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A Dynamic Social Network Matching Model for Virtual Power Plants and Distributed Energy Resources with Probabilistic Linguistic Information

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Abstract: Virtual power plants (VPPs) offer an effective means to address the imbalance issue between electricity supply and demand to advance the world's low-carbon development. To fully utilize the limited resources in the virtual power plant planning stage, a two-sided match between VPPs and distributed energy companies is needed to better implement resource aggregation management. Because of the vagueness in this matching environment, the probabilistic linguistic term set (PLTS) is necessary to apply to express the decision makers' preference. Considering the complex social relationships and intense competition among companies, a dynamic social network two-sided matching model is proposed for solving the multi-attribute two-sided matching decision-making problem. Firstly, we present a matching satisfaction degree described by PLTS. A dynamic social trust degree based on the sliding time concept is proposed. Secondly, the social trust network relationships are built based on the direct and indirect dynamic trust degree among companies. This relationship is then combined with an improved trust rank algorithm to identify the most authoritative and the most trusted company to provide the target company with a recommendation for the next moment. Besides, given that companies compete for limited resources, we further define the competitive satisfaction degree and apply the two-sided matching model. Additionally, then a two-sided matching model is developed. Finally, our model is tested numerically to ensure its accuracy and reliability.

Keywords: virtual power plants (VPPs); two-sided matching decision-making; probabilistic linguistic term set (PLTS); dynamic social trust network; competitive relationship

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1. Introduction

Due to the greenhouse effect, energy, environmental and climate problems are now an unavoidable reality for humanity. As a result, countries have come to a significant consensus that vigorously developing renewable and clean energy is essential to reducing greenhouse gas emissions and advancing energy transformation [1]. Virtual Power Plant (VPP) is the primary strategy to promote the energy revolution and facilitate the transformation of the power industry. It is a new type of power system, which organically merges different distributed energy resources (DER), controllable loads and energy storage systems through the virtual power plant control center and takes part in grid operation as a whole. The advantage of VPP is that it can greatly reduce the pressure of peak electricity consumption and play the part of filling in the valleys and shaving the peaks [2]. At present, the practice of VPP is more mature in Europe and the United States [3]. Germany, as the representative of the European countries, has aggregated DER, such as follows: Next Kraftwerke company, E. ON company and the Sonnen company. Additionally, now Germany's VPP has basically achieved commercialization. The United States [4–7] is dominated by controllable loads and does not require the large-scale construction of DER infrastructure. Their business structures are all user-based business models. Japan [8–10] focuses on aggregating customer-side energy storage and DER and promotes VPP in six major areas, such as residential, office buildings, factories, commercial facilities, public utilities and electric vehicles. Australia [11] mainly aggregates customer-side energy storage, with independent operators represented by Tesla responsible for building platforms, integrating resources, selling electricity to the grid and providing ancillary services. However, the domestic virtual power plants in China are still in the primary stage, mainly in a pilot demonstration, with VPP demonstration projects in Hebei, Shanghai, Jiangsu, Guangdong, and Zhejiang. China is expected to achieve a certain scale of DER, controlled load aggregation and commercial operation during the 14th Five-Year Plan period, coordinated by the government, implemented by grid companies and developed by projects [12–15].

VPPs are receiving increasing attention from academia, industry and the ecological design field, and many researchers are further investigating the concept. At present, the research on VPP mainly includes the integration and optimal dispatching of resources [16–25], operation management [26–32] and market transaction and control mechanisms [33–37]. Among them, the selection aggregation and optimal dispatching of VPP resources in the project planning stage have been extensively researched. The related papers are summarized in Figure 1. Reviewing the related papers, we find that most of the studies focus on profit allocation and product pricing for various types of DER resources within VPP, as well as collaborative management of external VPP resources, selection of VPP partners and selection of DER partners. However, the number of VPP and DER companies in the market is limited, and how to allocate the limited resources effectively and rationally has become the most prominent concern for the government and company managers. To avoid idle resources, the two-sided matching decision-making method (TSMDM) [38,39] can be regarded as a valuable tool for the rational allocation of resources.

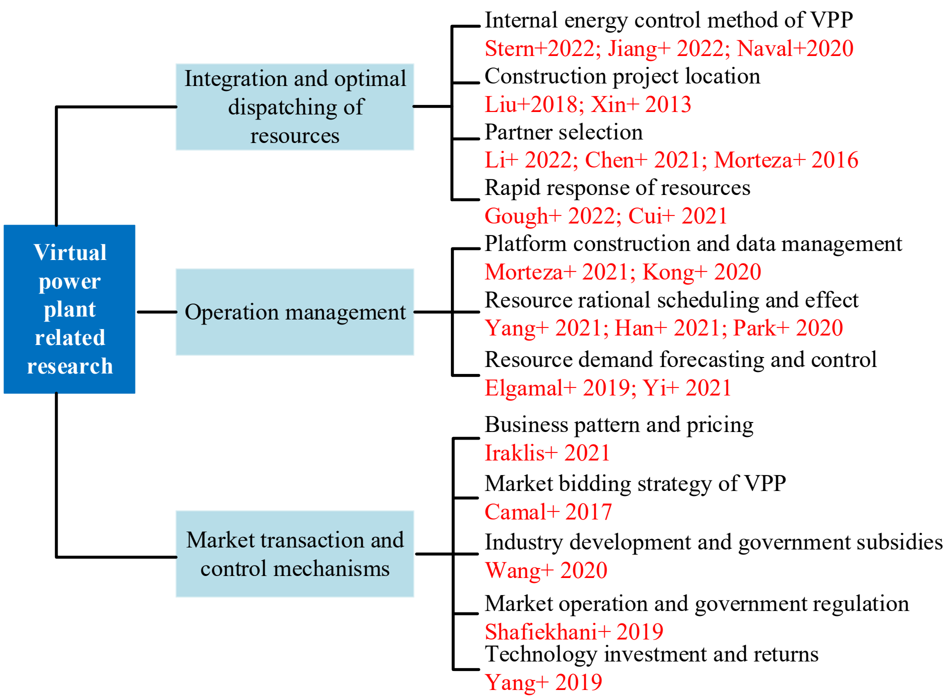

Figure 1. The brain map of VPP-related papers [14–35].

Recent studies on TSMDM have focused on the expansion of application scopes and the innovation of methods. In terms of application scopes, the TSMDM problem is applied to marriage matching [40], personnel matching [41–43], sharing economies [44–47], full product life cycles [48,49] and knowledge service matching [50,51]. In terms of methods innovation, the TSMDM problem aims to obtain a matching result that maximizes the satisfaction of both sides. Additionally, the existing relevant TSMDM technique can be mainly classified into the following three categories: the information form-based approach, the ideal solution-based approach and the behavior-based approach. The information form-based approach is based on the matching object's specific preferred information form to achieve two-sided matching. The TSMDM with decision information structure [52,53], the TSMDM with preference information structure [54–57] and the TSMDM with linguistic information structure [58,59] belong to this category. The ideal solution-based approach is to realize the matching of alternatives by means of the positive and negative ideal solutions. The TOPSIS-based two-sided matching [43,53,60], and the VIKOR-based two-sided matching [61,62] belong to this category. The behavior-based approach considers that the behavioral characteristics of the matching object have an important influence on the final decision results. The psychological behavior of the matching object [63,64], the peer effect of the matching object [65], the competitive behavior of the matching object [66] and the social interactive behavior among matching objects [67] belong to this category. However, it is noteworthy that, by now, the dynamic social interactive behavior among companies has not yet been applied in the TSMDM. In fact, dynamic social interactive behavior is an important influence on the decision-making judgment of the company's management. Therefore, how to model the inter-company social interactive relationship and incorporate this relationship into the TSMDM will be considered in this paper.

It is worth noting that the existing TSMDM are gradually being used to address such decision-making situations where attributes are evaluated in a linguistic environment [58,59]. Particularly, it can be applied to the two-sided matching problem of VPP and DER companies. Because the development of VPP is still in the early stages of exploration, many attributes are difficult to quantify. Coupled with the ambiguity of subjective thinking and the high uncertainty of the company's environment, it is difficult for company managers to give clear evaluation figures. Therefore, the qualitative language can better convey the company manager's ideas, opinions and satisfaction evaluation. The probabilistic linguistic term set (PLTS) is a valuable instrument for describing decision makers' uncertainty and limited cognition in fuzzy language theory. Pang et al. [68] initially proposed the definition of PLTS. Up to now, there have been many studies on PLTS, such as the operational rules of PLTS [68–70], the aggregation operator of PLTS [68,71–73] and probabilistic linguistic decision-making methods [71–77]. Due to the obvious advantages of PLTS as an evaluation tool, a growing number of scholars [65,78,79] have begun to apply it to the study of two-sided matching in recent years. Therefore, in this paper, we will explore how to solve the problem of partner selection for VPP and DER companies based on the PLTS.

Motivated by the above analysis, in this paper, we will address the problem of matching the resources of limited VPP and DER companies in the VPP project planning stage. So as to save on the cost of building centralized power plants for VPP companies and enhance the benefits of operating energy for DER companies. To achieve the above purposes, we propose a dynamic two-sided matching model under a social network environment, in which the evaluation information of a company over other companies can be expressed by a PLTS. The following are the primary contributions of our model:

- Propose a social trust network-based probabilistic linguistic two-sided matching model that takes into account the social interaction and competition among companies;
- Put forward a new calculation method for the dynamic trust degree and the construction method of the trust network among companies.

The structure of this paper is arranged as follows: Section 2 briefly introduces some basic theoretical knowledge that will be helpful for our research. In Section 3, we first put forward a probabilistic linguistic matching satisfaction degree by taking into account the difference between the expected and actual evaluation of the company. Then, the dynamic social trust degree based on the sliding time concept is present and then construct a social trust network. After that, we develop a new trust rank algorithm by combining it with the social trust degree to find two types of companies, thus updating the social trust degree between companies at the next moment. In Section 4, a two-sided matching decision-making model considering the competitive relationship between VPP companies is constructed. In Section 5, a numerical empirical case for the matching of the VPP companies and the DER companies is presented to demonstrate the applicability and the implementation process of the proposed model. Section 6 is the conclusion of this paper.

2. Preliminaries

In this section, we briefly review some basic theories that will be used in our study.

2.1. Probabilistic Linguistic Term Sets

The use of linguistic variables to describe qualitative features has been seen as a valuable tool. In this paper, we consider a definite and totally ordered linguistic term set $S = \{s_\alpha | \alpha = -\tau, \ldots, 0, \ldots, \tau\}$, where S is a positive integer, $s_\alpha (\alpha = -\tau, \ldots, 0, \ldots, \tau)$ is a linguistic term. S should satisfy the following conditions:

(1) There is the following negation operator: $neg(s_i) = s_j$ if $i = -j$;
(2) The set has the following order: $s_i \leq s_j$ if and only if $i \leq j$.

Based on the concept of the linguistic term set, Pang et al. [68] put forward the concept of probabilistic linguistic term sets (PLTSs), which allow the decision maker to express his/her evaluation using several possible linguistic terms and the corresponding probabilities.

Let $S = \{s_\alpha | \alpha = -\tau, \ldots, 0, \ldots, \tau\}$ be a linguistic term set, then a probabilistic linguistic term set (PLTS) $L(p)$ on S is defined as follows:

$$L(p) = \{l_i(p_i) | l_i \in S, p_i \geq 0, i = 1, 2, \ldots, \#L(p), \textstyle\sum_{i=1}^{\#L(p)} p_i \leq 1\}$$

where l_i denotes the ith linguistic term in $L(p)$, p_i denotes the probability of occurrence of the linguistic term l_i and $\#L(p)$ is the number of all different linguistic terms in $L(p)$. If $\sum_{i=1}^{\#L(p)} p_i < 1$, then it means that some probability information in $L(p)$ is missing, and thus the corresponding normalized PLTS can be denoted as $\overline{L}(p) = \{l_i(\overline{p}_i) | l_i \in S, \overline{p}_i = \frac{p_i}{\sum_{i=1}^{\#L(p)} p_i}, i = 1, 2, \ldots, \#L(p)\}$.

Since the traditional PLTS is simply computed by means of subscripts or conversion functions of linguistic terms during information aggregation [69–73], the ambiguity and randomness involved in linguistic variables are ignored, leading to the loss and distortion of the original information. For this reason, Zhao et al. [80] introduced probability distributions to describe PLTSs and proposed the definitions of the generalized probability distribution and the generalized cumulative distribution function as follows.

Let L be a discrete stochastic variable, $S = \{s_\alpha | \alpha = -\tau, \ldots, 0, \ldots, \tau\}$ be a, ordered linguistic term set, and $L(p) = \{l_i(p_i) | l_i \in S, p_i \geq 0, i = 1, 2, \ldots, \#L(p), \sum_{i=1}^{\#L(p)} p_i \leq 1\}$ be a PLTS of L, then the generalized probability distribution $p(L)$ of the PLTS $L(p)$ is defined as follows:

$$p(L = s_\alpha) = p_\alpha^* = \begin{cases} p_i, & \exists l_i = s_\alpha \\ 0, & otherwise \end{cases}, \ \alpha = -\tau, \ldots, 0, \ldots, \tau$$

and the generalized cumulative distribution function $F(L)$ of the PLTS $L(p)$ is defined as follows:

$$F(L) = \begin{cases} 0, & L < s_{-\tau}, \\ p_{-\tau}^*, & s_{-\tau} \leq L < s_{-\tau+1}, \\ p_{-\tau}^* + p_{-\tau+1}^*, & s_{-\tau+1} \leq L < s_{-\tau+2}, \\ \vdots & \vdots \\ \sum_{\alpha=1}^{\tau-1} p_\alpha^*, & s_{\tau-1} \leq L < s_\tau, \\ \sum_{\alpha=1}^{\tau} p_\alpha^*, & L = s_\tau. \end{cases}$$

To calculate the distance between two PLTSs, Zhao et al. [80] proposed the definition of the probabilistic linguistic distance as follows.

Given probabilistic linguistic term sets $L_1(p) = \{l_i^1(p_i^1) | l_i^1 \in S, p_i^1 \geq 0, \ i = 1, 2, \ldots, \#L_1(p), \sum_{i=1}^{\#L_1(p)} p_i^1 \leq 1\}$ and $L_2(p) = \{l_i^2(p_i^2) | l_i^2 \in S, p_i^2 \geq 0, \ i = 1, 2, \ldots, \#L_2(p),$

$\sum_{i=1}^{\#L_2(p)} p_i^2 \leq 1\}$, $F_1(L)$ and $F_2(L)$ be the generalized cumulative distribution functions of $L_1(p)$ and $L_2(p)$ respectively. Then the distance between the PLTSs $L_1(p)$ and $L_2(p)$ is defined as follows:

$$D(L_1(p), L_2(p)) = |\,|F_1(L) - F_2(L)|\,| = (\int_{-\tau}^{\tau+1} |F_1(L) - F_2(L)| dL)$$

In the actual two-sided matching process between VPP and DER companies, there are many factors considered by both matching objects. Different matching objects will judge and choose the suitable match for themselves according to different evaluation attributes, and finally achieve a reasonable match. Among them, VPP company's selection of DER company mainly considers quality, price, service capacity and technology level attributes; DER company's consideration of VPP company mainly depends on quality, price, service capacity and economic strength attributes. Therefore, the two-sided matching between VPP and DER companies is essentially a multi-attribute complex problem. In a multi-attribute decision problem, the managers in companies expect the evaluation object to reach the expected level, and in this paper, we consider the positive ideal point of Zhao et al. [80] as the probabilistic linguistic expectation level of the company.

For company $a_k(k = 1, 2, \ldots, m+n)$, its probabilistic linguistic expectation evaluation information under the attribute $c_h(h = 1, 2, \ldots, q)$ at the moment $z_t(t = 1, 2, \ldots, v)$ is $EL_h^t(L)$, and its corresponding cumulative distribution function is $EF_h^t(L)$, which is defined as follows:

$$EF_h^t(L) = \max\{F_{kh}^t(L) | k = 1, 2, \ldots, m+n\},\ h = 1, 2, \ldots, q,\ t = 1, 2, \ldots, v,$$

where the max operator is calculated as follows:

$$\max(F_1(L), F_2(L)) = \begin{cases} 0, & L < s_{-\tau}, \\ \max(p_{-\tau}^{1*}, p_{-\tau}^{2*}), & s_{-\tau} \leq L < s_{-\tau+1}, \\ \max(p_{-\tau}^{1*} + p_{-\tau+1}^{1*}, p_{-\tau}^{2*} + p_{-\tau+1}^{2*}), & s_{-\tau+1} \leq L < s_{-\tau+2}, \\ \vdots & \vdots \\ \max(\sum_{t_1=1}^{\tau-1} p_{t_1}^{1*}, \sum_{t_2=1}^{\tau-1} p_{t_2}^{2*}), & s_{\tau-1} \leq L < s_\tau, \\ \max(\sum_{t_1=1}^{\tau} p_{t_1}^{1*}, \sum_{t_2=1}^{\tau} p_{t_2}^{2*}), & L = s_\tau. \end{cases}$$

2.2. Two-Sided Matching

The two-sided matching model seeks to establish a match between two decision makers, each of whom has a ranking preference for the other's decision-maker, to obtain a stable two-sided matching result by making the overall satisfaction maximum. It is worth noting that for stable matching, any pair of decision makers prefer to match with their assigned partners rather than the other [40]. In what follows, we briefly review this basic theory.

