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Collaborative Energy Price Computing Based on Sarima-Ann and Asymmetric Stackelberg Games

Tiantian Zhang [1,2], Yongtang Wu [3], Yuling Chen [1,3,*], Tao Li [1] and Xiaojun Ren [3]

1 State Key Laboratory of Public Big Data, College of Computer Science and Technology, Guizhou University, Guiyang 550025, China
2 Guangxi Key Laboratory of Cryptography and Information Security, Guilin University of Electronic Technology, Guilin 541004, China
3 Blockchain Laboratory of Agricultural Vegetables, Weifang University of Science and Technology, Weifang 262700, China
* Correspondence: ylchen3@gzu.edu.cn

Abstract: The energy trading problem in smart grids has been of great interest. In this paper, we focus on two problems: 1. Energy sellers' inaccurate grasp of users' real needs causes information asymmetry in transactions, making it difficult for energy sellers to develop more satisfactory pricing strategies for users based on those real needs. 2. The uneven variation of user demand causes the grid costs to increase. In this paper, we design a collaborative pricing strategy based on the seasonal autoregressive integrated moving average-artificial neural network (Sarima-Ann) and an asymmetric Stackelberg game. Specifically, we propose a dissatisfaction function for users and an incentive function for grid companies to construct a utility function for both parties, which introduces an incentive amount to achieve better results in equilibrating user demand while optimizing the transaction utility. In addition, we constructed a demand fluctuation function based on user demand data and introduced it into the game model to predict the demand by Sarima-Ann, which achieves better prediction accuracy. Finally, through simulation experiments, we demonstrate the effectiveness of our scheme in balancing demand and improving utility, and the superiority of our Sarima-Ann model in terms of forecasting accuracy. Specifically, the peak reduction can reach 94.1% and the total transaction utility increase can reach 4.6×10^7, and better results can be achieved by adjusting the incentive rate. Our Sarima-Ann model improves accuracy by 64.95% over Arima and 64.47% over Sarima under MAE metric evaluation, and also shows superior accuracy under other metrics evaluation.

Keywords: Sarima-Ann; demand; Stackelberg game; dissatisfaction; incentive amount

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1. Introduction

With the development of big data and artificial intelligence, the smart grid is receiving more and more attention in academia and industry. The smart grid is seen as the intelligence of the grid, which can better detect, manage and predict consumers' electricity consumption than the traditional grid [1]. The application of wireless sensor networks makes it easier to collect valuable information about customers in the smart grid [2]. Through the combination of wireless sensor networks and smart meters, customer transaction information can be collected and uploaded to the grid company. The collected customer data can be used to predict the future electricity demand [3], calculate electricity prices [4], detect undesirable behaviors in the grid [5], etc. Making full use of this data can not only bring more value to the smart grid, but also solve some of the current problems of the smart grid.

Uneven fluctuations in electricity demand [6] and unreasonable calculation methods resulting in low customer satisfaction [7] are two of the problems currently faced by smart grids. A large amount of user data is generated on the smart grid every day, which have good application value, and how to use the user data to better serve users and improve the utility of users and the grid is the focus of research. This paper aims to use the user data to calculate the optimal energy price through a cooperative game between the users and the grid to solve the problem of unbalanced demand and low utility on both sides of the transaction that the grid is currently facing. Since power companies need to ensure a continuous supply of electricity and set prices based on the future demand of customers, the demand information asymmetry problem must be solved, and we need a method to accurately predict the demand in advance. However, uneven fluctuations in electricity demand make forecasting more difficult, increase costs, and reduce system efficiency. Demand-side management technology [8] can be a good solution to this problem, which is user-centered and can achieve peak shaving by encouraging users to adjust their electricity consumption and load shifting. Therefore, finding a way to motivate customers to participate in the peak-shaving task and ensure a stable and efficient operation of the system is the focus of the research. Dynamic pricing [9] is a common approach in demand management that allows companies to calculate flexible prices for goods or customer services based on real-time demand, with prices that will adjust to costs, changes in demand, and other market conditions. Compared to fixed prices, dynamic pricing allows for good peak regulation. Electric utilities can encourage customers to shift load by raising prices during peak hours and lowering them during low-peak hours, or they can give customers incentives to participate in peak avoidance during peak hours or low-peak hours.

