sustainability

Article

Profit Allocation Strategy of Virtual Power Plant Based on Multi-Objective Optimization in Electricity Market

Yuqing Wang *, Min Zhang, Jindi Ao, Zhaozhen Wang, Houqi Dong and Ming Zeng

Department of Economic Management, North China Electric Power University, Baoding 071000, China; 220212218099@ncepu.edu.com (M.Z.); 220212218105@ncepu.edu.com (J.A.); 201806000720@ncepu.edu.com (Z.W.); dong@ncepu.edu.com (H.D.); zengmingbj@sina.vip.com (M.Z.)
* Correspondence: wangyuqingncepu@foxmail.com; Tel.: +86-15033799506

Abstract: A virtual power plant (VPP) can aggregate distributed renewable energy and flexible load to participate in the electricity market as a virtual controllable assembly. This pattern can effectively avoid the bidding risk of users, and produce cooperation benefits such as reducing transaction costs. Reasonable profit allocation is the key factor to determine the formation and survival of a VPP, which means a reasonable allocation for the VPP's market income among participating members. In view of that, this paper proposes a framework of profit allocation in VPPs based on cooperative game theory. Aiming at the competitive environment with multiple VPPs in the electricity market, a VPP's profit allocation model based on bidding optimization is built, which considers multiple objectives such as fairness of profit allocation, stability of cooperation alliance, and attraction of participating members. Furthermore, a multi-objective evolutionary optimization algorithm based on reference points is introduced to solve the model. Then, a VPP composed of prosumers is taken as an example to carry out the emulation. The results show that all participating members can get satisfactory profit allocation. Its cost-saving ratio ranges from 7.82% to 18.66%, and it confirms that the proposed profit allocation method can encourage prosumers of small size to participate in the VPP cooperation effectively.

Keywords: virtual power plant; profit allocation; cooperation game; market bidding; multi-objective optimization

Citation: Wang, Y.; Zhang, M.; Ao, J.; Wang, Z.; Dong, H.; Zeng, M. Profit Allocation Strategy of Virtual Power Plant Based on Multi-Objective Optimization in Electricity Market. *Sustainability* **2022**, *14*, 6229. https://doi.org/10.3390/su14106229

Academic Editor: Mouloud Denai

Received: 30 March 2022
Accepted: 11 May 2022
Published: 20 May 2022

1. Introduction

In recent years, distributed renewable energy (DRE) has become the focus of renewable energy development and utilization all over the world [1]. A large number of prosumers with DRE have emerged. In an electricity market environment, users or microgrid systems with DRE are allowed to participate in electricity trading [2]. However, it is difficult for DREs to participate in the electricity market competition as an independent individual due to the characteristics of small capacity, scattered layout, and strong randomness of output. In this context, virtual power plants (VPPs) provide a solution for prosumers with DREs to participate in electricity market transactions. VPPs integrate different DREs and flexible load resources into a virtual controllable aggregate through the energy management system to participate in electricity market transactions. VPPs can effectively avoid the market bidding risk brought by uncertain factors such as DRE output, electricity load, and market price. In addition, VPPs can produce cooperation benefits such as reducing energy consumption cost. Many studies have shown that the participation of VPPs in energy and reserve markets can significantly increase the profits of prosumers [3,4].

Although VPPs can participate in electricity market bidding as a unified whole, the investment and finance of each DRE in a VPP are independent. Each DRE is likely to belong to different property rights entities. If the market transaction costs and benefits of the VPP cannot be reasonably distributed among the participating members, the existing participating members will leave the VPP. At the same time, it is not conducive to attracting new DREs to join the VPP. Therefore, designing a fair, reasonable, and transparent VPP profit allocation strategy within the VPP is crucial to maintain the cooperative relationship between DREs and the VPP, and it is an urgent problem to be solved.

There are mainly two ways to realize the profit allocation within a VPP in existing research. The first way is to optimize the VPP bidding strategy based on the electricity market environment which refers to the settlement of power supply revenue and energy cost based on the electricity market price and the actual energy production and consumption of VPP members. Such studies are mentioned in [5–12]. Refs. [8,9] proposed a joint bidding optimization model for VPPs to participate in the energy market and the reserve capacity market. It analyzed the changes of the benefits and electricity costs of DREs, electric vehicles, and flexible load users before and after participating in the VPP. The second way is to solve the internal market transaction equilibrium based on the VPP internal market transaction mechanism. Ref. [13] designed the internal market and operation mechanism of VPPs with multi-investment subjects and established a controllable distributed power reserve bidding model under uncertain information based on non-cooperative game theory. Refs. [14,15] proposed a VPP internal equilibrium strategy based on the Stackelberg game model, which took a distributed energy producer with thermal production capability as the leader. Refs [16,17] proposed a VPP two-layer dynamic game bidding model based on the Multi-Agent and Stackelberg dynamic game considering the external power market.

However, neither of the above two ways considers the contribution of participating members to the VPP cooperation benefits. At present, a few scholars use the cooperative game model to study the allocation of VPP benefits. Based on the cooperative game theory, [18] analyzed the cooperation space and fair allocation of benefits between electricity-distribution companies and VPPs including wind power, photovoltaic power, and hydropower generation. Refs. [19,20] applied nucleolar theory to study the profit allocation for VPPs. Refs. [21,22] established a VPP income allocation model by using bargaining game theory. Refs. [23–25] established a VPP profit allocation model by applying Shapley value theory. Among them, [23] proposed a multi-factor improved Shapley value method based on the risk level, profit contribution, and profit growth rate of VPP internal members. Refs. [24,25] proposed a Shapley value method based on the improved heat-to-electric ratio of the combined heat and power (CHP). Although the above-mentioned commonly used cooperative game solutions such as nucleolus and Shapley value can quickly generate a unique profit allocation strategy for VPP, there may be a better profit allocation strategy in the core. On the basis of solving the core of the VPP cooperative game, Ref. [26] further established a dual-objective optimization model of VPP profit allocation. In the core of a large number of potential profit allocation schemes, it proposed a feasible profit allocation scheme that met the objectives of fairness of profit allocation and stability of cooperative alliance. The research in [26] showed that the multi-objective optimization based on core allocation could effectively explore a large number of potential profit allocation strategies in the core, and provided a good solution for the design of flexible and efficient VPP profit allocation strategies.

To sum up, it can be seen that most of the existing studies focus on the single VPP market environment, which refers to DRE, flexible load users, and other individuals only being able to choose whether to participate in a specific VPP. With the development of VPPs, there will be multiple VPPs in the market for DRE and other individuals to choose to participate in. So far, no research has considered the issue of profit allocation under the competitive environment of multiple VPPs. In multiple VPP competition environments, participating members of the VPPs have the risk of breaking away from the existing VPP and participating in other VPP cooperation. Therefore, the profit allocation scheme for VPP should not only ensure the fairness of profit allocation and the stability of cooperative alliance, but also try to maintain the attraction of participating members. However, in reality, the VPP profit allocation strategy is usually difficult to satisfy the optimal goals of stability, fairness, and attractiveness at the same time. Taking the allocation of transaction costs in the VPP market as an example, the stability objective requires increasing the minimum cost savings of participating members. They tend to allocate as low cost as possible to participants of small volumes, resulting in this part of participants to have an advantage in VPP cooperation. This is not only against the fairness goal [23], but also reduces the attractiveness of the VPP to participating members of large volumes. How to achieve the balance among the three goals of stability, fairness, and attractiveness of participating members is a problem that needs to be solved now. At this time, the establishment and solution of the VPP's profit allocation model will face the following two challenges: (1) how to measure the attractiveness of the VPP to participating members; and (2) considering fairness, stability, and attractiveness goals at the same time, the profit allocation model based on bidding strategy optimization will become a high-dimensional multi-objective stochastic programming problem, and the solution of the model will face great challenges.

In order to solve the above problems, this paper takes the VPP composed of prosumers as the research object and considers the fairness of benefit distribution, the stability of the cooperative alliance and the attractiveness of participating members based on the electricity market including the day-ahead market and the real-time market. This paper applies cooperative game theory to construct a VPP's profit allocation model based on multi-objective optimization in the electricity market environment, and it introduces a high-dimensional multi-objective evolutionary optimization algorithm based on reference points to solve the model. The main contributions of this paper can be summarized as follows:

(1) This paper designs the measurement index of a VPP's attractiveness to participants. The ratio of the loss caused to the cooperative alliance when a participant leaves VPP to the loss suffered by the participant itself is recorded as the attraction index of VPP to the participant. It can quantitatively assess the risk of participants leaving the existing VPP and participating in other VPP cooperation.
(2) This paper establishes a multi-objective-based profit allocation model for a VPP based on bidding optimization including fairness of profit allocation, stability of cooperative alliance, and attraction of participating entities. This model can be applied to both a single VPP market environment and to a multi-VPPs competition environment.
(3) In this paper, a multi-objective evolutionary optimization algorithm based on reference points is introduced to effectively solve the Pareto solution set of VPP profit allocation. The algorithm can adaptively generate a series of reference points with superior performance based on the current population, and greatly improve the individual selection pressure by calculating the distance between the reference point and the individual.

The remaining parts of this article are organized as follows. In Section 2, the cooperative game model of VPP is constructed and the process of determining the profit allocation scheme of VPP is proposed. This paper establishes the VPP bidding model based on CVaR in the electricity market in Section 3. This paper establishes the VPP transaction cost allocation model in Section 4. In Section 5, the algorithm solving process is introduced. Section 6 of this paper presents an example analysis. Finally, this paper summarizes the content in Section 7.

2. Problem Statement

2.1. VPP Cooperative Game Problem

The VPP studied in this paper is composed of multiple prosumers. Each prosumer load includes DRE output load, flexible load, and non-flexible rigid load. All users are coordinated by VPPs for joint bidding in the electricity market. Assuming that all prosumers operate in the mode of surplus Internet access, the VPP can interact with the power grid in both directions. The VPP can purchase electricity from the market to make up for its own energy balance gap, and can sell its surplus DREs in the market.