Let $A = \{a_i | i = 1, 2, \ldots, m\}$ and $B = \{b_j | j = 1, 2, \ldots, n\}$ be the sets of matching objects on two sides, where a_i and b_j are the $i-th$ matching object and the $j-th$ matching object in A and B respectively. Thus, a stable match with maximum mutual satisfaction is obtained.

Given a two-sided matching B is a one-to-one mapping. If and only if the following conditions are satisfied:

$\forall a_i \in A, \forall b_j \in B$, $\mu(a_i) \in B$, $\mu(b_j) \in A \cup b_j$, if $\mu(b_j) = a_i$, then $\mu(a_i) \notin B \backslash b_j$, where $\mu(a_i) = b_j$ means that a_i and b_j form a matching pair. If $\mu(b_j) = b_i$ means that b_j has no matching object.

3. Probabilistic Linguistic Dynamics Social Trust Degree

In this section, we introduce the calculation method for the dynamics social trust degree, which is an important parameter in the dynamic two-sided matching model.

The framework of a dynamic social trust degree calculation in the probabilistic linguistic environment for portraying the dynamic trust relationship between companies is depicted in Figure 2.

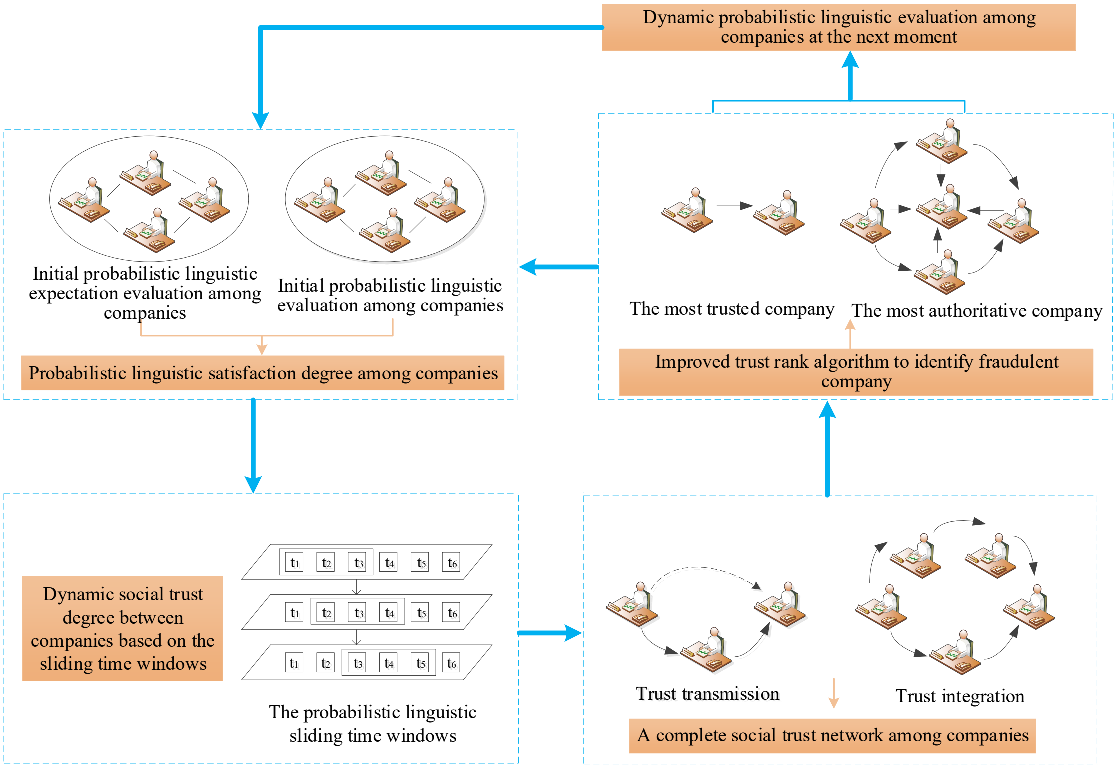

Figure 2. The framework of probabilistic linguistic dynamics social trust degree calculation.

3.1. Matching Satisfaction Degree

We consider a social network to be composed of the following two kinds of companies: VPP companies and DER companies. Since there is a mutual evaluation between any two companies, for simplicity of the description below, here let $a_k(k = 1, 2, \ldots, m)$ and $a_l(l = 1, 2, \ldots, m)$ be any two companies in the social network.

The matching satisfaction degree [64] is the relative difference between the expected value of the company and the final value obtained. The existing PLTS information aggregation process uses subscripts or conversion functions of linguistic terms to operate, ignoring the ambiguity and randomness involved in linguistic variables. For this reason, Zhao et al. [80] used probability distributions to describe PLTS and without normalization, which better preserves more original information. According to Zhao et al.'s probabilistic linguistic distance [80], we can obtain the following matching satisfaction degree based on PLTS.

The matching satisfaction degree SS^t_{klh} of company $a_k(k = 1, 2, \ldots, m + n)$ to company $a_l(l \neq k, l = 1, 2, \ldots, m + n)$ under the attribute $c_h(h = 1, 2, \ldots, q)$ at the moment $z_t(t = 1, 2, \ldots, v)$ is defined as follows:

$$SS^t_{klh} = D(L^t_{klh}(p), EL^t_{kh}(p)) = (\int_{-\tau}^{\tau+1} |F^t_{klh}(L) - EF^t_{kh}(L)|dL) \quad (1)$$

where $L^t_{klh}(p)$ is the probabilistic linguistic evaluation information of a_k to a_l under attribute c_h at the moment z_t, $EL^t_{kh}(p)$ is the probabilistic linguistic expectation evaluation information of a_k under attribute c_h at the moment z_t. $F^t_{klh}(L)$ is the generalized cumulative distribution functions of $L^t_{klh}(p)$, $EF^t_{kh}(L)$ is the generalized cumulative distribution functions of $EL^t_{kh}(p)$, and $EF^t_{kh}(L) = \max\{F^t_{klh}(L)|l = 1, 2, \ldots, m + n\}$.

3.2. Dynamics Social Trust Degree

In the traditional social trust calculation, the transient value of social trust is calculated by mainly collecting the trust evaluation of the companies in social networks at a special moment. In the process of company interaction, social trust changes in real-time due to the complexity and variability of the market. Trust between companies is usually based on a long-term cordial and cooperative relationship between the two parties, which is the result of continuous strengthening of one party's satisfaction with the other [81]. If only calculate the transient value of social trust, the social trust degree obtained may not match the actual social trust degree. Therefore, we introduce the concept of a sliding time window [82] in order to add new social trust data between any two companies to the current window at each moment. It is convenient to be used to calculate the dynamic social trust between any two companies, as shown in Figure 3.

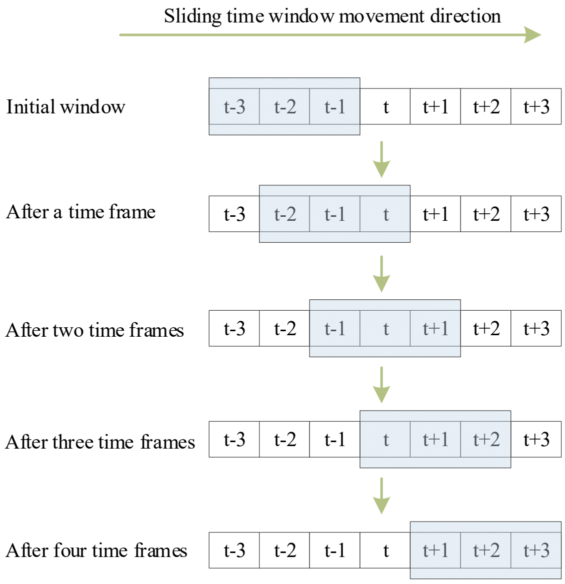

Figure 3. The principle of sliding time windows.

The real-time social trust degree between companies is calculated from the matching satisfaction information of historical transactions within the sliding time window. For each time frame elapsed, the sliding time window slides one time frame to the right and removes the leftmost time frame. The dynamic social trust degree TD_{klh}^{t} of company a_k in company a_l under the attribute c_h at the moment $z_t(t = 1, 2, \ldots, v)$, is defined as follows:

$$TD_{klh}^{t} = \frac{\sum\limits_{x=r}^{t} \theta(x) \times SS_{klh}^{t}}{\sum\limits_{x=r}^{t} \theta(x)} \tag{2}$$

where $r = \min\{x|z_x \subset window\}$, $\theta(x)$ is the time decay function, and $\theta(x) = \lambda^{(z_t - z_x)/\eta}$, $0 < \lambda < 1$, η is the coordination factor, which is adjusted with the time window size. It is worth noting that the dynamic social trust degree between companies changes dynamically with the matching satisfaction.

In the actual decision-making process, because of the dynamics of resources on the market, companies have different matching satisfaction degrees at each decision moment. This means that both the social trust degree and the matching satisfaction between companies change in real-time. In addition, due to the limitations of the company's perception, this dynamism is reflected in the fact that the company's decision-making behavior is influenced not only by its own satisfaction at the current moment but also by the satisfaction of both its most trusted company and the most authoritative company in the market at the previous moment. The most trusted company is the one with the highest trust degree from the target company. Additionally, the most authoritative company is the one that has the most influence among all companies. Therefore, in order to measure the matching satisfaction degree of a company at the current moment, we need to find its most trusted company and its most authoritative company at the previous moment.

The accuracy of recommendations is improved by taking into account the social trust relationships of every company in the social network. In the actual decision-making process, the matching choice of a company is influenced not only by the same type of companies but also by the evaluation environment in which the matching objects are situated. As a result, for the effectiveness of recommendation, we construct a social trust network as below.

In general, the trust relationship between companies can be divided into direct trust relationship and indirect trust relationship.

(1) Direct trust relationship

If a_k and a_l with direct trust relationship at the moment z_t, then the direct social trust degree STD_{klh}^t between a_k and a_l under the attribute c_h at the moment z_t can be obtained by Equation (2), and then the direct social trust network relationships matrix $[STD_{klh}^t]_{(m+n)\times(m+n)}$ between companies under the attribute c_h at the moment z_t can be constructed.

(2) Indirect trust relationship

If a_k and a_l with indirect trust relationship under the attribute c_h at the moment z_t, then the indirect social trust degree ITD_{klh}^t between a_k and a_l needs to be obtained through indirect trust transfer from a trusted third party. In the Three Degrees of Influence Rule theory, Christakis and Fowler [83] pointed out that individuals influence each other through strong relationships and the transmission of influence is only in the range of three degrees. So, a company usually relies on the views of other companies in its three-degree trust range in the decision-making process. Inspired by Christakis and Fowler [83], we use this theory to reflect indirectly related relationships between companies. In the following, combining Einstein's product operator [84], we give the formula for calculating the social trust degree between any two indirectly connected companies.

Let the shortest trust path of a_k to a_l under the attribute c_h at the moment z_t be $a_k \to a_{x_1} \to a_{x_2} \to \ldots \to a_{x_{\psi-1}} \to a_l$, where a_{x_i} is denoted as the ith company connecting companies a_k and a_l, and the path length is ψ. Let the indirect social trust degree $a_k \to a_{x_1}, a_{x_1} \to a_{x_2}, \ldots, a_{x_{\psi-1}} \to a_l$ from a_k to a_l denote as $STD_{kx_1h}^t, STD_{kx_2h}^t, \ldots, STD_{kx_\psi h}^t$. Then, the indirect social trust degree $\overline{ITD}_{klh}^t$ from a_k to a_l with respect to company a_k under the attribute c_h at the moment z_t can be denoted as follows:

$$\overline{ITD}_{klh}^t \triangleq E_{\otimes}(STD_{kx_1h}^t, STD_{kx_2h}^t, \ldots, STD_{kx_\psi h}^t) = \frac{2\prod_{i=1}^{\psi} STD_{kx_ih}^t}{\prod_{i=1}^{\psi}(2 - STD_{kx_ih}^t) + \prod_{i=1}^{\psi} STD_{kx_ih}^t} \tag{3}$$

where the number of $STD_{kx_ih}^t$ should be less than three.

In reality, the trust paths between a pair of companies may not be unique. When multiple paths exist, the combined trust transfer value of the companies is calculated using the multi-path penalty idea [85].

Let there be g trust paths between a pair of companies a_k and a_l under the attribute c_h at the moment z_t, and $\{T_1, T_2, \ldots, T_g\}$ be the set of trust relationships between them, then the estimate of the transfer final result is as follows:

$$ITD_{klh}^t = \sum_{i=1}^{g} \gamma_{klh}^{it} \overline{ITD}_{klh}^{it} \tag{4}$$

where $\gamma_{klh}^{yt} = 1/(\eta_{klh}^{yt} \cdot \sum_{y=1}^{g}(1/\eta_{klh}^{yt}))$ is the weight vector that penalizes the decay of penalized trust based on the transfer path length, η_{klh}^{yt} represents the length of the yth $(y = 1, \ldots, g)$ transfer path, $\overline{ITD}_{klh}^{yt}$ is the yth trust path between a pair of companies a_k and a_l under the attribute c_h at the moment z_t. Additionally, then we can construct the indirect social trust network relationships matrix $[ITD_{klh}^t]_{(m+n)\times(m+n)}$ between companies under the attribute c_h at the moment z_t.

Consequently, a complete social trust network relationship matrix $[CTD_{klh}^t]_{(m+n)\times(m+n)}$ between companies can be constructed by combining matrix $[STD_{klh}^t]_{(m+n)\times(m+n)}$ and matrix $[ITD_{klh}^t]_{(m+n)\times(m+n)}$.

$$CTD_{klh}^t = STD_{klh}^t + ITD_{klh}^t \tag{5}$$

Through the complete social trust network analysis, we can obtain the following two types of companies: the most trusted company and the most authoritative company. However, in the actual decision-making process, companies may provide false evaluation information in order to increase their trustworthiness. Therefore, it is very necessary to identify and exclude fraudulent companies first after obtaining the complete social trust network. We apply the trust rank algorithm [86] to measure the influence of a web page based on the number and quality of incoming and outgoing links between pages, and then manually identify the fraudulent company. Hence, we introduce the idea of social trust degree to improve this algorithm for computing the influence weight of a company so as to find the most trusted company and the most authoritative company.

According to the trust rank algorithm [86], the inverse transition matrix $U_{h(k,l)}^t$ and the transition matrix $H_{h(k,l)}^t$ under the attribute c_h at the moment z_t are defined as follows:

$$U_{h(k,l)}^t = \begin{cases} 0 & if(k,l) \notin \varepsilon \\ 1/\xi(l) & if(k,l) \in \varepsilon \end{cases} \tag{6}$$

$$H_{h(k,l)}^t = \begin{cases} 0 & if(l,k) \notin \varepsilon \\ 1/\varphi(l) & if(l,k) \in \varepsilon \end{cases} \tag{7}$$

where $\xi(l)$ and $\varphi(l)$ are the social trust degree of inlinks and the social trust degree of outlinks of the company a_l under the attribute c_h at the moment z_t respectively.

Furthermore, the seed set under the attribute c_h at the moment z_t can be found by the inverse page rank value, which can be defined as follows:

$$s_h^t = \beta \cdot U_h^t \cdot s_h^t + (1-\beta) \cdot \frac{1}{N} \cdot 1_N \tag{8}$$

where β is a decay factor, $0 \leq \beta \leq 1$, N is the number of nodes, s_h^t represents the inverse page rank vector under the attribute c_h at the moment z_t.

Additionally, identify good seeds (i.e., companies) from the "seed set". Experts are involved in determining whether a company is trustworthy company, and if there exists a company that is not, it is eliminated from the seed set. The experts referred to in this paper are the outsiders jointly developed by VPP and DER.

Consequently, as described above, after mutually identifying the fraudulent company, we can utilize the social trust network among companies to find the most trusted company and most authoritative company.

(1) The most trusted company

The company that the target company a_k trusts the most is described as follows:

Let $a_{koh}^t (o = 1, 2, \ldots, m+n)$ be the company trusted by the company a_k under the attribute c_h at the moment z_t, CTD_{koh}^t be the social trust degree of company a_{koh}^t. Then, the company with the largest social trust degree $\max CTD_{koh}^t$ and not excluded by manual identification is considered the most trusted company of the target company a_k, denoted as $\hat{a}^t_{koh}$. Additionally, that company's probabilistic linguistic evaluation information about other companies SF^t_{olh} is considered as the recommendation information in the next moment for the target company a_k.