Game theory is often used in dynamic pricing [10]. In fact, in the transaction process, each party is often selfish and wants to obtain more income for itself. However, it is not conducive to long-term development if it pursues its immediate income to the detriment of others [11]. The emergence of game theory can guarantee the utility of each party to the transaction, and achieve the equilibrium of the utility of each participant. Game theory can be considered a process in which the parties to a game collaborate to compute the optimal solution. By playing the game, a Nash equilibrium can be computed to maximize utility [12]. Nash equilibrium refers to a stable state that the game finally reaches, in which any player who unilaterally changes his strategy does not increase his utility [13]. Applying the ideas of game theory to dynamic pricing can simulate the process of collaborative gaming among the parties to a transaction, and then compute a price that satisfies all parties and maximizes the utility of each party. Since the strategies of the trading parties in this process are different, it is called an asymmetric game. There are many factors affecting the utility of each stakeholder in the transaction process, and a reasonable analysis of the factors affecting each stakeholder in the transaction process can better improve the utility of the transaction, as well as the service quality of the company to the users. Therefore, how to represent these factors and construct the utility functions of the participants based on these factors is the basis and key of the pricing process. When constructing a game model, an important step is to represent the utility functions of each participant in the game. In the utility function, cost, customer satisfaction (or dissatisfaction), and user demand are the key factors. A reasonable expression of cost and user satisfaction (or dissatisfaction) can ensure the reasonableness of pricing.

In addition, the customer demand for electricity, an input parameter in the pricing model, must be accurately predicted. Currently, numerous technologies have emerged to accurately predict the electricity demand based on these data. The most traditional methods used for electricity demand forecasting are the autoregressive integrated moving average (Arima) mode and the seasonal autoregressive integrated moving average (Sarima), but they can only process the linear part of the historical data. Artificial neural network (Ann) has shown excellent advantages as a deep learning algorithm [14] in the field of electricity demand forecasting, which can process the nonlinear part of the historical data and thus make up for the deficiencies in the Arima and Sarima algorithms.

In this paper, we design a new strategy for collaborative price computation and represent the cost of the electric company, customer satisfaction, customer dissatisfaction, and customer demand for electricity. We designed utility functions for the electric utility and customers based on these parameters and obtained the optimal price by solving the

Nash equilibrium. Under this optimal price, the electricity consumption becomes more balanced, and the utility of both the electric company and the customer is improved. In addition, for the sake of the demand forecasting results and the validity of the pricing model, this paper forecasts user demand through the Sarima-Ann model. The contributions of this paper are as follows, and the overall scheme architecture is shown in Figure 1.

1. We propose a new dissatisfaction function, construct an incentive cost based on load shifting volume and electricity demand, consider the dissatisfaction function and incentive cost into the utility functions of electric companies and customers, and construct a new collaborative game dynamic pricing model to equalize the electricity consumption distribution and improve the utility of electric companies and customers.

2. We construct load fluctuation costs based on electricity demand, forecast electricity demand using the Sarima-Ann intelligent forecasting model, and use the forecast results as input to the pricing model to improve the accuracy of the pricing results.

3. Through experimental simulation, we demonstrate the accuracy of the prediction effect of the Sarima-Ann intelligent forecasting model and the effectiveness of our dynamic pricing model for balancing the electricity consumption distribution and improving utility. In addition, we prove the uniqueness of the Nash equilibrium solution of the game model using backward induction.

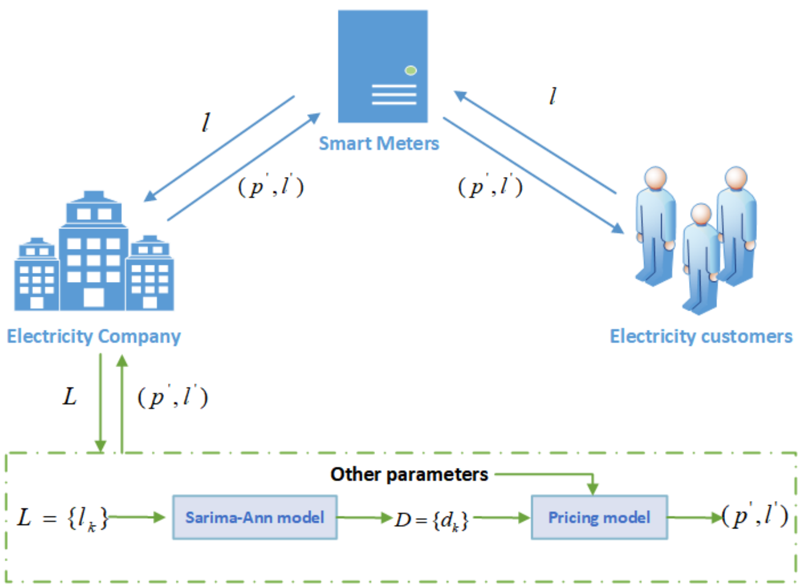

Figure 1. Overall structure diagram of the program.