2.1.1. Interest Relationship between VPP's Internal Subjects

As shown in Figure 1, from the perspective of interest relationship, the relationship between prosumers in VPP is a cooperative relationship, while the relationship between the VPP and prosumers is a principal-agent relationship, which is the subject and medium of internal and external interaction in VPP. On the basis of collecting DREs and loading forecasting data of internal prosumers, VPPs participate in electricity market transactions, and then make internal scheduling arrangements according to the transaction results. At the same time, scheduling adjustments are made timely in real-time operation, and after the settlement of market transactions, benefits are allocated among internal prosumers. It should be noted that the DRE configured by prosumers can generally only meet part of the load demand of users, so users still need to purchase electricity outside to achieve their own energy balance. Therefore, the power purchase cost of DREs aggregated by prosumers in the market is often higher than the income of DRE surplus Internet access and auxiliary services. The profit allocation of VPPs is the sharing of market transaction costs. The cooperation benefit is the reduction of energy consumption cost of prosumers. It is the main interest demand of VPP operators to minimize the transaction cost of VPP market and maintain the stability of VPP cooperation by making a reasonable market bidding strategy and cost allocation strategy. Minimizing electricity cost by participating in VPP cooperation is the fundamental benefit of prosumers.

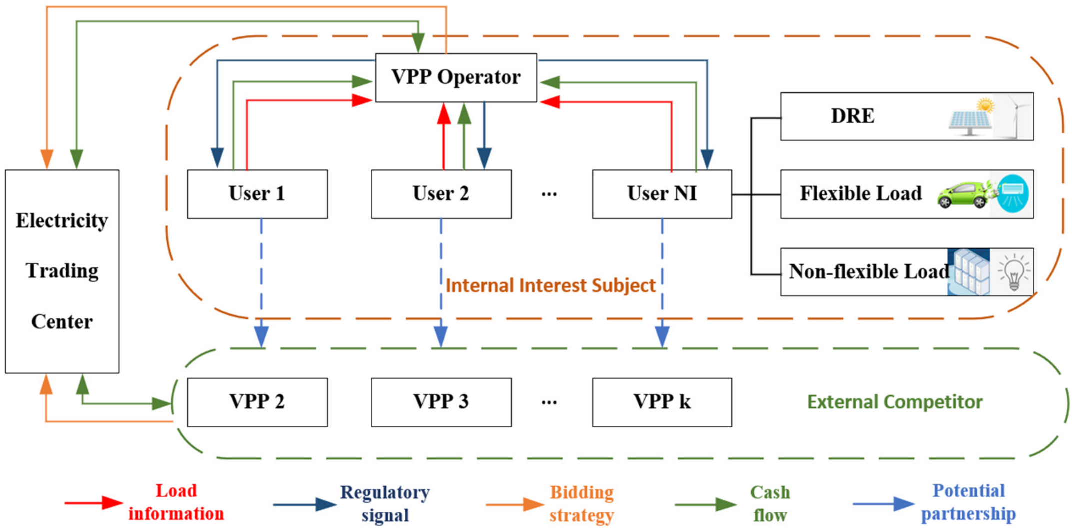

Figure 1. Interest relationship between internal and external subjects in VPP.

2.1.2. Establishment of VPP Cooperative Game Model

Since a VPP is formed by the cooperation of prosumers, the cost allocation among VPP entities can be regarded as a cooperative game problem. Each prosumer in a VPP is a participant in the cooperative game, and the market transaction cost under the optimal bidding strategy of VPP is the characteristic function of the cooperative game. Let $I = \{1, 2, \ldots, NI\}$ represent the set of participating members (prosumers), $H(I;v)$ is a VPP cooperation game with optimal transaction cost as its characteristic function, and the characteristic function $V(s)$ determines the minimum cooperation cost of any subset $S \subseteq I$. Each subset $S \subseteq I$ can form an alliance S, which is represented by an indicator vector $a^S = \left[a_1^S, a_2^S, \ldots, a_{NI}^S\right]$, if $i \in S$, then $a_i^S = 1$, otherwise $a_i^S = 0$.

Since $H(I;v)$ is a cost-based cooperative game and the cost is non-negative, its super additivity is as follows: when S_1, S_2 meets $S_1 \cap S_2 = \varnothing$, there is $v(S_1 \cup S_2) \leq v(S_1) + v(S_2)$, which means that if all members participate in coalition C, the total cost can be minimized.

Let $x = \{x_1, x_2, \ldots, x_{NI}\}$ represent the cost allocation vector of VPP cooperative game, where x_i is the cost proportion allocated to participating members i. In this section, the concept of "core" in cooperative game is used to determine the cost sharing vector x. The definition of core $core(H)$ of cost cooperative game $H(I;v)$ is shown in Equation (1), which means no alliance can save more cost than the total cost currently allocated by participating members.

$$core(H) \equiv \left\{ x \in R^N : \sum_{i=1}^{N} x_i = 1, \sum_{i \in S} x_i v(I) \le v(S), \forall S \subseteq I \right\} \quad (1)$$

If $x \in core(H)$ and x is in the core of cooperative game $H(I;v)$, then x is called reasonable distribution. Establishing a new cooperation cannot make participants gain greater benefits in this game, so alliance S has no splitting motivation.

2.2. Determination Process of VPP Cost Allocation Strategy

Since there is no physical connection among the members of the VPP, the distributed energy power owned by the members can only be used by themselves or sold in the market. Therefore, the cost allocated by all members in the VPP does not include the distributed energy cost and is only the market transaction cost of the VPP. The electricity market studied in this paper includes day-ahead market and real-time market. It is assumed that VPP is the market price receiver, and its quotation does not affect the settlement price of the day-ahead market and the real-time market. Due to the uncertainty of renewable energy generation, load demand, and market price, the final market transaction cost of VPP cannot be determined at the equation stage of the day-ahead bidding strategy. Thus, a fixed amount of costs cannot be allocated to participating members. Therefore, this paper proposes the cost allocation strategy determination process of VPP as shown in Figure 2:

(1) In the equation stage of day-ahead bidding strategy, transaction cost of VPP market is optimized through VPP market bidding strategy model.
(2) Before submitting the bidding curve of day-ahead bidding market, the paper determines the expected cost proportion of each participant in VPP through VPP cost allocation model, which is regarded as the basis of the final cost allocation. Based on the optimization results of transaction costs in the expected market of VPP, this paper takes the fairness of cost allocation, the stability of cooperative alliances, and the attractiveness of participating members as objectives.
(3) After the settlement of the real-time market, this paper calculates the cost borne by each participant according to the cost allocation proportion of VPP determined in the bidding stage and the final transaction cost of VPP market.

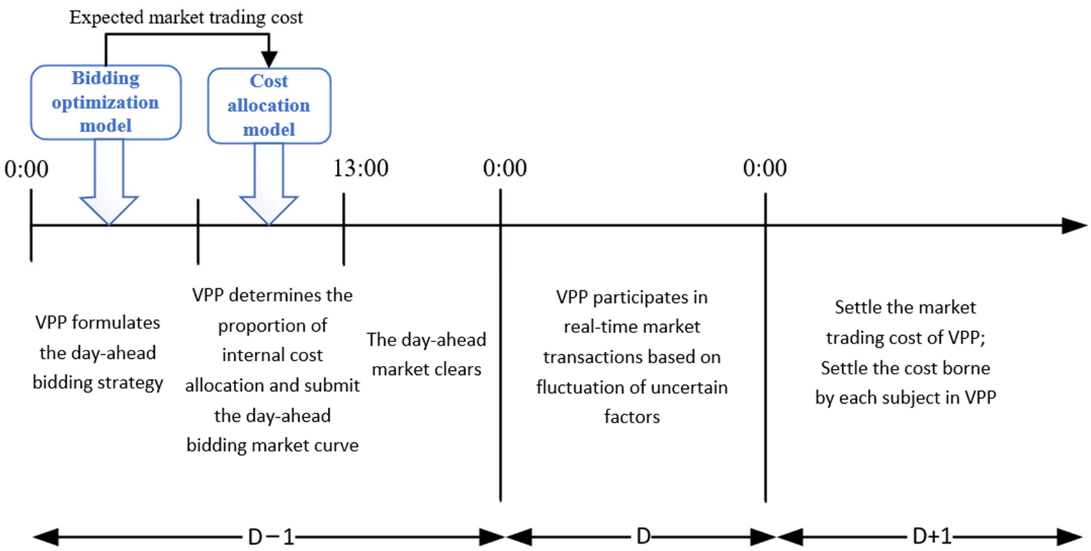

Figure 2. Strategy determination process of VPP bidding and cost allocation in the electricity market.

3. Bidding Optimization Model of VPP Based on CVaR

3.1. Model Building of Uncertain Characteristics

Under the electricity market environment, there are three kinds of uncertain factors in the bidding and operation for VPP including distributed renewable energy output, load demand, and market price. The all probability distribution models of various uncertain factors are as follows.

(1) Distributed wind power

The output of distributed wind turbine is affected by wind speed. In this paper, Weibull distribution is used to determine the probability distribution of wind speed [27]. Then, the probability density function of distributed wind turbine's output is as follows.

$$f_W(Q_W) = \begin{cases} b\{1 - e^{[-(\frac{V_c}{\tau})^k]} + e^{[-(\frac{V_f}{\tau})^k]}\}, Q_W = 0 \\ b(\frac{k}{\tau})(\frac{c}{\tau})^{k-1} e^{[-(\frac{c}{\tau})^k]}, 0 \le Q_W \le Q_W^{\max} \\ b\{e^{[-(\frac{V_c}{\tau})^k]} - e^{[-(\frac{V_f}{\tau})^k]}\}, Q_W = Q_W^{\max} \end{cases} \tag{2}$$

$$b = \frac{V_r - V_c}{Q_W^{\max}} \tag{3}$$

$$c = V_c + bQ_W \tag{4}$$

In equations above, $Q_W^{\max}$ is the rated power of the wind turbine. v_c is the cut-in wind speed, and v_f is the cut-out wind speed. v_r is the rated wind speed. k and t are the shape parameters and scale parameters of Weibull distribution, respectively.