(2) The most authoritative company

Based on the identification of trusted companies, compute the trust rank value of other companies under the attribute c_h at the moment z_t

$$r^t_h = \beta \cdot H^t_h \cdot r^t_h + (1-\beta) \cdot \left(v^t_h\right)^T \tag{9}$$

where β is a decay factor, $0 \leq \beta \leq 1$, r^t_h represents the trust rank vector, $\left(v^t_h\right)^T$ is a static score distribution vector of good seeds after manual identification, which can be used to assign non-zero static scores to other companies.

Then, normalize all of the company's trust rank values. Additionally, the influence weight of the company a_k under the attribute c_h at the moment z_t can be expressed as the normalized value of the i-th trust rank value in the trust rank vector, denoted as π^t_{ih}.

Let a^t_{MAh} be the company trusted by all companies under the attribute c_h at the moment z_t, then the company with the largest normative trust rank value is considered as a^t_{MAh}. Additionally, the company a^t_{MAh}'s probabilistic linguistic evaluation information about other companies SG^t_{MAlh} is considered as the recommendation information in the next moment for other companies.

Consequently, the dynamic probabilistic linguistic evaluation information SS^{t+1}_{klh} of company a_k to a_l under the attribute c_h at the moment z_{t+1} is defined as follows:

$$(SS^{t+1}_{klh})'' = \omega_1 SS^{t+1}_{klh} + \omega_2 SF^t_{olh} + \omega_3 SG^t_{MAlh} \tag{10}$$

where SS^{t+1}_{klh} is the new probabilistic linguistic evaluation information given by the company a_k at the moment z_{t+1} for the attribute c_h of company a_l. $(SS^{t+1}_{klh})''$ is the new probabilistic linguistic evaluation information influenced by the opinions of others.

Finally, after obtaining the above two types of companies, we can obtain the new satisfaction among companies at the next moment, calculated by Equation (1).

In this section, we give the process of constructing a dynamic social trust network for companies. VPP and DER companies first provide the satisfaction degree of other companies (both for the same types of companies and for different types of companies). Then two-sided matching is achieved using the model in Section 4, and if the results of this round of matching are unsatisfactory, all companies move on to the next stage of the matching process. At this point, the satisfaction degree of VPP and DER companies will be influenced by the information on the satisfaction degree of the most authoritative companies as well as their most trusted companies in the previous round of the matching process. For this reason, we need to be clear about the social trust relationship between companies at each stage in order to find the most authoritative company as well as its most trusted company. However, in the actual decision, in order to increase their influence, some companies will intentionally give wrong information to increase or decrease their influence factor to make themselves the most authoritative company or the most trustworthy company for others. So, we introduce the trust rank anti-fraud algorithm to identify the companies with fraud. Finally, through social networks, we can obtain the satisfaction degree of the company among other companies in each round.

4. Dynamic Two-Sided Matching Model Considering Competitive Relationships

4.1. Problem Description

The greenhouse effect has resulted in increasingly severe extreme weather events in many countries. Coal-fired power generation in the power industry is the main source of greenhouse gas emissions. So, it is urgent for the power industry to build a new power system with new energy as the main source. The two-sided matching of VPP companies and DER companies is the key means to building a new power system. As described in the introduction, both VPP companies and DER companies will consider how to choose the right partner from a business point of view so that they can obtain a larger aggregation benefit.

In order to reduce the construction cost of power infrastructure, VPP companies are bound to attract quality DER resources by investing in DER companies. Simultaneously, VPP is a new industry with a large development space and promising development prospects. So VPP companies are communicating and learning from each other, hoping to promote the development of the industry and there will be a benign competition among companies [30,87]. DER companies, as service providers, form social relationships based on the interaction of business and social factors, and influence the matching preferences of other companies through mutual resources, information and knowledge.

To fulfill the two-sided matching between VPP and DER companies better, in this part we put forward the dynamic social network two-sided matching model. For a good understanding of our model, the notation in the actual two-sided matching decision problem is first clarified.

We consider a dynamic two-sided matching decision-making problem, which involves a linguistic term set $S = \{s_\alpha | \alpha = -\tau, \ldots, 0, \ldots, \tau\}$, a discrete set of VPP companies $A = \{a_i | i = 1, 2, \ldots, m\}$ faces a discrete set of DER companies $B = \{b_j | j = 1, 2, \ldots, n\}$. The VPP company a_i can only choose one company in the DER company b_j for matching at the moment $z_t (t = 1, 2, \ldots, v)$, while the DER company b_j can also only choose one company in the VPP company a_i at the moment $z_t (t = 1, 2, \ldots, v)$.

The finite set of evaluative attributes of company a_i to company b_j is $C = \{c_h | h = 1, 2, \ldots, q\}$, where $c_1, c_2, \ldots, c_q$ are independent of each other, and its weight vector is $w^C = (w_1^C, w_2^C, \ldots, w_q^C)$, where w_h^C is the importance weight of c_h, satisfying the following conditions: $0 \leq w_h^C \leq 1$, $h = 1, 2, \ldots, q$ and $\sum\limits_{h=1}^{q} w_h^C = 1$. The probabilistic linguistic evaluation matrix of a_i to b_j on c_h at moment z_t is $L^{it} = (L_{hj}^{it}(p))_{q \times n}$ $(i = 1, 2, \ldots, m; t = 1, 2, \ldots, v)$, where $L_{hj}^{it}(p)$ is a PLTS, and the aspiration-level of a_i to b_j on c_h at moment z_t is an expectation matrix $EL^{it} = (EL_{hj}^{it}(p))_{q \times n} (i = 1, 2, \ldots, m;$ $t = 1, 2, \ldots, v)$, where $EL_{hj}^{it}(p)$ is also a PLTS. The matching satisfaction degree of VPP company a_i to DER company b_j under the attribute c_h at the moment z_t is SA_{ijh}^t.

The finite set of evaluative attributes of company b_j to company a_i is $D = \{d_h | h = 1, 2, \ldots, q\}$, where $d_1, d_2, \ldots, d_q$ are independent of each other, and its weight vector is $w^D = (w_1^D, w_2^D, \ldots, w_q^D)$, where w_h^D is the importance weight of d_h, satisfying the following conditions: $0 \leq w_h^D \leq 1$, $h = 1, 2, \ldots, q$ and $\sum\limits_{h=1}^{q} w_h^D = 1$. The probabilistic linguistic evaluation matrix of b_j to a_i on d_h at moment z_t is $L^{jt} = (L_{hi}^{jt}(p))_{q \times m}$ $(j = 1, 2, \ldots, n;\ t = 1, 2, \ldots, v)$, where $L_{hi}^{jt}(p)$ is a PLTS, and the aspiration-level of b_j to a_i on d_h at moment z_t is an expectation matrix $EL^{jt} = (EL_{hi}^{jt}(p))_{q \times m} (j = 1, 2, \ldots, n;$ $t = 1, 2, \ldots, v)$, where $EL_{hi}^{jt}(p)$ is also a PLTS. The matching satisfaction degree of DER company b_j to VPP company a_i under the attribute d_h at the moment z_t is SB_{jih}^t.

In addition, VPP companies inevitably compete for quality DER companies when investing; thus, a competitive relationship is formed among VPP companies. Additionally, the finite set of evaluative attributes of a_i to its peer competitor a_k and b_j to its peer competitor b_k is $F = \{f_h | h = 1, 2, \ldots, q\}$, where $f_1, f_2, \ldots, f_q$ are independent of each other, and its weight vector is $w^F = (w_1^F, w_2^F, \ldots, w_q^F)$, where w_h^F is the importance weight of f_h, satisfying the following conditions: $0 \leq w_h^F \leq 1$, $h = 1, 2, \ldots, q$ and $\sum\limits_{h=1}^{q} w_h^F = 1$. The probabilistic linguistic evaluation matrix of a_i to a_k and b_j to on f_h at moment z_t are $L^{Akt} = (L_{hi}^{Akt}(p))_{q \times m} (k = 1, 2, \ldots, m; k \neq i; t = 1, 2, \ldots, v)$ and $L^{Bkt} = (L_{hj}^{Bkt}(p))_{q \times n}$

$(k = 1, 2, \ldots, n; k \neq j; t = 1, 2, \ldots, v)$ respectively, where $L_{hi}^{Akt}(p)$ and $L_{hj}^{Bkt}(p)$ are both PLTS, and the aspiration-level of a_i to a_k and b_j to b_k on f_h at moment z_t are expectation matrix $EL^{Akt} = (EL_{hi}^{Akt}(p))_{q\times m}(k = 1, 2, \ldots, m; k \neq i; t = 1, 2, \ldots, v)$ and $EL^{Bkt} = (EL_{hj}^{Bkt}(p))_{q\times n}(k = 1, 2, \ldots, n; k \neq j; t = 1, 2, \ldots, v)$, where $EL_{hi}^{Akt}(p)$ and $EL_{hj}^{Bkt}(p)$ are both PLTS. The matching satisfaction degree of VPP company a_i to its competitor company a_k under the attribute f_h at the moment z_t is SA_{ikh}^{At}. The matching satisfaction degree of DER company b_j to its competitor company b_k under the attribute f_h at the moment z_t is SB_{jkh}^{Bt}.

The main purpose of this paper is to build a dynamic two-sided matching decision model so as to obtain high-quality matching results.

4.2. Measurement of the Dynamic Competitive Satisfaction between Companies

As mentioned in Section 4.1., there are competitive relationships among the VPP companies, and the mutual evaluation among VPP companies is benign evaluation. For this purpose, we give a definition of the intensity of resource competition between a company a_i and its competitor a_k, which is shown as follows:

$$CI_{ik}^{t} = \sum_{j=1}^{n} \frac{y_{ij}^{t}}{y_{i}^{t}} \cdot \frac{y_{kj}^{t}}{y_{k}^{t}} \quad (11)$$

where y_{ij}^t represents the investment share of the VPP company a_i in the DER company at the moment z_t, y_i^t represents the investment share of a_i in all DER companies; y_{kj}^t is the investment share of competitor a_k in b_j, y_k^t is the investment share of a_k in all DER companies investment share; CI_{ik}^t represents the competitive pressure on company a_i from the competitor a_k's investment value on all companies.

Such competitive relationships affect the decision-making behavior of the VPP companies and thus affect their matching satisfaction degree. In particular, companies pay significant attention to the satisfaction of their competitors' matching outcomes when there is a competitive relationship present [88]. Even if their personal pleasure is high, individuals will still feel frustrated and dissatisfied if there is a significant gap between their own satisfaction and that of their rivals, which is not conducive to a stable matching of solutions. The discontent brought on by the satisfaction gap increases in strength with the competitive relationship. Toward this end, we present the following competitive satisfaction degree.

For the company a_i and its competitor a_k under the attribute f_h at the moment z_t, the competitive satisfaction degree CS_{ikh}^t is defined as follows:

$$CS_{ikh}^{t} = \left(1 + CI_{ik}^{t}\right)^{\delta} \times \sum_{j=1}^{n} \left| SA_{ijh}^{t} - SA_{kjh}^{t} \right| \quad (12)$$

where δ is a constant given that $\delta = 1.5$, CI_{ik}^t is the resource competition intensity between a_i and a_k.

Since the greater the satisfaction difference, the greater the dissatisfaction of the company, it will be standardized in order to reduce the dissatisfaction of the company. Then the dynamic standardized competitive satisfaction degree matrix $[\overline{CS}_{ikh}^{t}]_{m\times m}$ can be constructed.

It is worth pointing out that competitive satisfaction among companies varies with the satisfaction among companies.

4.3. Two-Sided Matching Model

Considering real-time social and competitive relationships between companies in the two-sided matching decision-making problem will improve the accuracy and learnability of the matching decision problem results. Therefore, we establish a multi-objective, two-sided matching model, considering the competitive relationships under the PLTSs environment. The research framework of this paper is shown in Figure 4.

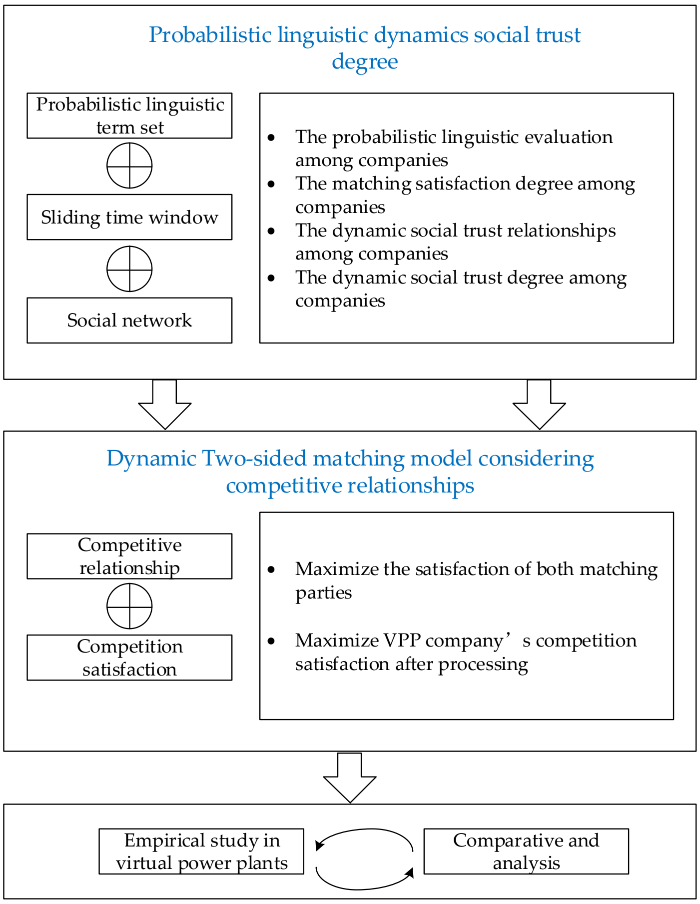

Figure 4. The research framework of the proposed model.

From Section 4.1., we can use the vector $(SA_{ij1}^t, SA_{ij2}^t, \ldots, SA_{ijh}^t)$ to denote the matching satisfaction evaluation of the VPP company a_i on the DER company b_j under the attribute c_h at the moment z_t. Use the vector $(SB_{ji1}^t, SB_{ji2}^t, \ldots, SB_{jih}^t)$ to denote the matching satisfaction evaluation of the DER company b_j on the VPP company a_i under the attribute d_h at the moment z_t. Additionally, use the vector $(SA_{ik1}^{At}, SA_{ik2}^{At}, \ldots, SA_{ikh}^{At})$ to denote the matching satisfaction evaluation of the VPP company a_i on the competitive VPP company a_k under the attribute f_h at the moment z_t.

Using the linear weighting method, we can obtain the comprehensive satisfaction degree matrix $[SA_{ij}^t]_{m\times n}$, which matches VPP company a_i to DER company b_j. Similarly, we can obtain the comprehensive satisfaction degree matrix $[SB_{ji}^t]_{n\times m}$, which DER company b_j matches VPP company a_i. In a similar way, we can obtain the comprehensive competitive satisfaction degree matrix $[SA_{ik}^{At}]_{m\times m}$, which VPP company a_i matches VPP company a_k.

Suppose that x_{ij} be a 0–1 decision variable, if the VPP company a_i and the DER company b_j match, then $x_{ij} = 1$, otherwise $x_{ij} = 0$. Then, we can construct the following 0–1 maximizing multi-objective integer programming model (P1).

$$\max Z_1 = \sum_{i=1}^{m} \sum_{j=1}^{n} SA_{ij}^t x_{ij} \tag{13}$$

$$\max Z_2 = \sum_{i=1}^{m} \sum_{j=1}^{n} SB_{ji}^t x_{ji} \tag{14}$$

$$\max Z_3 = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{\substack{k=1\\k\neq i}}^{m} SA_{ik}^{At}x_{ij}x_{kj} \tag{15}$$

$$s.t. \quad \sum_{i=1}^{m} x_{ij} = 1, j = 1,2,\ldots,n \tag{16}$$

$$\sum_{j=1}^{n} x_{ji} = 1, i = 1,2,\ldots,m \tag{17}$$

$$x_{ij} = 0 \quad or \quad 1, i = 1,2,\ldots,m; j = 1,2,\ldots,n \tag{18}$$

In the above model, the objective function Z_1 represents that the matching satisfaction is maximized when VPP company a_i is matched with DER company b_j. Additionally, the objective function Z_2 represents that the matching satisfaction is maximized when DER company b_j is matched with VPP company a_i. Z_3 denotes the sum of the competitive satisfaction of VPP company a_i and its competition company a_k matching the same downstream company b_j. Equations (13)–(15) show that this is a one-to-one, two-sided match. Where Equation (13) indicates that only one DER company b_j can match VPP company a_i. Equation (14) indicates that no match or one VPP company a_i is assigned to DER company b_j.