Figure 1 shows the overall framework diagram of this paper. After the energy seller receives the buyer transaction data, the user demand is predicted by the Sarima-Ann model, then the user demand and other parameters are input into the pricing model, and the other parameters refer to marginal cost, etc. The pricing model in this paper contains the setting of the dissatisfaction function, the setting of the incentive amount, the construction of the game model, and the solution of the Nash equilibrium. Finally, the pricing model outputs an optimal price p′ and optimal transaction volume l', which the energy seller announces to the energy buyer through the smart meter, and the buyer then adjusts their transaction volume based on this information. At this point, the smart meter acts as the equivalent of a sensor deployed in each customer's home [15], which will collect the customer's electricity consumption data and upload it to the electricity seller.

The rest of the paper is organized as follows: Section 2 introduces the related work; Section 3 introduces the basic knowledge to be used in this paper; Section 4 introduces the specific scheme, which contains variable and parameter definitions, the composition of electricity costs, the forecast of electricity demand based on the Sarima-Ann hybrid model, the dynamic pricing model of electricity based on the Stackelberg game, and the solution of the Nash equilibrium; and Section 5 applies the constructed scheme to the electricity trading scenario for simulation experiments and obtains the simulation results. We discuss the experimental results in Section 6 and conclude the paper in Section 7.

2. Related Work

Currently, the main approaches to electricity demand-side management include price-based [16] and incentive-based [17] approaches. The price-based method means that electricity companies encourage users to participate in peak shaving by adjusting prices. Currently, the Internet of Things is used in many fields, such as smart grids, because it enables the interconnection of many devices. Grid companies can interact with customers through smart meters, through which they collect data on customers' electricity transactions for pricing purposes. The price adjustment methods can be divided into peak pricing, time-sharing pricing, and real-time dynamic pricing. There have been many related studies, time-sharing pricing and real-time pricing are the most common. Yang et al. proposed a time-sharing pricing method based on the game theory. They constructed the user satisfaction function and the electricity load fluctuation cost function and took them into account in the utility functions of both sides of the game. Experiments show that this method can adjust the power peak, reduce the cost of electricity companies, increase user income and increase social welfare [18]. However, time-sharing pricing cannot play a good role in peaking in some special periods. For example, at 0:00 on Double 11, there is a sudden increase in customer usage, but a lower electricity price is still applied. Subsequently, based on this scheme, Srinivasan et al. proposed a real-time dynamic pricing strategy and compared the effect of half-hour real-time pricing with time-sharing pricing to reduce the peak value. It can compensate for the above-mentioned problems caused by time-sharing pricing strategies. Finally, the experiment proved that half-hour real-time pricing has a better effect [19]. The above price-based studies have something in common. That is, the final optimal price is determined by the game, and the satisfaction of users is taken into account in the process of building the game model. However, these articles do not take into account the dissatisfaction of users caused by peak shaving. Xu et al. proposed that users' dissatisfaction is caused by load transfer, which is regarded as a factor affecting users' utility [20]. However, they only consider the factor of load shifting when constructing the user's dissatisfaction function, while in reality, there is often more than one influencing factor. Lu et al. proposed a non-cooperative Stackelberg model based on game theory. This model not only takes into account the influence of electricity load fluctuations on electricity companies, but also the dissatisfaction of users caused by peak shaving. At the same time, it classifies dissatisfaction [21], but it does not fully consider the influence of price on the dissatisfaction function when designing the dissatisfaction function. Incentive-based refers to changing users' behavior through incentive amounts or bonuses, and often higher bonuses drive people to be more enthusiastic about a behavior [22]. During the trading process, to encourage customers to participate in peak shaving, the power company can issue incentive amounts or bonuses directly to customers. If users reduce electricity consumption during peak hours or increase electricity consumption during low peak hours, they will receive corresponding compensation [23]. Ma et al. utilized auction theory and introduced incentives for both supply and consumption to ensure that all customers disclose truthful information in the process of declaring their electricity demand and consumption [24]. Hong et al. proposed a demand response game model based on incentives. This model includes three participants, namely, grid operators, service providers, and customers. The grid operator provides incentives to service providers as a way to encourage them to negotiate demand reductions with customers [25]. In the case of electricity trading, the continued increase in electricity usage can be reduced by granting incentive credits during peak hours. Table 1 summarizes the above studies and shows the differences between our scheme and existing schemes. Among them, although dissatisfaction has been considered in the user utility function in the literature, there is still room for improvement in the design of the dissatisfaction function. Based on the existing literature, we design a more reasonable dissatisfaction function for users by considering multi-faceted factors.