(2) Distributed photometry

The output of distributed photovoltaic units is related to the photometry. In this paper, the intensity of light is set to obey Beta distribution [28]. The probability density function of the output of distributed photovoltaic units is as follows.

$$f_{PV}(Q_{PV}) = \frac{1}{Q_{PV}^{\max}} \frac{\Gamma(\xi + \psi)}{\Gamma(\xi)\Gamma(\psi)} \left(\frac{Q_{PV}}{Q_{PV}^{\max}} \right)^{\xi - 1} \left(1 - \frac{Q_{PV}}{Q_{PV}^{\max}} \right)^{\psi - 1} \tag{5}$$

In Equation (5), $Q_{PV}^{\max}$ is the maximum output of photovoltaic power generation. ξ and ψ are the shape parameters of Beta distribution.

(3) Load demand

The load demand of VPP internal users can usually be predicted by historical load data, and the predicted value is $\overline{D_t}$. Assuming that the prediction error Δ_t^l follows the standard normal distribution [29].

$$D_t = \overline{D_t} + \Delta_t^l \tag{6}$$

(4) Market transaction price

It is assumed that the day-ahead market price and real-time market price in the power electricity market obey the lognormal distribution [30]. Its probability density function is as follows.

$$f_p(P, \mu, \sigma) = \frac{1}{P\sqrt{2\pi}\sigma} e^{[-\frac{(\ln P - \mu)^2}{2\sigma^2}]} \tag{7}$$

3.2. VPP Bidding Model

Optimizing the expected market transaction cost of a VPP and determining the characteristic function of cooperative game $H(I; v)$ of a VPP are the foundation of formulating the cost allocation strategy of the VPP. Therefore, a bidding optimization model of VPP market should be established to obtain the expected market transaction cost of VPP under the optimal bidding strategy. A VPP participating in market transaction and its operation will face the volatility risk in three types of uncertain factors: renewable energy output, load demand, and market price. The market bidding decision can be defined as a stochastic programming problem. The VPP bidding model under the electricity market environment is shown below.

Objective Function:

$$\begin{aligned} v(S) = \min_{\Omega}(1-\beta)\sum_{s=1}^{NS}\rho_s\sum_{t=1}^{NT}\left(C_{t,s}^{DA}+C_{t,s}^{RT}+C_{t,s}^{DP}+C_{t,s}^{DR}\right) \\ +\beta\left(\mu+\frac{1}{1-\alpha}\sum_{s=1}^{NS}\rho_s\eta_s\right) \end{aligned} \tag{8}$$

Including:

$$C_{t,s}^{DA} = P_{t,s,in}^{DA}Q_{t,in}^{DA}\lambda - P_{t,s,out}^{DA}Q_{t,out}^{DA}\lambda \tag{9}$$

$$Q_{t,in}^{DA} = \max\left\{0, Q_t^{DA}\right\} \tag{10}$$

$$Q_{t,out}^{DA} = -\min\left\{0, Q_t^{DA}\right\} \tag{11}$$

$$C_{t,s}^{RT} = P_{t,s,in}^{RT}\left(Q_{t,s,in}^{RT}-Q_{t,in}^{DA}\right)\lambda - P_{t,s,out}^{RT}\left(Q_{t,s,out}^{RT}-Q_{t,out}^{DA}\right)\lambda \tag{12}$$

$$C_{t,s}^{DP} = P^{DP}\left[\varepsilon_{t,s,in}Q_{t,in}^{DA}+\varepsilon_{t,s,out}Q_{t,out}^{DA}\right]\lambda \tag{13}$$

$$\varepsilon_{t,s} = \begin{cases} \varphi_{t,s}-\delta & \varphi_{t,s}>\delta \\ 0 & 0\le\varphi_{t,s}\le\delta \end{cases} \tag{14}$$

$$\varphi_{t,s} = \frac{\left|Q_{t,s}^{RT}-Q_t^{DA}\right|}{Q_t^{DA}} \tag{15}$$

$$C_{t,s}^{DR} = \sum_{i=1}^{NI}\sum_{o=1}^{NO_i}P_{i,o}^{R}D_{i,o,t,s}^{R}\lambda \tag{16}$$

Constraints:

$$Q_{i,t,s}^{G,\min}a_i^S \le Q_{i,t,s}^{G} \le Q_{i,t,s}^{G,\max}a_i^S \tag{17}$$

$$D_{i,t} \le D_i^{\max}a_i^S \tag{18}$$

$$0 \le D_{i,o,t,s}^{R} \le D_{i,o,t}^{R,\max}a_i^S \tag{19}$$

$$D_{i,t,s}^{R} = \sum_{o=1}^{NO_i}D_{i,o,t,s}^{R}, 0 \le D_{i,t,s}^{R}\lambda \le R_{i,t,s}a_i^S \tag{20}$$

$$D_{i,t,s}^{R} - D_{i,t-1,s}^{R} \le R_i^{up}a_i^S \tag{21}$$

$$D_{i,t-1,s}^{R} - D_{i,t,s}^{R} \le R_i^{down}a_i^S \tag{22}$$

$$Q_{t,s} = \sum_{i=1}^{NI}\left(D_{i,t,s}a_i^S - D_{i,t,s}^{R} - Q_{i,t,s}^{G}\right) \tag{23}$$

$$-\sum_{i=1}^{NI}Q_i^{G,\max}a_i^S \le Q_{t,s} \le \sum_{i=1}^{NI}D_i^{\max}a_i^S \tag{24}$$

$$\eta_s \ge \lambda\sum_{t=1}^{NT}\left(C_{t,s}^{DA}+C_{t,s}^{RT}+C_{t,s}^{DP}+C_{t,s}^{DR}\right)-\mu \tag{25}$$

$$\eta_s \ge 0 \tag{26}$$

The VPP bidding model under electricity market environment aims to minimize VPP market transaction cost, which includes four parts: day-ahead market transaction cost, real-time market transaction cost, unbalanced electricity penalty cost, and flexible load regulation cost. The decision variable is $\Omega = \left\{ Q_{t,in}^{DA}, Q_{t,out}^{DA}, Q_{t,s,in}^{PT}, Q_{t,s,out}^{RT}, D_{i,t,s}^{R}, Q_{i,t,s}^{G} \right\}$. Since the market transaction cost will change with uncertain factors such as renewable energy output, load demand, and market price, this model takes conditional value at risk (CVaR) as a risk measure value into the objective function, which aims to measure the impact of uncertain factors fluctuations on the VPP's market transaction cost. The objective function is shown in Equations (2)–(10).

In Equation (8), β is usually valued in interval $[0, 1]$ according to the decision maker's risk preference, and if the value of β is larger, the decision maker is risk-averse. The value of α is usually between 0.9 and 0.99. When the value of uncertain factors is determined through scenario generation, $CVaR_{\alpha}(C)$ can be defined as the expected cost of VPP market transaction in the worst scenario with scenario probability that is $(1 - \alpha) \times 100\%$.

Equation (9) indicates that the day-ahead market transaction cost of VPP is the difference between the power purchase cost and the electricity sales revenue in the day-ahead market. Q_t^{DA} is the expected interaction power between the VPP and the grid in the day-ahead market during the period t. In the case of two-direction interaction, Q_t^{DA} will be positive when the grid sends power to VPP. $Q_{t,in}^{DA}$ represents the electricity purchased by the VPP during t period of the day-ahead market. Moreover, Q_t^{DA} will be negative when the grid buys electricity from the VPP. At the same time, it represents the surplus renewable energy electricity sold by the VPP during t period in the day-ahead market. It can be seen that Q_t^{DA} means that the VPP can only be in one of the states of purchasing electricity from the main grid or selling electricity at any time. As Equation (12) shows, the real-time market transaction cost of the VPP is also the difference between the real-time market power purchase cost and the electricity selling income.

As shown in Equations (13)–(15), the penalty cost of the unbalanced power of VPP is determined by the unbalanced power penalty price and the unbalanced power. Equation (16) represents the cost of flexible load regulation of the VPP. Participating members provide a stepwise bidding curve of flexible load regulation for the VPP according to their own demand elasticity. The VPP should compensate participating members according to the bidding price when reducing flexible load.

The constraints mainly include four aspects: distributed energy unit operating constraints, load constraints, power balance constraints, and CVaR constraints, which are shown in Equations (17)–(24). It should be noted that the objective function $v(S)$ is applicable to any alliance $S \subseteq I$, and the constraints of VPP bidding model also depend on the alliance S. Therefore, the indicator vector a_i^S needs to be considered in the constraints to ensure that when $i \in S$, the corresponding parameters and variables of participating member i can be called by the model. Taking Equation (17) as an example, the output of distributed energy units should be positioned between its minimum and maximum. For participating member i that belongs to $i \notin S$, if $a_i^S = 0$, $Q_{i,t,s}^{G} = 0$. The operating constraints and output of the power generation units of participating member will not be included in the bidding model S of VPP, and they will not affect the power balance constraints.

Equation (18) is the load demand constraint. It should be within the maximum load range for participant i during t period. From Equation (19) to Equation (22) are the flexible load constraints. The total load reduction of participating members and the load reduction of each bidding stage should be within its load reduction capacity, and the load adjustment of the adjacent period must meet the ramping up and down constraints. Equations (23) and (24) are the power balance constraints. The interactive power between the VPP and the grid is equal to the load demand minus the flexible load reduction and the output of the distributed energy unit. The value should be between the maximum output load of the distributed energy unit and the maximum electrical load demands. Equations (25) and (26) are CVaR computing constraints.

4. Cost Allocation Model of VPP Based on Multi-Objective Optimization

4.1. Model Building

The non-empty core of cooperative game $H(I;v)$ for a VPP contains lots of potential cost allocation vectors x. Different allocation vectors x will correspond to different cost allocation effects. Arbitrary allocation of vector x in the core may lead to a very small reduction of the market transaction cost for some alliances. The alliance cannot get great cost-saving benefits in the VPP cooperation, which makes the VPP cooperation alliance unstable. The allocation of vector x may also lead to a much smaller reduction in transaction costs for some participating members than for other members, resulting in unfair cost allocation. The distribution vector x may also cause some participating members' market transaction cost reduction value not to match their contribution to VPP cooperation benefits. It will result in the VPP not being attractive enough to the participating members, and the participating members are likely to withdraw from the existing cooperative alliance to participate in another VPP cooperation. Therefore, VPP cost allocation model should meet the three objectives including the stability of the cooperative alliance, the fairness of cost allocation, and the attractiveness of participating members. Finally, an effective cost allocation scheme in the core of the game is proposed.

