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Optimization Research on Electricity Retail Package Design and Intelligent Recommendation Model Based on Differential Evolutionary Algorithm

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Abstract With the deepening of electricity market reform, the diversity of users' electricity demand and the complexity of electricity retail packages have put forward higher requirements for package design and recommendation technology. In this paper, we propose a three-stage collaborative approach that integrates the modeling of users' electricity consumption behavior, the global optimization of differential evolution (DE) algorithm and the intelligent recommendation of attention factor decomposition machine (AFM), aiming at achieving the dynamic design and accurate recommendation of electricity retail packages. An extensible package product family GBOM is constructed based on the quintuple information expression model and modular design rules, and the differential evolution (DE) algorithm is used to efficiently search for the optimal bidding strategy in the high-dimensional solution space, combined with the constraint rules to adaptively deal with the complex coupling relationship between modules. An intelligent recommendation algorithm based on AFM is further proposed to enhance the model's sensitivity to the key features of users' electricity behavior by introducing an attention mechanism to dynamically assign feature cross weights. The experimental results show that the differentiated pricing strategy has a significant effect in peak and valley time regulation, and the peak time price is 45.4% higher than the fixed price (e.g., the peak time price of user 1 is 453.28 yuan/MWh), and the valley time price is reduced by 47.3% (the valley time price of user 1 is 164.23 yuan/MWh).The AFM recommendation algorithm combines the user's load characteristics with the monthly electricity consumption grading, and the recommendation accuracy rate is reaches 94.09% (when the number of historical purchases Te=7), which is a significant improvement over traditional methods (e.g., 89.41% accuracy rate of the mean weight method). Through comparative analysis, the DE-AFM method performs optimally in terms of balancing error and practicality (RMSE=0.0144, accuracy rate 94.09%), which verifies its stability and accuracy in complex scenarios.

Index Terms differential evolutionary algorithm, electricity retail packages, attention factor decomposer, differential pricing

I. Introduction

In the context of building a unified power market and promoting the market operation of the new power system, the construction and operation of the power retail market constitutes the basic guarantee of power supply [1], [2]. The new type of power system is characterized by security and efficiency, cleanness and low carbon, flexibility and wisdom integration, and the multi-level unified system of the power market is the key to achieving the goal of “double carbon”, and the power retail market, as a part of the provincial power market, should play a fundamental role in ensuring the optimal allocation of power resources [3]-[5]. Currently, the design of energy retail packages for the diversified needs of multiple user groups is a key issue, and factors such as the sharp increase in the number of marketized electricity users, the risk of wholesale tariff fluctuations, and the multiplication of demand for accurate electricity retail packages have posed a great challenge to the design of retail packages [6]-[9].

Retail tariffs occupy a central position in the development of the electricity retail market. Retail tariffs are mostly determined by electricity selling companies and electricity retail users based on bilateral negotiation, and when retail tariffs are too high, the relevant government departments will set retail tariff ceilings, and at the initial stage of the liberalization of the electricity sales side, the electricity selling companies will develop and formulate a variety of flexible and convenient electric power retail package plans to enhance the attractiveness by optimizing their services [10]-[13]. However, the current electricity retail package design objective is single, to protect the electricity sales company to obtain profits as the main goal, less consideration for retail customers' electricity feelings and satisfaction [14], [15]. Retail tariffs are arbitrary and simple, mostly negotiated between the electricity sales company and retail customers, and are not able to effectively transmit the price signals from the wholesale side of the medium- and long-term market and the spot market to the retail side [16], [17].

Electricity retail package price form solidification, it is difficult to guide the flexibility of users to participate in peak shaving and valley filling, resulting in a waste of power resources, but also increase the cost of electricity for retail users [18], [19]. In addition, the application of smart meters expands relevant electricity data, and intelligent algorithms for electricity sales to different users contribute to user classification and retail package recommendation, but traditional clustering algorithms are difficult to guarantee the accuracy of classification and push [20], [21]. In summary, the existing packages are still deficient in meeting the diversified needs of users and enhancing the revenue of the power seller, so it is urgent and necessary to carry out retail package design optimization.

This study proposes a three-stage collaborative approach that integrates user electricity behavior modeling, differential evolution algorithm (DE) global optimization and attention factor decomposition machine (AFM) intelligent recommendation, aiming to achieve dynamic design and accurate recommendation of electricity retail packages. Firstly, the design method of electricity package system based on user's electricity consumption behavior is proposed as a five-element information expression model with modular design rules. By defining the versions, constraint rules and attribute variables of configuration modules, a scalable package product family GBOM is constructed, and the mutual exclusion, association and numerical constraints between modules are combined to ensure the rationality and flexibility of package design. Then for the global optimization problem of dynamic pricing, differential evolution (DE) algorithm is introduced for strategy optimization. By initializing the population, mutation, crossover and selection operations, DE can efficiently search for the optimal bidding strategies in the high-dimensional solution space, and adaptively handle the complex coupling relationship between modules through the constraint rules. The differential evolution algorithm performs better in convergence speed and avoiding premature phenomenon, and provides high-quality inputs for subsequent recommendation algorithms. The article further proposes an AFM package recommendation algorithm based on electricity prediction, which enhances the differential representation of feature interactions by introducing an attention mechanism.AFM uses an attention network to dynamically distribute feature interaction weights on the basis of the factor decomposition machine (FM), which significantly improves the model's sensitivity to key features of the user's electricity consumption behavior.

