaUCF_RFMP and NBHXUCF_RFMP obtain much better results than their competing algorithms in the framework of MaOEA and NBHXMAOEA.

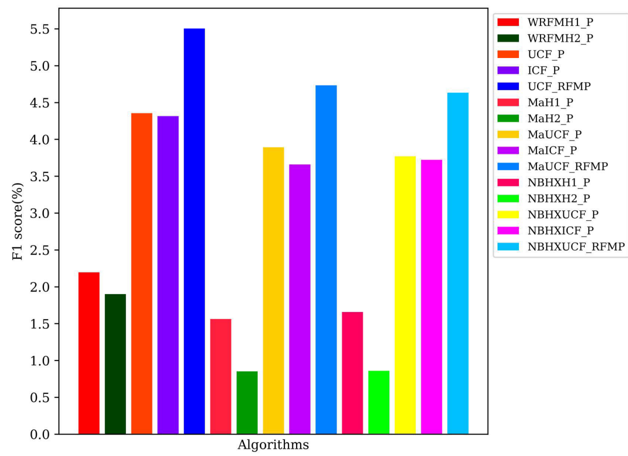

FIGURE 9. Accuracy of competing algorithms.

From Fig. 10, we can observe that the three recommendation algorithms UCF_P, ICF_P, and UCF_RFMP perform well in terms of diversity with or without the many-object optimizing process. In contrast, WRFMH1_P and WRFMH2_P achieve inferior results, which are

TABLE 4. Diversity of recommendation list for competing algorithms for 10 sample users.

ALGORITHM		User 1	User 2	User 3	User 4	User 5	User 6	User 7	User 8	User 9	User 10
WRFMH1_P		49.826	49.971	49.900	49.808	49.831	49.956	49.977	39.976	16.617	49.969
WRFMH2_P		39.863	3.332	23.267	49.820	16.611	39.948	23.322	16.656	6.650	49.972
UCF_P		49.824	49.970	49.970	49.832	49.827	49.970	49.971	49.970	49.944	49.971
ICF_P		49.838	**49.975**	49.975	49.833	49.830	49.976	49.974	49.974	49.972	**49.976**
UCF_RFMP		49.834	49.969	49.970	49.825	49.833	49.977	49.968	49.975	49.919	49.971
	Max	23.255	16.657	31.016	49.822	39.869	11.105	6.664	6.663	3.326	49.972
MaH1_P	Min	23.247	6.663	11.090	49.821	39.869	11.097	6.664	6.662	3.326	49.970
	Mean	23.252	9.661	14.168	49.822	39.869	11.097	6.664	6.662	3.326	49.970
	Max	6.645	0.000	6.645	23.255	3.324	11.098	6.663	3.331	1.109	6.663
MaH2_P	Min	6.645	0.000	6.645	23.255	3.324	11.098	6.663	3.331	1.109	6.663
	Mean	6.645	0.000	6.645	23.255	3.324	11.098	6.663	3.331	1.109	6.663
	Max	49.832	49.974	49.972	49.831	49.834	49.974	49.974	49.974	49.957	49.975
MaUCF_P	Min	49.823	49.966	49.969	49.824	49.822	49.972	49.972	49.972	49.940	49.971
	Mean	49.827	49.972	49.971	49.829	49.825	49.974	49.973	49.973	49.942	49.971
MaICF_P	Max	49.839	**49.975**	**49.977**	49.840	49.837	49.977	**49.978**	49.976	**49.981**	49.975
	Min	49.824	49.974	49.974	49.825	49.833	49.971	49.974	49.969	49.972	49.973
	Mean	49.836	49.975	49.974	49.834	49.835	49.977	49.975	49.969	49.974	49.975
	Max	49.837	**49.975**	49.976	49.828	49.828	49.979	49.972	49.974	49.924	49.972
MaUCF_RFMP	Min	49.835	49.962	49.976	49.817	49.823	49.979	49.971	49.974	49.902	49.972
	Mean	49.836	49.969	49.976	49.822	49.828	49.979	49.971	49.974	49.922	49.972
	Max	49.826	49.971	49.898	49.816	49.831	49.956	49.977	39.976	16.617	49.974
NBHXH1_P	Min	16.608	6.664	11.070	49.808	31.006	6.662	6.664	6.663	3.326	49.968
	Mean	26.407	25.319	23.120	49.814	34.771	17.983	26.849	14.991	7.149	49.972
	Max	11.075	3.332	6.648	31.003	11.075	11.093	11.105	6.662	3.322	6.664
NBHXH2_P	Min	3.032	0.000	3.325	16.604	3.321	6.657	3.332	1.110	0.000	6.663
	Mean	8.555	1.361	5.319	23.194	7.890	9.541	6.414	4.192	0.527	6.663
	Max	**49.840**	49.974	49.973	49.832	**49.840**	49.976	49.975	**49.977**	49.963	49.974
NBHXUCF_P	Min	49.811	49.968	49.970	49.809	49.821	49.970	49.971	49.970	49.939	49.970
	Mean	49.833	49.971	49.972	49.823	49.831	49.972	49.972	49.973	49.953	49.971
	Max	49.839	**49.975**	**49.977**	**49.842**	49.836	49.978	**49.978**	49.976	49.977	**49.976**
NBHXICF_P	Min	49.824	49.974	49.973	49.829	49.827	49.976	49.974	49.971	49.972	49.974
	Mean	49.832	49.975	49.976	49.837	49.835	49.976	49.976	49.974	49.974	49.975
	Max	49.837	**49.975**	49.976	49.828	49.833	**49.980**	49.974	49.975	49.926	49.974
NBHXUCF_RFMP	Min	49.827	49.966	49.970	49.817	49.816	49.975	49.968	49.969	49.913	49.971
	Mean	49.834	49.971	49.973	49.820	49.826	49.978	49.970	49.973	49.918	49.973

