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Dynamic Aggregation Method for Load Aggregators Considering Users' Deviation Electricity

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Abstract: Constructing a new energy-based power system is not only an important direction for the transformation and upgrade of China's power system, but also a key to achieving peak carbon and carbon neutrality. How to fully utilize situation awareness technology to adapt to diverse and differentiated scenarios has become a crucial breakthrough point for ensuring the reliable, safe, high-quality, low-carbon, and economical operation of the new power system. Starting from the distribution network demand resources, this paper proposes a dynamic aggregation method for load aggregators considering the user deviation quantity, to deal with the current situation that the adjustable load-side resource points are multi-faceted and wide, and the operating subjects are complex and difficult to participate directly in the grid dispatch. First, considering there is subjectivity in the electricity behavior of users under the jurisdiction of the load aggregator, a deviation amount may be generated during the actual aggregation process, which reduces the profit of the load aggregator. Therefore, a load aggregator-level user deviation dynamic volume forecasting method based on the Markov chain is proposed, which is used to predict the deviation quantity of users during the dispatch cycle and achieve a dynamic status estimate on the load side of the new power system. On this basis, a dynamic aggregation model for load aggregators based on the deviation volume was constructed with the objective of maximizing the revenue of load aggregators. The examples, by comparing the aggregation results of users under three scenarios, show the proposed method can effectively guarantee the income of load aggregators, verify the effectiveness of the proposed dynamic aggregation strategy, and provide technical support for the operation situation awareness of the load side of the new power system.

Keywords: load aggregators; dynamic aggregation; Markov chain; load forecasting; state estimation

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1. Introduction

Constructing a new power system under the premise of ensuring energy and power supply has become an important measure to implement the "dual-carbon" goal. With the development of informationization and intelligence of the new power system, situational awareness of the new power system with a high proportion of new energy can help power dispatchers to obtain real-time operation information in a timely manner, so as to quickly discover potential problems. This is an important way to achieve observable and controllable operation of the power system, as well as to improve the safety level of power system operation and ensure the popularization of renewable energy [1].

The safety and stability of new electricity systems containing a significant proportion of renewable energy face great challenges [2]. On the one hand, the power supply side experiences leap in the development of clean energy represented by wind and solar power, and the share of new elements such as controlled loads and electric vehicles on the demand side gradually increases, bringing the potential for rapid response and aggregation to the power grid, while also introducing more uncertainty factors into the system [3]. On the other hand, due to the grid connection of large wind and solar power projects, the proportion of conventional supporting power sources such as coal power is decreasing, the system tends to be electronified, the control modes are diversified, and the safety and stability analysis of the system becomes more complex [4].The rapid development from various sides brings great difficulty in real-time balance of power systems, the issue of power supply shortage becomes more severe. And, it will be difficult to maintain the balance of supply and demand in the power system only by the dispatchable resources on the power generation side [4]. In this context, load aggregators have emerged as a new independent subject. They can optimize the electricity usage methods of residential consumers in many flexible ways, while aggregating user participation in grid management, thereby substantially improving the flexibility and reliability of grid regulation [5].

The current increase in the penetration rate of renewable energy poses challenges to the integration of new energy sources. Balancing the supply and demand of electricity and making accurate predictions have become key research directions in modern power systems. Reference [6] proposes the use of Markov prediction methods for forecasting medium- to long-term electricity loads. Reference [7] suggests the Gray–Fuzzy–Markov Chain Method for three-stage short-term load forecasting, providing a basis for grid planning. Reference [8] introduces a short-term load forecasting model based on Markov chains, designed for continuous training during operation and capable of pre-training, making it universally applicable. However, there is limited research considering the subjective nature of user electricity consumption habits, as well as factors like temporality, randomness, and responsiveness. Utilizing load forecasting techniques to predict deviations in user electricity consumption is an area that is less explored.

However, there are certain challenges in dynamically aggregating users through load aggregators to enable them to participate in grid dispatch at the current stage. One of the main challenges is that the types of adjustable loads are diverse, geographically dispersed, and have small individual adjustment capabilities, which make it difficult to efficiently call upon users.

To address this limitation, domestic and foreign scholars have conducted corresponding research on adjustable load aggregation. Reference [9] introduces active aggregation objects and application scenarios, and then constructs an aggregation model for electric vehicle users aggregated by load aggregators in their jurisdiction, fully tapping into the regulation ability of electric vehicles to participate in ancillary services. Reference [10] proposes a general composite load model aggregation method that comprehensively considers the topology of load networks and conducts detailed equivalent error analysis of load model aggregation to illustrate the possible error factors and their impact mechanisms on equivalent accuracy. Specifically, a large number of researchers focus on the aggregation strategies of single loads of electric vehicles, air conditioners, energy storage, and electric heating in typical scenarios. Reference [11] takes the load of a park as the research object, proposes a proactive aggregation method for park loads, and constructs an aggregation optimization model based on historical data. Reference [12] conducts a comprehensive review of modeling strategies for air conditioning load aggregation and provides research directions for future air conditioning load aggregation technologies. Reference [13] takes electric vehicles as the research object, adopts a heterogeneity parameter equivalent aggregation method, constructs an aggregation model for electric vehicles, and effectively extracts the overall power regulation characteristics of electric vehicles. Reference [14] takes air conditioning load as the research object, models and aggregates air conditioning load in the region through load aggregators, proposes a variable frequency air conditioning total scheduling optimization strategy considering incentive compensation measures, and introduces temperature rise compensation factors for sensitivity analysis to demonstrate the effectiveness of load aggregation technologies for different electricity consumption scenarios of air conditioning loads in the region. Reference [15] takes temperature control load as the research object, constructs an aggregation model based on the physical characteristics of temperature control load, and introduces sparrow search algorithm for model solving. Reference [16] uses load aggregators to aggregate air conditioning loads in the region, and proposes a central air conditioning aggregation strategy from three aspects: physical characteristics of central air conditioning, economic benefits of load aggregators, and impact on user comfort. The example results show the proposed model can be used to smooth out the output of distributed power sources. Reference [17] takes air conditioning load as the research object, considers user decision uncertainty, establishes a dynamic response model based on the risk-averse multi-arm mechanism theory, and proposes a massive air conditioning load aggregation strategy. Reference [18] has developed a two-layer optimization model for an active distribution system, considering the participation of two different load aggregators, to achieve economic profit optimization. However, the above aggregation methods mostly focus on single-type loads, lack aggregation strategies for different types of loads, and only consider the adjustable potential theoretically possessed by users during aggregation, without considering the actual electricity consumption deviation situations of users, which results in load aggregators bearing a portion of the default costs. At the same time, research on aggregation methods from the user's perspective is still in its infancy, and there is a lack of economic analysis of aggregation benefits.