II. Differential Evolutionary Algorithm Based Electricity Retail Package Optimization and AFM Intelligent Recommendation Approach

II. A. Design method of tariff package system based on users' electricity consumption behavior

II. A. 1) Five-element information representation model for the tariff package design module

In order to facilitate computer processing of the tariff package configuration model, this paper proposes a five-element information expression to describe the various information in the configuration module. The five-element information model is of the form:

$$Mod = \left(M-id, M=Version, M-Type, M_{cr}, M_{ij}\right) \tag{1}$$

where, Mod denotes the module, $M-id$ denotes the specific token of the module, $M=Version$ denotes the module version of the configurable product, the system default recommends the latest modified version, $M-Type$ denotes the configurable module, when the value of $M-Type$ is 0, it means that the selected module is a basic module; when the value of $M-Type$ is 1, it means that the selected module is a mandatory module; when the value of $M-Type$ is 2, it means that the selected module is an optional module, M_{cr} denotes the set of constraint rules for configuration modules, which creates constraints on the relationship between configuration modules. M_{cr} consists of two attributes: constraints plus configuration results, $M_{cr}=\left(Cond, \mathrm{Re}\,sult\right)$ corresponds to the constraints and the configuration results, respectively, M_{ij} denotes the set of attribute variables in a configuration module that can take values, denoted by $M=(M_{11}, M_{12}, \cdots M_{ij})\left(i=1,2,\cdots; j=1,2,\cdots\right)$, with M_{ij} representing the value of the j th variable of the i th module.

II. A. 2) Rules for modular design of tariff packages

Based on the electricity demand, the constituent modules of the electricity demand package are selected and combined based on the configuration rules, so as to ensure the correctness and effectiveness of the demand package design results. There are mutual constraints between modules in the design model, and the constraints of modules are shown in Figure 1.

(1) Constraints arising between modules. A constraint relationship between modules is given as a global constraint as in Figure 1, 1. Such constraints have appeared in the model library stored by the company, but do not appear internally in the configuration module. This type of relationship includes association and mutual exclusion relationships. The association relationship that arises between modules is a mandatory association, i.e., at the time

of configuration, module 1 and module 2 must exist at the same time. For example, in a tariff package configuration, the kWh tariff must be present at the same time as the basic tariff module. The mutually exclusive relationship between modules is a mutual exclusion, i.e., when configuring, module 1 and module 2 cannot coexist at the same time. For example, when configuring a tariff package product, time-of-day tariffs and time-of-abundance tariffs cannot coexist at the same time.

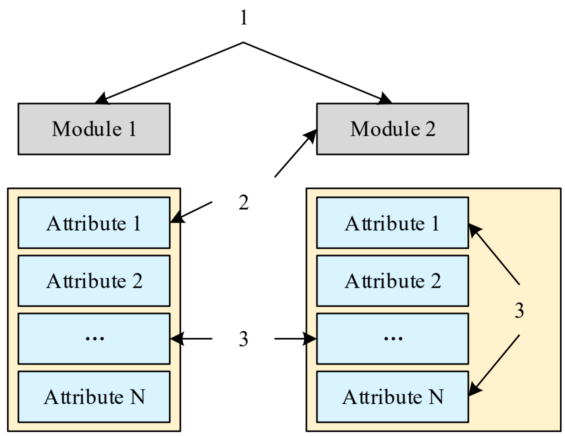

Figure 1: Constraint relation of module

(2) Numerical relationships between different attributes of a module and other modules. Such a relationship between module 2 and attribute 1 in module 1 is shown in Figure 1 in 2. For example, the load factor electricity price package apportions the transmission and distribution price among the basic electricity price and the kWh price according to a certain percentage.

(3) Local constraint relationship between a module attribute and other module attributes. For example, the relationship between attribute 2 in module 1 and attribute 2 in module 2 as demonstrated in Figure 1, 3. For example, the peak and valley tariff levels corresponding to the high and low load rate attributes in the load rate peak and valley tariff package are different, and there is a certain constraint relationship between them.

(4) Logical relationships between different attributes within the same module. For example, the constraint relationship between attribute 1 and attribute N in module 2 is shown in Figure 1, 4. For example, the peak hourly tariffs, the usual period tariffs and the valley tariffs set in the Peak and Valley Tariff Package produce user electricity costs that are lower than the user's current tariffs, therefore, the level of the tariffs for each period of time should be considered as a whole when setting the peak and valley tariffs.

Based on the above description of the attributes of the design module, each variable, and the configuration rules, we obtain the product family GBOM that can be used to configure the tariff package.