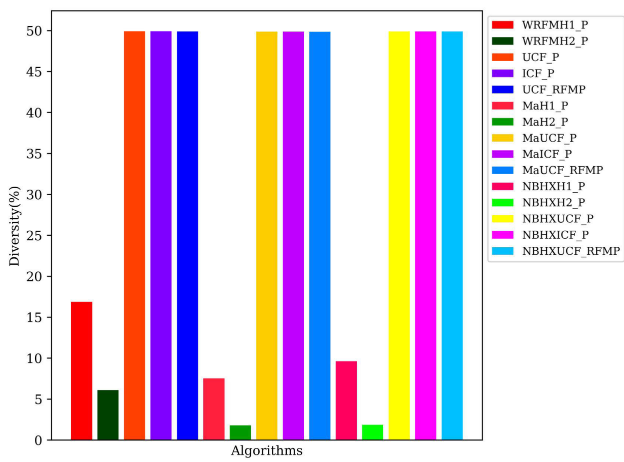

FIGURE 10. Diversity of competing algorithms.

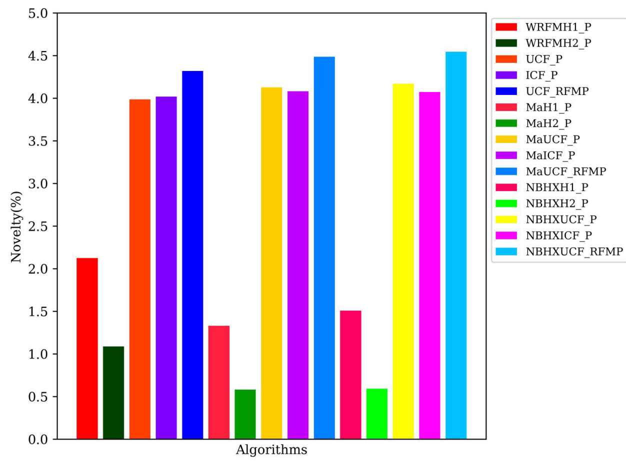

FIGURE 11. Novelty of competing algorithms.

far from their competing algorithms. Their corresponding many-objective optimization algorithms MaH1_P and NBHXH1_P, MaH2_P, and NBHXH1_P have similar outcomes.