Table 1. Summary of literature related to demand management.

Literature	Game Based	Real-Time	Dissatisfaction	Incentive
[18]	√			
[19]	√	√		
[20,21]	√	√	√	
[22–25]				√
Our work	√	√	√	√

In the pricing process, demand is often considered a key factor influencing prices, in addition to considering the impact of cost and customer satisfaction (or dissatisfaction) on price. Accurate electricity demand forecasting can not only guide the power company's generation capacity, but also alleviate the decision errors caused by information asymmetry during the gaming process, thus improving the accuracy of the pricing results and enhancing the quality of service to customers. Among the current electricity forecasting methods, the most common are traditional time series regression algorithms (e.g., autoregressive integrated moving average, Arima) and machine learning algorithms (e.g., neural networks, NN [26]). As early as 1951, the Arima model was proposed and applied to time series forecasting [27]. The Arima model can be used to forecast the short-term electricity demand [28], but this model cannot deal with seasonal factors in the series. Al-Shaikh et al. introduced seasonal factors based on the Arima model. The Seasonal comprehensive autoregressive moving average model Sarima is used to forecast electricity demand, which proves that this model has a good short-term forecasting effect [29]. The Arima model and Sarima model are used to forecast the power demand, and the forecasting effect is evaluated, which shows that the Sarima model has better forecasting accuracy [30]. However, the Sarima model is only good at dealing with the linear part of power data, but not the nonlinear part of electricity data. The artificial network model can solve this problem well, and it can predict the nonlinear part of the data, so it is also widely used in the electricity forecasting process [31]. Through experimental comparison, it is found that the artificial neural network model has higher prediction accuracy than the traditional time series or regression model [32], but the accuracy still needs to be optimized. The future research direction is to explore the use of hybrid forecasting methods [33]. Combining the traditional time series prediction method with the artificial neural network model can make a better prediction [34]. Azad et al. proposed a Sarima-Ann hybrid model to predict the monthly water quantity and water level, and the experiment proves that this hybrid model can achieve better prediction accuracy than the Sarima model [35]. Table 2 presents the summary of Arima, Sarima, and our Sarima-Ann in terms of electricity demand forecasting. In addition, the other literature in this paragraph, particularly that related to Ann, provides us with great help in designing the algorithm and carrying out simulation experiments.

Table 2. Summary of the literature related to Arima and Sarima compared to our work.

Literature	Arima	Sarima	Sarima-Ann	Features
[27,28]	√			Neglected seasonal factors and non-linear parts.
[29,30]		√		Cannot handle non-linear parts.
Our work			√	Make up for the above deficiencies.

In previous studies, the authors have tended to consider the effect of a single factor, such as the price or reward amount. However, a combination can often achieve better peak regulation and increased utility. In our paper, we combine the influence of both factors on customers' electricity consumption behavior and introduce incentives into a single price-based approach to achieve better efficiency and peak reduction. In addition, in previous studies, the setting of the dissatisfaction function often only takes into account the effect of price without considering the effect of load shifting on dissatisfaction, or the setting of the dissatisfaction function does not fully reflect the actual situation. In this paper, we design a new classified dissatisfaction function and add it to the customer's utility function to make up for the existing literature. Finally, most of the previous studies use a single forecasting method when forecasting electricity demand, while in this paper, considering that electricity consumption is affected by seasonal and extreme weather factors, there is not only a linear part, but also a nonlinear part in the data. Therefore, in this paper, we use the Sarima-Ann intelligent hybrid algorithm to forecast electricity demand and use the forecast results as input for a dynamic pricing model. Finally, the optimal price is calculated through a collaborative game between the two trading parties.

3. Preliminaries

This section introduces some relevant knowledge used in our subsequent scenarios, mainly containing dynamic games, a periodic time series Sarima model and the Ann model.

3.1. Dynamic Game

The game refers to the process in which two or more participants gain benefits according to certain strategies. The process of the game includes the following three aspects:

1. Participant set $N = \{1, 2, \ldots, n\}$;
2. Strategy set $S_i, i \in N$;
3. Utility function set $U_i, i \in N$.

Participants refer to two or more players who participate in the game. Strategy refers to the method chosen by the participants in the game, and utility refers to the benefits gained by the participants through the game.