II. B.Heuristic Global Optimization Method Differential Evolutionary Algorithm

In this section, differential evolutionary algorithms (DEs) are introduced to achieve efficient search of optimal bidding strategies under complex constraints through adaptive mutation and crossover mechanisms.

Differential evolutionary algorithm (DE) is used to solve real number optimization problems. Differential evolutionary algorithms are used in constrained optimization computation, clustering optimization computation, and nonlinear optimization control. Differential Evolutionary Algorithm like Genetic Algorithm is also an optimization algorithm based on modern intelligence theory. The core of the differential evolutionary algorithm is to randomly generate an initial population and use appropriate mutation strategies to generate a mutant population, calculate the fitness value and then compare the new individuals with the corresponding individuals in the original population, select the better individuals to be retained, and then guide the search results to the optimal solution vector through iterations.

Steps of Differential Evolutionary Algorithm

(1) Initialization. Generate NP population individuals randomly and uniformly in the solution space. The dimension D of each individual needs to be determined. X_{Low} and X_{High} denote the vectors of upper and lower bounds on the upper values of the D dimensions, respectively. The i th individual of the generated population is as follows: $x_i^0 = X_{Low} + random(0,1) * (X_{High} - X_{Low})$, where $i \in [1, 2, \cdots, NP]$.

An initial population of NP individuals $X^0 = [x_1^0, x_2^0, \cdots, x_{NP}^0]$ is obtained, the variation factor F and crossover factor CR are determined, and the maximum number of generations G_{max} is determined. The number of individuals NP is generally greater than 4.

(2) For the individuals $x_i^G \left(i = 1, 2, \cdots, Np\right)$ in the G th generation, compute the fitness value $PE(x_i^G)$ for each individual and retain the optimal individual x_{best}^G with the best fitness.

(3) Variation. For the i th individual x_i^G in generation G, randomly select 3 different individuals x_{r1}^G, x_{r2}^G, x_{r3}^G in generation G besides x_i^G, i.e., r_1, r_2, r_3, $i \in [0, NP]$ and $r_1 \neq r_2 \neq r_3 \neq i$, generating new variant individuals $v_i^{G+1} = x_{r1}^G + F(x_{r2}^G - x_{r3}^G)$, generating variant populations $V^{G+1} = [v_1^{G+1}, v_2^{G+1}, \cdots, v_{NP}^{G+1}]$. $F \in [0, 2]$.

(4) Crossover. Crossover the original individual x_i^G with the variant individual v_i^{G+1} to obtain the crossover individual u_i^{G+1}, $CR \in [0,1]$ is the crossover probability, and $r = random(0,1)$ is the distribution obeying the mean on 0 to 1. The crossover operation maintains the diversity of the population.

$$u_{ij}^{G+1} = \begin{cases} v_{ij}^{G+1} & , r_{ij} \leq CR \\ x_{ij}^G & , \text{else} \end{cases} \tag{2}$$

where $j \in [0, D]$, denotes one dimension for each individual. Generally speaking, the larger the value of CR, the faster the convergence speed will be, but beyond a certain value the convergence speed will be decreased instead, and the phenomenon of precocity occurs when the value of CR is biased.

(5) Selection. To decide whether the mutant individual u_i^{G+1} becomes a new individual in the next generation. According to the greedy strategy, the better adaptation of x_i^G and u_i^{G+1} is selected as the individual x_i^{G+1} in the $G+1$ generation.

$$x_i^{G+1} = \begin{cases} u_i^{G+1} & , P(u_i^{G+1}) \leq P(x_i^G) \\ x_i^G & , \text{else} \end{cases} \tag{3}$$

Generate the $G+1$th generation population $X^{G+1} = \left[x_1^{G+1}, x_2^{G+1}, \cdots, x_{NP}^{G+1}\right]$.

(6) Repeat steps (2)-(5) until the termination condition of the iteration is reached.

Figure 2 shows the flow of the cross-variance algorithm.

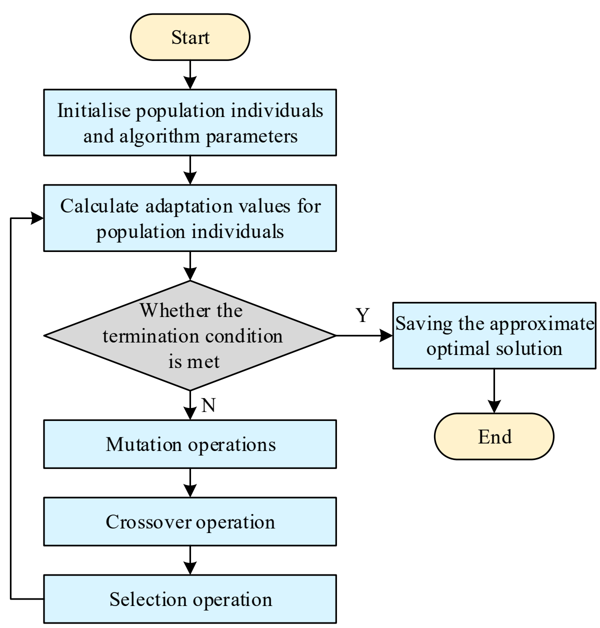

Figure 2: The process of the cross-mutation algorithm

II. C.AFM package recommendation algorithm based on power prediction

Although the package strategy optimized by the differential evolution algorithm can improve market revenue, its application needs to match the personalized needs of users. Therefore, this section proposes an intelligent recommendation algorithm based on AFM, which dynamically captures the potential correlation between the user's electricity consumption behavior and the package characteristics through the attention mechanism to realize the accurate recommendation of “thousands of people with thousands of faces”.