In response to this, the paper proposes a dynamic aggregation method for load aggregators that takes into account the default electricity consumption of users. Unlike traditional research on load aggregation, this paper integrates various types of resources for aggregation and considers deviations in user electricity consumption in aggregation strategies. The dynamic optimization is performed at an hourly time scale based on a Markov chain prediction method. The specific contributions of the paper are outlined as follows:

1. proposes a dynamic electricity consumption deviation prediction method for load aggregators at the user level based on Markov chains, which is used to predict the electricity consumption deviations of users during the dispatch cycle.
2. Constructs a dynamic load aggregation model for load aggregators based on electricity consumption deviations: the optimization objective is to maximize the expected revenue of load aggregators composed of declared electricity consumption revenue and default costs, considering constraints such as user load reduction boundary, power balance, declared capacity constraints of load aggregators, and capacity deviation.
3. Through simulation studies, the effectiveness of the proposed dynamic aggregation strategy is verified, and it is proved it can improve the declared accuracy and expected revenue of load aggregators in capacity declaration.

In Section 2, the dynamic load aggregation architecture for load aggregators that takes into account electricity consumption deviations of users is outlined. In Section 3, a dynamic electricity consumption deviation prediction method is proposed, which is used to predict the electricity consumption deviations of users during the dispatch cycle. In Section 4, a dynamic load aggregation model for load aggregators based on electricity consumption deviations is proposed. The simulation system's test results are presented in Section 5. Finally, in Section 6, this paper is concluded, and future work suggestions are proposed.

2. Dynamic Aggregation for Load Aggregators Considering Users' Deviation Electricity

Load aggregators can aggregate users' adjustable loads through price compensation [19], thereby profiting from the price difference between the selling price to the power grid and the compensation price to the participating users [20]. In the scenario described in this paper, the load aggregator aggregates users in its jurisdiction who are willing to participate in power grid dispatching, taking into account the actual deviation electricity volume of the participating users, and reports the optimal electricity volume to the power grid dispatching center. At the same time, the load aggregator will also provide corresponding financial compensation to the participating users. The aggregation framework of the load aggregator described in this paper is illustrated in Figure 1.

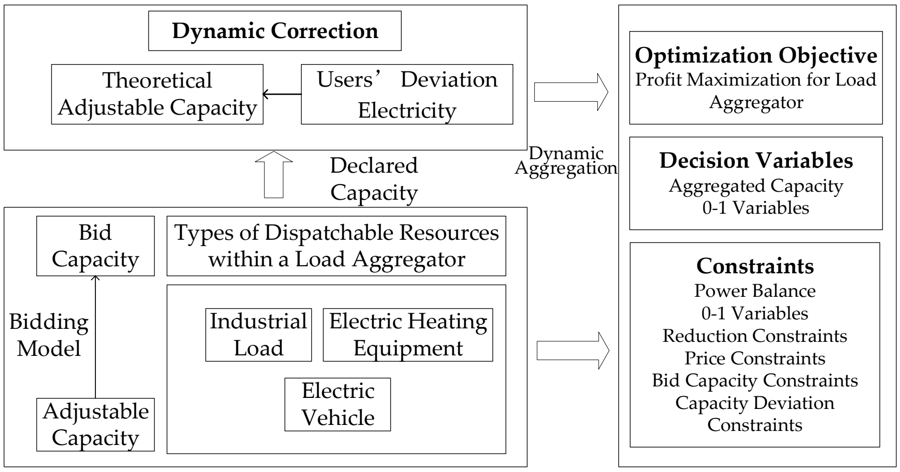

Figure 1. Aggregation framework of the load aggregator.

First, use a demand-side adjustable resource potential calculation method based on data processing to obtain the theoretical adjustment capability of users; second, based on the proposed deviation electricity volume dynamic prediction method, obtain the actual deviation electricity volume of users; finally, with the goal of maximizing the expected profit of the load aggregator, considering power balance constraints, price constraints, capacity deviation constraints, etc., dynamically adjust the declared response capacity of the load aggregator.

3. Dynamic Prediction Model for Deviation Electricity Volume

3.1. User Participation Volume Assessment

Most current studies calculate the adjustable potential of users based on theoretical values, but in reality, the subjective nature of user electricity consumption can lead to the generation of deviation electricity. For the deviation electricity, the power grid will charge corresponding default fees. If the power dispatch center is reported based on the theoretical adjustable potential, it results in high default costs, therefore, it is necessary to establish the relationship between the actual reduction number of residential users and the level of price compensation, as shown in Figure 2. At the same time, the actual load reduction of users at different economic incentive levels given in reference [21] is specifically expressed as follows:

$$p_i^{real}(t) = \gamma_i(j)Q_i^{max}(t) \quad (1)$$

where, $p_i^{real}(t)$ is the actual load reduction of the i-th user in the previous day in period t,$\gamma_i(j)$ is the load reduction rate of the i-th user under economic incentive j, i.e., the ratio of the user's actual load reduction and the theoretical load adjustable potential, and $Q_i^{max}(t)$ is the maximum value of the theoretical load adjustable potential of the i-th user at time t.

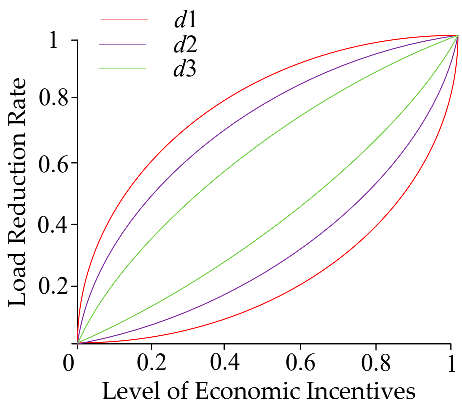

Figure 2. Load response degree.