Game theory can be divided into static games and dynamic games according to the time sequence of participants' behaviors. A static game means that, in the game, participants choose what strategies to adopt at the same time, or, although they do not choose at the same time, the post-actor does not know what specific actions the first actor has taken. A dynamic game means that, in the game, the actions of the participants are in order, and the later actor can observe the actions chosen by the first actor. In this scheme, the game between power companies and users is dynamic.

3.2. Periodic Time Series Sarima Model

3.2.1. Arima Model

Before introducing the Sarima model, we introduce the Arima model [36]. Arima (p, d, q) is a typical time series prediction model, which is widely used in time series prediction. The time series used for prediction must be a non-white noise series and satisfy the condition of stability. If the time series is unstable, the time series can be made stable by some operations (e.g., taking the logarithm, differencing). Here are some basic concepts and components of the Arima model [37].

Stationary time series: A series whose statistical characteristics do not change with time. Specifically, a time series is considered smooth if it is generated by a series of stochastic processes and if the series satisfies that the mean, variance, and covariance are all time-independent constants. There are two ways to determine whether a time series is a smooth series, i.e., by unit root test or by looking at the autocorrelation and partial autocorrelation function plots of the time series. The Augmented Dickey–Fuller (ADF) test is one of the unit root tests that is used in this paper to test the smoothness of the time series. In the process of the experiment, when p value < 0.05 in the stationarity test results, there is a 95% probability that the sequence is stable, and when p value < 0.01, there is a 99% probability that the sequence is stable.

White noise sequence: If a sequence is a white noise sequence, it means that the sequence is completely random and the past behavior does not have the slightest effect on the future development, nor does it contain any useful information, so there is no need for further analysis and should be discarded. Specifically, the white noise series has three characteristics: The mean value is zero, the variance exists and is constant, and the data are not correlated before and after. The main methods of white noise test are the autocorrelation diagram, the Box–Pierce test, and the Ljung–Box test. Our scheme uses the Ljung–Box test to test the time series for white noise. During the experiment, if the p value is < 0.05 in the white noise test results, there is a 95% probability that the sequence is not a white noise sequence; if the p value is < 0.01, there is a 99% probability that the sequence is not a white noise sequence.

The basic components of the Arima model: The Arima model consists of three parts, namely the autoregressive (AR) model, moving average (MA) model, and order I of difference. AR denotes an autoregressive model, meaning that the value at the current point in time is equal to the regression of the values at several past points in time—called autoregressive because it does not depend on other explanatory variables, but only on its past historical values. If it relies on the p most recent historical values in the past, the order is said to be p, and is noted as the AR (p) model. MA denotes the moving average model, meaning that the value at the current time point is equal to the regression of the forecast error at several past time points. The forecast error is equal to the model forecast value minus the true value. If the series relies on the q most recent historical forecast error values in the past, the order is said to be q and is noted as the MA (q) model. I means that the model has differenced the time series because time series analysis requires smoothness, and the unstable series needs to be transformed into a smooth series by some means, and the means generally used is differencing. If the differencing technique is d, the model can be expressed as I (d), so Arima is called an autoregressive integrated moving average model. In this model, p represents the number of autoregressive orders, q represents the number of moving average terms, and d represents the difference number (order) that makes this model a stationary sequence.

Differential operation: When the sequence is non-stationary, it is necessary to perform a differential operation on the sequence. In the Arima model, d denotes the order of the difference, and the value at time t minus the value at time t-1 yields a new time series called the 1st-order difference series. The 1st-order difference series of the 1st-order difference series is called the 2nd-order difference series, and so on. The common formula is as follows:

$$y_t - y_{t-1} = (\alpha - 1)y_{t-1} + \varepsilon_t \tag{1}$$

$$\Delta y_t = y_t - y_{t-1} = (\alpha - 1)y_{t-1} + \varepsilon_t \tag{2}$$

$$\Delta(\Delta y_t) = \Delta^2 y_t = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2}) \tag{3}$$

This paper chooses to develop forecasting based on Arima because the electricity trading data in this paper are time-dependent. The Arima model is a commonly used model in time series forecasting, and there are a large number of studies that can be used as the basis of this paper. In addition, the Arima model has the advantage of being simple and only requires endogenous variables without the help of other exogenous variables. Therefore, it is chosen as the base model for power forecasting in this paper.