The AFM algorithm introduces the attention mechanism into the FM algorithm, so that the AFM can express the contribution of each pair of feature intersection to the result in a more detailed way on the basis of the original FM algorithm.

To add the attention mechanism, AFM adopts a neural network structure reconstruction algorithm, and the network structure of the AFM algorithm is shown in Fig. 3. It can be seen that the AFM algorithm consists of a sparse input layer (SIL), an embedding layer (EL), a pairwise interaction layer (PIL), an attention pooling layer (APL), and an output layer, which passes through the attention network between the pairwise interaction layer and the attention pooling layer.

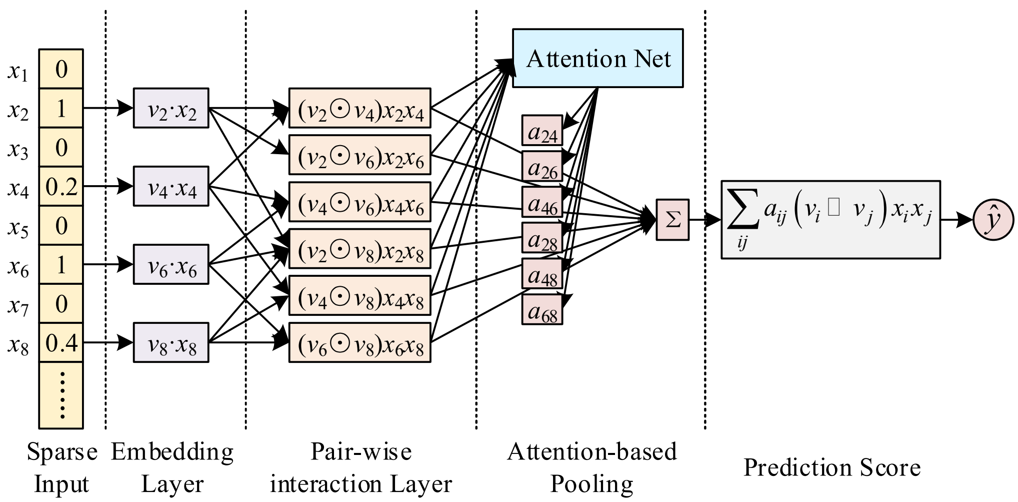

Figure 3: AFM network structure

The AFM algorithm is the same as the FM algorithm, for each feature x_i, there exists a corresponding hidden vector v_i. Only in the AFM algorithm, the function of mapping feature x_i to the corresponding hidden vector v_i is accomplished by the sparse input layer together with the embedding layer.

The function realized by the pairwise interaction layer of the AFM algorithm is the feature crossing function of the FM algorithm. After the pairwise interaction layer, the output of the network is a set of vectors:

$$f_{PI}(\varepsilon)=\left\{\left(v_i \odot v_j\right)x_i x_j\right\}_{(i,j)\in \mathrm{R}_s} \tag{4}$$

For a set of vectors output by pairs of interaction layers, if defined:

$$\hat{y}=p^T \sum_{(i,j)\in \mathrm{R}_s}(v_i \odot v_j)x_i x_j + b \tag{5}$$

where p is the parameter column vector with the same dimension as v and b is the bias parameter, it is clear that if both p and b are set to 1, Eq. (5) will be completely equivalent to the second term on the right side of the middle sign in Eq. (5), i.e., it is completely equivalent to the FM algorithm.

The difference between the AFM algorithm and the FM algorithm lies in the introduction of the attention pooling layer in the AFM algorithm, and the output of the pairwise interaction layer after the attention pooling layer is:

$$f_{at}\left(f_{PI}(\varepsilon)\right)=\sum_{(i,j)\in \mathrm{R}_s} a_{ij}(v_i \odot v_j)x_i x_j \tag{6}$$

where, a_{ij} represents the weight of the feature crossover generated by the i th feature and the j th feature in the output, in the FM algorithm, a_{ij} is all 1, i.e., each pair of feature crossover has the same weight in the output, but in practice, some feature crossover contributes a lot to the prediction result, some feature crossover contributes a small amount, and it may not be reasonable for FM to treat each pair of feature crossover equally may be unreasonable, and if it is for useless feature crossings, it may even reduce the prediction ability of the algorithm. Instead, the AFM algorithm utilizes the attention mechanism to calculate the weight of each pair of feature crossings in the final result:

$$
\begin{aligned}
a'_{ij} &= h^{T} \operatorname{Re}LU\left(W(v_i \odot v_j)x_i x_j + b\right) \\
a_{ij} &= \frac{\exp\left(a'_{ij}\right)}{\sum_{(i,j)\in R_s} \exp\left(a'_{ij}\right)}
\end{aligned}
\tag{7}
$$

where h, W, b are the parameters to be trained and ReLU is the activation function:

$$
\operatorname{Re}LU(z) = \begin{cases} z & z \ge 0 \\ 0 & z < 0 \end{cases} \tag{8}
$$