In the Figure 2, $d1$, $d2$, and $d3$, respectively, represent the upper and lower limits of reduction for users with high, medium, and low levels of variability. As can be seen from the above figure, when the level of price compensation is low, the actual degree of reduction by users is also low. As the level of compensation continues to increase, the response level of users also increases accordingly. However, when the level of price compensation reaches a certain level, the actual load reduction by users approaches the limit of their response capacity.

Based on the actual load reduction amount of the user, the deviation electricity volume that the load aggregator needs to bear for the user can be calculated, as shown in the following formula:

$$w_i(t) = \sum_i^s Q_i^{max}(t) - \sum_i^s p_i^{real}(t) \tag{2}$$

where, 's' represents the number of users within the jurisdiction of the load aggregator. It denotes the deviation electricity volume of the load aggregator in period 't' at the initial stage.

3.2. Forecasting of User Deviation Electricity Volume at the Load Aggregator Level

Forecasting user deviation electricity volume plays a crucial role in ensuring the profits of load aggregators. Due to the subjectivity of user electricity usage habits, their response levels also exhibit temporal and random characteristics. How to accurately predict user deviation electricity volume is a question that needs to be researched.

This paper proposes a rolling forecasting mechanism for user deviation electricity volume to update the declared volume at the next moment. This allows for the dynamic aggregation of user volumes at the next moment. The framework of the dynamic prediction method for deviation electricity volume is shown in Figure 3. According to Section 3.1, the value of deviation electricity volume 24 h before moment t1 is set, and the possible deviation electricity volume at this moment is predicted using the Markov chain prediction model. Then, by rolling at a certain step length, the possible deviation electricity volume that users may generate at the moment is obtained. The declaration volume of the load aggregator is dynamically corrected, thereby reducing the default cost incurred by the load aggregator due to user default when declaring the volume. Through this method, the deviation electricity volume can be updated for several future periods.

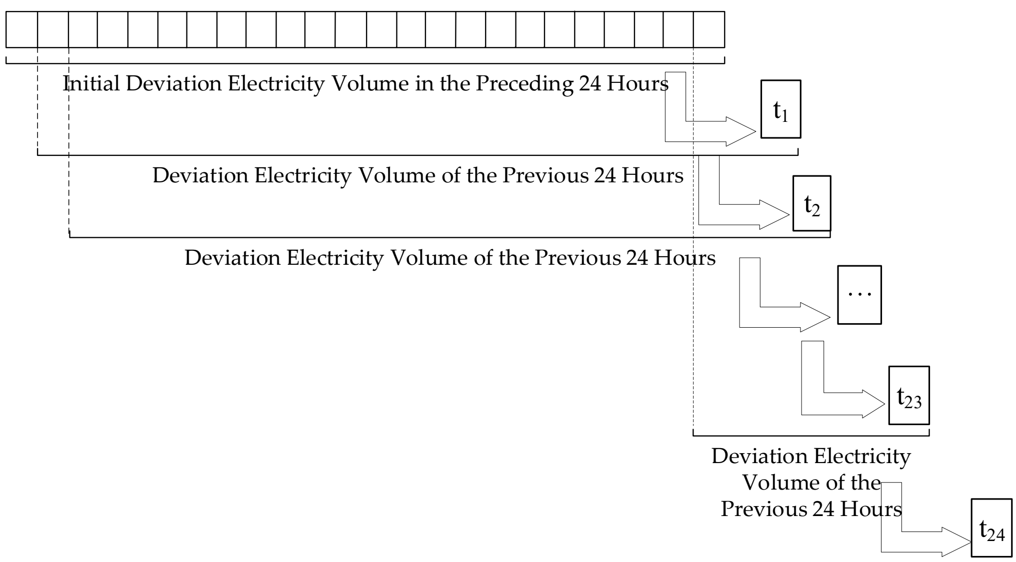

Figure 3. Dynamic forecasting structure for deviation electricity volume.

The steps of model prediction are as follows:

1. grouping of historical data by mean-mean-square deviation grouping method.

Set the input sequence as $x_1, x_2, \cdots x_n$, and find the mean $\overline{x}$ and variance σ. The mean-standard deviation grading method is used to categorize the user response in each period into five states: low response period, low response period, flat response period, high response period, and high response period (equivalent to determining the state space of a Markov chain) as shown in Table 1. Thus, the sequence is divided into the following five groups:

$$(-\infty, \overline{x} - 1.1\sigma), [\overline{x} - 1.1\sigma, \overline{x} - 0.5\sigma), [\overline{x} - 0.5\sigma, \overline{x} + 0.5\sigma), [\overline{x} + 0.5\sigma, \overline{x} + 1.1\sigma), [\overline{x} + 1.1\sigma, +\infty)$$

Table 1. Grouping standards and levels.

State	Grouping Criteria
1	$x < \overline{x} - 1.1\sigma$
2	$\overline{x} - 1.1\sigma \le x < \overline{x} - 0.5\sigma$
3	$\overline{x} - 0.5\sigma \le x < \overline{x} + 0.5\sigma$
4	$\overline{x} + 0.5\sigma \le x < \overline{x} + 1.1\sigma$
5	$x \ge \overline{x} + 1.1\sigma$

2. Identify the state corresponding to the index value in the deviation electricity sequence.

According to the mean and variance in the first step, the deviation power sequence is classified into corresponding intervals based on the grouping criteria. Each interval corresponds to a state that represents a different level of power deviation.

3. Calculate the autocorrelation coefficients and weights of each order.

As previously mentioned, the electricity usage habits of users are subjective. The deviation in power consumption is a random variable, the strength of the relationship between the deviations in power consumption can be represented using autocorrelation coefficients of various orders, the calculation formula is as follows:

$$r_k = \frac{\sum\limits_{i=1}^{n-k} (x_i - \overline{x})(x_{i+k} - \overline{x})}{\sum\limits_{i=1}^{n} (x_i - \overline{x})^2} \tag{3}$$

where, n is the length of the default power series, k = 1,2. . .5, and x_i is the indicator value. The specification of the above equation can be obtained:

$$W_k \triangleq |r_k| / \sum_{k \in E} |r_k| \tag{4}$$

where, $\sum\limits_{k \in E} W_k = 1$ and $W_k \ge 0$, W_k are the magnitude of the weighting of the initial moment of prediction, characterizing the weight of each state in the prediction process in relation to the predicted value. The larger W_k is, the greater the weighting of its corresponding transfer probability.