As shown in Fig.11, UCF_P, ICF_P, and UCF_RFMP also have favorable performance when dealing with novelty problems that are similar to diversity. In terms of coverage, UCF_RFMP, MaUCF_RFMP, and NBHXMAOEA obtain far superior results compared with their competing algorithms. Fig. 13 describes the performance of these compared algorithms on the metric of gross merchandise volume value.

TABLE 5. Novelty of recommendation list for competing algorithms for 10 sample users.

Algorithm		User 1	User 2	User 3	User 4	User 5	User 6	User 7	User 8	User 9	User 10
WRFMH1_P		5.288	**4.669**	**4.892**	5.871	5.316	5.071	3.635	3.376	3.215	3.815
WRFMH2_P		4.479	1.440	3.404	5.439	2.997	4.317	2.493	2.077	1.876	3.611
UCF_P		5.237	3.460	3.422	5.236	5.052	3.406	3.649	3.500	4.832	3.530
ICF_P		5.223	3.648	3.488	5.157	5.072	3.779	3.837	3.422	4.133	3.574
UCF_RFMP		5.269	3.524	3.358	5.220	5.018	4.100	3.706	3.616	4.831	3.529
MaH1_P	Max	3.688	2.828	4.065	5.871	4.659	2.559	1.568	1.605	1.561	3.688
	Min	3.591	1.936	2.403	5.851	4.659	2.448	1.568	1.528	1.561	3.561
	Mean	3.642	2.204	2.615	5.857	4.659	2.553	1.568	1.530	1.561	3.665
MaH2_P	Max	2.063	0.449	1.961	3.660	1.461	2.423	1.321	1.009	0.956	1.433
	Min	2.063	0.449	1.961	3.660	1.461	2.423	1.321	1.009	0.956	1.432
	Mean	2.063	0.449	1.961	3.660	1.461	2.423	1.321	1.009	0.956	1.433
MaUCF_P	Max	5.559	3.530	3.497	5.743	**5.591**	3.693	3.842	3.768	4.988	3.780
	Min	5.456	3.435	3.467	5.471	5.210	3.532	3.708	3.584	4.836	3.567
	Mean	5.529	3.463	3.468	5.548	5.327	3.583	3.761	3.628	4.857	3.741
MaICF_P	Max	5.447	3.810	3.584	5.518	5.480	3.976	3.949	3.596	4.325	3.768
	Min	5.289	3.631	3.491	5.249	5.168	3.667	3.747	3.523	4.217	3.617
	Mean	5.389	3.675	3.579	5.450	5.411	3.940	3.785	3.529	4.273	3.749
MaUCF_RFMP	Max	5.601	3.743	3.627	5.585	5.458	4.176	3.750	3.727	**5.179**	3.724
	Min	5.504	3.635	3.627	5.552	5.263	4.176	3.711	3.727	4.995	3.588
	Mean	5.547	3.689	3.627	5.568	5.439	4.176	3.745	3.727	5.013	3.676
NBHXH1_P	Max	5.288	**4.669**	**4.892**	**5.909**	5.316	**5.072**	3.635	3.376	3.215	3.817
	Min	3.154	1.888	2.342	5.747	4.270	2.117	1.455	1.530	1.450	3.774
	Mean	3.811	3.195	3.189	5.835	4.463	3.047	2.575	2.035	2.073	3.792
NBHXH2_P	Max	2.511	1.441	1.976	4.090	2.501	2.423	1.694	1.419	1.347	1.588
	Min	1.500	0.396	1.428	3.098	1.461	1.780	1.128	0.638	0.426	1.333
	Mean	2.228	0.879	1.763	3.623	2.091	2.241	1.395	1.100	0.636	1.425
NBHXUCF_P	Max	**5.711**	3.568	3.670	5.562	5.463	3.782	3.894	3.825	4.922	3.790
	Min	5.237	3.421	3.423	5.236	5.052	3.406	3.649	3.496	4.679	3.530
	Mean	5.529	3.486	3.559	5.534	5.304	3.523	3.770	3.658	4.772	3.701
NBHXICF_P	Max	5.522	3.710	3.561	5.440	5.365	3.877	**4.008**	3.620	4.299	3.712
	Min	5.223	3.609	3.488	5.157	5.072	3.684	3.825	3.422	4.123	3.574
	Mean	5.393	3.669	3.531	5.385	5.328	3.765	3.909	3.534	4.238	3.628
NBHXUCF_RFMP	Max	5.684	3.780	3.704	5.726	5.512	4.386	3.969	**3.836**	5.152	**3.846**
	Min	5.269	3.524	3.358	5.220	5.018	4.100	3.706	3.616	4.831	3.529
	Mean	5.504	3.602	3.577	5.564	5.283	4.235	3.780	3.675	5.047	3.742