Finally, the output of the AFM algorithm used for the regression problem can be written Eq:

$$
\hat{y}_{AFM}(x) = \theta^{T} x + p^{T} \sum_{i=1}^{d} \sum_{j=i+1}^{d} a_{ij} (v_i \odot v_j) x_i x_j \tag{9}
$$

And the output of the AFM algorithm used for the classification problem can be written Eq:

$$
\hat{y}_{AFM}(x) = sigmoid\left(\theta^{T} x + p^{T} \sum_{i=1}^{d} \sum_{j=i+1}^{d} a_{ij} (v_i \odot v_j) x_i x_j\right) \tag{10}
$$

In this case, the sigmoid function is also a type of activation function and can also be used as an output function for the binary classification problem, which is given by:

$$
sigmoid(z) = \frac{1}{1+e^{-z}} \tag{11}
$$

Similarly, the AFM algorithm can be used for both classification and regression problems.

For regression problems, MSE is commonly used as the loss function. And for classification problems, cross-entropy loss (CE) is commonly used as the loss function, and the formula for cross-entropy loss is:

$$
CE = -\frac{1}{N} \sum_{i=1}^{N} \left(y^{(i)} \log(\hat{y}^{(i)}) + (1-y^{(i)}) \log(1-\hat{y}^{(i)}) \right) \tag{12}
$$

After selecting a suitable loss function, the backpropagation algorithm can be utilized to solve the parameters.

Compared with the FM algorithm, the AFM algorithm introduces the attention mechanism to calculate the weight of each feature interaction on the prediction, which is a more delicate treatment, and can enhance the contribution of beneficial feature interactions in the output and prevent useless feature interactions from damaging the model, and does not increase too many parameters and computational complexity, and achieves useful results on various datasets.

III. Empirical Analysis and Recommendation Accuracy Verification of Electricity Retail Packages Based on DE-AFM Optimization

The three-stage synergistic approach based on user behavior modeling, differential evolutionary algorithm (DE) global optimization and AFM intelligent recommendation proposed in Chapter 2 provides a theoretical framework for the dynamic design and accurate recommendation of electricity retail packages. In order to verify the practical effectiveness of the framework, Chapter 3 analyzes a typical customer example, combines real load data and market scenarios, and explores the economy of the differential pricing model, the personalized adaptability of the recommendation algorithm, and the multi-dimensional impact of user behavioral characteristics on the recommendation accuracy, so as to comprehensively evaluate the practical value of the method.

III. A. Arithmetic validation of user-differentiated package pricing model and dynamic pricing effect analysis

Taking three typical electricity retail customers as the research objects, this chapter develops an example analysis of the differentiated package pricing model constructed in the previous section based on customers' electricity consumption behaviors. The differentiated package pricing results are calculated and analyzed by the pricing model.

III. A. 1) Initial load of retail electricity consumers

In this paper, three typical electricity retail customers in a Chinese city are taken as research objects, and their load characteristic data are combined to verify the feasibility of a differentiated electricity retail package pricing model based on the users' electricity consumption behavior. To make the results more representative, it is assumed that when the electricity sales company acts as an agent for electricity retail users 1, 2 and 3 to purchase electricity, 80% of the electricity consumption of the electricity retail users is purchased in the medium- and long-term wholesale market, 15% of the electricity consumption is purchased in the day-ahead market, while 5% of the electricity consumption is purchased in the spot market. In order to comprehensively consider multiple scenarios and reduce the amount of calculation, the scenarios are reduced to some extent, and the data from different seasons and weekday scenarios are processed in a weighted average manner, and the load profiles of electricity consumption of the three typical retail electricity users after processing are shown in Figure 4 below.