4. Find the transition matrix.

Based on the state sequence of the deviation in power, the transition probability matrix is calculated as follows:

$$p_{ij} = \frac{f_{ij}}{\sum\limits_{j=1}^{m} f_{ij}}, (p_{ij}) i, j \in (1, 2, 3, 4, 5) \tag{5}$$

where, m is the number of states, $f_{ij}(i, j \in 1, 2, 3, 4, 5)$ is the transfer frequency matrix, and f_{ij} is the frequency at which state i passes through the transfer and thus arrives at state j.

5. According to the aforementioned steps, we obtain the transition probability matrices at all levels.

Use the predicted indicator values of the previous 5 h as the initial state. Then, calculate the prediction probability for the same state, as shown below:

$$p_i = \sum_{k=1}^{m} W_k P_i^{(k)} \tag{6}$$

where, $P_i^{(k)}$ is the state probability of the indicator value, k is the step size, and k = {1,2,3,4,5}, $max\{p_i\}$ are the predicted states of the indicator value at that time.

6. Calculate the weight set.

The aforementioned steps can predict the range of default electricity, but it is impossible to know the specific predicted value, therefore, it is considered to introduce level feature values to address this issue.

Based on the probabilities of the five states at the predicted moment as found in the previous step, each state corresponds to a weight respectively, then the set of weights it constitutes is denoted as $W = \{w_1, w_2, w_3, w_4, w_5\}$, and the calculation formula is shown below:

$$W_i = \frac{(P_i)^{\eta}}{\sum\limits_{k=1}^{5} (P_k)^{\eta}} \tag{7}$$

where, η is the coefficient of action for maximum probability.

7. Calculation of level eigenvalues.

The specific calculation formula is shown below:

$$H = \sum_{i=1}^{5} i \cdot W_i \tag{8}$$

8. Calculation of deviation in power prediction values.

Based on the above $P_i(i = 1, 2, 3, 4, 5)$, the state i with the largest probability among them is selected, and the final predicted value $W(t)$ is $\frac{T_i H}{i+0.5}$ when $H > i$, and the final predicted value $W(t)$ is $\frac{B_i H}{i-0.5}$ when $H < i$. Where T_i and B_i denote the upper and lower bounds of the desired state interval respectively [21].

4. Dynamic Aggregation Model for Load Aggregators Based on Deviation Power

To effectively ensure the profits of load aggregators, this chapter considers the case of user power deviation, and proposes a rolling correction method for the declared capacity of load aggregators, thus constructing a dynamic aggregation model for load aggregators, and updating the optimal aggregation amount for load aggregators.

4.1. Objective Function

This chapter sets the scene with load aggregators aggregating adjustable power from users. It constructs an aggregation optimization model where load aggregators take into account the user's adjustment capabilities. The final profit of the designed load aggregator consists of the declared power profit C_1 by the load aggregator and the default cost C_2. With the aim of maximizing the profit of the load aggregator, the following objective function is established.

$$\begin{aligned} maxC &= C_1 - C_2 \\ &= \sum_{t=1}^{T}\left[p(t)\lambda^s(t) - \sum_{i}^{s} Q_i(t)u_i(t)\lambda^b(t)\right] - \left[p(t) - \sum_{i=1}^{s} Q_i(t)u_i(t)\right]\lambda^v(t) \end{aligned} \quad (9)$$

$$p(t) = \sum_{i=1}^{s}\left(Q_i^{max}(t) - W_i(t)\right) \quad (10)$$

where, T is the aggregation period, which is 24 h in this article. $P(t)$ is the declared capacity of the load aggregator in period t, i.e., the declared capacity of the load aggregator after rolling forecast of defaulted electricity, $\lambda^s(t)$ is the unit price of electricity sold to the grid by the load aggregator in period t, $\lambda^b(t)$ is the compensation price of the load aggregator to the customer in period t, $\lambda^v(t)$ is the penalty price of the defaulted electricity of the load aggregator in period t, $Q_i(t)$ is the curtailment amount of the i-th customer in period t, $u_i(t)$ is the participation or non-participation of the i-th customer among load aggregators in period t. is a 0–1 variable, when indicates participation in aggregation in that period, and when indicates participation in aggregation in that period. aggregation, $u_i(t)$ is a 0–1 variable, when $u_t(t) = 1$, it means participating in aggregation in that period, when $u_i(t) = 0$, it means not participating in aggregation in that period. $Q_i^{max}(t)$ is the maximum regulation potential of the i-th user in period t, and $W_i(t)$ is the rolling forecast of defaulted electricity of the i-th user in period t.

4.2. Constraint Condition

1. Constraint on the upper and lower limits of load reduction for a single user.

For each user, to ensure the basic operation of user load, the reduction capacity when participating in aggregation should not exceed the theoretical adjustable capacity value. Meanwhile, for users whose actual reduction is less than the lower limit, their participation in the aggregation should be less than the actual reduction. It can be specifically described as:

$$Q_i^{min}(t) \le Q_i(t) \le Q_i^{max}(t) \quad (11)$$

$$0 \le Q_i(t) \le Q_i^{max}(t) - W_i(t) \quad (12)$$

where, $Q_i^{min}(t)$ is the lower limit of the regulation potential of the i-th user at time t.

2. Constraints on the upper and lower limits of the total load reduction for users.

The total reduction of all users within the load aggregator in the same period should be less than the capacity declared to the grid during that period. The specific constraint is described as:

$$\sum_{i=1}^{h} Q_i(t) \le p(t) \quad (13)$$

where, h is the number of users participating in the aggregation.

3. User compensation price constraint.

The compensation price applied by the user when participating in the aggregation should be less than the maximum compensation price. The specific constraint description is as follows:

$$0 < \lambda^b(t) \le \lambda^b_{max}(t) \quad (14)$$

4. Power Balance Constraint.

Power balance constraints ensure the stable operation of the power system; therefore, it is necessary to establish power balance constraints for load aggregators and the user side. The power balance constraint for the declared capacity of load aggregators is specifically described as:

$$p_i(t) = \sum_{i}^{h} Q_i(t) + W_i(t) \tag{15}$$

5. Load aggregator capacity declaration constraint.

The load aggregator should declare a capacity to the power grid at time t that is less than the sum of the theoretical adjustable capacity of each user at time t. The specific constraint is described as follows:

$$0 \leq p_i(t) \leq \sum_{i=1}^{h} Q_i^{max}(t) \tag{16}$$

6. Load aggregator price declaration constraint.

The sale price of electricity by the load aggregator should be lower than the average market sale price of electricity, with the specific constraint described as follows:

$$\lambda^s(t) \leq \frac{1}{T}\sum_{t=1}^{T} \lambda_t^{\text{maket}} \tag{17}$$

where, λ_t^{maket} is the average value of the market electricity price respectively.