To tackle the multi-objective model described above, a linear weighting method is used to convert the multi-objective function to a single-objective function. $\varepsilon_1, \varepsilon_2$ and ε_3 represent the weights of the objective functions Z_1, Z_2 and Z_3, respectively. Then, the transformed single-objective model (P2) can be expressed as follows:

$$\begin{aligned} & \max\overline{Z} = \varepsilon_1 Z_1 + \varepsilon_2 Z_2 + \varepsilon_3 Z_3 \\ s.t. \quad & \sum_{i=1}^{m} x_{ij} = 1, j = 1,2,\ldots,n \\ & \sum_{j=1}^{n} x_{ji} = 1, i = 1,2,\ldots,m \\ & x_{ij} = \quad 0 \quad or \quad 1 \ , \ i = 1,2,\ldots,m; \ j = 1,2,\ldots, \ n \end{aligned}$$

Based on the above analysis, a group dynamics social network matching method is introduced for solving the multi-attribute, two-sided matching decision-making problem, in which the evaluation information from one company to another over attributes at every moment is represented by PLTSs. The schematic diagram of the proposed model is presented in Figure 5, and the detailed calculation steps are summarized as follows:

Stage 1. Data collection

Step 1. Collect the evaluation information from VPP and DER companies.

For the multi-attribute, two-sided matching decision-making problem described in Section 4.1., construct the probabilistic linguistic decision matrix $L^{it} = (L_{hj}^{it}(p))_{q\times n}$ $(i = 1,2,\ldots,m; t = 1,2,\ldots,v)$ and $L^{jt} = (L_{hi}^{jt}(p))_{q\times m}(j = 1,2,\ldots,n; t = 1,2,\ldots,v)$ for the VPP company a_i and the DER company b_j respectively. The expectation matrix $EL^{it} = (EL_{hj}^{it}(p))_{q\times n}(i = 1,2,\ldots,m; t = 1,2,\ldots,v)$ and $EL^{jt} = (EL_{hi}^{jt}(p))_{q\times m}(j = 1,2,\ldots,n;$ $t = 1,2,\ldots,v)$. The probabilistic linguistic decision matrix $L^{Akt} = (L_{hi}^{Akt}(p))_{q\times m}$ $(k = 1,2,\ldots,m; k \neq i; t = 1,2,\ldots,v)$ and $L^{Bkt} = (L_{hj}^{Bkt}(p))_{q\times n}(k = 1,2,\ldots,n; k \neq j;$ $t = 1,2,\ldots,v)$ for company a_i and company b_j respectively in the same type companies, and the expectation matrix $EL^{Akt} = (EL_{hi}^{Akt}(p))_{q\times m}(k = 1,2,\ldots,m; k \neq i; t = 1,2,\ldots,v)$ and $EL^{Bkt} = (EL_{hj}^{Bkt}(p))_{q\times n}(k = 1,2,\ldots,n; k \neq j; t = 1,2,\ldots,v)$.

Stage 2. Resolution process

Step 2. Determine the matching satisfaction degree for each attribute.

Calculate the matching satisfaction degree between any two companies under each attribute at the current moment by Equation (1).

Step 3. Construct the dynamic social network among companies.

In this step, calculate the dynamic social trust degree between any two companies under each attribute at the current moment by Equation (2). Then, by Equations (2)–(4), obtain the direct social trust degree and indirect social trust degree between any two companies, and then construct the complete social trust network relationship matrix between companies $[CTD]^t_{klh}$ under each attribute at the current moment by Equation (5).

Step 4. Determine two types of companies.

Based on step 3, we can compute the inverse transition matrix $U^t_{h(k,l)}$ and the transition matrix $H^t_{h(k,l)}$ by Equations (6) and (7), and then, by Equation (8), obtain the inverse page rank value to conveniently identify good seeds. Furthermore, find the trusted company of each company and, by Equation (9), obtain the trust rank value to find the most authoritative company under each attribute at the current moment.

Step 5. Construct the competitive satisfaction degree matrix among VPP companies.

In this step, calculate the dynamic competitive satisfaction degree between company a_i and its competitor a_k under each attribute at the current moment based on Equations (11) and (12), and then construct the dynamic competitive satisfaction degree matrix $[CS^t_{ikh}]_{m\times m}$ of company a_i.

Stage 3. Matching process

Step 6. Construct the two-sided matching model.

Based on the linear weighting method, obtain the comprehensive satisfaction degree matrix $[SA^t_{ij}]_{m\times n}$, $[SB^t_{ji}]_{n\times m}$ and $[SA^{At}_{ir}]_{m\times m}$, and then construct a two-sided matching model (P1) considering the competitive relationships between companies and the dynamic trust degree.

Step 7. Solve the model (P2) and obtain the best matching pair. Then, determine whether it is necessary to readjust the two-sided matching decision result. If yes, let $t = t+1$ and obtain the new probabilistic linguistic evaluation information of each company under each attribute at the moment z_{t+1} by Equation (10) and then return to step 1; if not, the matching decision process is terminated.

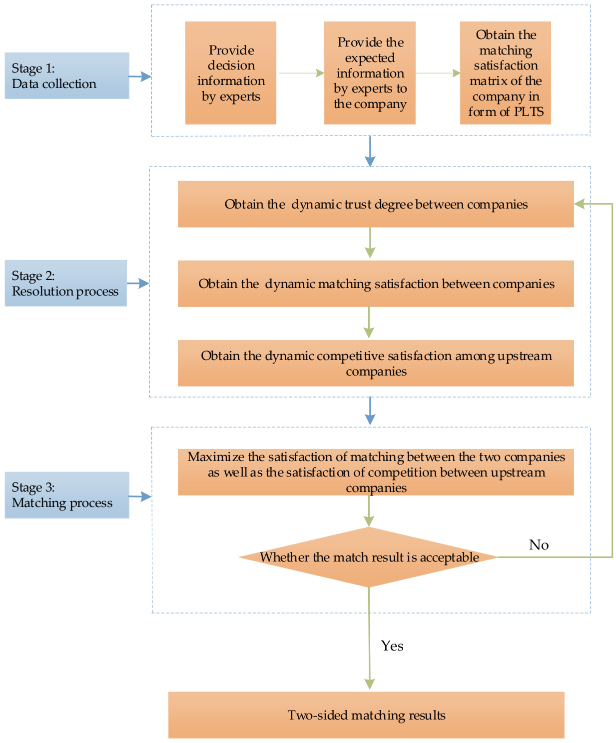

Figure 5. The schematic diagram of the proposed model for social network two-sided matching.

5. An Empirical Study of Virtual Power Plants

In this section, a numerical empirical case concerning the mutual selection of VPP companies and DER companies in a social network environment is adopted to demonstrate the applicability and the detailed implementation process of our proposed method.

5.1. Decision Background

With the aim of helping the VPP companies and the DER companies to better achieve the two-sided matching, the third-party platform now receives the matching information from four VPP companies (a_1, a_2, a_3, a_4) and four DER companies (b_1, b_2, b_3, b_4). The social trust relationship among companies can be shown in Figure 6.

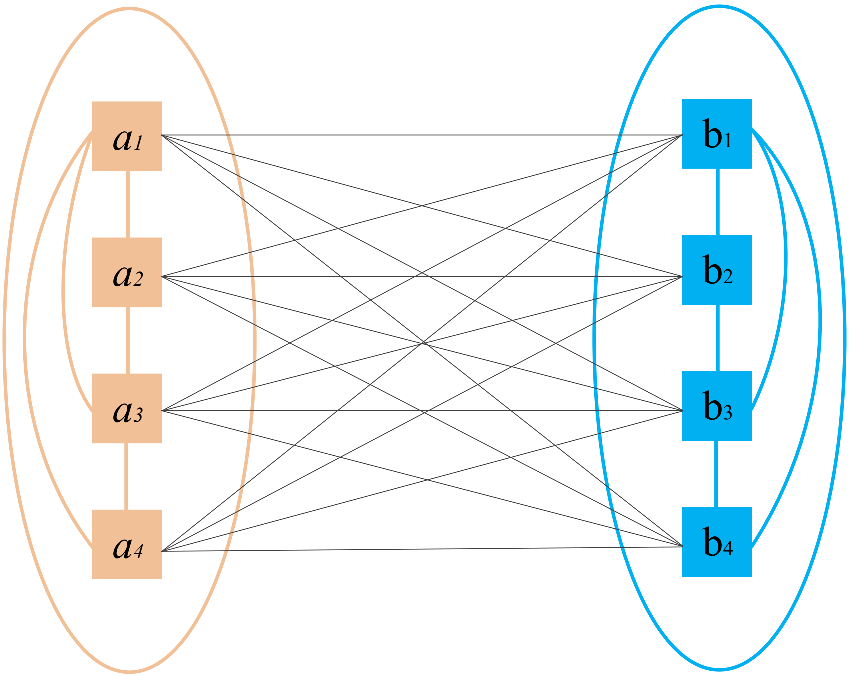

Figure 6. The schematic diagram of two-sided matching based on the social network among companies.

Recognizing the incomplete knowledge of other companies, companies may consult their most trusted social network company and the most authoritative company in the industry to determine if the candidate is worthy of being selected. For this purpose, we also need to collect the assessment information between the same type of companies.

Based on the opinions of experts in the relevant field and surveys of companies, the following evaluation indicators are given. The set of evaluation indicators for VPP companies are as follows: c_1, c_2, c_3, c_4, representing quality, price, service capacity and technology level; the set of evaluation indicators for DER companies are as follows: d_1, d_2, d_3, d_4, representing quality, price, service capacity and economic strength. The indicators for mutual evaluation between companies are as follows: f_1, f_2, f_3, f_4, representing quality, price, service capacity and technology level.

Due to the ambiguity and uncertainty of the evaluation information given by the group members, this study employs intuitive linguistic figures to describe the evaluation indicators. In the example, based on the linguistic term set $S = \{s_{-2} : \text{none}, s_{-1} : \text{low}, s_0 : \text{medium}, s_1 : \text{high}, s_2 : \text{perfect}\}$, ten relevant experts from one company provide evaluation information of each other company. For example, company a_1's evaluation information about company a_2 regarding attribute c_1 at moment z_1, among the ten experts, two experts give "low", one expert gives "medium", three experts give "high", three experts give "perfect" and one expert does not provide his/her evaluation. At this time, the evaluation information from company a_1 to company a_2 about attribute c_1 at moment z_1 can be represented by the PLTS $\{s_{-1}(0.2), s_0(0.1),\ s_1(0.3), s_2(0.3)\}$.

In addition, for the convenience of the calculation, we assume that the evaluation indicators are equally important.

5.2. Implement

Obviously, the problem shown in Section 4.1. is a social network two-sided matching decision-making problem with probability linguistic information. In this part, we apply the proposed method to solve this problem. The solving process and computation results are summarized as follows:

Stage 1. Data collection

Step 1. Collect the evaluation information and expectation evaluation information from both sides, and then organize it in the form of PLTS. The specific evaluation information is shown in Tables 1–8. Additionally, the VPP company's investments are shown in Table 9.

Table 1. Probabilistic linguistic evaluation information of VPP companies to DER companies.

		b_1	b_2	b_3	b_4
a_1	c_1	$\{s_{-2}(0.1), s_{-1}(0.05), s_0(0.25), s_1(0.2), s_2(0.4)\}$	$\{s_{-2}(0.2), s_{-1}(0.25), s_0(0.2), s_1(0.3), s_2(0.05)\}$	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.2), s_1(0.3), s_2(0.05)\}$	$\{s_{-2}(0.1), s_{-1}(0.3), s_0(0.35), s_1(0.2), s_2(0.05)\}$
	c_2	$\{s_{-2}(0.05), s_{-1}(0.3), s_0(0.1), s_1(0.1), s_2(0.45)\}$	$\{s_{-2}(0.1), s_{-1}(0.05), s_0(0.25), s_1(0.2), s_2(0.4)\}$	$\{s_{-2}(0.1), s_{-1}(0.3), s_0(0.1), s_1(0.4), s_2(0.1)\}$	$\{s_{-2}(0.3), s_{-1}(0.2), s_0(0.3), s_1(0.1), s_2(0.1)\}$
	c_3	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.2), s_1(0.25), s_2(0.2)\}$	$\{s_{-2}(0.15), s_{-1}(0.15), s_0(0.2), s_1(0.3), s_2(0.2)\}$	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.15), s_1(0.25), s_2(0.25)\}$	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.2), s_1(0.25), s_2(0.2)\}$
	c_4	$\{s_{-2}(0.05), s_{-1}(0.15), s_0(0.3), s_1(0.1), s_2(0.4)\}$	$\{s_{-2}(0.2), s_{-1}(0.05), s_0(0.25), s_1(0.35), s_2(0.15)\}$	$\{s_{-2}(0.1), s_{-1}(0.2), s_0(0.2), s_1(0.1), s_2(0.4)\}$	$\{s_{-2}(0.2), s_{-1}(0.2), s_0(0.35), s_1(0.15), s_2(0.1)\}$
a_2	c_1	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.15), s_1(0.25), s_2(0.25)\}$	$\{s_{-2}(0.05), s_{-1}(0.15), s_0(0.25), s_1(0.4), s_2(0.15)\}$	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.15), s_1(0.3), s_2(0.1)\}$	$\{s_{-2}(0.1), s_{-1}(0.25), s_0(0.1), s_1(0.35), s_2(0.2)\}$
	c_2	$\{s_{-2}(0.15), s_{-1}(0.05), s_0(0.35), s_1(0.1), s_2(0.35)\}$	$\{s_{-2}(0.15), s_{-1}(0.3), s_0(0.1), s_1(0.2), s_2(0.25)\}$	$\{s_{-2}(0.1), s_{-1}(0.35), s_0(0.1), s_1(0.25), s_2(0.2)\}$	$\{s_{-2}(0.15), s_{-1}(0.25), s_0(0.2), s_1(0.1), s_2(0.3)\}$
	c_3	$\{s_{-2}(0.1), s_{-1}(0.05), s_0(0.4), s_1(0.15), s_2(0.3)\}$	$\{s_{-2}(0.2), s_{-1}(0.35), s_0(0.2), s_1(0.15), s_2(0.1)\}$	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.15), s_1(0.25), s_2(0.25)\}$	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.1), s_1(0.15), s_2(0.3)\}$
	c_4	$\{s_{-2}(0.15), s_{-1}(0.4), s_0(0.05), s_1(0.2), s_2(0.2)\}$	$\{s_{-2}(0.1), s_{-1}(0.25), s_0(0.15), s_1(0.3), s_2(0.2)\}$	$\{s_{-2}(0.1), s_{-1}(0.25), s_0(0.2), s_1(0.1), s_2(0.35)\}$	$\{s_{-2}(0.1), s_{-1}(0.05), s_0(0.5), s_1(0.25), s_2(0.1)\}$
a_3	c_1	$\{s_{-2}(0.05), s_{-1}(0.35), s_0(0.25), s_1(0.3), s_2(0.05)\}$	/	$\{s_{-2}(0.2), s_{-1}(0.05), s_0(0.15), s_1(0.35), s_2(0.25)\}$	$\{s_{-2}(0.1), s_{-1}(0.15), s_0(0.2), s_1(0.4), s_2(0.15)\}$
	c_2	$\{s_{-2}(0.1), s_{-1}(0.2), s_0(0.15), s_1(0.05), s_2(0.5)\}$	$\{s_{-2}(0.1), s_{-1}(0.35), s_0(0.35), s_1(0.1), s_2(0.1)\}$	$\{s_{-2}(0.1), s_{-1}(0.05), s_0(0.2), s_1(0.3), s_2(0.35)\}$	$\{s_{-2}(0.2), s_{-1}(0.25), s_0(0.15), s_1(0.25), s_2(0.15)\}$
	c_3	$\{s_{-2}(0.15), s_{-1}(0.05), s_0(0.1), s_1(0.2), s_2(0.5)\}$	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.15), s_1(0.05), s_2(0.45)\}$	$\{s_{-2}(0.3), s_{-1}(0.1), s_0(0.25), s_1(0.25), s_2(0.1)\}$	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.15), s_1(0.1), s_2(0.3)\}$
	c_4	$\{s_{-2}(0.25), s_{-1}(0.3), s_0(0.25), s_1(0.05), s_2(0.15)\}$	$\{s_{-2}(0.2), s_{-1}(0.1), s_0(0.2), s_1(0.3), s_2(0.2)\}$	$\{s_{-2}(0.2), s_{-1}(0.35), s_0(0.1), s_1(0.15), s_2(0.2)\}$	$\{s_{-2}(0.15), s_{-1}(0.05), s_0(0.1), s_1(0.15), s_2(0.55)\}$
a_4	c_1	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.15), s_1(0.05), s_2(0.45)\}$	$\{s_{-2}(0.1), s_{-1}(0.35), s_0(0.25), s_1(0.15), s_2(0.15)\}$	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.2), s_1(0.25), s_2(0.2)\}$	$\{s_{-2}(0.25), s_{-1}(0.15), s_0(0.25), s_1(0.1), s_2(0.25)\}$
	c_2	$\{s_{-2}(0.15), s_{-1}(0.15), s_0(0.05), s_1(0.35), s_2(0.3)\}$	$\{s_{-2}(0.1), s_{-1}(0.05), s_0(0.2), s_1(0.25), s_2(0.4)\}$	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.2), s_1(0.15), s_2(0.3)\}$	$\{s_{-2}(0.1), s_{-1}(0.1), s_0(0.25), s_1(0.35), s_2(0.2)\}$
	c_3	$\{s_{-2}(0.05), s_{-1}(0.4), s_0(0.25), s_1(0.15), s_2(0.15)\}$	$\{s_{-2}(0.05), s_{-1}(0.35), s_0(0.15), s_1(0.1), s_2(0.35)\}$	$\{s_{-2}(0.1), s_{-1}(0.2), s_0(0.25), s_1(0.2), s_2(0.25)\}$	$\{s_{-2}(0.05), s_{-1}(0.2), s_0(0.15), s_1(0.5), s_2(0.1)\}$
	c_4	$\{s_{-2}(0.1), s_{-1}(0.2), s_0(0.35), s_1(0.05), s_2(0.3)\}$	$\{s_{-2}(0.2), s_{-1}(0.35), s_0(0.1), s_1(0.2), s_2(0.15)\}$	$\{s_{-2}(0.1), s_{-1}(0.05), s_0(0.1), s_1(0.25), s_2(0.5)\}$	$\{s_{-2}(0.1), s_{-1}(0.15), s_0(0.35), s_1(0.1), s_2(0.3)\}$