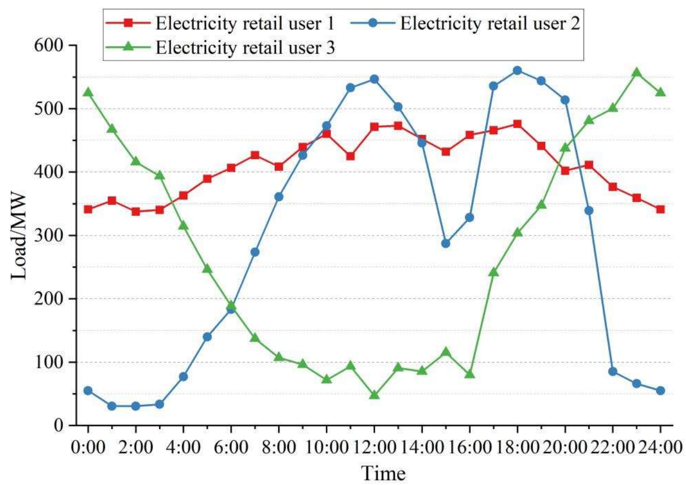

Figure 4: Initial load curve for retail electricity users

Typical daily average load of retail electricity user 1 is 9,912 MW, with a stable load throughout the day, a more even load distribution in different hours, small load volatility, and short-time medium peaks during the day, which is typical of a smooth-type user; typical daily average load of retail electricity user 2 is 7,371 MW, with a large load during the daytime and a small load during the rest of the day, and two peaks during the day, which is typical of a daily peak-type user; typical daily average load of retail electricity user 3 is 6,345 MW, with a large load at night, large load fluctuations during the day, and long-time peaks, which is typical of a night peak-type user. users; Retail Electricity User 3, with a typical daily average load of 6,345 MW, has a large nighttime load, large load fluctuations during the day, and two peaks during the day, which is a typical nighttime-peak type of user.

III. A. 2) Differentiated Package Pricing Results and Analysis

After the calculation of the pricing model based on differential evolutionary algorithm, the package prices of the differentiated packages based on users' electricity consumption behavior are finally obtained. The comparison of fixed price packages for retail electricity users 1, 2 and 3 with the package prices of differentiated packages based on users' electricity consumption behavior is shown in Fig. 5.

Figure 5 illustrates the comparison of the electricity prices of the fixed price package and the differentiated package for three typical retail electricity users (steady 1, daily peak 2, and night peak 3) at different time periods. The fixed-price package is unified at 311.65 yuan/MWh, while the differentiated package dynamically adjusts the price according to the user's electricity consumption behavior.

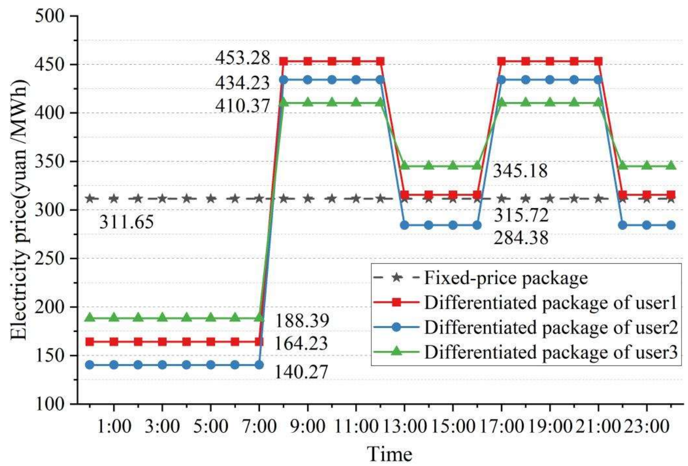

Figure 5: Comparison of user fixed price and differentiated price packages

During peak hours (8:00-12:00, 17:00-21:00): The electricity price of the differentiated package is significantly higher than that of the fixed-price package, and the electricity price of the user's 1 peak hour is 453.28 yuan/MWh, which is 45.4% higher than the 311.65 yuan/MWh of the fixed-price package, reflecting the regulating effect of dynamic pricing on peak electricity consumption.

Weektime (13:00-17:00, 22:00-24:00): The electricity price of the differentiated package is between peak and valley, and the electricity price of user 1 during the normal period is 315.72 yuan/MWh, which is slightly higher than the fixed-price package, but much lower than the price during peak hours, reflecting the reasonable pricing of the intermediate load period. The electricity price of night peak users3 is 345.18 yuan/MWh from 22:00 to 24:00, and the contradiction between supply and demand needs to be balanced.

Valley Hour (0:00-8:00): The electricity price of the differentiated package is significantly lower than that of the fixed-price package, and the electricity price of users during the valley period is only 164.23 yuan/MWh, a decrease of 47.3%, encouraging users to use electricity during low-load hours.

III. B. Typical user package recommendation results based on AFM package recommendation algorithm

Through the validation of the differentiated package pricing model for typical users in Section 3.1, it is clear that the dynamic pricing strategy has significant advantages in peak and valley time adjustment and user type adaptation. However, the optimized package strategy needs to further match the user's individualized demand to achieve accurate landing. To this end, this section proposes a staggered package recommendation scheme based on the AFM recommendation algorithm, combining the user load profile and monthly electricity consumption characteristics, and the results of the user's power package recommendation are shown in Table 1.