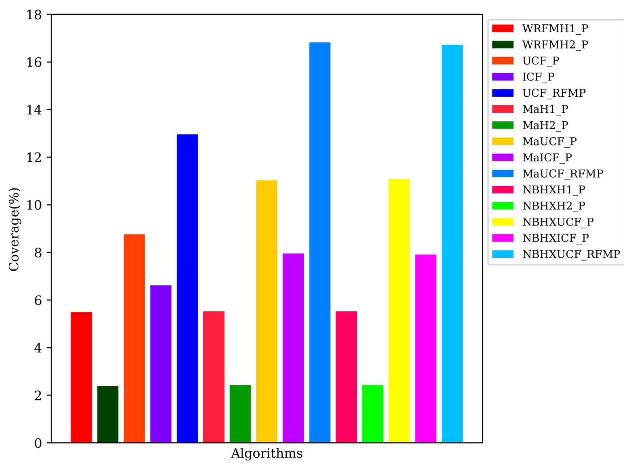

FIGURE 12. Coverage of competing algorithms.

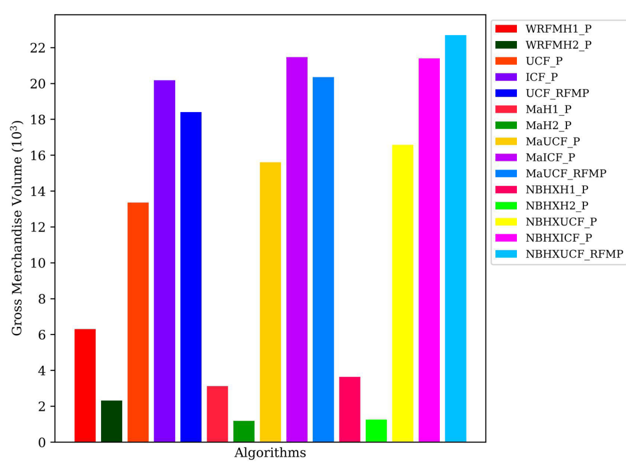

FIGURE 13. Gross merchandise volume value of competing algorithms.

Both ICF_P and UCF_RFMP have obvious advantages. In the framework of MaOEA, MaICF_P performs slightly better than MaUCF_RFMP, whereas MaUCF_RFMP is better than MaICF_P in NBHXMAOEA.

Figs. 9 to 13 indicate that the combination of our novel similarity model sim_RFMP and the many-objective evolutionary algorithm NBHX can obtain superior results in recommendation systems.

TABLE 6. Coverage of recommendation list for competing algorithms for 10 sample users.