Table 2. Probabilistic linguistic evaluation information of DER companies to VPP companies.

		a_1	a_2	a_3	a_4
b_1	d_1	$\{s_{-2}(0.2), s_{-1}(0.25), s_0(0.1), s_1(0.1), s_2(0.35)\}$	$\{s_{-2}(0.05), s_{-1}(0.25), s_0(0.2), s_1(0.25), s_2(0.25)\}$	$\{s_{-2}(0.25), s_{-1}(0.15), s_0(0.35), s_1(0.1), s_2(0.15)\}$	$\{s_{-2}(0.2), s_{-1}(0.1), s_0(0.15), s_1(0.2), s_2(0.35)\}$
	d_2	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.15), s_1(0.1), s_2(0.3)\}$	$\{s_{-2}(0.1), s_{-1}(0.15), s_0(0.4), s_1(0.2), s_2(0.15)\}$	$\{s_{-2}(0.15), s_{-1}(0.05), s_0(0.25), s_1(0.35), s_2(0.2)\}$	$\{s_{-2}(0.1), s_{-1}(0.25), s_0(0.15), s_1(0.35), s_2(0.15)\}$
	d_3	$\{s_{-2}(0.15), s_{-1}(0.05), s_0(0.35), s_1(0.4), s_2(0.05)\}$	$\{s_{-2}(0.05), s_{-1}(0.35), s_0(0.15), s_1(0.1), s_2(0.35)\}$	$\{s_{-2}(0.05), s_{-1}(0.1), s_0(0.15), s_1(0.35), s_2(0.35)\}$	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.05), s_1(0.1), s_2(0.5)\}$
	d_4	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.2), s_1(0.15), s_2(0.3)\}$	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.1), s_1(0.25), s_2(0.3)\}$	$\{s_{-2}(0.05), s_{-1}(0.05), s_0(0.1), s_1(0.1), s_2(0.7)\}$	$\{s_{-2}(0.25), s_{-1}(0.15), s_0(0.2), s_1(0.25), s_2(0.15)\}$
b_2	d_1	$\{s_{-2}(0.05), s_{-1}(0.35), s_0(0.15), s_1(0.15), s_2(0.3)\}$	$\{s_{-2}(0.1), s_{-1}(0.15), s_0(0.15), s_1(0.2), s_2(0.4)\}$	$\{s_{-2}(0.35), s_{-1}(0.2), s_0(0.1), s_1(0.2), s_2(0.15)\}$	$\{s_{-2}(0.05), s_{-1}(0.15),s_0(0.05), s_1(0.35), s_2(0.4)\}$
	d_2	$\{s_{-2}(0.3), s_{-1}(0.1), s_0(0.2), s_1(0.2), s_2(0.2)\}$	$\{s_{-2}(0.35), s_{-1}(0.1), s_0(0.3), s_1(0.15), s_2(0.1)\}$	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.1), s_1(0.35), s_2(0.2)\}$	$\{s_{-2}(0.2), s_{-1}(0.1), s_0(0.15), s_1(0.2), s_2(0.35)\}$
	d_3	$\{s_{-2}(0.15), s_{-1}(0.3), s_0(0.05), s_1(0.05), s_2(0.45)\}$	$\{s_{-2}(0.25), s_{-1}(0.15), s_0(0.2), s_1(0.05), s_2(0.35)\}$	$\{s_{-2}(0.1), s_{-1}(0.15), s_0(0.1), s_1(0.05), s_2(0.6)\}$	$\{s_{-2}(0.1), s_{-1}(0.1), s_0(0.15), s_1(0.1), s_2(0.55)\}$
	d_4	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.1), s_1(0.15), s_2(0.4)\}$	$\{s_{-2}(0.15), s_{-1}(0.2), s_0(0.05), s_1(0.1), s_2(0.5)\}$	$\{s_{-2}(0.15), s_{-1}(0.2), s_0(0.15), s_1(0.35), s_2(0.15)\}$	$\{s_{-2}(0.05), s_{-1}(0.15), s_0(0.2), s_1(0.05), s_2(0.55)\}$
b_3	d_1	$\{s_{-2}(0.1), s_{-1}(0.15), s_0(0.25), s_1(0.1), s_2(0.4)\}$	$\{s_{-2}(0.1), s_{-1}(0.05), s_0(0.35), s_1(0.1), s_2(0.4)\}$	/	$\{s_{-2}(0.2), s_{-1}(0.1), s_0(0.15), s_1(0.2), s_2(0.35)\}$
	d_2	$\{s_{-2}(0.05), s_{-1}(0.2), s_0(0.5), s_1(0.15), s_2(0.1)\}$	$\{s_{-2}(0.15), s_{-1}(0.05), s_0(0.25), s_1(0.35), s_2(0.2)\}$	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.05), s_1(0.05), s_2(0.55)\}$	$\{s_{-2}(0.1), s_{-1}(0.15), s_0(0.35), s_1(0.05), s_2(0.35)\}$
	d_3	$\{s_{-2}(0.2), s_{-1}(0.25), s_0(0.2), s_1(0.15), s_2(0.2)\}$	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.05), s_1(0.2), s_2(0.4)\}$	$\{s_{-2}(0.2), s_{-1}(0.35), s_0(0.2), s_1(0.2), s_2(0.05)\}$	$\{s_{-2}(0.35), s_{-1}(0.25), s_0(0.05), s_1(0.15), s_2(0.2)\}$
	d_4	$\{s_{-2}(0.15), s_{-1}(0.05), s_0(0.15), s_1(0.2), s_2(0.45)\}$	$\{s_{-2}(0.05), s_{-1}(0.2), s_0(0.15), s_1(0.1), s_2(0.5)\}$	$\{s_{-2}(0.05), s_{-1}(0.1), s_0(0.15), s_1(0.1), s_2(0.6)\}$	$\{s_{-2}(0.2), s_{-1}(0.05), s_0(0.15), s_1(0.1), s_2(0.5)\}$
b_4	d_1	$\{s_{-2}(0.1), s_{-1}(0.15), s_0(0.4), s_1(0.2), s_2(0.15)\}$	$\{s_{-2}(0.1), s_{-1}(0.2), s_0(0.25), s_1(0.35), s_2(0.1)\}$	$\{s_{-2}(0.15), s_{-1}(0.1), s_0(0.2), s_1(0.25), s_2(0.3)\}$	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.2), s_1(0.2), s_2(0.25)\}$
	d_2	$\{s_{-2}(0.15), s_{-1}(0.05), s_0(0.35), s_1(0.25), s_2(0.2)\}$	$\{s_{-2}(0.05), s_{-1}(0.25), s_0(0.1), s_1(0.05), s_2(0.55)\}$	$\{s_{-2}(0.1), s_{-1}(0.1), s_0(0.35), s_1(0.15), s_2(0.3)\}$	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.35), s_1(0.1), s_2(0.2)\}$
	d_3	$\{s_{-2}(0.15), s_{-1}(0.1), s_0(0.25), s_1(0.05), s_2(0.45)\}$	$\{s_{-2}(0.1), s_{-1}(0.05), s_0(0.2), s_1(0.05), s_2(0.6)\}$	$\{s_{-2}(0.25), s_{-1}(0.15), s_0(0.1), s_1(0.05), s_2(0.45)\}$	$\{s_{-2}(0.1), s_{-1}(0.25), s_0(0.15), s_1(0.1), s_2(0.4)\}$
	d_4	$\{s_{-2}(0.05), s_{-1}(0.05), s_0(0.15), s_1(0.3), s_2(0.45)\}$	$\{s_{-2}(0.15), s_{-1}(0.3), s_0(0.15), s_1(0.1), s_2(0.3)\}$	$\{s_{-2}(0.05), s_{-1}(0.1), s_0(0.35), s_1(0.1), s_2(0.4)\}$	$\{s_{-2}(0.05), s_{-1}(0.1), s_0(0.05), s_1(0.15), s_2(0.65)\}$

Table 3. Probabilistic linguistic mutual evaluation information among VPP companies.

		$\mathbf{a_1}$	$\mathbf{a_2}$	$\mathbf{a_3}$	$\mathbf{a_4}$
a_1	f_1	/	/	$\{s_{-2}(0.2), s_{-1}(0.3), s_0(0.25), s_1(0.1), s_2(0.15)\}$	$\{s_{-2}(0.25), s_{-1}(0.15), s_0(0.35), s_1(0.2), s_2(0.1)\}$
	f_2	/	$\{s_{-2}(0.2), s_{-1}(0.25), s_0(0.2), s_1(0.15), s_2(0.2)\}$	$\{s_{-2}(0.15), s_{-1}(0.2), s_0(0.05), s_1(0.2), s_2(0.4)\}$	$\{s_{-2}(0.05), s_{-1}(0.05), s_0(0.2), s_1(0.3), s_2(0.4)\}$
	f_3	/	$\{s_{-2}(0.05), s_{-1}(0.05), s_0(0.3), s_1(0.1), s_2(0.5)\}$	$\{s_{-2}(0.35), s_{-1}(0.15), s_0(0.1), s_1(0.25), s_2(0.15)\}$	$\{s_{-2}(0.2), s_{-1}(0.05), s_0(0.15), s_1(0.35), s_2(0.25)\}$
	f_4	/	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.35), s_1(0.25), s_2(0.05)\}$	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.15), s_1(0.35), s_2(0.15)\}$	$\{s_{-2}(0.1), s_{-1}(0.2), s_0(0.25), s_1(0.05), s_2(0.4)\}$
a_2	f_1	$\{s_{-2}(0.05), s_{-1}(0.15), s_0(0.05), s_1(0.25), s_2(0.5)\}$	/	$\{s_{-2}(0.15), s_{-1}(0.15), s_0(0.05), s_1(0.2), s_2(0.45)\}$	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.2), s_1(0.15), s_2(0.3)\}$
	f_2	$\{s_{-2}(0.1), s_{-1}(0.4), s_0(0.35), s_1(0.05), s_2(0.1)\}$	/	$\{s_{-2}(0.2), s_{-1}(0.1), s_0(0.35), s_1(0.25), s_2(0.1)\}$	$\{s_{-2}(0.35), s_{-1}(0.05), s_0(0.05), s_1(0.1), s_2(0.45)\}$
	f_3	$\{s_{-2}(0.15), s_{-1}(0.2), s_0(0.25), s_1(0.2), s_2(0.2)\}$	/	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.05), s_1(0.15), s_2(0.35)\}$	$\{s_{-2}(0.2), s_{-1}(0.3), s_0(0.35), s_1(0.15), s_2(0.0)\}$
	f_4	$\{s_{-2}(0.1), s_{-1}(0.1), s_0(0.15), s_1(0.05), s_2(0.6)\}$	/	$\{s_{-2}(0.05), s_{-1}(0.25), s_0(0.2), s_1(0.15), s_2(0.35)\}$	$\{s_{-2}(0.05), s_{-1}(0.35), s_0(0.05), s_1(0.2), s_2(0.35)\}$
a_3	f_1	$\{s_{-2}(0.15), s_{-1}(0.2), s_0(0.25), s_1(0.05), s_2(0.35)\}$	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.25), s_1(0.05), s_2(0.35)\}$	/	$\{s_{-2}(0.05), s_{-1}(0.15), s_0(0.2), s_1(0.25), s_2(0.35)\}$
	f_2	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.2), s_1(0.15), s_2(0.3)\}$	$\{s_{-2}(0.15), s_{-1}(0.2), s_0(0.1), s_1(0.2), s_2(0.35)\}$	/	$\{s_{-2}(0.3), s_{-1}(0.25), s_0(0.1), s_1(0.25), s_2(0.1)\}$
	f_3	$\{s_{-2}(0.25), s_{-1}(0.15), s_0(0.2), s_1(0.15), s_2(0.25)\}$	$\{s_{-2}(0.2), s_{-1}(0.25), s_0(0.25), s_1(0.05), s_2(0.25)\}$	/	$\{s_{-2}(0.1), s_{-1}(0.15), s_0(0.15), s_1(0.05), s_2(0.55)\}$
	f_4	$\{s_{-2}(0.15), s_{-1}(0.2), s_0(0.15), s_1(0.2), s_2(0.3)\}$	$\{s_{-2}(0.15), s_{-1}(0.05), s_0(0.1), s_1(0.25), s_2(0.45)\}$	/	$\{s_{-2}(0.15), s_{-1}(0.2), s_0(0.1), s_1(0.1), s_2(0.45)\}$
a_4	f_1	$\{s_{-2}(0.4), s_{-1}(0.2), s_0(0.25), s_1(0.05), s_2(0.1)\}$	$\{s_{-2}(0.1), s_{-1}(0.15), s_0(0.25), s_1(0.2), s_2(0.3)\}$	$\{s_{-2}(0.1), s_{-1}(0.2), s_0(0.2), s_1(0.25), s_2(0.25)\}$	/
	f_2	$\{s_{-2}(0.35), s_{-1}(0.05), s_0(0.2), s_1(0.1), s_2(0.3)\}$	$\{s_{-2}(0.2), s_{-1}(0.2), s_0(0.2), s_1(0.15), s_2(0.25)\}$	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.15), s_1(0.05), s_2(0.45)\}$	/
	f_3	$\{s_{-2}(0.25), s_{-1}(0.15), s_0(0.15), s_1(0.2), s_2(0.25)\}$	$\{s_{-2}(0.15), s_{-1}(0.35), s_0(0.15), s_1(0.05), s_2(0.35)\}$	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.1), s_1(0.1), s_2(0.35)\}$	/
	f_4	$\{s_{-2}(0.15), s_{-1}(0.1), s_0(0.1), s_1(0.25), s_2(0.4)\}$	$\{s_{-2}(0.15), s_{-1}(0.1), s_0(0.1), s_1(0.25), s_2(0.4)\}$	$\{s_{-2}(0.2), s_{-1}(0.25), s_0(0.1), s_1(0.35), s_2(0.1)\}$	/

Table 4. Probabilistic linguistic mutual evaluation information among DER companies.