Table 1: The recommended results of the user's electricity package

Electric power user	Type	Monthly electricity consumption /MW	Recommended package	Peak price/ yuan	Regular period price/ yuan	Off-peak price/ yuan
User1	Stationarity	9912	FT7500	453.28	315.72	164.23
User2	Sunrise peak	7371	FU7500	434.23	284.38	140.27
User3	Night rush hour type	6345	FT5000	410.37	345.18	188.39
User4	Sunrise peak	13842	FU12500	427.37	276.39	133.81
User5	Sunrise peak	5935	FU5000	437.01	288.53	142.02
User6	Sunrise peak	10274	FU10000	432.77	282.05	138.54
User7	Night rush hour type	8374	FT7500	407.44	343.19	184.95
User8	Stationarity	11356	FT10000	449.7	313.24	160.52

Table 1 shows the personalized package recommendation results of the AFM algorithm for different user types and monthly electricity consumption. The recommended packages are categorized into fixed-rate packages (FU) and time-sharing tariff packages (FT), and are graded by combining user load characteristics.

Matching of user types and packages: Day-peak users (e.g., User2, User4) are recommended fixed-rate packages (FU series), whose peak-time tariffs (434.23 yuan/MWh) and normal-time tariffs (284.38 yuan/MWh) are lower than peak-time pricing of the differentiated packages but higher than the valley-time tariffs (140.27 yuan/MWh), which are suitable for daytime high-load users. Night-peak type users (e.g., User3, User7) are recommended for time-sharing tariff packages (FT series), which have significantly lower valley-time tariffs (e.g., 188.39 yuan/MWh in the valley time for User3), which are suitable for night-time electricity demand.

Electricity Consumption and Package Segmentation: Among them, the fixed-rate flat tariff (FU) packages are divided into eight segments from FU-base to FU-12500 according to the amount of electricity consumed, which are applicable to customers with monthly electricity consumption ranging from 0 to 10,000 MWh to 10,000 MWh and above; in addition to the F-base packages, there is one additional segment for every 2,500 MWh of electricity consumed. Monthly electricity consumption directly affects the selection of packages; User1 (smooth type, monthly electricity consumption of 9912MWh) recommends FT7500 package, which covers the range of 7500-10000MWh; while User4 (daily peak type, monthly electricity consumption of 13842MWh) recommends FU12500 package, which applies to users of more than 10,000MWh, reflecting the accurate adaptation of the algorithm to the scale of electricity consumption. This reflects the accurate adaptation of the algorithm to the scale of electricity consumption.

Price gradient design: the price of electricity in the package gradient changes. Taking the FU series as an example, the peak hour tariff for the FU5000 package is 437.01 yuan/MWh, while the FU10000 package is reduced to 432.77 yuan/MWh, indicating that users with large power consumption can enjoy marginal price concessions and enhance the attractiveness of the package.

Overall, the AFM algorithm captures the correlation between users' electricity consumption behavior and package characteristics through the attention mechanism, and realizes the recommendation effect of “thousands of people, thousands of faces”.

III. C. Research on the multi-dimensional influence of user behavioral characteristics and recommendation parameters on package recommendation accuracy

Although the AFM algorithm shows significant advantages in personalized recommendation, its recommendation accuracy is still affected by the complexity of user behavioral characteristics (e.g., the number of historical purchases) and algorithmic parameters (e.g., the number of nearest-neighbor users). In this section, we further quantitatively analyze the mechanism of these factors on the recommendation results from a multi-dimensional perspective, and reveal the change rule of accuracy under different parameter configurations through comparative experiments.

III. C. 1) Influence of the number of times a user purchases a package and the number of nearest neighbor users on the accuracy of package recommendation

The power package recommendation system realizes the most economical package recommendation for the target user based on the user's power forecast and the package history purchase information with the load information of the sample users. Table 2 compares the changes in package recommendation accuracy of the proposed method for different number of package purchases Te and number of near-neighbor users k. Among them, with more historical package purchase information provided by users, the user profile based on implicit scoring of packages can more accurately reflect their consumption preferences, thus improving the package recommendation accuracy. When the number of package purchase records available from the target user increases, the root mean square error indicator IR of the economy score of the recommended Top-N most economical package decreases from 0.076 (Te=1) to 0.013 (Te=6), and the package recommendation accuracy indicator increases from 65.6% to 90.1%.

Table 2: Comparison of recommendation accuracy under different k and Te

The number of purchases for different packages	RMSE	Accuracy/%				
		K=1	K=3	K=5	K=7	K=9
Te=1	0.077	61.28	62.12	63.09	63.47	64.58
Te=2	0.034	75.53	79.47	79.04	78.31	78.37
Te=3	0.027	81.86	81.34	83.31	81.31	85.59
Te=4	0.023	84.67	84.19	85.18	86.26	87.03
Te=5	0.019	87.93	86.49	88.08	89.08	89.18
Te=6	0.015	90.39	90.23	92.93	88.23	91.52
Te=7	0.010	92.72	93.69	93.11	92.28	94.09

The significant effect of the number of historical purchases, Te, is that as Te increases from 1 to 7, the root mean square error (RMSE) decreases from 0.077 to 0.010, and the recommendation accuracy increases from 61.28% to

94.09%. When Te=6, the RMSE is 0.015 with an accuracy of 90.39%, while when Te=7, the RMSE further decreases to 0.010 with an accuracy of 94.09%. This indicates that the more purchase records provided by users, the more accurate the algorithm is in modeling user preferences and the more reliable the recommendation results are.