ALGORITHM		User 1	User 2	User 3	User 4	User 5	User 6	User 7	User 8	User 9	User 10
WRFMH1_P		0.140	0.373	0.233	0.186	0.186	**0.419**	**0.373**	0.326	0.140	0.326
WRFMH2_P		0.140	0.140	0.140	0.233	0.140	0.233	0.280	0.186	0.093	0.373
UCF_P		0.186	0.233	0.280	0.186	0.186	0.326	0.280	0.280	0.326	0.280
ICF_P		0.280	0.419	0.326	0.186	0.186	0.326	0.280	0.326	0.326	**0.419**
UCF_RFMP		0.280	0.280	0.280	0.186	0.186	0.326	0.233	0.326	0.186	0.326
	Max	0.140	0.233	0.186	0.280	0.233	0.233	0.186	0.186	0.093	0.326
MaH1_P	Min	0.093	0.186	0.140	0.233	0.233	0.186	0.186	0.140	0.093	0.280
	Mean	0.123	0.200	0.157	0.247	0.233	0.189	0.186	0.141	0.093	0.282
	Max	0.140	0.047	0.093	0.186	0.140	0.140	0.186	0.093	0.093	0.140
MaH2_P	Min	0.140	0.047	0.093	0.186	0.140	0.140	0.186	0.093	0.093	0.140
	Mean	0.140	0.047	0.093	0.186	0.140	0.140	0.186	0.093	0.093	0.140
	Max	0.280	0.326	0.326	**0.326**	0.186	0.326	0.326	0.326	0.326	0.326
MaUCF_P	Min	0.186	0.232	0.280	0.186	0.140	0.280	0.280	0.280	0.233	0.280
	Mean	0.262	0.319	0.315	0.301	0.148	0.325	0.298	0.304	0.243	0.325
	Max	0.280	0.373	0.373	0.280	**0.326**	0.326	**0.373**	**0.373**	**0.373**	**0.419**
MaICF_P	Min	0.186	0.326	0.326	0.233	0.233	0.233	0.280	0.186	0.326	0.280
	Mean	0.255	0.366	0.329	0.267	0.301	0.319	0.282	0.204	0.329	0.355
	Max	**0.373**	0.373	0.373	0.280	0.233	0.373	0.326	**0.373**	0.233	0.326
MaUCF_RFMP	Min	0.326	0.186	0.373	0.186	0.186	0.373	0.233	0.373	0.186	0.326
	Mean	0.347	0.280	0.373	0.233	0.228	0.373	0.247	0.373	0.228	0.326
	Max	0.140	0.373	0.233	0.326	0.233	**0.419**	**0.373**	0.326	0.140	0.326
NBHXH1_P	Min	0.140	0.186	0.093	0.186	0.186	0.186	0.186	0.140	0.093	0.233
	Mean	0.140	0.268	0.171	0.267	0.224	0.257	0.282	0.211	0.122	0.324
	Max	0.140	0.140	0.093	0.186	0.140	0.140	0.186	0.140	0.093	0.186
NBHXH2_P	Min	0.093	0.047	0.093	0.140	0.093	0.093	0.140	0.047	0.047	0.140
	Mean	0.135	0.087	0.093	0.161	0.122	0.139	0.163	0.103	0.058	0.185
	Max	0.280	0.326	0.373	0.280	0.280	0.326	**0.373**	**0.373**	0.326	0.326
NBHXUCF_P	Min	0.140	0.186	0.233	0.140	0.140	0.280	0.233	0.233	0.233	0.233
	Mean	0.227	0.291	0.312	0.210	0.220	0.312	0.298	0.302	0.302	0.298
	Max	0.280	**0.419**	**0.419**	0.280	0.280	0.373	**0.373**	**0.373**	0.326	**0.419**
NBHXICF_P	Min	0.186	0.373	0.326	0.186	0.186	0.326	0.280	0.233	0.326	0.326
	Mean	0.241	0.377	0.364	0.242	0.270	0.333	0.336	0.318	0.326	0.362
	Max	0.326	0.373	**0.419**	0.233	0.186	0.373	**0.373**	**0.373**	0.326	0.373
NBHXUCF_RFMP	Min	0.280	0.233	0.280	0.186	0.140	0.280	0.233	0.233	0.186	0.326
	Mean	0.304	0.260	0.330	0.195	0.180	0.326	0.269	0.313	0.241	0.363

4) COMPARISON OF OBJECTIVES OF RANDOM USERS IN THE COMPETING ALGORITHMS

We randomly select 10 users and all of their Pareto solutions. Note that our devised NBHXMAOEA method aims to improve diversity, novelty, coverage, and GMV in the case of little harm to accuracy, i.e., all of the Pareto solutions can balance the objectives well. Therefore, all the solutions from the Pareto front are considered. In Tables 3-7, the term "mean" refers to the average value of the metric for each user of all solutions, "min" refers to the minimum value of the metric for each user of all solutions, and "max" refers to the maximum value of the metric of all solutions. The best scores are shown in a gray background and bold.