7. Capacity deviation constraint.

To ensure the safe operation of the power grid, the actual response capacity of the load aggregator must be considered when participating in power grid scheduling, therefore, it is necessary to ensure the scheduling capacity of the power grid is within a certain deviation, so as not to affect the safe operation of the power grid. The specific constraint description is as follows:

$$\sum_{t=1}^{T} \frac{\alpha_t}{T} \geq \varsigma \tag{18}$$

$$\alpha_t = \frac{\sum\limits_{i}^{h} Q_i(t)}{p(t)} \tag{19}$$

where, ς is the permissible deviation capacity.

The solution process is shown in Figure 4.

As illustrated in Figure 4, the resolution process begins with the determination of the initial power deviation for each user, using the Markov forecasting algorithm to dynamically predict the power deviation for each user over the next 24 periods, and adjusting the declared capacity of the load aggregator at time t based on the forecasted power deviation. Subsequently, considering the objective function and associated constraints, the dynamic aggregation model of the load aggregator is optimized, optimizing the reduction quantity of users selected by the load aggregator for aggregation at time t. Finally, the reduction quantities of the users participating in aggregation over the 24 periods are output.

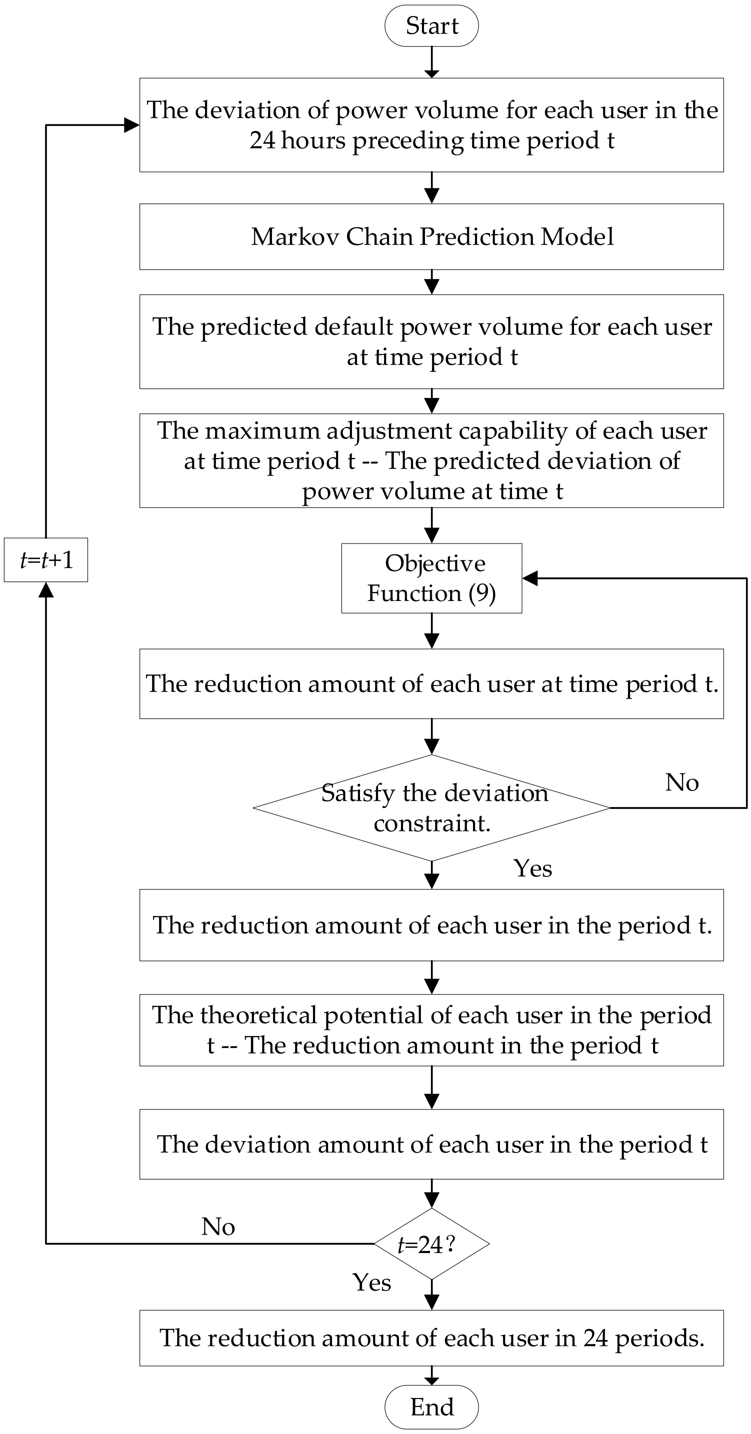

Figure 4. Dynamic aggregation solution process of load aggregator.

5. Example Analysis

5.1. Basic Case Data

This chapter analyses the optimal aggregation scheme and the declared capacity of the load aggregator to aggregate the adjustable loads in the region when it participates in grid scheduling, based on the user regulation potential calculated. The load aggregator is set to aggregate five types of users in the region. To ensure the security and stability of the grid, the capacity deviation of the grid dispatch center δ is set at 10%, and the dispatch is considered successful if and only if the dispatch deviation between the actual aggregated quantity and the declared quantity of the load aggregator is within 10%.

1. Price parameter configuration.

Different load aggregators, with varying scales of aggregated resources, also have different amounts of power deviation. It would be unfair if the market applies the same default price across the board. Therefore, different default prices will be applied to the power deviations of different load aggregators. This paper, referencing [22], sets a graded penalty price. Based on the power deviation situation of the load aggregators, penalty levels are divided according to their declared capacities. Different penalty prices are applied to different penalty levels, with specific penalty prices shown in Table 2, and the time of use electricity price of the power grid is shown in Figure 5.

Table 2. Division of penalty levels for load aggregators.