The marginal effect of the number of near-neighbor users (k) is reflected in the fluctuating upward trend of the accuracy rate when k increases from 1 to 9. Taking Te=6 as an example, the accuracy rate is 90.39% at k=1, peaks at 92.93% at k=5, and falls back to 91.52% at k=9. This suggests that a moderate k value may enhance the recommendation effect by balancing local and global information, while too large k may introduce noise.

III. C. 2) Comparison of Recommendation Accuracy of Different Package Recommendation Methods

In order to verify the effectiveness of the proposed package recommendation method based on package implicit scoring and user profiling, Figure 6 compares the power package recommendation accuracy under different recommendation methods. Among them, the proposed package recommendation method based on dual-scale similarity load clustering with profile coefficients (DSM); in terms of the package label assignment method, the entropy weight method (EWM) determines the label weights according to the information entropy of the labels within the user clusters, and the larger the information entropy of the labels is, the smaller the degree of dispersion of corresponding labels' scores within the user clusters, and the larger the degree of correlation of package labels with the user loads are; the uniform weight method (UWM) uses a uniform weight ω = 0.150 for package labels. In addition, under the proposed profile coefficient-based package label weight model, the sample user load profiles can also be clustered using Euclidean Distance (EDC) and Cosine Distance (CDC), respectively, to obtain differentiated package label weights for package recommendation; and the Content-Based Recommendation (CBR) method matches power packages with similar label scores by user profile labels for recommendation.

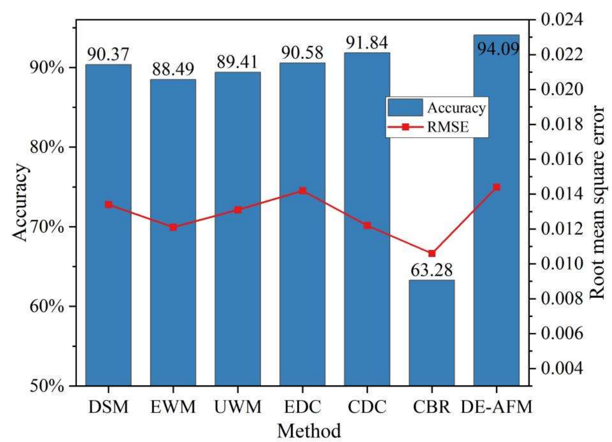

Figure 6: Comparison of electricity recommendation accuracy under different methods

The method DE-AFM in this paper has the highest accuracy of 94.09%, but the RMSE is slightly higher than some of the methods (0.0144.) The CBR method has the lowest RMSE of 0.0106, but the accuracy is only 63.28%, which suggests that it may ignore the dynamic nature of the user's behavior due to its over-reliance on label matching. In contrast, DE-AFM is more stable in complex scenarios by fusing differential evolutionary algorithms with attention mechanisms. The entropy weight method (EWM)-based method has an RMSE of 0.0121 and an accuracy of 88.49%, which is better than the uniform weight method UWM with RMSE=0.0131 and an accuracy of 89.41%, which verifies that the information entropy assignment is effective in distinguishing the importance of labels. Meanwhile, the 91.84% accuracy of the clustering method based on cosine distance (CDC) is higher than the 90.58% of the Euclidean distance EDC, indicating that the cosine distance is more suitable for capturing the similarity pattern of the user load profile.

Comprehensive performance ranking: DE-AFM > CDC > EDC > DSM > UWM > EWM > CBR Although the RMSE of DE-AFM is slightly higher, its accuracy is significantly ahead of that of EDC, reflecting its superiority in balancing error and practicality.

IV. Conclusion

In this paper, the dynamic design and accurate recommendation of electricity retail packages are realized through a three-stage synergistic approach, and the effectiveness of the fusion model based on differential evolution algorithm (DE) and attention factor decomposition machine (AFM) is verified. The differentiated pricing strategy significantly optimizes the adjustment effect of peak and valley electricity price, and the peak hour electricity price is enhanced by 45.4% (e.g., the peak hour electricity price of user 1 is 453.28 yuan/MWh) and the valley hour electricity price is reduced by 47.3% (the valley hour electricity price of user 1 is 164.23 yuan/MWh) compared with that of fixed-price packages, which effectively balances the contradiction between supply and demand.

The AFM recommendation algorithm dynamically captures user behavioral characteristics through the attention mechanism, with a recommendation accuracy of 94.09%, significantly better than the 89.41% of the uniform weight method and the 63.28% of the content-based recommendation method, and the root mean square error (RMSE=0.0144) is stable in complex scenarios.

The DE algorithm converges fast and avoids premature phenomenon in global optimization, and its optimized package strategy provides high-quality inputs for AFM recommendation, and the two synergistically significantly improve the recommendation accuracy and economy. In addition, the accurate adaptation of the user's electricity consumption scale and package slotting further validates the practicality of the model.

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