Table 3 indicates that accuracy is improved significantly in UCF_RFMP, MaUCF_RFMP, and NBHXUCF_RFMP in comparison to their corresponding competitors for most of the users. The three algorithms obtain 6, 4, and 8 times the highest F1 scores for ten users, and the sum of these scores is more than half of the total F1 highest scores. According to User 6, although there are difficulties in some extreme cases, our model can still maintain excellent performance when other algorithms cannot recommend accurately. Additionally, the mean accuracy value of NBHXUCF_RFMP is higher than that of the corresponding algorithms according to User 3, User 6, User 7, and User 9. Even with minimal accuracy, NBHXUCF_RFMP is better than that of its competitors according to User 1, User 2, and User 6.

Table 4 and Table 5 describe the diversity and novelty results of fifteen competing algorithms for the 10 random users. Although the number of maximum diversity achieved by our UCF_RFMP and NBHXUCF_RFMP is not the largest, NBHXICF_P also obtains the optimal diversity value of recommendation lists for User 2 and User 6. UCF_RFMP has better results than UCF_RFMP on diversity, which also reflects the effectiveness of NBHX in many-objective optimization.

The recommendation lists generated by NBHXUCF_P for User 1, User 5, and User 8 also reflect remarkable diversity, which has not been achieved through UCF_P and MaUCF_P. Similar to diversity, the total best records of NBHXICF_P is less than that of NBHXH1_P in terms of novelty, yet NBHXICF_P still recommends the two highest novelty lists for User 8 and User 10. For User 6 and User 9, the mean novelty of NBHXUCF_RFMP is higher than that of its competing algorithms.

TABLE 7. Gross merchandise volume value of recommendation list for competing algorithms for 10 sample users.

ALGORITHM		User 1	User 2	User 3	User 4	User 5	User 6	User 7	User 8	User 9	User 10
WRFMH1_P		1.122	3.052	3.455	1.405	2.421	4.850	2.250	4.550	0.602	3.500
WRFMH2_P		0.763	1.600	2.304	2.802	0.303	4.850	1.650	2.550	0.600	2.900
UCF_P		2.501	2.850	2.050	3.202	1.062	3.650	2.950	1.950	3.101	4.700
ICF_P		3.501	8.180	3.350	2.403	0.804	5.300	7.430	3.150	4.550	5.330
UCF_RFMP		3.602	5.900	5.100	2.303	0.804	8.880	3.600	7.400	4.051	3.850
	Max	0.861	2.051	2.955	2.903	0.862	3.500	0.950	2.300	0.301	3.100
MaH1_P	Min	0.503	0.252	0.503	1.703	0.862	3.100	0.950	2.100	0.301	2.350
	Mean	0.708	0.792	1.000	2.063	0.862	3.120	0.950	2.295	0.301	2.511
	Max	0.361	0.100	0.303	1.603	0.102	3.550	0.850	0.600	0.200	1.600
MaH2_P	Min	0.361	0.100	0.303	1.603	0.102	3.550	0.850	0.600	0.200	1.600
	Mean	0.361	0.100	0.303	1.603	0.102	3.550	0.850	0.600	0.200	1.600
	Max	4.202	5.400	3.550	**4.302**	1.863	4.000	5.100	4.050	5.150	4.750
MaUCF_P	Min	1.802	3.850	2.000	1.102	1.063	2.150	3.750	1.950	3.301	3.050
	Mean	2.245	4.369	3.099	3.894	1.153	2.589	4.560	3.140	4.374	3.542
	Max	3.701	**8.800**	5.300	4.003	1.863	8.550	**9.180**	3.700	6.550	**8.330**
MaICF_P	Min	0.714	6.900	3.300	1.962	1.063	5.300	6.300	2.900	3.800	5.450
	Mean	3.102	7.167	3.444	2.218	1.743	8.180	7.122	3.925	4.762	5.946
	Max	**5.203**	6.550	5.700	3.561	**3.001**	8.300	8.000	5.400	4.450	4.850
MaUCF_RFMP	Min	3.902	2.600	5.700	0.962	0.803	8.300	5.800	5.400	2.651	4.300
	Mean	4.487	4.575	5.700	2.261	2.781	8.300	6.130	5.400	4.270	4.492
	Max	1.122	3.052	3.455	4.103	2.422	4.850	2.250	4.550	0.602	5.600
NBHXH1_P	Min	0.363	0.802	0.154	1.404	0.762	1.600	0.950	2.100	0.302	3.200
	Mean	0.638	2.236	2.129	2.222	1.098	3.148	1.608	3.044	0.453	3.979
	Max	0.461	1.600	2.002	2.501	0.302	4.150	1.250	2.100	0.500	1.600
NBHXH2_P	Min	0.261	0.100	0.202	0.702	0.102	2.650	0.800	0.550	0.100	1.500
	Mean	0.395	0.893	0.885	1.434	0.259	3.310	0.952	1.384	0.180	1.538
	Max	3.201	4.700	4.800	3.602	2.063	3.850	4.200	3.950	4.950	4.700
NBHXUCF_P	Min	2.501	2.100	2.050	1.003	1.062	1.900	2.700	1.950	3.101	3.050
	Mean	2.833	3.617	3.740	2.287	1.400	3.100	3.640	2.951	4.063	3.750
	Max	3.501	8.180	6.650	3.761	2.062	8.500	9.100	3.700	**6.850**	7.700
NBHXICF_P	Min	2.103	6.500	2.150	1.804	0.804	5.200	7.430	2.900	4.200	5.330
	Mean	2.684	6.888	4.419	2.258	1.772	5.905	8.237	3.296	4.934	6.024
	Max	4.902	6.550	**9.180**	2.362	2.901	**10.250**	7.400	**8.300**	4.800	6.750
NBHXUCF_RFMP	Min	2.702	3.900	4.400	0.962	0.804	7.030	3.600	3.300	2.850	3.850
	Mean	4.112	5.201	5.676	1.723	1.310	9.257	5.328	5.689	3.860	5.608