Penalty Level	Deviation Electricity Volume (kW·h)	Penalty Price CNY/(kW·h)
Level 1	$\leq 0.2\ P(t)$	0.1
Level 2	$(0.2 \sim 0.4)\ P(t)$	0.3
Level 3	$\geq 0.4\ P(t)$	Real-time electricity price

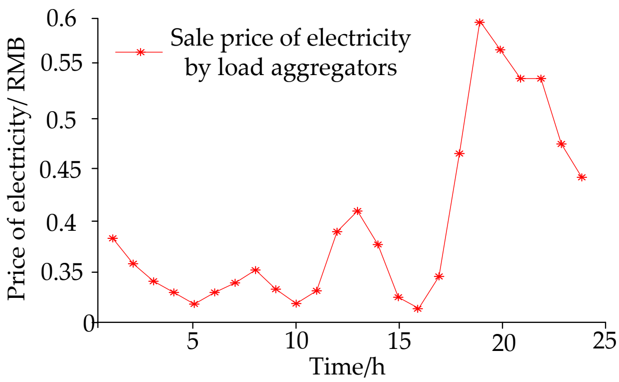

Figure 5. Grid electricity sale price.

To maximize the profits of the load aggregators, the price of electricity they sell to the grid increases during peak periods at noon and in the evening. For example, at 19:00 in the evening, the price of electricity from the load aggregators reaches its highest. However, considering the cost of purchasing electricity from the grid should not be too high, the price of electricity sold by the load aggregators is relatively lower during other normal periods and off-peak periods.

2. Scenario Configuration.

To verify the effectiveness of the proposed dynamic aggregation method, the following three scenarios are set up for comparative analysis.

S1: the load aggregator does not consider user deviation and declares capacity to the grid according to the maximum adjustment ability.

S2: the load aggregator considers users' deviation but does not dynamically adjust the declared capacity according to the deviation.

S3: the load aggregator considers user deviation and dynamically adjusts the declared capacity according to the deviation.

5.2. Analysis of Dynamic Aggregation Effectiveness

5.2.1. Setting and Prediction of Deviation in Electricity Volume

The compensation prices offered by the load aggregator to the users are 0.22 CNY/(kW·h), 0.22 CNY/(kW·h), 0.20 CNY/(kW·h), 0.23 CNY/(kW·h), and 0.21 CNY/(kW·h), respectively. According to Section 3.1, taking into account the impact of user response uncertainty, it is assumed when the economic incentive level j = 0.9, the load reduction rate under the condition of user heterogeneity d1 is extracted, determining the actual reduction amount of the user. At the same time, considering the influence of grid electricity prices on users, it is therefore set there is a difference in the reduction rate of users during peak and off-peak periods, as shown in Figure 6, thus obtaining the deviation of electricity for each user.

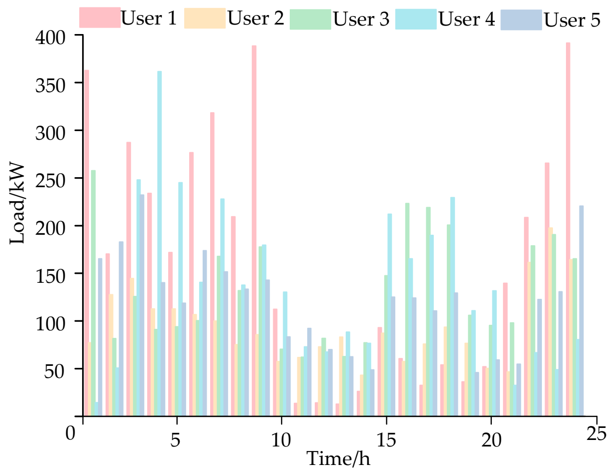

Figure 6. Deviation electricity volume setting.

For the initial deviation in electricity set by the user for the preceding 24 h, the deviation in electricity for the aggregation day is dynamically predicted based on the method proposed in Section 3.2. The characterized deviation in electricity is shown in Figure 7.

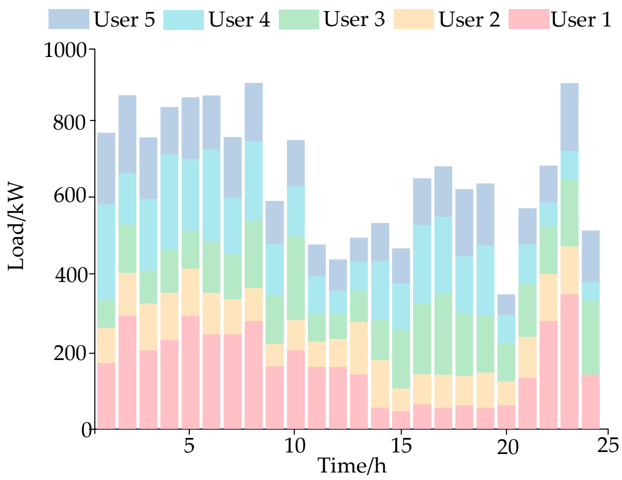

Figure 7. Deviation electricity volume forecast results.

The load aggregator, based on the results of dynamic deviation electricity forecasts, adjusts the declared capacity, and dynamically aggregates users.

5.2.2. Comparative Analysis of Load Aggregator's Declared Amount

The load aggregator declares to the grid the dispatchable capacity that can participate in regulation. The load aggregator declares the capacity based on the maximum adjustable ability of the user when the user's deviation electricity is not considered. When the load aggregator takes into account the deviation electricity, it sets up a comparison between not predicting the user's deviation electricity and making rolling predictions. The resulting declared capacity of the load aggregator is obtained, as shown specifically in Figure 8.

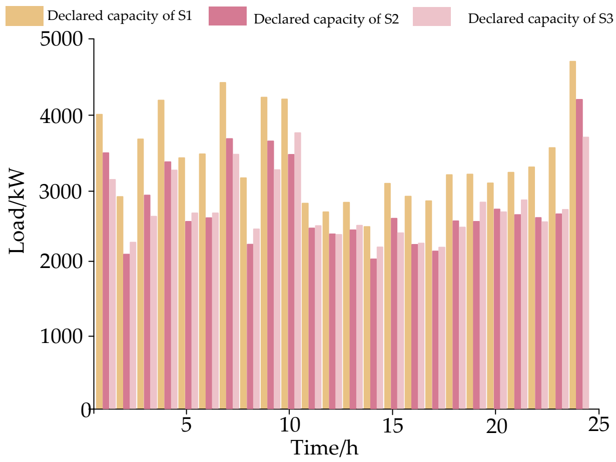

Figure 8. The load aggregator of each scenario declares the capacity.