(1) Stability objective

The excess $e(S;x)$ to the allocation vector x of the alliance S can be used to measure the satisfaction of the alliance or participating members to the allocation vector, because the satisfaction of participating members is a key factor affecting the stability of the cooperative alliance in the VPP cooperative alliance. Compared with its independent operation, $e(S;x)$ represents the cost saving amount that the alliance S can get by participating in the VPP cooperative alliance under the cost allocation vector x. The larger the value of $e(S;x)$ is, the greater the cost saving amount is and the larger the sum of the cost savings of participating members in the alliance S is. Moreover, the greater the cost savings available to each participating member, the higher the satisfaction of the participants with the cost allocation vector x. In this paper, the minimum transition $e(S;x)$ in the VPP cooperative alliance is taken as the stability measure, which is marked as ω. It is also the lowest cost saving in all alliances S. ω represents the lowest satisfaction in VPP cooperative alliance under the cost allocation vector x. The higher the satisfaction is, the more stable the cooperative alliance is. Therefore, the stability objective functions of VPP cost allocation model are as follows:

$$\max_{x_i} \omega = \{ S \subseteq I | \min e(S;x) \} \tag{27}$$

$$e(S;x) = v(S) - \sum_{i \in S} x_i v(I) \tag{28}$$

(2) Fairness objective

The fairness of VPP cost allocation will be affected by the proportion of market transaction cost saving among participating members with the cost allocation vector x. Therefore, the difference between the saving proportion in market transaction of the member with the highest proportion and that of the member with the lowest proportion as the fairness measure index, which is marked as π. π represents the maximum cost saving difference among participating members of VPP with the cost allocation vector x. The smaller the difference is, the fairer the cost allocation s. Therefore, the fairness objective functions of VPP cost allocation model are as follows:

$$\min_{x_i} \pi = \overline{\theta} - \underline{\theta} \tag{29}$$

$$\overline{\theta} = \left\{ i \in I \middle| \max \left[1 - \frac{x_i v(I)}{v(\{i\})} \right] \right\} \tag{30}$$

$$\underline{\theta} = \left\{ i \in I \middle| \min \left[1 - \frac{x_i v(I)}{v(\{i\})} \right] \right\} \tag{31}$$

(3) Attraction objective

After the participant i rejects the alliance, due to the broken alliances, the ratio of the sum of losses caused to other participants to the losses suffered by participant I is taken as the attractiveness index of the VPP to participant i. It is marked as γ. The smaller the value of γ is, the more attractive the VPP cooperative alliance is to participating member i. If participating members leave the VPP, they will suffer a large loss. Compared with the loss of leaving members, the VPP will suffer a smaller loss. Therefore, the minimum attractiveness index of each participating member is taken as the attractiveness measure index, which is marked as $\overline{\gamma}$. The smaller $\overline{\gamma}$ is, the more attractive the VPP is to the participating members, and the participating members are less likely to leave the cooperative alliance and participate in other VPPs. Therefore, the attractiveness objective function of the VPP cost sharing model is as follows:

$$\min_{x_i} \overline{\gamma} = \left\{ i \in I \middle| \max \frac{v(I/\{i\}) - (1 - x_i)v(I)}{v(\{i\}) - x_i v(I)} \right\} \tag{32}$$

It should be noted that the VPP cost allocation scheme is difficult to meet three objectives of stability, fairness, and attractiveness simultaneously. For example, the stability goal requires maximizing the lowest saving-cost of all alliances. The VPP needs to allocate less cost for participating members of the alliance that save the lowest cost. On the one hand, the saving-cost rate of participants will increase, which will lead to the larger deviation of all members in VPP. Therefore, it is irreconcilable with the goal of minimizing the fairness index. On the other hand, the participating members in the alliance with the lowest cost saving are usually of small volumes. The VPP tends to allocate the cost as low as possible to participants of small volumes with the stability goal. It not only results in the advantage of participants with small volumes in the VPP cooperation, but also reduces the attractiveness of the VPP to participating members of large volumes. Under the stability goal, the VPP tends to allocate the lowest cost to the smaller participating members, which leads to the advantages of the smaller participating members in the VPP cooperation and reduces the attraction of the VPP to the larger participating members.

VPP cost allocation scheme must be in the core of the game, so it also needs to meet the following constraints.

$$\sum_{i=1}^{NI} x_i = 1 \tag{33}$$

$$x_i \geq 0 \tag{34}$$

$$v(S) - \sum_{i \in S} x_i v(I) \geq 0, \forall S \subseteq I \tag{35}$$

Equations (33) and (34) are the basic requirements for cost allocation in the cooperative game, which can ensure that the cost allocation vector is non-negative and the transaction costs in VPP market can be fully allocated to the participating members. Equation (35) represents the allocating constraints of the core in cooperative game, which means no alliance can save more costs than the sum of costs currently allocated by participating members.

4.2. Model Simplification

The multi-objective optimization model of VPP cost allocation constructed above is a min-max double-level programming problem. The outer model takes the cost allocation vector as the decision variable. It aims to explore the VPP cost allocation scheme under multi-objective optimization. The inner model takes participating members or alliance combinations as the decision variables, then the minimum transition ratio, the maximum cost saving ratio, the minimum cost saving ratio, and the minimum attractiveness under the current cost allocation vector are calculated, which provides the basis for the calculation of stability, fairness, and attractiveness indicators in the objective function of the outer model. Due to the difficulty of solving the two-level programming model, this paper adopts the objective function for the element method to transform VPP cost sharing model into a single-level programming problem. The simplified model is as follows:

$$\max_{x_i,\omega} \omega \tag{36}$$

$$\min_{x_i,\pi,\overline{\theta},\underline{\theta},\omega} \pi \tag{37}$$

$$\min_{x_i,\omega} \overline{\gamma} \tag{38}$$

subject to Equations (33) and (34)

$$\omega \le v(S) - \sum_{i \in S} x_i v(I), \forall S \subseteq I \tag{39}$$

$$\omega \ge 0 \tag{40}$$

$$\underline{\theta} \le 1 - \frac{x_i v(I)}{v(\{i\})} \le \overline{\theta}, \forall i \in I \tag{41}$$

$$\pi = \overline{\theta} - \underline{\theta} \tag{42}$$

$$\underline{\gamma} \ge \frac{v(I/\{i\}) - (1 - x_i)v(I)}{v(\{i\}) - x_i v(I)}, \forall i \in I \tag{43}$$

5. Multi-Objective Evolutionary Optimization Based on Reference Points

The cost allocation model of a VPP based on bidding strategy optimization is a multi-objective stochastic programming problem, and there are conflicts among sub-objectives. Mathematically, the cost allocation vector that maximizes the stability index, the allocation vector with the best fairness, and the allocation vector with the strongest attractiveness are the different points of the polyhedral core $x \in core(H)$. Therefore, it is needed to obtain the Pareto optimal solutions set, and the solution in the optimal solution set cannot improve the value of other objective functions without deteriorating the value of one objective function. Since the cost allocation model of VPP based on bid optimization is a nonlinear multi-objective optimization problem, a heuristic algorithm is chosen to solve the model.

In 2014, Deb K proposed NSGA-III algorithm for the multi-objective optimization problem [31]. Based on the adaptation of NSGA-II algorithm with the crowd-distance sort, NSGA-III overcomes the problem that the Pareto dominance criterion cannot distinguish the performance of individuals due to non-dominated individuals at a ratio of exponential increase in the population and the objective function increases by introducing widely distributed reference points to maintain the diversity of the population. NSGA-III has a good search capability in multi-objective space, but since the shape of the Pareto front of the optimization problem is usually unknown, the inconsistency between the pre-given reference points and the Pareto front shape will lead to the degradation of the algorithm's search performance. In view of this, this paper proposes a reference point adaptive generation method for NSGA-III improvement. The improved algorithm can adaptively generate a series of reference points with good convergence performance and uniform distribution based on the current population information in the evolution process to guide the population evolution and improve the performance of the solution set.

5.1. Generation of Reference Points and Selection Strategy for Individuals

5.1.1. Generation of Reference Points

The basic idea of reference points adaptive generation is that for the current population, it finds a local ideal point in each dimensional target space and uses it as a reference point. The specific computational steps of reference point generation are as shown below.

(1) Set the initial parameter: the population to be selected $G(k)$, the step size for generating reference points φ ($\varphi \in (0,1)$), the sampling rate of reference points α ($\alpha \in [1/M, 1]$), and the number of reference points NR ($NR \leq N$);
(2) Select the nondominated solutions of $G(k)$ to form $G'(k)$;
(3) Sort $G'(k)$ according to the crowding distance of the m dimensional target space;
(4) Based on the αN individuals with the largest crowding distance, reference points are generated according to Equations (42) and (43) which form the set of reference points R_m in the m dimensional target space;

$$r = (f_1(x), \ldots, f_m(x) - v_m, \ldots, f_M(x)) \tag{44}$$

$$v_m = \varphi\left(f_m^{\max} - f_m^{\min}\right) \tag{45}$$

where $f_m^{\max}$ and $f_m^{\min}$ are, respectively, the maximum and minimum values of the m objective function in the known solution set;
(5) Reference point set $R = R \cup R_m$, judge the size of m, if $m < M$, then m increase by 1, then return to step 3 and repeat the above process, otherwise go to step 6;
(6) Delete the dominated points in R and judge the number of reference points in R, if it is greater than NR, delete the $|R| - NR$ points with the largest congestion distance in R, otherwise go to step 7;
(7) Output the set of reference points R.

5.1.2. Individual Selection Strategy Based on Reference Points

Based on the adaptively generated reference points, the Chebyshev distance between the individuals in the current population to be selected and the reference points are calculated to evaluate the performance of individuals, and then the closest one is selected for each reference point to form the new generation population. In the selection process, if an individual is the closest individual for multiple reference points, the individual can be selected only once, thus increasing the diversity of the population. In addition, given that the size of the reference points may be smaller than the population size, after each reference point has selected the nearest individual, all reference points will be available for selecting individuals again. Under this individual selection strategy, the individual selection pressure will be increased and a new population with better performance will be obtained for each evolutionary generation, resulting in a Pareto optimal solution set for the optimization problem at the end of evolution.