		$\mathbf{b_1}$	$\mathbf{b_2}$	$\mathbf{b_3}$	$\mathbf{b_4}$
b_1	f_1	/	$\{s_{-2}(0.4), s_{-1}(0.2), s_0(0.15), s_1(0.2), s_2(0.05)\}$	$\{s_{-2}(0.25), s_{-1}(0.25), s_0(0.1), s_1(0.2), s_2(0.2)\}$	$\{s_{-2}(0.05), s_{-1}(0.25), s_0(0.15), s_1(0.1), s_2(0.45)\}$
	f_2	/	$\{s_{-2}(0.35), s_{-1}(0.25), s_0(0.2), s_1(0.1), s_2(0.1)\}$	$\{s_{-2}(0.2), s_{-1}(0.25), s_0(0.15), s_1(0.2), s_2(0.2)\}$	$\{s_{-2}(0.2), s_{-1}(0.1), s_0(0.2), s_1(0.2), s_2(0.3)\}$
	f_3	/	$\{s_{-2}(0.05), s_{-1}(0.2), s_0(0.25), s_1(0.2), s_2(0.3)\}$	$\{s_{-2}(0.25), s_{-1}(0.05), s_0(0.15), s_1(0.1), s_2(0.45)\}$	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.25), s_1(0.1), s_2(0.3)\}$
	f_4	/	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.1), s_1(0.25), s_2(0.3)\}$	$\{s_{-2}(0.1), s_{-1}(0.2), s_0(0.2), s_1(0.2), s_2(0.3)\}$	$\{s_{-2}(0.2), s_{-1}(0.25), s_0(0.25), s_1(0.15), s_2(0.15)\}$
b_2	f_1	$\{s_{-2}(0.2), s_{-1}(0.25), s_0(0.05), s_1(0.1), s_2(0.4)\}$	/	$\{s_{-2}(0.05), s_{-1}(0.3), s_0(0.35), s_1(0.25), s_2(0.05)\}$	$\{s_{-2}(0.05), s_{-1}(0.15), s_0(0.05), s_1(0.25), s_2(0.5)\}$
	f_2	$\{s_{-2}(0.1), s_{-1}(0.25), s_0(0.1), s_1(0.2), s_2(0.35)\}$	/	$\{s_{-2}(0.1), s_{-1}(0.25), s_0(0.05), s_1(0.2), s_2(0.4)\}$	$\{s_{-2}(0.1), s_{-1}(0.05), s_0(0.15), s_1(0.1), s_2(0.6)\}$
	f_3	$\{s_{-2}(0.2), s_{-1}(0.05), s_0(0.25), s_1(0.05), s_2(0.45)\}$	/	$\{s_{-2}(0.25), s_{-1}(0.15), s_0(0.25), s_1(0.2), s_2(0.15)\}$	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.2), s_1(0.25), s_2(0.2)\}$
	f_4	$\{s_{-2}(0.1), s_{-1}(0.15), s_0(0.1), s_1(0.2), s_2(0.45)\}$	/	$\{s_{-2}(0.05), s_{-1}(0.1), s_0(0.2), s_1(0.05), s_2(0.6)\}$	$\{s_{-2}(0.05), s_{-1}(0.1), s_0(0.05), s_1(0.25), s_2(0.55)\}$
b_3	f_1	$\{s_{-2}(0.2), s_{-1}(0.2), s_0(0.15), s_1(0.35), s_2(0.1)\}$	$\{s_{-2}(0.2), s_{-1}(0.25), s_0(0.1), s_1(0.1), s_2(0.35)\}$	/	$\{s_{-2}(0.25), s_{-1}(0.15), s_0(0.1), s_1(0.25), s_2(0.25)\}$
	f_2	$\{s_{-2}(0.15), s_{-1}(0.15), s_0(0.1), s_1(0.25), s_2(0.35)\}$	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.2), s_1(0.15), s_2(0.3)\}$	/	$\{s_{-2}(0.15), s_{-1}(0.2), s_0(0.2), s_1(0.15), s_2(0.3)\}$
	f_3	$\{s_{-2}(0.1), s_{-1}(0.35), s_0(0.25), s_1(0.15), s_2(0.15)\}$	$\{s_{-2}(0.05), s_{-1}(0.2), s_0(0.15), s_1(0.3), s_2(0.3)\}$	/	$\{s_{-2}(0.1), s_{-1}(0.2), s_0(0.15), s_1(0.05), s_2(0.5)\}$
	f_4	$\{s_{-2}(0.1), s_{-1}(0.2), s_0(0.15), s_1(0.1), s_2(0.45)\}$	$\{s_{-2}(0.1), s_{-1}(0.15), s_0(0.2), s_1(0.25), s_2(0.3)\}$	/	$\{s_{-2}(0.1), s_{-1}(0.25), s_0(0.2), s_1(0.15), s_2(0.3)\}$
b_4	f_1	$\{s_{-2}(0.15), s_{-1}(0.25), s_0(0.25), s_1(0.15), s_2(0.2)\}$	$\{s_{-2}(0.15), s_{-1}(0.35), s_0(0.25), s_1(0.15), s_2(0.12)\}$	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.25), s_1(0.2), s_2(0.2)\}$	/
	f_2	$\{s_{-2}(0.2), s_{-1}(0.1), s_0(0.15), s_1(0.1), s_2(0.45)\}$	$\{s_{-2}(0.15), s_{-1}(0.1), s_0(0.2), s_1(0.15), s_2(0.4)\}$	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.15), s_1(0.15), s_2(0.35)\}$	/
	f_3	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.2), s_1(0.2), s_2(0.15)\}$	$\{s_{-2}(0.1), s_{-1}(0.2), s_0(0.15), s_1(0.2), s_2(0.35)\}$	$\{s_{-2}(0.3), s_{-1}(0.1), s_0(0.2), s_1(0.15), s_2(0.25)\}$	/
	f_4	$\{s_{-2}(0.35), s_{-1}(0.25), s_0(0.15), s_1(0.1), s_2(0.15)\}$	$\{s_{-2}(0.15), s_{-1}(0.2), s_0(0.1), s_1(0.15), s_2(0.4)\}$	$\{s_{-2}(0.35), s_{-1}(0.25), s_0(0.15), s_1(0.05), s_2(0.2)\}$	/

Table 5. Probabilistic linguistic expectation evaluation information of VPP companies to DER companies.

	c_1	c_2	c_3	c_4
a_1	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.3), s_1(0.2), s_2(0.05)\}$	$\{s_{-2}(0.3), s_{-1}(0.2), s_0(0.3), s_1(0.1), s_2(0.1)\}$	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.2), s_1(0.25), s_2(0.2)\}$	$\{s_{-2}(0.2), s_{-1}(0.2), s_0(0.35), s_1(0.15), s_2(0.1)\}$
a_2	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.15), s_1(0.3), s_2(0.1)\}$	$\{s_{-2}(0.15), s_{-1}(0.3), s_0(0.15), s_1(0.2), s_2(0.2)\}$	$\{s_{-2}(0.25), s_{-1}(0.3), s_0(0.2), s_1(0.15), s_2(0.1)\}$	$\{s_{-2}(0.15), s_{-1}(0.4), s_0(0.1), s_1(0.25), s_2(0.1)\}$
a_3	$\{s_{-2}(0.3), s_{-1}(0.25), s_0(0.25), s_1(0.15), s_2(0.05)\}$	$\{s_{-2}(0.2), s_{-1}(0.25), s_0(0.35), s_1(0.1), s_2(0.1)\}$	$\{s_{-2}(0.3), s_{-1}(0.15), s_0(0.2), s_1(0.25), s_2(0.1)\}$	$\{s_{-2}(0.25), s_{-1}(0.3), s_0(0.25), s_1(0.05), s_2(0.15)\}$
a_4	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.25), s_1(0.15), s_2(0.15)\}$	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.2), s_1(0.25), s_2(0.2)\}$	$\{s_{-2}(0.1), s_{-1}(0.35), s_0(0.25), s_1(0.2), s_2(0.1)\}$	$\{s_{-2}(0.2), s_{-1}(0.35), s_0(0.1), s_1(0.2), s_2(0.15)\}$

Table 6. Probabilistic linguistic expectation evaluation information of DER companies to VPP companies.

	d_1	d_2	d_3	d_4
b_1	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.3), s_1(0.1), s_2(0.15)\}$	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.2), s_1(0.2), s_2(0.15)\}$	$\{s_{-2}(0.2), s_{-1}(0.2), s_0(0.15), s_1(0.4), s_2(0.05)\}$	$\{s_{-2}(0.25), s_{-1}(0.15), s_0(0.2), s_1(0.25), s_2(0.15)\}$
b_2	$\{s_{-2}(0.35), s_{-1}(0.2), s_0(0.1), s_1(0.2), s_2(0.15)\}$	$\{s_{-2}(0.35), s_{-1}(0.1), s_0(0.3), s_1(0.15), s_2(0.1)\}$	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.15), s_1(0.05), s_2(0.35)\}$	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.15), s_1(0.35), s_2(0.15)\}$
b_3	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.15), s_1(0.15), s_2(0.35)\}$	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.4), s_1(0.15), s_2(0.05)\}$	$\{s_{-2}(0.35), s_{-1}(0.2), s_0(0.1), s_1(0.2), s_2(0.15)\}$	$\{s_{-2}(0.2), s_{-1}(0.2), s_0(0.1), s_1(0.2), s_2(0.15)\}$
b_4	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.3), s_1(0.25), s_2(0.1)\}$	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.35), s_1(0.1), s_2(0.2)\}$	$\{s_{-2}(0.25), s_{-1}(0.15), s_0(0.1), s_1(0.1), s_2(0.4)\}$	$\{s_{-2}(0.15), s_{-1}(0.3), s_0(0.15), s_1(0.1), s_2(0.3)\}$

Table 7. Probabilistic linguistic expectation evaluation information among VPP companies.

	c_1	c_2	c_3	c_4
a_1	$\{s_{-2}(0.2), s_{-1}(0.3), s_0(0.25), s_1(0.15), s_2(0.1)\}$	$\{s_{-2}(0.2), s_{-1}(0.25), s_0(0.2), s_1(0.15), s_2(0.2)\}$	$\{s_{-2}(0.35), s_{-1}(0.15), s_0(0.1), s_1(0.25), s_2(0.15)\}$	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.35), s_1(0.25), s_2(0.05)\}$
a_2	$\{s_{-2}(0.3), s_{-1}(0.15), s_0(0.1), s_1(0.15), s_2(0.3)\}$	$\{s_{-2}(0.35), s_{-1}(0.15), s_0(0.35), s_1(0.05), s_2(0.1)\}$	$\{s_{-2}(0.25), s_{-1}(0.25), s_0(0.35), s_1(0.15), s_2(0)\}$	$\{s_{-2}(0.1), s_{-1}(0.3), s_0(0.1), s_1(0.15), s_2(0.35)\}$
a_3	$\{s_{-2}(0.2), s_{-1}(0.25), s_0(0.15), s_1(0.05), s_2(0.35)\}$	$\{s_{-2}(0.3), s_{-1}(0.25), s_0(0.1), s_1(0.25), s_2(0.1)\}$	$\{s_{-2}(0.35), s_{-1}(0.1), s_0(0.25), s_1(0.05), s_2(0.25)\}$	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.2), s_1(0.15), s_2(0.3)\}$
a_4	$\{s_{-2}(0.4), s_{-1}(0.2), s_0(0.25), s_1(0.05), s_2(0.1)\}$	$\{s_{-2}(0.35), s_{-1}(0.05), s_0(0.2), s_1(0.15), s_2(0.25)\}$	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.15), s_1(0.15), s_2(0.25)\}$	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.1), s_1(0.35), s_2(0.1)\}$

Table 8. Probabilistic linguistic expectation evaluation information among DER companies.

	d_1	d_2	d_3	d_4
b_1	$\{s_{-2}(0.4), s_{-1}(0.2), s_0(0.15), s_1(0.2), s_2(0.05)\}$	$\{s_{-2}(0.35), s_{-1}(0.25), s_0(0.25), s_1(0.1), s_2(0.05)\}$	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.25), s_1(0.1), s_2(0.3)\}$	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.25), s_1(0.15), s_2(0.15)\}$
b_2	$\{s_{-2}(0.2), s_{-1}(0.25), s_0(0.25), s_1(0.25), s_2(0.05)\}$	$\{s_{-2}(0.1), s_{-1}(0.25), s_0(0.1), s_1(0.2), s_2(0.35)\}$	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.2), s_1(0.2), s_2(0.15)\}$	$\{s_{-2}(0.1), s_{-1}(0.2), s_0(0.05), s_1(0.25), s_2(0.4)\}$
b_3	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.1), s_1(0.35), s_2(0.1)\}$	$\{s_{-2}(0.25), s_{-1}(0.2), s_0(0.2), s_1(0.1), s_2(0.15)\}$	$\{s_{-2}(0.15), s_{-1}(0.3), s_0(0.25), s_1(0.15), s_2(0.15)\}$	$\{s_{-2}(0.2), s_{-1}(0.15), s_0(0.2), s_1(0.15), s_2(0.3)\}$
b_4	$\{s_{-2}(0.25), s_{-1}(0.25), s_0(0.25), s_1(0.15), s_2(0.1)\}$	$\{s_{-2}(0.25), s_{-1}(0.1), s_0(0.15), s_1(0.15), s_2(0.35)\}$	$\{s_{-2}(0.3), s_{-1}(0.15), s_0(0.2), s_1(0.2), s_2(0.15)\}$	$\{s_{-2}(0.35), s_{-1}(0.25), s_0(0.15), s_1(0.1), s_2(0.15)\}$

Table 9. The investment of VPP companies in DER companies (million yuan).

	b_1	b_2	b_3	b_4
a_1	42	28	17	33
a_2	50	20	40	20
a_3	31	27	25	18
a_4	46	34	58	55

Stage 2. Resolution process

Using Equation (1), we obtain the following matching satisfaction degree matrix:

$$[SA_{hj}^{i1}] = \begin{array}{cc} & \begin{array}{cccccccccccccccc} & a_1 & & & & a_2 & & & & a_3 & & & & a_4 & & \\ b_1 & b_2 & b_3 & b_4 & b_1 & b_2 & b_3 & b_4 & b_1 & b_2 & b_3 & b_4 & b_1 & b_2 & b_3 & b_4 \end{array} \\ \begin{array}{c} c_1 \\ c_2 \\ c_3 \\ c_4 \end{array} & \begin{pmatrix} 1.15 & 0.15 & 0.10 & 0.20 & 0.40 & 0.65 & 0.00 & 0.50 & 0.55 & / & 1.00 & 0.95 & 0.60 & 0.75 & 0.10 & 0.40 \\ 1.10 & 1.25 & 0.60 & 0.00 & 0.45 & 0.10 & 0.10 & 0.15 & 0.95 & 1.00 & 0.10 & 0.25 & 0.45 & 0.50 & 0.45 & 0.55 \\ 0.00 & 0.20 & 0.15 & 0.00 & 0.95 & 0.05 & 0.60 & 0.50 & 1.15 & 0.70 & 0.05 & 0.30 & 0.10 & 0.00 & 1.25 & 0.60 \\ 0.90 & 0.45 & 0.75 & 0.00 & 0.15 & 0.50 & 0.60 & 0.45 & 0.00 & 0.65 & 0.25 & 1.35 & 0.50 & 0.00 & 0.00 & 0.00 \end{pmatrix} \end{array}$$

$$[SB_{hi}^{j1}] = \begin{array}{cc} & \begin{array}{cccccccccccccccc} & b_1 & & & & b_2 & & & & b_3 & & & & b_4 & & \\ a_1 & a_2 & a_3 & a_4 & a_1 & a_2 & a_3 & a_4 & a_1 & a_2 & a_3 & a_4 & a_1 & a_2 & a_3 & a_4 \end{array} \\ \begin{array}{c} c_1 \\ c_2 \\ c_3 \\ c_4 \end{array} & \begin{pmatrix} 0.45 & 0.70 & 0.05 & 0.70 & 0.70 & 1.05 & 0.00 & 0.00 & 0.25 & 0.35 & / & 0.10 & 0.30 & 0.30 & 0.60 & 0.25 \\ 0.20 & 0.35 & 0.60 & 0.40 & 0.35 & 0.00 & 0.00 & 0.00 & 0.25 & 0.60 & 0.80 & 0.60 & 0.35 & 0.85 & 0.50 & 0.00 \\ 0.25 & 0.45 & 0.95 & 0.65 & 0.30 & 0.00 & 0.05 & 0.00 & 0.55 & 1.10 & 0.20 & 0.25 & 0.30 & 0.75 & 0.05 & 0.20 \\ 0.25 & 0.35 & 1.45 & 0.00 & 0.30 & 0.00 & 0.00 & 0.00 & 0.15 & 0.20 & 0.50 & 0.05 & 0.95 & 0.00 & 0.60 & 1.15 \end{pmatrix} \end{array}$$

$$[SA_{hi}^{Ak1}] = \begin{array}{cc} & \begin{array}{cccccccccccccccc} & a_1 & & & & a_2 & & & & a_3 & & & & a_4 & & \\ a_1 & a_2 & a_3 & a_4 & a_1 & a_2 & a_3 & a_4 & a_1 & a_2 & a_3 & a_4 & a_1 & a_2 & a_3 & a_4 \end{array} \\ \begin{array}{c} c_1 \\ c_2 \\ c_3 \\ c_4 \end{array} & \begin{pmatrix} / & / & 0.05 & 0.20 & 1.00 & / & 0.65 & 0.15 & 0.15 & 0.10 & / & 0.60 & 0.00 & 1.20 & 1.10 & / \\ / & 0.00 & 0.60 & 1.05 & 0.25 & / & 0.55 & 0.85 & 0.55 & 0.80 & / & 0.00 & 0.05 & 0.15 & 0.50 & / \\ / & 1.25 & 0.00 & 0.70 & 0.70 & / & 0.75 & 0.05 & 0.25 & 0.15 & / & 1.05 & 0.10 & 0.20 & 0.15 & / \\ / & 0.00 & 0.30 & 0.65 & 0.60 & / & 0.15 & 0.10 & 0.10 & 0.60 & / & 0.30 & 0.80 & 0.80 & 0.05 & / \end{pmatrix} \end{array}$$

$$[SB_{hj}^{Bk1}] = \begin{array}{cc} & \begin{array}{cccccccccccccccc} & b_1 & & & & b_2 & & & & b_3 & & & & b_4 & & \\ b_1 & b_2 & b_3 & b_4 & b_1 & b_2 & b_3 & b_4 & b_1 & b_2 & b_3 & b_4 & b_1 & b_2 & b_3 & b_4 \end{array} \\ \begin{array}{c} c_1 \\ c_2 \\ c_3 \\ c_4 \end{array} & \begin{pmatrix} / & 0.00 & 0.55 & 1.35 & 0.55 & / & 0.25 & 1.30 & 0.10 & 0.30 & / & 0.25 & 0.40 & 0.10 & 0.40 & / \\ / & 0.10 & 0.70 & 1.05 & 0.00 & / & 0.10 & 0.60 & 0.80 & 0.45 & / & 0.55 & 0.25 & 0.30 & 0.05 & / \\ / & 0.40 & 0.35 & 0.00 & 0.70 & / & 0.05 & 0.30 & 0.05 & 0.75 & / & 0.80 & 0.05 & 0.75 & 0.20 & / \\ / & 0.50 & 0.65 & 0.05 & 0.10 & / & 0.40 & 0.50 & 0.40 & 0.30 & / & 0.10 & 0.00 & 1.00 & 0.05 & / \end{pmatrix} \end{array}$$