The graph above illustrates the declared capacity of the load aggregator under different scenarios, providing a relatively intuitive depiction of the declared capacity in three scenarios. As the graph shows, after considering the user's deviation in electricity usage and making adjustments to the declared amount, the load aggregator's declared amount decreases in varying degrees within 24 periods. Overall, considering the subjectivity in users' electricity usage habits, the total declared capacity in Scenario S3 is approximately 14.947 MW·h less than that in Scenario S1 within a day. Meanwhile, for users, as the electricity price during peak hours is higher than during off-peak hours, and the user's deviation amount is greater during off-peak hours, the reduction in the load aggregator's declared amount during peak hours is less than that during off-peak hours.

Through the above analysis, after adjusting the declared capacity of the load aggregator, it can reduce the default cost caused by the users' own reasons, thereby protecting the profits of the load aggregator and enhancing its competitiveness in participating in grid dispatching.

5.2.3. Analysis of Dynamic Aggregation Plan of Load Aggregators

To further analyze how the load aggregator in this area selects users for dynamic aggregation, we examine the aggregation situation under scenario S3, as shown in Figure 9. Figure 9 represents the total load aggregation plan of the load aggregator in this area over 24 periods, considering maximizing its own profit.

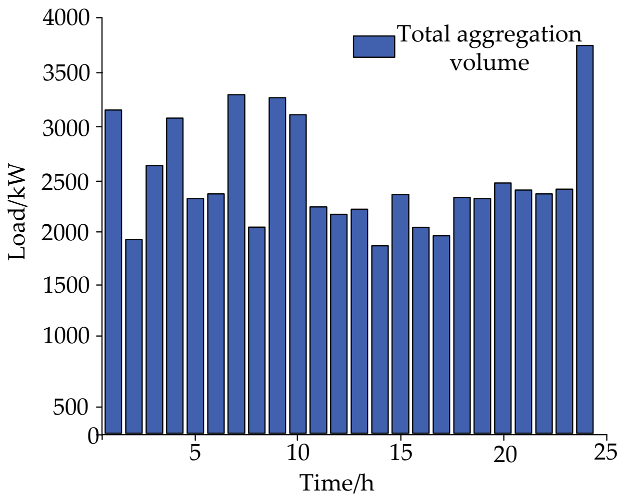

Figure 9. Aggregation volume of the load aggregator at each period.

As the graph indicates, the maximum aggregation volume of the load aggregator occurs at 24:00, reaching up to 3739.559 kW·h. Moreover, the load aggregator's aggregation volume can generally reach 2000 kW·h within the 24 h period. Therefore, by aggregating user-adjusted electricity through the load aggregator, the load in this area can be significantly reduced, thereby effectively improving the load curve of the power grid. Overall, the load aggregator's aggregation capacity is roughly the same as its declared volume, with only a small amount of deviation. The difference is minimal between 11:00–13:00 and 18:00–23:00, which is due to the limitations of user adjustment capabilities. The load aggregator's declared capacity, corrected after rolling forecasts, is close during this period. Although different users will have different adjustment capabilities, the values achieved after aggregation by the load aggregator will be similar.

Meanwhile, this paper presents the specific reduction amounts for each user within the region across 24 periods, as shown in Figure 10.

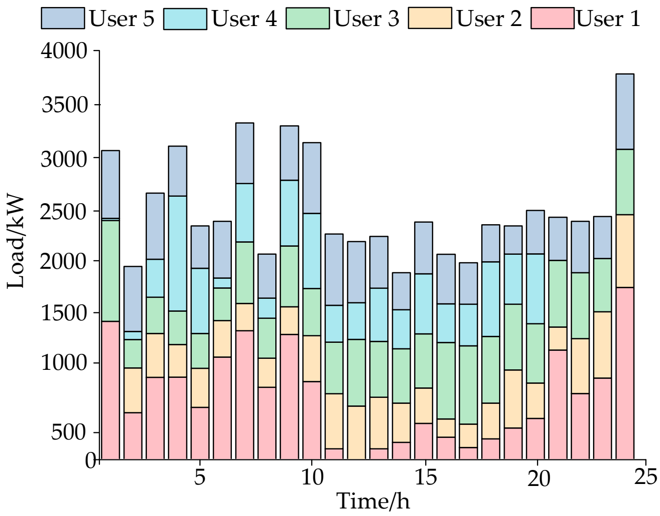

Figure 10. Reduction of each user.

As the graph illustrates, due to the varying adjustment capabilities of different users, the volume of aggregation and whether the load aggregator chooses to include a user in the aggregation can vary. Regarding the load aggregator's selection of users for aggregation, user 1 did not participate in the aggregation at 12:00, user 2 did not partake at 1:00, user 4 participated throughout the period from 21:00 to 24:00, and both user 3 and user 5 were included in the aggregation. This is because the compensation prices for user 3 and user 5 are lower than those of other users, thus, the load aggregator prioritizes aggregating these types of users within their adjustment capability range. It's worth noting among the five users, user 1's aggregation volume is higher than the other four users, with a reduction volume approximately 59%, 12%, 58%, and 20% higher, respectively. This is due to the different adjustment capabilities of each user, to some extent, the reduction volume is directly proportional to the user's adjustment capability. Taking user 1 as an example, the reduction volume reached 1242 kW·h at 7:00, the aggregation volumes of other users were significantly smaller, and their adjustment capabilities were far less than user 1 during this period.

Through the above analysis, the load aggregator, considering the rolling forecast of deviation power, can reasonably allocate and utilize the reduction amounts of users, thereby achieving dynamic aggregation of users, and further improving the economic efficiency of the load aggregator.

5.3. Economic Benefit Analysis of Load Aggregators

The profit of the load aggregator is related to parameters such as the electricity price for the grid, the actual reduction amount of the user, and the economic compensation paid to the user for participating in the aggregation. The profit of the load aggregator is the difference between the revenue from electricity sales obtained from the grid and the compensation amount paid to the user and the default amount to the grid. The effectiveness of the model was verified by comparing the aggregated users when the declared capacity was dynamically corrected and when it was not corrected. The profits, revenues, and costs of each load aggregator are shown in Table 3.

Table 3. Comparison of revenue of load aggregators in different scenarios.