5.2. Algorithm Flow

The specific solution process of the NSGA-III algorithm based on the improvement of reference points is shown in Figure 3. The reference point based on multi-objective evolutionary optimization algorithm is practically applied to the VPP cost allocation model in this paper with the following computational steps.

Step 1: Read the equipment parameters of each participating member in the VPP, forecasts of DRE, load, and market price. Generate an initial population $F(k)$ of size N randomly, and set crossover probability, mutation probability, and the interval generation for generating reference points k_{gr}.

Step 2: Use evolutionary operators, generate offspring populations $F'(k)$, and merge parent-offspring populations $G(k) = F(k) \cup F'(k)$.

Step 3: Determine whether the number of iterations k is an integer multiple of k_{gr}. If it is an integer multiple, proceed to step 4 to generate a new reference point, otherwise proceed to step 5.

Step 4: Based on the current population $G(k)$, find the local ideal points respectively in each dimensional target space for the stability, fairness, and attractiveness objectives, and generate the reference point set using the reference point adaptive generation method, $R = \{r_1, \ldots r_{NR}\}$;

Step 5: Based on the reference point R, select individuals from $G(k)$ that are closer to the reference point into the next generation population to form $F(k+1)$.

Step 6: Determine whether to meet the terminating condition. If not meeting the terminating condition, then k is increased by 1, then return to step 2 and repeat the above process, otherwise go to step 7.

Step 7: Select the nondominated solutions in $F(k)$ to form the output of Pareto optimal solution set.

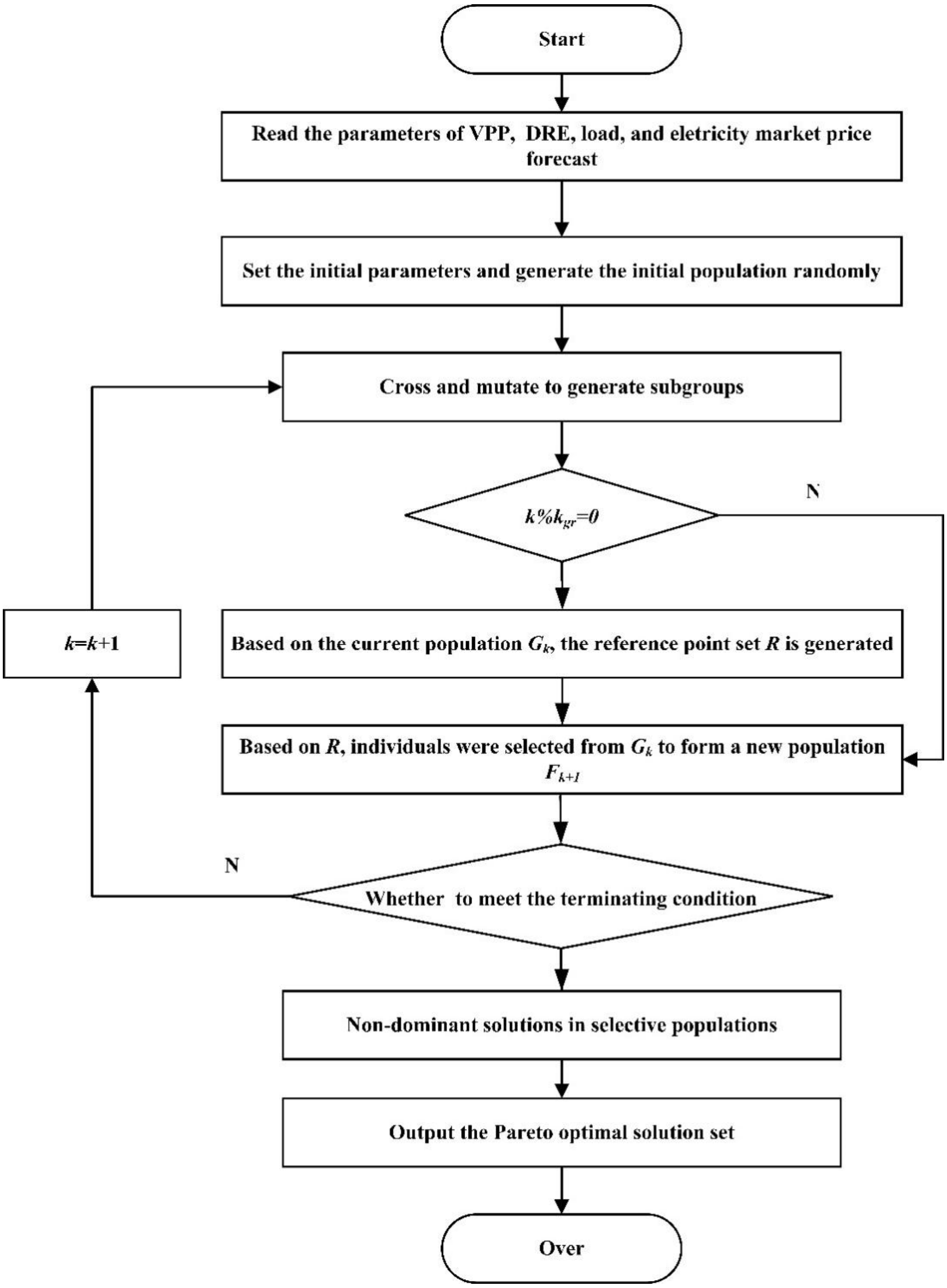

Figure 3. NSGA-III algorithm flow chart based on reference point improvement.

6. Case Study

6.1. Simulation Data

In order to verify the effectiveness of the VPP cost allocation model, this section takes a VPP composed of prosumers as an example to provide a case study. VPPs are composed of 8 prosumers including industrial parks, commercial complexes, and office buildings. The data on user load and DRE's operation are from the VPP demonstration project in north Hebei, China. The load demand and renewable energy output forecast of each user are shown in Figures 4 and 5. Assume that 15% of the user's total load demand belongs to flexible load, and its adjustment compensation price is shown in Figure 6. There are 24 bidding periods in the electricity market. Each period lasts one hour. As shown in Figure 7, the market price of Guangdong electricity market on a certain day is selected as the predicted value of the power market price of day-ahead and real-time market. The deviating electricity assessing standard is ±5%. The penalty price is 700 yuan/MWh. The predicted deviations of electricity price and load demand are set as ±15%, and the risk parameters α and β were set as 0.9 and 0.1, respectively.

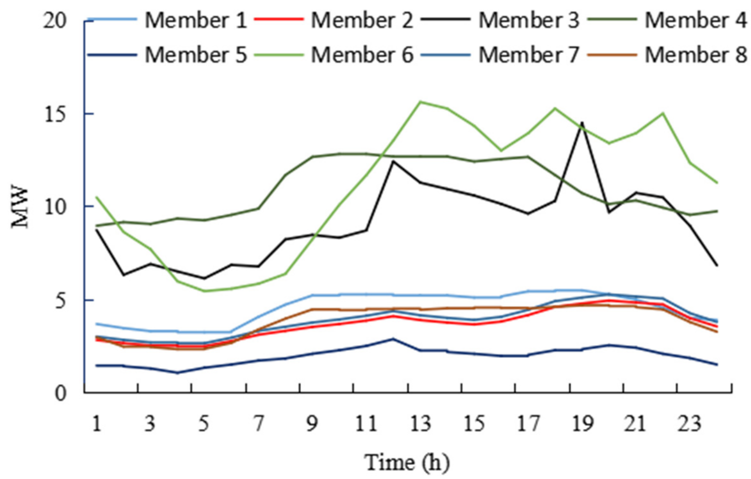

Figure 4. Load demand forecast of VPP participating member.

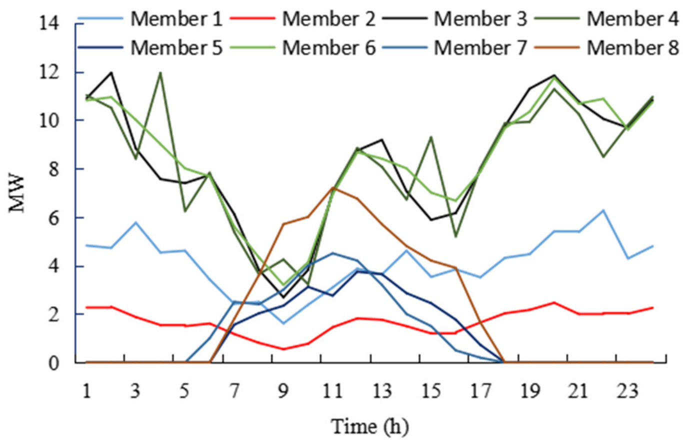

Figure 5. DRE output forecast of VPP participating member.

According to the probability density function of DRE's output, load demand, and market price, 10 situations were extracted by the proportion of Monte Carlo simulation based on uncertain factors. A total of 1000 generated situations were reduced to 50 by the scenario reduction technology based on Kantorovich distance [27]. The model was solved by MATLAB 2014A in a computer with Windows 10, Intel Core i7 processor, and 8 GB of RAM.

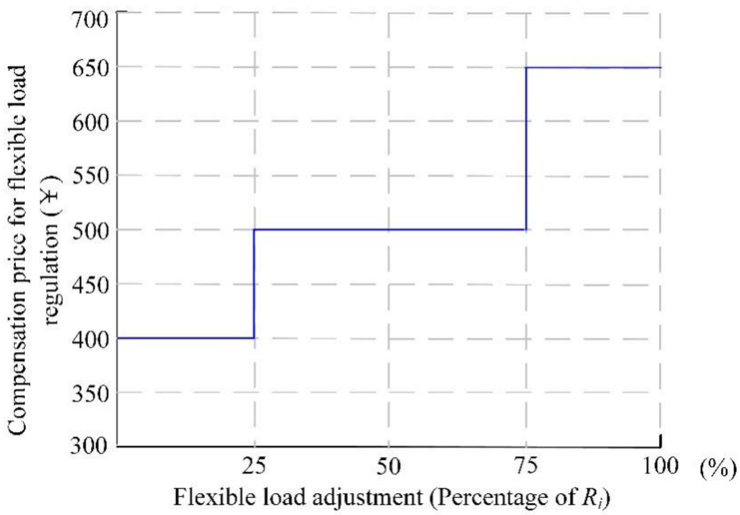

Figure 6. Stepwise compensation price for flexible load regulation.