Then, by Equation (2), obtain the dynamic social trust degree between any two companies. Here we let $\lambda = 0.88$, $\eta = 3$ and acquire the past satisfaction evaluation information of companies are 1. The dynamic social trust degree between any two companies can be obtained, as shown in the following matrix $[TD_{klh}^{t}]_{8\times 8}$:

$$TD_{kl1}^{1} = \begin{pmatrix} / & / & 0.670 & 0.722 & 1.052 & 0.705 & 0.687 & 0.722 \\ 1.000 & / & 0.878 & 0.705 & 0.791 & 0.878 & 0.652 & 0.826 \\ 0.705 & 0.687 & / & 0.861 & 0.844 & / & 1.00 & 0.983 \\ 0.652 & 1.071 & 1.035 & / & 0.861 & 0.913 & 0.687 & 0.791 \\ 0.809 & 0.896 & 0.670 & 0.896 & / & 0.652 & 0.844 & 1.122 \\ 0.896 & 1.017 & 0.652 & 0.652 & 0.844 & / & 0.739 & 1.104 \\ 0.739 & 0.774 & / & 0.687 & 0.687 & 0.757 & / & 0.739 \\ 0.757 & 0.757 & 0.861 & 0.739 & 0.791 & 0.687 & 0.791 & / \end{pmatrix}$$

$$TD_{kl2}^{1} = \begin{pmatrix} / & 0.652 & 0.861 & 1.017 & 1.035 & 1.087 & 0.861 & 0.652 \\ 0.739 & / & 0.844 & 0.948 & 0.809 & 0.687 & 0.687 & 0.705 \\ 0.844 & 0.930 & / & 0.652 & 1.000 & 0.687 & 1.035 & 0.739 \\ 0.670 & 0.705 & 0.826 & / & 0.809 & 0.826 & 0.809 & 0.844 \\ 0.722 & 0.774 & 0.861 & 0.791 & / & 0.687 & 0.896 & 1.017 \\ 0.774 & 0.652 & 0.652 & 0.652 & 0.652 & / & 0.687 & 0.861 \\ 0.739 & 0.861 & 0.930 & 0.861 & 0.930 & 0.809 & / & 0.844 \\ 0.774 & 0.948 & 0.826 & 0.652 & 0.739 & 0.757 & 0.670 & / \end{pmatrix}$$

$$TD_{kl3}^{1} = \begin{pmatrix} / & 1.087 & 0.652 & 0.896 & 0.652 & 0.722 & 0.705 & 0.652 \\ 0.896 & / & 0.913 & 0.670 & 0.983 & 0.670 & 0.861 & 0.826 \\ 0.739 & 0.705 & / & 1.017 & 1.052 & 0.896 & 0.670 & 0.757 \\ 0.687 & 0.722 & 0.705 & / & 0.687 & 0.652 & 1.087 & 0.861 \\ 0.739 & 0.809 & 0.983 & 0.878 & / & 0.791 & 0.774 & 0.652 \\ 0.757 & 0.652 & 0.670 & 0.652 & 0.896 & / & 0.670 & 0.757 \\ 0.844 & 1.035 & 0.722 & 0.739 & 0.670 & 0.913 & / & 0.930 \\ 0.757 & 0.913 & 0.670 & 0.722 & 0.670 & 0.913 & 0.722 & / \end{pmatrix}$$

$$TD_{kl4}^{1} = \begin{pmatrix} / & 0.652 & 0.757 & 0.878 & 0.965 & 0.809 & 0.913 & 0.652 \\ 0.861 & / & 0.705 & 0.687 & 0.705 & 0.826 & 0.861 & 0.809 \\ 0.687 & 0.861 & / & 0.757 & 0.652 & 0.878 & 0.739 & 1.122 \\ 0.930 & 0.930 & 0.670 & / & 0.826 & 0.652 & 0.652 & 0.652 \\ 0.739 & 0.774 & 1.156 & 0.652 & / & 0.826 & 0.878 & 0.670 \\ 0.757 & 0.809 & 0.652 & 0.652 & 0.687 & / & 0.791 & 0.826 \\ 0.705 & 0.722 & 0.826 & 0.670 & 0.791 & 0.757 & / & 0.687 \\ 0.983 & 0.652 & 0.861 & 1.052 & 0.652 & 1.000 & 0.670 & / \end{pmatrix}$$

Furthermore, according to Equations (3) and (4), calculate the indirect social trust degree under each attribute at the current moment. For example, for the attribute c_1, the indirect social trust degree between the company a_1 and the company a_2 is calculated as follows:

$$ITD_{121}^{AB1} = 0.670$$

In a similar way, for the attribute $c_j (j = 1, 2, \ldots, n)$, the indirect social trust degree between any two of companies is obtained, shown in the following matrix $[ITD_{klh}^{t}]_{8\times 8}$:

$$ITD_{kl1}^{1} = \begin{pmatrix} / & 0.670 & / & / & / & / & / & / \\ / & / & / & / & / & / & / & / \\ / & / & / & / & / & 0.515 & / & / \\ / & / & / & / & / & / & / & / \\ / & / & / & / & / & / & / & / \\ / & / & / & / & / & / & / & / \\ / & / & 0.620 & / & / & / & / & / \\ / & / & / & / & / & / & / & / \end{pmatrix}.$$

Then, with the constructed direct and indirect dynamic social trust relationship matrix, we can obtain the complete social trust network relationship matrix $[CTD_{klh}^{t}]_{8\times 8}$ between companies under each attribute at the current moment, which can be constructed as follows:

$$CTD_{kl1}^{1} = \begin{pmatrix} / & 0.670 & 0.670 & 0.722 & 1.052 & 0.705 & 0.687 & 0.722 \\ 1.000 & / & 0.878 & 0.705 & 0.791 & 0.878 & 0.652 & 0.826 \\ 0.705 & 0.687 & / & 0.861 & 0.844 & 0.515 & 1.00 & 0.983 \\ 0.652 & 1.071 & 1.035 & / & 0.861 & 0.913 & 0.687 & 0.791 \\ 0.809 & 0.896 & 0.670 & 0.896 & / & 0.652 & 0.844 & 1.122 \\ 0.896 & 1.017 & 0.652 & 0.652 & 0.844 & / & 0.739 & 1.104 \\ 0.739 & 0.774 & 0.620 & 0.687 & 0.687 & 0.757 & / & 0.739 \\ 0.757 & 0.757 & 0.861 & 0.739 & 0.791 & 0.687 & 0.791 & / \end{pmatrix}$$

$$CTD_{kl2}^{1} = \begin{pmatrix} / & 0.652 & 0.861 & 1.017 & 1.035 & 1.087 & 0.861 & 0.652 \\ 0.739 & / & 0.844 & 0.948 & 0.809 & 0.687 & 0.687 & 0.705 \\ 0.844 & 0.930 & / & 0.652 & 1.000 & 0.687 & 1.035 & 0.739 \\ 0.670 & 0.705 & 0.826 & / & 0.809 & 0.826 & 0.809 & 0.844 \\ 0.722 & 0.774 & 0.861 & 0.791 & / & 0.687 & 0.896 & 1.017 \\ 0.774 & 0.652 & 0.652 & 0.652 & 0.652 & / & 0.687 & 0.861 \\ 0.739 & 0.861 & 0.930 & 0.861 & 0.930 & 0.809 & / & 0.844 \\ 0.774 & 0.948 & 0.826 & 0.652 & 0.739 & 0.757 & 0.670 & / \end{pmatrix}$$

$$CTD_{kl3}^{1} = \begin{pmatrix} / & 1.087 & 0.652 & 0.896 & 0.652 & 0.722 & 0.705 & 0.652 \\ 0.896 & / & 0.913 & 0.670 & 0.983 & 0.670 & 0.861 & 0.826 \\ 0.739 & 0.705 & / & 1.017 & 1.052 & 0.896 & 0.670 & 0.757 \\ 0.687 & 0.722 & 0.705 & / & 0.687 & 0.652 & 1.087 & 0.861 \\ 0.739 & 0.809 & 0.983 & 0.878 & / & 0.791 & 0.774 & 0.652 \\ 0.757 & 0.652 & 0.670 & 0.652 & 0.896 & / & 0.670 & 0.757 \\ 0.844 & 1.035 & 0.722 & 0.739 & 0.670 & 0.913 & / & 0.930 \\ 0.757 & 0.913 & 0.670 & 0.722 & 0.670 & 0.913 & 0.722 & / \end{pmatrix}$$

$$CTD_{kl4}^{1} = \begin{pmatrix} / & 0.652 & 0.757 & 0.878 & 0.965 & 0.809 & 0.913 & 0.652 \\ 0.861 & / & 0.705 & 0.687 & 0.705 & 0.826 & 0.861 & 0.809 \\ 0.687 & 0.861 & / & 0.757 & 0.652 & 0.878 & 0.739 & 1.122 \\ 0.930 & 0.930 & 0.670 & / & 0.826 & 0.652 & 0.652 & 0.652 \\ 0.739 & 0.774 & 1.156 & 0.652 & / & 0.826 & 0.878 & 0.670 \\ 0.757 & 0.809 & 0.652 & 0.652 & 0.687 & / & 0.791 & 0.826 \\ 0.705 & 0.722 & 0.826 & 0.670 & 0.791 & 0.757 & / & 0.687 \\ 0.983 & 0.652 & 0.861 & 1.052 & 0.652 & 1.000 & 0.670 & / \end{pmatrix}$$

In addition, by Equations (6) and (7) calculate the inverse transition matrix $U_{h(k,l)}^{t}$ and the transition matrix $H_{h(k,l)}^{t}$, which can be shown as follows:

$$U_{1(k,l)}^{1} = \begin{pmatrix} / & 1.000 & 1.418 & 1.534 & 1.236 & 1.116 & 1.353 & 1.321 \\ 1.493 & / & 1.456 & 0.934 & 1.116 & 0.983 & 1.292 & 1.321 \\ 1.493 & 1.139 & / & 0.966 & 1.493 & 1.534 & 1.613 & 1.161 \\ 1.385 & 1.418 & 1.161 & / & 1.116 & 1.534 & 1.456 & 1.353 \\ 0.951 & 1.264 & 1.185 & 1.161 & / & 1.185 & 1.456 & 1.264 \\ 1.418 & 1.139 & 1.942 & 1.095 & 1.534 & / & 1.321 & 1.456 \\ 1.456 & 1.534 & 1.00 & 1.456 & 1.185 & 1.353 & / & 1.264 \\ 1.385 & 1.211 & 1.017 & 1.264 & 0.891 & 0.906 & 1.353 & / \end{pmatrix}$$

$$U_{2(k,l)}^{1} = \begin{pmatrix} / & 1.353 & 1.185 & 1.493 & 1.385 & 1.292 & 1.353 & 1.292 \\ 1.534 & / & 1.075 & 1.418 & 1.292 & 1.534 & 1.161 & 1.055 \\ 1.161 & 1.185 & / & 1.211 & 1.161 & 1.534 & 1.075 & 1.211 \\ 0.983 & 1.055 & 1.534 & / & 1.264 & 1.534 & 1.161 & 1.534 \\ 0.966 & 1.236 & 1.000 & 1.236 & / & 1.534 & 1.075 & 1.353 \\ 0.920 & 1.456 & 1.456 & 1.211 & 1.456 & / & 1.236 & 1.321 \\ 1.161 & 1.456 & 0.966 & 1.236 & 1.116 & 1.456 & / & 1.493 \\ 1.534 & 1.418 & 1.353 & 1.185 & 0.983 & 1.161 & 1.185 & / \end{pmatrix}$$

$$U_{3(k,l)}^{1} = \begin{pmatrix} / & 1.116 & 1.353 & 1.456 & 1.353 & 1.321 & 1.185 & 1.321 \\ 0.920 & / & 1.418 & 1.385 & 1.236 & 1.534 & 1.035 & 1.095 \\ 1.534 & 1.095 & / & 1.418 & 1.017 & 1.493 & 1.385 & 1.493 \\ 1.116 & 1.493 & 1.017 & / & 1.139 & 1.534 & 1.353 & 1.385 \\ 1.534 & 1.017 & 1.052 & 1.456 & / & 1.116 & 1.493 & 1.493 \\ 1.385 & 1.493 & 1.116 & 1.534 & 1.264 & / & 1.095 & 1.095 \\ 1.418 & 1.161 & 1.493 & 0.920 & 1.292 & 1.493 & / & 1.385 \\ 1.534 & 0.826 & 1.321 & 1.161 & 1.534 & 1.321 & 1.075 & / \end{pmatrix}$$

$$U^1_{4(k,l)} = \begin{pmatrix} / & 1.161 & 1.456 & 1.075 & 1.353 & 1.321 & 1.418 & 1.017 \\ 1.534 & / & 1.161 & 1.075 & 1.292 & 1.236 & 1.385 & 1.534 \\ 1.321 & 1.418 & / & 1.493 & 0.865 & 1.534 & 1.211 & 1.161 \\ 1.139 & 1.456 & 1.321 & / & 1.534 & 1.534 & 1.493 & 0.951 \\ 1.036 & 1.418 & 1.534 & 1.211 & / & 1.456 & 1.264 & 1.534 \\ 1.236 & 1.211 & 1.139 & 1.534 & 1.211 & / & 1.321 & 1.000 \\ 1.095 & 0.861 & 1.353 & 1.534 & 1.139 & 1.264 & / & 1.493 \\ 1.534 & 1.236 & 0.891 & 1.534 & 1.493 & 1.211 & 1.456 & / \end{pmatrix}$$

$$H^1_{1(k,l)} = \begin{pmatrix} / & / & 1.493 & 1.385 & 0.951 & 1.418 & 1.456 & 1.385 \\ 1.000 & / & 1.139 & 1.418 & 1.264 & 1.139 & 1.534 & 1.211 \\ 1.418 & 1.456 & / & 1.161 & 1.185 & / & 1.00 & 1.017 \\ 1.534 & 0.934 & 0.966 & / & 1.161 & 1.095 & 1.456 & 1.264 \\ 1.236 & 1.116 & 1.493 & 1.116 & / & 1.534 & 1.185 & 0.891 \\ 1.116 & 0.983 & 1.534 & 1.534 & 1.185 & / & 1.353 & 0.906 \\ 1.353 & 1.292 & / & 1.456 & 1.456 & 1.321 & / & 1.353 \\ 1.321 & 1.321 & 1.161 & 1.353 & 1.264 & 1.456 & 1.264 & / \end{pmatrix}$$