Scenario	Profit/CNY (USD)	Revenue/CNY (USD)	Cost/CNY (USD)
Scenario 1	11,286.51 CNY (1580.74 USD)	30,899.58 CNY (4327.67 USD)	19,643.07 CNY (2757.13 USD)
Scenario 2	11,156.11 CNY (1562.48 USD)	24,992.96 CNY (3500.41 USD)	13,836.85 CNY (1937.93 USD)
Scenario 3	11,430.46 CNY (1600.90 USD)	25,204.28 CNY (3530.01 USD)	13,773.82 CNY (1929.10 USD)

As shown in Table 3, the load aggregator can obtain a revenue of 30,899.58 CNY (4327.67 USD, 1 USD = 7.14) by declaring to the power grid based on the maximum adjustment capacity. However, since Scenario S1 did not consider the existence of user bias, the load aggregator needs to bear a substantial default cost after paying compensation to users, resulting in a final profit of 11,286.51 CNY(1580.74 USD). This is not conducive to the load aggregator's participation in the power grid to enhance its trading competitiveness. Relatively speaking, Scenario S2 considered the deviation of electricity, which would reduce the cost. Although there is a slight decrease in profit compared to Scenario S1, due to the reduction of default costs, it can improve its competitiveness to a certain extent. Scenario S3's profit is 11,430.46 CNY(1600.90 USD), an increase of 1.27% compared to S1 and 2.46% compared to S2. Also, due to the rolling prediction of the deviation of electricity, it performs better than Scenario S2 in terms of both revenue from the power grid and payments to users, as well as default costs. From this, it can be seen the method proposed in this paper can enhance the load aggregator's own income.

Meanwhile, the aggregator achieves compensation and aggregation of the residential load. The profits of the aggregator at each period are shown in Figure 11.

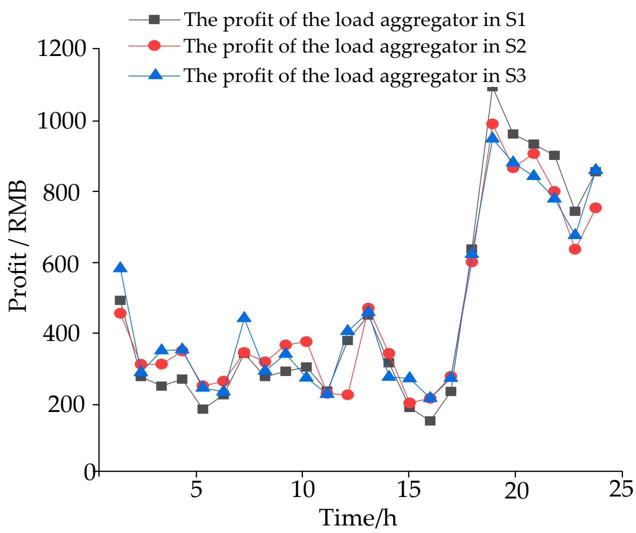

Figure 11. Profit of load aggregator in each scenario.

Figure 11 illustrates the profit variations of the load aggregator when selecting user aggregation and selling electricity to the grid under three scenarios across 24 periods. As can be seen from the figure, the level of profit variation for the load aggregator essentially aligns with the trend of electricity selling price to the grid. It is observable when the selling price of electricity is higher, a larger aggregation capacity can bring more profit to the load aggregator. Between 18:00 and 24:00, because the selling price of electricity by the load aggregator is higher, the profit that the load aggregator can obtain is greater than other periods. Notice the aggregation profit of scene 1 from 18:00–23:00 is higher than the other two scenes, this is because this paper sets the deviation penalty price as a step-type penalty, when the response deviation is greater than 0.4 the penalty price is the real-time price of electricity, and by the aforementioned time period belongs to the valley time period, the declared amount of scene 1 decreases to a larger extent, and the price of electricity is relatively low, so its aggregation of a higher return and a lower cost of the penalty and the obtains a higher profit. However, such a capacity declaration strategy is not conducive to the long-term development of the aggregator and is not conducive to the real-time scheduling of the grid, so this paper does not recommend this form of responsive power declaration.

Through the above analysis, under the guidance of the grid electricity selling price, the load aggregator integrates the users when participating in grid scheduling and obtains the optimal user aggregation plan through dynamic aggregation. This can optimize the way users use electricity, reduce the pressure on the power grid, and enable both users and load aggregators to benefit.

6. Conclusions

Addressing the issue of default power volume due to the subjectivity in user electricity usage, this chapter makes a rolling prediction of the user's default power volume. A method for correcting the deviation of the declared capacity by the load aggregator is proposed, constructing a dynamic aggregation model for the load aggregator. Through the numerical examples in this chapter, the main conclusions are drawn.

1. A dynamic aggregation model for the load aggregator has been established, based on the potential for user adjustment and considering the default electricity volume of users. This can provide a reference for the load aggregator in the optimization selection of users during the aggregation process. It can ensure the overall aggregation volume of the load aggregator can reach 2000 kW·h in 24 periods, and the maximum can reach 3739.559 kW·h.
2. By making a rolling forecast of the default electricity volume and adjusting the declared capacity of the load aggregator, it can effectively safeguard the interests of the load aggregator. Both excessively high and low declared capacities will affect the profits of the load aggregator. Analysis indicates the dynamic aggregation method proposed in this paper can effectively increase the profits of the load aggregator by approximately 1.2%.
3. Case analysis was conducted with users from a specific region, and the dynamic aggregation model for load aggregators was solved, which validated the effectiveness of the proposed dynamic aggregation model and method.

This study considers the situation where the user's subjectivity in electricity usage leads to default electricity volumes. In practice, the user's adjustable capacity is also affected by factors such as environment and policy. In subsequent research, it is necessary to take into account other influencing factors to improve the calculation model of user load adjustment potential. This allows load aggregators to aggregate user participation in grid scheduling more accurately. The model and case analysis proposed in this paper indicate, considering deviations in user electricity consumption, load aggregators have significant profit potential through optimizing aggregation strategies. As the power market continues to mature, load aggregators can actively participate in the market, serving as key players. Future commercial models for load aggregators in the power market can be designed based on this theoretical approach. On one hand, this can provide economically sound decision-making for load aggregators, and on the other hand, it can enhance the flexibility and reliability of the power grid operations.

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