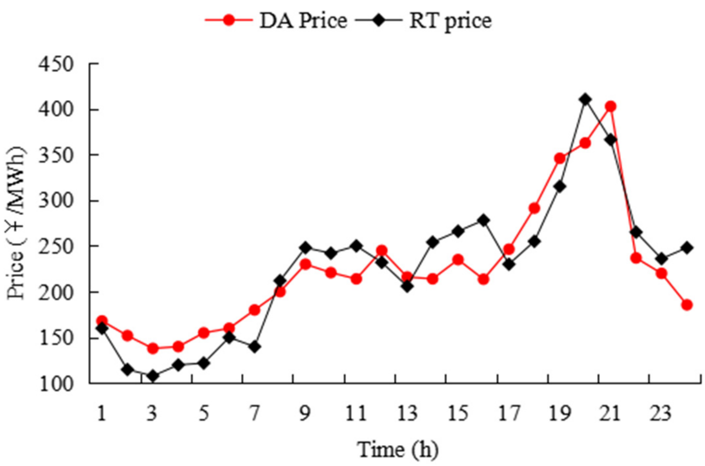

Figure 7. Electricity market price forecast.

6.2. Cost Allocation Results and Analysis

6.2.1. Cost Allocation Result

The Pareto optimal solution set of multi-objective optimization of VPP cost allocation is achieved by solving the optimization model, as shown in Figure 8. In the Pareto optimal solution set, the stability index, fairness index, and attraction index of cost allocation scheme range from 534.6 yuan to 1199.93 yuan, 6.29% to 19.49%, and 1.35 to 2.57, respectively. Compared with the profit allocation scheme based on Shapley value in [23] (the stability index is 103 yuan accounting for 2.98% of the VPP's cooperation benefits; the fairness index is 34.63%; the attraction index is 7.25), the profit allocation strategy proposed in this paper improves the stability of virtual cooperative alliance, the fairness of profit allocation, and its attraction to participating members.

As is shown in Figure 8, there are no optimal results in Pareto optimal solution set that can meet the high stability index, low fairness index, and low attraction index simultaneously. It can be seen that they are contradictory among three objective functions constructed in the paper. Therefore, it is difficult to get optimal solutions. Take the cost allocation scheme with the optimal stability objective of Pareto optimal solution set as an example. The allocation scheme allocates less cost to participating members with the lowest cost savings of the alliance to increase their cost savings and improve the stability of the cooperation alliance, which leads the deviation among cost saving ratios of participants to increase to 19.49%. At the same time, the attraction of participating members who contribute more to the cooperation benefit of VPP is reduced, and the attraction index is 2.23, indicating that participating members have greater risks in participating in other VPPs' cooperation. In the Pareto optimal solution set, the optimal fairness-objective-based cost allocation scheme tends to close the gap among the cost-saving ratio of participating members. It will lead to the low-cost savings achieved by individual participants of low bidding cost. The lowest cost savings of alliance *S* fell to 654.92 yuan. Then, the satisfaction of participating members and the stability of the VPP's alliance both decreased.

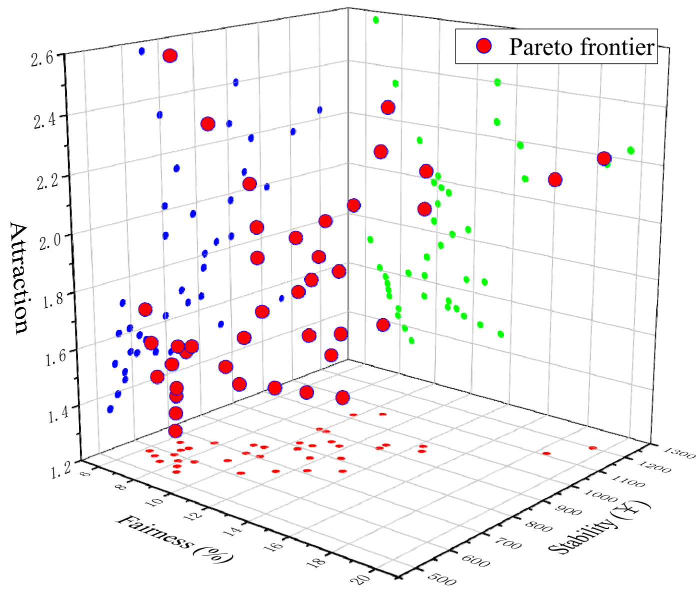

Figure 8. Pareto set of VPP cost allocation model.

The model constructed in this paper can provide a variety of cost allocation schemes in the core of the game for VPP operators. In the actual operation of a VPP, the VPP operators can choose the optimal cost allocation scheme in the Pareto solution set according to their own business needs through the multi-objective decision-making method. This also proves that the VPP cost allocation mechanism designed in this paper has high flexibility. In this paper, the decision is made by calculating the distance between each cost allocation scheme, the constructed ideal scheme, and negative ideal scheme using the TOPSIS method. Then, the cost allocation scheme with the best comprehensive effect is obtained. Considering the importance of maintaining cooperative relations among participating members of the VPP, the weights of stability index, fairness index, and attraction index are set as 0.35, 0.35, and 0.3, respectively, in the scheme comparison.

The optimal cost allocation scheme after screening is shown in Figure 9. Figures 9 and 10 describe the cost allocation ratio, cost allocation amount, and cost saving of each member in the optimal cost allocation scheme, respectively. Under this cost allocation scheme, the cost saving ratio of each member of the VPP is between 7.82% and 18.66%, and the maximum deviation is 10.84%. The lowest cost saving of alliance *S* is 822.55 yuan, and the worst attraction index of participating members is 1.8. As is seen from the figure, the cost allocation ratio of each member of VPP is correlated with its individual bidding cost. Members with higher individual bidding cost tend to get more cost allocation. On the one hand, members of large size allocate the market trading cost through the size of power purchase marketization. On the other hand, in order to reduce the dissatisfaction of cooperation and maximize the minimum cost saving of the alliance *S*, the member of the low-cost allocation is allocated less cost. More cost shall be borne by the individual bidding members.

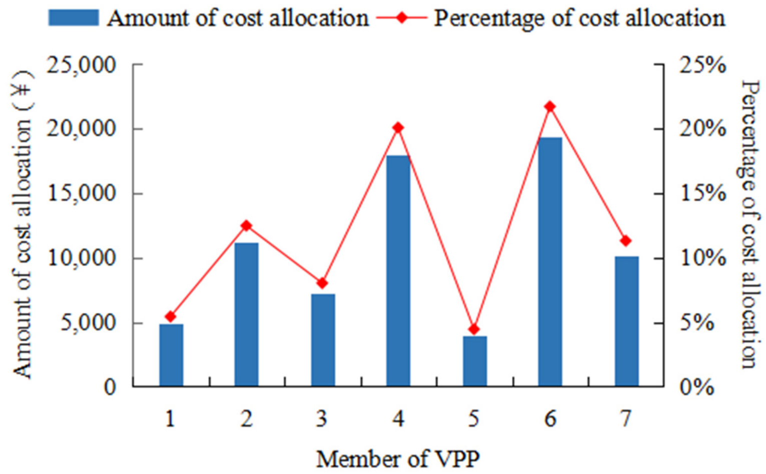

Figure 9. Cost allocation of VPP participating member.

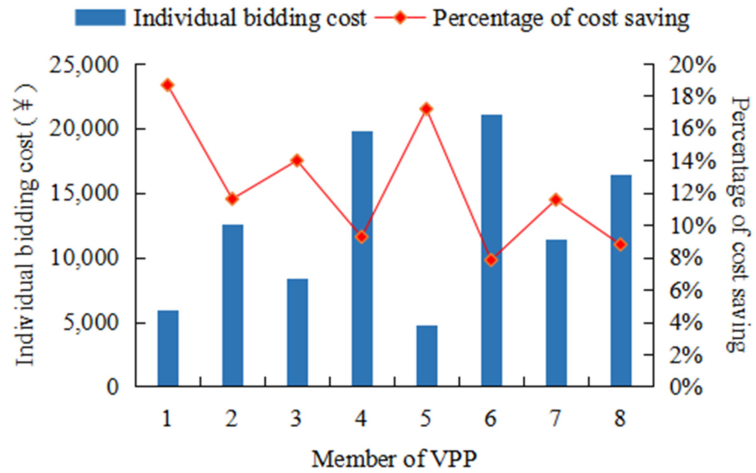

Figure 10. Cost saving of VPP participating member.

In addition, as individual members with low bidding cost are more sensitive to cost savings, it can be seen from the figure that members with small size generally get a higher cost saving ratio in the VPP cooperative alliance. For example, the individual member 1 and member 5 with the lowest bidding cost have cost saving ratios of 18.66% and 17.18%, respectively. It is beneficial to encourage small prosumers to participate in VPP cooperation and reduce the influence of uncertainty of renewable energy output and load demand on power market and system operation. At the same time, the individual member 6 with the highest bidding cost, and its cost savings ratio is 7.82%. Its attraction index is 1.8. The VPP has the worst attraction to the member 6 among the existing participating members. It suggests that prosumers tend to participate in VPPs with larger scale. Meanwhile, internal participating members with smaller size in the VPP will make the alliance more stable.