$$H^1_{2(k,l)} = \begin{pmatrix} / & 1.534 & 1.161 & 0.983 & 0.966 & 0.920 & 1.161 & 1.534 \\ 1.353 & / & 1.185 & 1.055 & 1.236 & 1.456 & 1.456 & 1.418 \\ 1.185 & 1.075 & / & 1.534 & 1.000 & 1.456 & 0.966 & 1.353 \\ 1.493 & 1.418 & 1.211 & / & 1.236 & 1.211 & 1.236 & 1.185 \\ 1.385 & 1.292 & 1.161 & 1.264 & / & 1.456 & 1.116 & 0.983 \\ 1.292 & 1.534 & 1.534 & 1.534 & 1.534 & / & 1.456 & 1.161 \\ 1.353 & 1.161 & 1.075 & 1.161 & 1.075 & 1.236 & / & 1.185 \\ 1.292 & 1.055 & 1.211 & 1.534 & 1.353 & 1.321 & 1.493 & / \end{pmatrix}$$

$$H^1_{3(k,l)} = \begin{pmatrix} / & 0.920 & 1.534 & 1.116 & 1.534 & 1.385 & 1.418 & 1.534 \\ 1.116 & / & 1.095 & 1.493 & 1.017 & 1.493 & 1.161 & 0.826 \\ 1.353 & 1.418 & / & 1.017 & 1.052 & 1.116 & 1.493 & 1.321 \\ 1.456 & 1.385 & 1.418 & / & 1.456 & 1.534 & 0.920 & 1.161 \\ 1.353 & 1.236 & 1.017 & 1.139 & / & 1.264 & 1.292 & 1.534 \\ 1.321 & 1.534 & 1.493 & 1.534 & 1.116 & / & 1.493 & 1.321 \\ 1.185 & 1.035 & 1.385 & 1.353 & 1.493 & 1.095 & / & 1.075 \\ 1.321 & 1.095 & 1.493 & 1.385 & 1.493 & 1.095 & 1.385 & / \end{pmatrix}$$

$$H^1_{4(k,l)} = \begin{pmatrix} / & 1.534 & 1.321 & 1.139 & 1.036 & 1.236 & 1.095 & 1.534 \\ 1.161 & / & 1.418 & 1.456 & 1.418 & 1.211 & 0.861 & 1.236 \\ 1.456 & 1.161 & / & 1.321 & 1.534 & 1.139 & 1.353 & 0.891 \\ 1.075 & 1.075 & 1.493 & / & 1.211 & 1.534 & 1.534 & 1.534 \\ 1.353 & 1.292 & 0.865 & 1.534 & / & 1.211 & 1.139 & 1.493 \\ 1.321 & 1.236 & 1.534 & 1.534 & 1.456 & / & 1.264 & 1.211 \\ 1.418 & 1.385 & 1.211 & 1.493 & 1.264 & 1.321 & / & 1.456 \\ 1.017 & 1.534 & 1.161 & 0.951 & 1.534 & 1.000 & 1.493 & / \end{pmatrix}$$

Then, let $\alpha = 0.85$ and iteration $M = 20$ the seed set can be found by the inverse page rank value

$$s^1_1 = (0.03, 0.05, 0.14, 0.20, 0.09, 0.10, 0.15, 0.08)^T;$$
$$s^1_2 = (0.12, 0.18, 0.07, 020, 0.14, 0.05, 0.15, 0.17)^T;$$
$$s^1_3 = (0.05, 0.12, 0.09, 0.14, 0.16, 0.07, 0.22, 0.10)^T;$$
$$s^1_4 = (0.13, 0.17, 0.06, 0.19, 0.14, 0.12, 0.13, 0.08)^T.$$

Later, manually identifying the good seed set, $S^1_1 = \{3,7\}; S^1_2 = \{4,8\}; S^1_3 = \{4,5\}; S^1_4 = \{2,5\}$.

So, through the complete dynamic social trust relationship matrix and the trust rank algorithm, we can identify the most trusted company $\hat{a}^t_{koh}$ of company $a_l (l = 1, 2, \ldots, 8)$.

For example, the most trusted company of company a_1 under the attribute c_1 at the moment z_1 is company b_1.

Additionally, then calculate the company's trust rank value.

$$r_1^1 = (0.14, 0.20, 0.07, 0.09, 0.13, 0.17, 0.16, 0.05)^T;$$
$$r_2^1 = (0.04, 0.13, 0.11, 0.16, 0.09, 0.20, 0.11, 0.15)^T;$$
$$r_3^1 = (0.22, 0.14, 0.05, 0.09, 0.14, 0.16, 0.15, 0.14)^T;$$
$$r_4^1 = (0.08, 0.11, 0.19, 0.15, 0.07, 0.13, 0.12, 0.11)^T.$$

Based on the normalized trust rank value, the influence weight of each company can be obtained, and the most authoritative company a_{MAh}^1 at moment z_1 can be found from it. For example, the influence weight of each company under the attribute c_1 at the moment z_1 are as follows:

$$\pi_{11}^1 = 0.14; \pi_{21}^1 = 0.20; \pi_{31}^1 = 0.07; \pi_{41}^1 = 0.09; \pi_{51}^1 = 0.13; \pi_{61}^1 = 0.17; \pi_{71}^1 = 0.16; \pi_{81}^1 = 0.05.$$

Hence, the most authoritative company is a_{21}^1.

After that, using Equation (11), the intensity of resource competition between any two of companies are as follows:

$$CI_{12}^t = 0.248, CI_{13}^t = 0.260, CI_{14}^t = 0.257, CI_{23}^t = 0.257, CI_{24}^t = 0.268, CI_{34}^t = 0.284.$$

Meanwhile, according to Equation (12), calculate the dynamic competitive satisfaction degree between the VPP company and its competitors at the moment. The dynamic standardized competitive satisfaction degree matrix $[\overline{CS}_{ikh}^t]_{m\times m}$ shown in the following matrix:

$$\overline{CS}_{ik1}^1 = \begin{pmatrix} / & 0.605 & 0.385 & 0.704 \\ 0.605 & / & 0.616 & 1.000 \\ 0.385 & 0.616 & / & 0.634 \\ 0.704 & 1.000 & 0.634 & / \end{pmatrix}$$

$$\overline{CS}_{ik2}^1 = \begin{pmatrix} / & 0.327 & 0.561 & 0.441 \\ 0.327 & / & 0.599 & 0.769 \\ 0.561 & 0.599 & / & 0.489 \\ 0.441 & 0.769 & 0.489 & / \end{pmatrix}$$

$$\overline{CS}_{ik3}^1 = \begin{pmatrix} / & 0.466 & 0.456 & 0.476 \\ 0.466 & / & 0.616 & 0.591 \\ 0.456 & 0.616 & / & 0.00 \\ 0.476 & 0.591 & 0.00 & / \end{pmatrix}$$

$$\overline{CS}_{ik4}^1 = \begin{pmatrix} / & 0.692 & 0.139 & 0.616 \\ 0.692 & / & 0.634 & 0.502 \\ 0.139 & 0.634 & / & 0.181 \\ 0.616 & 0.502 & 0.181 & / \end{pmatrix}$$

Stage 3. Matching process

Based on the linear weighting method, obtain the comprehensive dynamic satisfaction degree matrix $[SA_{ij}^t]_{m\times n}$, $[SB_{ji}^t]_{n\times m}$ and $[SA_{ik}^t]_{m\times m}$, and then construct a two-sided matching model (P1) considering the competitive relationships between companies and dynamic trust degree.

$$SA_{ij}^1 = \begin{pmatrix} 0.926 & 0.831 & 0.791 & 0.670 \\ 0.822 & 0.765 & 0.765 & 0.791 \\ 0.887 & 0.615 & 0.861 & 0.900 \\ 0.796 & 0.761 & 0.809 & 0.787 \end{pmatrix}$$

$$SB_{ji}^{1} = \begin{pmatrix} 0.752 & 0.813 & 0.917 & 0.804 \\ 0.796 & 0.783 & 0.657 & 0.652 \\ 0.757 & 0.848 & 0.620 & 0.739 \\ 0.817 & 0.817 & 0.804 & 0.791 \end{pmatrix}$$

$$SA_{ik}^{1} = \begin{pmatrix} / & 0.522 & 0.385 & 0.559 \\ 0.522 & / & 0.616 & 0.715 \\ 0.385 & 0.616 & / & 0.326 \\ 0.559 & 0.715 & 0.326 & / \end{pmatrix}$$

Finally, let $\varepsilon_1 = 0.35, \varepsilon_2 = 0.35, \varepsilon_3 = 0.3$, solve this single-objective optimal model (P2), we obtain the objective value and we also obtain $x_{13} = 1, x_{21} = 1, x_{34} = 1, x_{42} = 1$.

If this matching result is not satisfactory and needs to be adjusted. Then, by Equation (10), the dynamic evaluation information for each company under each attribute at the moment z_{t+1}. For example, let $\omega_1 = 0.5, \omega_2 = 0.25, \omega_3 = 0.25$, and the new probabilistic linguistic evaluation information for company a_1 to company b_1 under attribute c_1 at the moment z_{t+1} is $SA_{11}^{12} = \{s_{-2}(0.1), s_{-1}(0.2), s_0(0.2), s_1(0.3), s_2\ (0.2)\}$. Then according to the recommendation of company b_1 and a_2, the new probabilistic linguistic information for company a_1 to company b_1 under attribute c_1 at the moment z_2 is as follows: $(SA_{11}^{12})'' = \{s_{-2}(0.10), s_{-1}(0.18), s_0(0.21), s_1(0.28), s_2\ \ (0.23)\}$.

In the same way, we calculate the evaluation information between all companies for all attributes at the moment. Additionally, then return to step 1 and acquire the matching result again.

If the final result is satisfactory, the matching decision process is terminated.

5.3. Comparison and Analysis

5.3.1. Comparison

In this section, we will compare our proposed model with Wang et al.'s model considering peer effects [65] (model I) and Lu et al.'s model considering social network relationships [67] (mode II) to illustrate the characteristics of our model.

Wang et al. [65] introduced peer effects into the two-sided matching process by considering potential social network relationships between matching objects on the same side. That is, the matching objects whose behaviors and outcomes are influenced by the other matching objects on the same side. Lu et al. [67] considered social network relationships in the two-sided matching process. This is mainly reflected in the fact that the opinion of the matching object is usually influenced by close friends or people with similar interests in their social network, which can affect the matching object's evaluation process of the candidate and thus the overall two-sided matching result. Our proposed model not only takes into account the social network relationships of the two-sided matches, but also the competing relationships of the matches on one side. To properly compare and analyze these 3 models, we performed the following treatment. On the one hand, the impact of considering peer influence or competition on the optimal matching results is compared between model I and model III. On the other hand, the effects of considering unilateral or bilateral social network relationships on the optimal matching results are compared between model II and model III. Additionally, the optimal two-sided matching results obtained by three different matching decision-making models are shown in Table 10 and Figure 7.

Table 10. Comparison of solution results of three methods.

Two-Sided Matching Method	Optimal Matching Alternative
Wang et al.'s model considering peer effects [65] (model I)	$x_{13} = 1, x_{21} = 1, x_{32} = 1, x_{44} = 1$
Lu et al.'s model considering social network relationships [67] (model II)	$x_{12} = 1, x_{21} = 1, x_{34} = 1, x_{43} = 1$
Model considering agent behavior factors (The proposed model, model III)	$x_{13} = 1, x_{21} = 1, x_{34} = 1, x_{42} = 1$

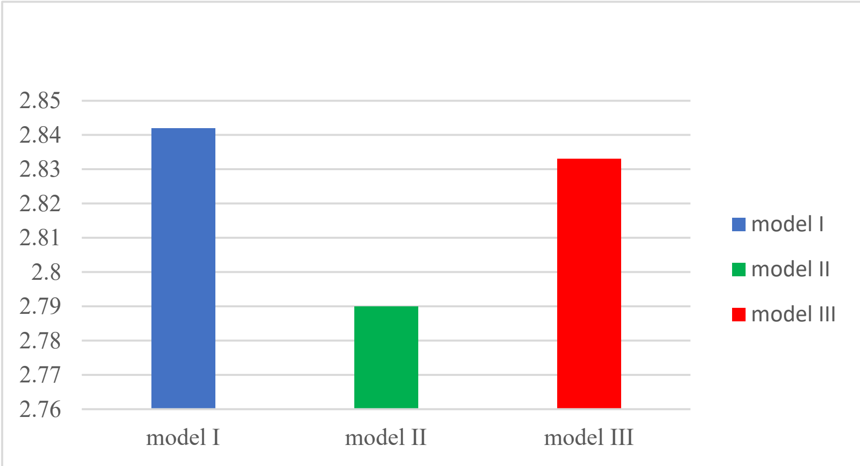

Figure 7. The matching satisfaction of different models.

According to Table 10 and Figure 7, we can find that there are significant differences in the optimal matching results obtained by different matching models. Here are some findings we obtain from this fact as follows: In the two-sided matching decision process, whether to consider competition and whether to consider bilateral social network relations has a significant impact on the choice of the final bilateral matching result. Compared with considering only peer influence, considering competitive behavior in the model helps to enhance the stability of the final stable matching result. Compared with considering unilateral social network relationships, considering bilateral social network relationships in the model helps to improve the match satisfaction of bilateral match objectives. Therefore, when solving the practical problem of two-sided matching, managers can integrate the actual situation and choose an appropriate two-sided matching decision model so as to maximize the satisfaction of bilateral match objectives.

5.3.2. Analysis

There are many studies on the models of resource integration and optimal dispatch of VPP under dual carbon targets [14–35]. However, most of the current relevant studies consider the one-way choice of VPP (or DER) company to DER (or VPP) company, and do not consider the two-way choice of VPP and DER. In reality, the VPP companies need to integrate different types of DER companies, which can reduce the construction investment of centralized power plants. At the same time, many idle DER companies are unable to meet the grid dispatch demand independently at present, so they need to choose suitable VPP companies to maximize their corporate benefits. In other words, the aggregation of VPP and DER companies is a two-sided matching decision problem. In this part, we highlight the characteristics of the proposed model through comparison with existing studies.

1. The dynamic social trust relationship between companies is introduced into the two-sided matching model.

VPP companies and DER companies are susceptible to the influence of the views of other companies in their social network when making actual decisions, thus changing their own views. Some existing studies have focused on how to reach a match on TSMDM issues in the context of social networks. Trust as an important social relationship between companies has been constructed in many papers. However, in existing studies, trust relationships between companies are often given directly by them and the trust relationships tend to remain unchanged once determined, which is inconsistent with reality. In addition, although existing studies have analyzed trust relationships between companies of the same type, trust relationships between different types of companies can also affect their decision. Therefore, we construct a dynamic trust network among different types of companies, in which trust relationships are enhanced or weakened based on historical satisfaction.

Additionally, this dynamic trust network will be updated with iterations to better model realistic social relationships.

2. The competitive relationships between companies are incorporated into the calculation of competitive satisfaction.

Due to the scarcity of resources, not all VPP companies are allocated to the DER company that satisfies them the most. Thus, in order to seize scarce resources, there are competition relationships among VPP companies. Competitive relationships are introduced into the two-sided matching model to help make the matching results between companies more relevant to the actual situation. In existing studies, the impact of the matching behavior of other companies on the satisfaction of this company is reflected by peer effects. However, this approach ignores the intensity of competition among companies. In fact, the stronger the competition intensity between companies, the lower the satisfaction of companies. Therefore, we introduce competition intensity into competitive satisfaction to better reflect the competitive relationship between companies.

3. Probabilistic linguistic term sets are applied to two-sided matching decision-making problem to imitate uncertain information.

The existing papers related to VPP are in a real-valued setting. However, because the indicators, policies and alternatives relating to VPP still have the potential for improvement, which makes the decision-making environment is complex and uncertain. Hence, managers in companies tend to utilize language to represent evaluation information during the real evaluation. Additionally, the PLTSs can well reflect the ambiguity of group opinions. Therefore, the PLTSs are introduced into our model to more accurately reflect managers' preference information.

6. Conclusions

Management of VPP commercial partners is becoming increasingly significant in the construction of new power systems. In particular, the management of the two-sided selection of VPP and DER companies is an important way to achieve sustainable development.

In this study, we introduce a new two-sided matching model to effectively realize the bidirectional selection of VPP and DER companies. The proposed model has four main advantages. Firstly, it can handle a TSMDM problem with competitive relationships based on social network analysis, which is in line with the actual decision-making environment. Secondly, it considers the dynamic trust between companies and adjusts the matching results in real-time. Further, it considers the scarcity of resources and incorporates the competitive nature of VPP into the matching process. Finally, to accommodate the assessment of corporate managers, language is used to express their preferences.

The two-sided matching model between VPP companies and DER companies will be a hot topic for future research. Although we have made some innovations in the method of this theme, there are still some areas that can be improved in the future. For example, it is usually difficult for companies to give the evaluation information of all matches on the other side at the same time, thus allowing the evaluation information of companies to be given in the form of a judgment matrix. In the future, we will focus more on exact algorithms for probabilistic linguistic preference relations and potential multilateral matching problems concerning VPP services in a dual-carbon environment.

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