The reason for our NBHXUCF_RFMP model tends to be suboptimal according to diversity, and novelty is that accuracy and diversity, accuracy, and novelty are completely opposite directions of optimization objectives. The improvement of accuracy inevitably leads to the loss of diversity and novelty. As shown in Table 3, the accuracy of NBHXUCF_RFMP was significantly improved for 8 users, which also explains why the effects of NBHXUCF_RFMP on diversity and novelty are not obvious. Nevertheless, Table 3-5 indicates that NBHXUCF_RFMP performs well in balancing accuracy, diversity, and novelty.

In Table 6, we evaluate the coverage of the compared algorithms. For User 3, User 7, and User 8, NBHXUCF_RFMP gains the maximum probability of provider coverage. In Table 7, NBHXUCF_RFMP achieves the largest number of highest GMV values of the ten users, which is similar to MaICF_P. For User 6 and User 8, the mean GMV value of NBHXUCF_RFMP is higher than that of its competing algorithms.

In Table 3-7, it can be proven that sim_RFMP can promote recommendation accuracy for most users, and the NBHXMAOEA model can work well in balancing the five objectives for the ten random users.

V. CONCLUSION AND FUTURE WORK

In this article, we incorporate the proposed sim_RFMP model with the traditional UCF algorithms, named UCF_RFMP, which significantly improves the accuracy of top-k recommendation. Additionally, a novel many-objective evolutionary algorithm, NBHX, is proposed to provide multiple tradeoff solutions in a single run for all users. Then, we formulate a many-objective model NBHXMAOEA, which incorporates the UCF_RFMP model with the proposed NBHX for optimizing the objectives of multistakeholders. Extensive experiments show that our proposed optimization algorithm NBHXMAOEA achieves superior performance in solving the many-objective problems in terms of average accuracy, diversity, novelty, provider coverage, and platform profit compared to its competing methods.

The NBHXMAOEA algorithm is a potential method for many-objective recommender systems, it is easy to implement and it combines with existing state-of-the-art algorithms. Although NBHX is designed for the combinational optimization problem of recommender systems, it can also be applied to solve various problems that are not limited to recommender systems. In the future, we aim to apply

NBHXMAOEA to a wide range of real-world datasets to assess its performance.

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