6.2.2. Cost Allocation Scheme under Situations of Different Risk Factors

Under various risk situations of different flexible load scale L^R and penalty electricity price P^{DP} of unbalanced power, Table 1 shows the distribution effect of the optimal cost allocation strategy of the VPP based on TOPSIS screening. As can be seen from Table 1, with the increasing bidding difficulty in the electricity market, which means that L^R becomes smaller and P^{DP} becomes larger, the stability of the VPP cooperation and the fairness of cost allocation will be affected, and the attraction of the VPP cooperation alliance to participants will increase. In the electricity market, VPPs mainly deal with the fluctuation of uncertain factors such as load demand and renewable energy output through flexible load regulation, which can reduce the deviating power. The increase of L^R means that both the participating members and the VPP have more controllable resources. On the one hand, it will improve the VPP's risk response ability and reduce the market transaction cost. Therefore, the minimum saving cost of the alliance is also increasing. On the other hand, the improvement of risk response ability of participating members makes them depend on VPP cooperation less. Thus, the attraction index decreases. At the same time, P^{DP} represents the risk cost. With the increase of P^{DP}, the VPP plays a significant role in saving the penalty cost of unbalanced electricity, and the minimum cost saving of the alliance and its attraction to participating members are improved.

Table 1. The effect of cost allocation under different risk scenarios.

Risk Scenario		The Effect of Cost Allocation		
		Stability	Fairness	Attraction
1	L^R = 10%, P^{DP}= 700	1005.84	9.85%	1.92
2	L^R = 15%, P^{DP} = 700	1020.68	9.82%	1.99
3	L^R = 20%, P^{DP} = 700	1030.75	9.80%	2.03
4	L^R = 15%, P^{DP} = 300	324.62	5.56%	3.54
5	L^R = 15%, P^{DP} = 500	792.85	7.66%	2.96

6.2.3. Cooperative Benefits of VPP

As the cost characteristic function of cooperative game has superadditivity, the transaction cost of VPP members participating in market bidding as an entity is lower compared with individual members participating in the electricity market. The transaction saving-cost is the cooperation benefit of VPP. Figures 11 and 12 respectively describe the bidding costs of cooperative and independent participation in the electricity market under different risk parameters β and flexible load scale L^R. As we see from the figure, with the increase of risk parameter β, a conservative bidding strategy will lead to the increase of VPP bidding cost and total market bidding cost of individual participating members. Meanwhile, the cooperation benefit and the proportion of cost saving of the VPP increase gradually. With the increase of flexible load scale L^R, cooperative bidding cost and individual bidding cost both decrease, and cooperation benefit and the proportion of cost saving of the VPP also increase. Overall, in all cases, the bidding transaction cost of VPP cooperation is always less than the total cost of the member involved in the electricity market alone. It is largely due to cooperation through VPP, the member can use available resources to cope with uncertainty of output of renewable energy, load demand, and market price more effectively, and it can reduce unbalanced power between the day-ahead and real-time market scheduling, which leads to the reduction of market transaction cost.

6.3. Algorithm Performance Analysis

In order to verify the performance of the improved multi-objective optimization algorithm, the NSGA-III and the improved NSGA-III based on the adaptive generation of reference points are applied to solve the VPP cost allocation model. The population size N is 100 and the number of iterations is 300. The crossover probability is 0.85 and mutation probability is 0.1. The number of reference points is 50, and the sampling parameters α and φ are, respectively, 0.4 and 0.1. The performance of the two algorithms is compared in terms of convergence, solution set distribution, and computation time, and the results are shown in Table 2. As can be seen from Table 2, the Generation Distance (GD) and Spacing (SP) of the improved NSGA-III are smaller than those of NSGA-III, and NSGA-III is slightly better than the improved NSGA-III in terms of computation time. The results show that, compared with NSGA-III, the Pareto solution set obtained by the improved NSGA-III can guarantee the distribution and extension performance, and has better convergence performance, while the reference points can be generated quickly and adaptively and its time consumption is within an acceptable range. Therefore, this paper proposes that the improved NSGA-III based on reference points can improve the performance of solving multi-objective optimization problems.

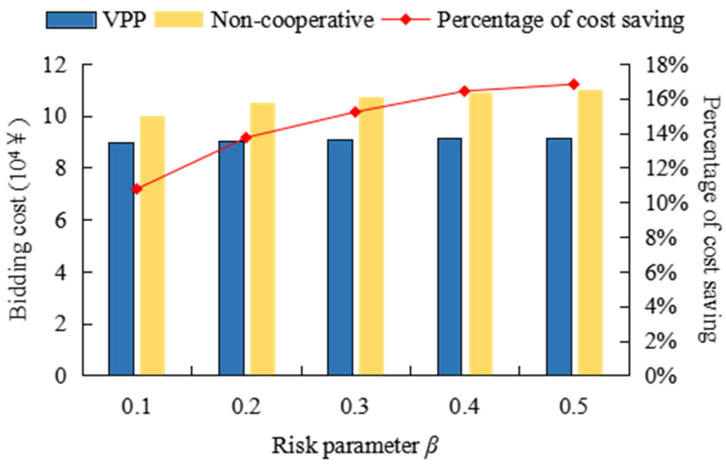

Figure 11. Cooperative benefits of VPP under different risk parameters.

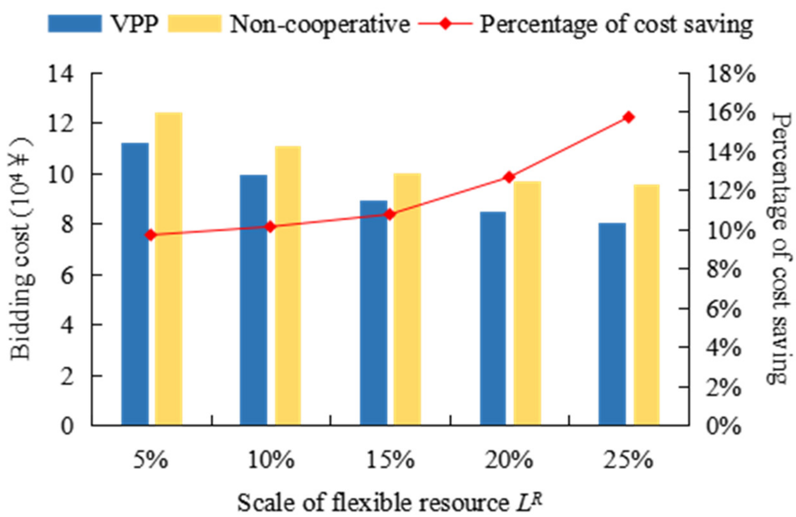

Figure 12. Cooperative benefits of VPP under different flexible load scales.

Table 2. Algorithm performance comparison.

Performance Index	Improved NSGA-III	NSGA-III
GD	0.0132	0.2124
SP	0.0436	0.6423
Computation time (s)	663	645

7. Conclusions

Cooperative game theory is applied in this paper to solve the problem of a VPP's profit allocation under the electricity market. In this paper, a VPP composed of prosumers is taken as the research object. According to the competitive environment of multiple virtual power plants, a VPP's profit allocation model based on bidding optimization is built considering multiple objectives such as fairness of profit allocation, stability of cooperation alliance, and attraction of participating members. An improved multi-objective evolutionary optimization algorithm based on reference points is used to solve the model.

The results show that the proposed method can effectively explore the cooperative game core of VPP which contains many potential allocation schemes. The findings are as follows.

(1) VPP cooperation can save the cost of 10.76% of overall market transaction, and the cost-saving ratio of each member is between 7.82% and 18.66%, which can ensure the sustainable stability of VPP cooperation alliance.
(2) The cooperation benefit and profit allocation effect of VPP are affected by its risk response and tolerance. Prosumers will be more willing to participate in VPP cooperation when bidding risk is high in electricity market.
(3) Individual members with low bidding cost have advantages in VPP cooperation, which can get a higher proportion of cost savings. It indicates that the profit allocation framework proposed in this paper is helpful to encourage prosumers of small size to participate in VPP cooperation.
(4) Compared with other members, a VPP is less attractive to individual members with higher bidding cost, and such members are more likely to participate in other VPP cooperative alliances. This indicates that in the multi-VPP competition environment, VPP cooperative alliances with a smaller gap between internal participating members' size are more solid.

In future studies, the profit allocation method of the VPP proposed in this paper can be improved for VPPs composed of multiple types of subjects, such as distributed energy producers, flexible load users, and energy storage operators. It can expand the application scope of the profit allocation method.

Author Contributions: Y.W., H.D. and M.Z. (Ming Zeng) contributed to conception and design of the study. M.Z. (Min Zhang) organized the database. Z.W. performed the statistical analysis. Y.W. and M.Z. (Min Zhang) wrote the first draft of the manuscript. M.Z. (Min Zhang), J.A. and Z.W. wrote sections of the manuscript. M.Z. (Ming Zeng) provided suggestions for amendments. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Natural Science Foundation of China, grant number 62133015; Special Fund for Basic Scientific Research Business Expenses of Central Universities, grant number 2021MS104, and the Science and Technology Project of SGCC, (Feasibility study of integrated energy production unit for carbon neutrality, grant number 5100-202155336A).

Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

Indices (Sets)	
I	Set of prosumers
S	Cooperation alliance between VPPs
a^S	Indicated vector
$v(I)$	Market trading cost of cooperation game $H(I;v)$
$v(\{i\})$	Transaction cost of individual participating members in the market
$core(H)$	Core set of cooperation game $H(I;v)$
t	Time indicator
s	Situation indicator
o	Stepwise bidding indicator
Parameters	
L^R	Flexible load scale (MW)
$P_{t,s,in}^{DA}$	Electricity purchasing price in the day-ahead market (¥/MW)
$P_{t,s,out}^{DA}$	Electricity selling price in the day-ahead market (¥/MW)
$P_{t,s,in}^{RT}$	Electricity purchasing price in the real-time market (¥/MW)
$P_{t,s,out}^{RT}$	Electricity selling price in the real-time market (¥/MW)
P^{DP}	Penalty power price of unbalanced power (¥/MW)
P_i^R	Compensation offer of flexible load adjustment (¥/MW)

$Q_{i,t,s}^{G,\min}$	DRE's minimum output (MW)
$Q_{i,t,s}^{G,\max}$	DRE's maximum output (MW)
$Q_{i,t,s}^{G}$	DRE's true output (MW)
$D_i^{\max}$	Participating member i's maximum load (MW)
$R_{i,t,s}$	Participating member i's load reduction capability in the situation s during t period (%)
R_i^{up}/R_i^{down}	The upper/lower limit of ramping up and down of participating member i's flexible load regulation
$D_{i,o,t}^{R,\max}$	Participating member i's maximum reduction load of bid section o
δ	Standard of deviating power assessment in the electricity market (%)
λ	Period length, 1 h
β	Risk parameter
α	Confidence coefficient
ρ_s	Probability of scene s
N	Population size
M	Number of objective functions
Variables	
Q_t^{DA}	Expected interaction power between VPP and grid in the day-ahead market (MW)
$Q_{t,s,in}^{DA}$	Electricity purchased by VPP in the day-ahead market (MW)
$Q_{t,s,out}^{DA}$	Surplus renewable energy sold by VPP in day-ahead market (MW)
$Q_{t,s,in}^{RT}$	VPP's expected purchasing power in real-time market (MW)
$Q_{t,s,out}^{RT}$	Electricity sold by VPP in the real-time market (MW)
$Q_{t,s}^{A}$	Actual interaction power between VPP and grid (MW)
$Q_{t,s}^{RT}$	Expected interaction power between VPP and grid in the real-time market during t period (MW)
$D_{t,s}^{Ri,}/D_{o,t,s}^{Ri,}$	Flexible load reduction (MW)
$D_{i,t,}$	Member i's load demand during t period (MW)
η_s	Risk deviation
μ	VaR
$C_{t,s}^{DA}$	VPP's trading cost in the day-ahead market (¥)
$C_{t,s}^{RT}$	VPP's trading cost in the real-time market (¥)
$C_{t,s}^{DP}$	Penalty cost of deviating power in VPP (¥)
$C_{t,s}^{DR}$	Adjustment cost of flexible load in VPP (¥)
$\varepsilon_{t,s}$	VPP's deviating power assessing rate (%)
$\varphi_{t,s}$	VPP's deviating power ratio (%)
ω	Minimum cost savings in all alliance s (¥)
π	The largest difference of trading saving-cost ratio in VPP (%)
$\overline{\theta}/\underline{\theta}$	The maximum/minimum proportion of members' market transaction cost savings in VPP (%)
γ	VPP's attraction indicator to participants
x	Cost allocation vector of cooperative game in VPP

References

1. Baez-Gonzalez, P.; Rodriguez-Diaz, E.; Vasquez, J.C.; Guerrero, J.M. Peer-to-Peer Energy Market for Community Microgrids. *IEEE Electrif. Mag.* **2018**, *6*, 102–107. [CrossRef]
2. Zeng, B.; Liu, Y.; Xu, F.; Liu, Y.; Sun, X.; Ye, X. Optimal Demand Response Resource Exploitation for Efficient Accommodation of Renewable Energy Sources in Multi-Energy Systems Considering Correlated Uncertainties. *J. Clean. Prod.* **2020**, *288*, 125666. [CrossRef]
3. Iria, J.; Soares, F.; Matos, M. Optimal bidding strategy for an aggregator of prosumers in energy and secondary reserve markets. *Appl. Energy* **2019**, *238*, 1361–1372. [CrossRef]
4. José, I.; António, C.; Filipe, S. Network-secure bidding strategy for aggregators under uncertainty. *Sustain. Energy Grids Netw.* **2022**, *30*, 100666.
5. Tan, Z.; Wang, G.; Ju, L.; Tan, Q.; Yang, W. Application of CVaR risk aversion approach in the dynamical scheduling optimization model for virtual power plant connected with wind-photovoltaic-energy storage system with uncertainties and demand response. *Energy* **2017**, *124*, 198–213. [CrossRef]

6. Rahimiyan, M.; Baringo, L. Strategic Bidding for a Virtual Power Plant in the Day-Ahead and Real-Time Markets: A Price-Taker Robust Optimization Approach. *IEEE Trans. Power Syst.* **2016**, *31*, 949–956. [CrossRef]
7. Yan, Q.; Ai, X.; Li, J. Low-Carbon Economic Dispatch Based on a CCPP-P2G Virtual Power Plant Considering Carbon Trading and Green Certificates. *Sustainability* **2021**, *13*, 12423. [CrossRef]
8. Tang, W.; Yang, H. Optimal Operation and Bidding Strategy of a Virtual Power Plant Integrated with Energy Storage Systems and Elasticity Demand Response. *IEEE Access* **2019**, *7*, 79798–79809. [CrossRef]
9. Wang, H.; Riaz, S.; Mancarella, P. Integrated techno-economic modeling, flexibility analysis, and business case assessment of an urban virtual power plant with multi-market co-optimization. *Appl. Energy* **2020**, *259*, 114142. [CrossRef]
10. Li, B.; Ghiasi, M. A New Strategy for Economic Virtual Power Plant Utilization in Electricity Market Considering Energy Storage Effects and Ancillary Services. *J. Electr. Eng. Technol.* **2021**, *16*, 2863–2874. [CrossRef]
11. Guo, W.; Liu, P.; Shu, X. Optimal dispatching of electric-thermal interconnected virtual power plant considering market trading mechanism. *J. Clean. Prod.* **2021**, *279*, 123446. [CrossRef]
12. Ko, R.; Kang, D.; Joo, S. Mixed Integer Quadratic Programming Based Scheduling Methods for Day-Ahead Bidding and Intra-Day Operation of Virtual Power Plant. *Energies* **2019**, *12*, 1410. [CrossRef]
13. Ling, Y. Research on the internal bidding mechanism of virtual power plant based on game theory. *North China Electr. Power Univ.* **2016**. [CrossRef]
14. Yin, S.; Ai, Q.; Li, Z.; Zhang, Y.; Lu, T. Energy management for aggregate prosumers in a virtual power plant: A robust Stackelberg game approach. *Int. J. Electr. Power Energy Syst.* **2020**, *117*, 105605. [CrossRef]
15. Wu, L.; Jing, Z.; Wu, Q.; Deng, S. Balanced Interaction Strategy Based on Stackelberg Game Model. *Power Syst. Autom.* **2018**, *42*, 142–150+207.
16. Gao, Y.; Zhou, X.; Ren, J.; Wang, X.; Li, D. Double Layer Dynamic Game Bidding Mechanism Based on Multi-Agent Technology for Virtual Power Plant and Internal Distributed Energy Resource. *Energies* **2018**, *11*, 3072. [CrossRef]
17. Yang, D.; He, S.; Chen, Q.; Li, D.; Pandžić, H. Bidding strategy of a virtual power plant considering carbon-electricity trading. *Power Energy Syst. CSEE J.* **2019**, *5*, 306–314.
18. Wenlu, D.; Qun, W.; Li, Y. Deconstruction and Dispatching Model with Virtual Power Plant and Distribution Company Containing Virtual Power Plant. *Power Syst. Autom.* **2015**, *39*, 75–81+207.
19. Davide, F.; Antonio, F.; Davide, P. Optimal sizing of energy communities with fair revenue sharing and exit clauses: Value, role and business model of aggregators and users. *Appl. Energy* **2021**, *299*, 117328.
20. Dabbagh, S.R.; Sheikh-El-Eslami, M.K. Risk-based profit allocation to DERs integrated with a virtual power plant using cooperative Game theory. *Electr. Power Syst. Res.* **2015**, *121*, 368–378. [CrossRef]
21. Chen, W.; Qiu, J.; Zhao, J.H.; Chai, Q.; Dong, Z.Y. Bargaining Game-Based Profit Allocation of Virtual Power Plant in Frequency Regulation Market Considering Battery Cycle Life. *IEEE Trans. Smart Grid* **2021**, *12*, 2913–2928. [CrossRef]
22. Fan, S.L.; Ai, Q.; Piao, L.J. Bargaining-based cooperative energy trading for distribution company and demand response. *Appl. Energy* **2018**, *226*, 469–482. [CrossRef]
23. Ma, X.; Yu, S.; Zhu, S.; Wang, G. Profit Distribution of Virtual Power Plant Based on Multi-Factors. *J. Electr. Technol.* **2020**, *35*, 585–595.
24. Wang, Y.F.; Gao, W.J.; Qian, F.Y.; Li, Y. Evaluation of economic benefits of virtual power plant between demand and plant sides based on cooperative game theory. *Energy Convers. Manag.* **2021**, *238*, 114180. [CrossRef]
25. Fang, F.; Yu, S.; Liu, M. An Improved Shapley Value-Based Profit Allocation Method for CHP-VPP. *Energy* **2020**, *213*, 118805. [CrossRef]
26. Nguyen, H.T.; Le, L.B. Bi-Objective-Based Cost Allocation for Cooperative Demand-Side Resource Aggregators. *IEEE Trans. Smart Grid* **2018**, *9*, 4220–4235. [CrossRef]
27. Zeng, M.; Yang, Y.; Wang, Y.; Wang, J. Research on the simulation of power supply side coordination planning based on Monte Carlo Method. *J. North China Electr. Power Univ. (Nat. Sci. Ed.)* **2016**, *43*, 94–104.
28. Good, N.; Karangelos, E.; Navarro-Espinosa, A.; Mancarella, P. Optimization Under Uncertainty of Thermal Storage-Based Flexible Demand Response with Quantification of Residential Users' Discomfort. *IEEE Trans. Smart Grid* **2015**, *6*, 2333–2342. [CrossRef]
29. Heydarian-Forushani, E.; Moghaddam, M.P.; Sheikh-El-Eslami, M.K.; Shafie-Khah, M.; Catalão, J.P.S. Risk-Constrained Offering Strategy of Wind Power Producers Considering Intraday Demand Response Exchange. *IEEE Trans. Sustain. Energy* **2014**, *5*, 1036–1047. [CrossRef]
30. Deb, K.; Jain, H. An Evolutionary Many-Objective Optimization Algorithm Using Reference Point-Based Nondominated Sorting Approach, Part I: Solving Problems with Box Constraints. *IEEE Trans. Evol. Comput.* **2014**, *18*, 577–601. [CrossRef]
31. Heitsch, H.; Romisch, W. Scenario reduction algorithms in stochastic programming. *Comput. Optim. Appl.* **2003**, *24*, 187–206. [CrossRef]