3.2.2. Sarima Model

There are significant periodic variations in some series that are caused by factors such as seasonality, and these time series associated with seasonal factors are also known as seasonal time series. These seasonal series cannot be handled well by using Arima alone. Sarima can handle seasonal time series well due to the introduction of seasonal factors on top of Arima [38]. The Sarima model is an extension of the Arima model, which can work with a periodic time series. When modeling, Arima is first performed at periodic intervals to remove the periodicity and obtain a non-stationary, non-periodic time series, and then Arima is used for analysis. It can be expressed as:

$$\mathrm{Arima}(p, d, q) \times (P, D, Q)S$$

The meanings of parameters in the model are shown in Table 3. It can be seen that the meanings of p, d, and q are the same as those in Arima above. Both the Arima and Sarima models are good at dealing with the linear parts of the data.

Table 3. Meaning of parameters of Sarima model.

Symbol	Definition
p	Autoregressive term number
d	Differential order
q	The average number of sliding terms
P	Periodic autoregressive order
D	Periodic difference order
Q	Periodic moving average order
S	Cycle time interval

In this paper, Sarima is chosen to forecast electricity demand because the Sarima model has the advantages of the Arima model and can compensate for its shortcomings in dealing with seasonal factors. The electricity trading data in this paper are influenced by seasonal factors and have the characteristics of periodicity, while Sarima can handle the periodic time series better and thus improve the prediction accuracy, so it is chosen as one of the base models for demand forecasting in this paper.

3.3. Ann Model

With the advancement of technology, the amount of human-centered data is increasing day by day, and this data contains both linear and nonlinear features. The artificial neural network is a powerful tool for dealing with nonlinear systems, and therefore, it is often applied in user data processing and prediction [39]. The development of big data, artificial intelligence, and other technologies provide greater opportunities for the application of models. The model is divided into a training phase and a prediction phase. In the training phase, the original data needs to be prepared as the input data, and the model is obtained by training with the corresponding classification labeled data as the output data. In the prediction phase, the model is applied to the new data to predict the category to which the new input data belongs. The steps to perform prediction with the Ann model are as follows.

1. Read data. Before constructing the Ann prediction model, it is necessary to read the historical data first, and this paper uses energy historical transaction data as the data set.

2. Data normalization. To improve the convergence speed of the model and improve the training efficiency, it is necessary to normalize the acquired data. The main normalization methods are standard normalization and maximum–minimum normalization. In this paper, we choose the maximum and minimum normalization method, which is a linear normalization method that refers to normalizing the original data to the $[0, 1]$ interval by linearization.

3. Divide the training set and test set. Before training the model, we first divide the data set into the training set and data set, use the training set to train the model, and use the test set to verify the performance of the model.

4. Build the Ann model. The Ann model is an artificial neural network model with a three-layer structure, namely the input layer, the hidden layer, and the output layer. The data signal are input through the input layer, computed in the hidden layer, and the result is output through the output layer. When building a model, it is necessary to determine the input, output, and parameters of the hidden layer of the model. The structure of the Ann model is shown in Figure 2.

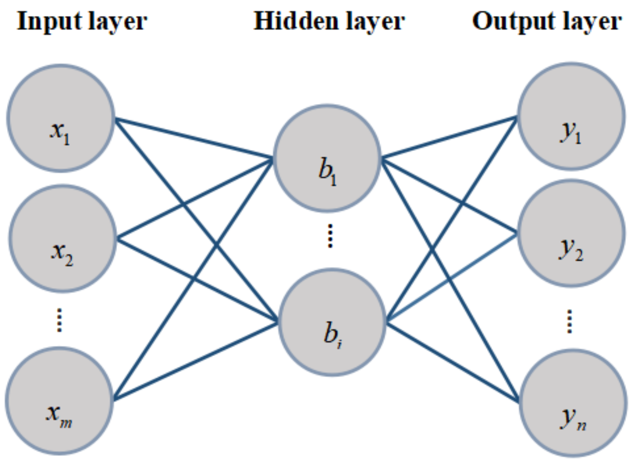

Figure 2. The structure of the Ann model.

From the existing literature in the related work of this paper, it is clear that there is not only a linear part, but also a nonlinear part in the energy trading data, and the Arima and Sarima models only excel in dealing with the linear part of the data, which will affect the accurate prediction of the demand. However, the Ann model can handle nonlinear problems and can make up for the shortcomings of the Arima and Sarima models in dealing with nonlinear problems. In addition, the Ann model, as a machine learning model [40], also has the advantages of fewer parameters, strong generalization ability, and good prediction performance. Therefore, it is chosen as one of the basic models for electricity demand forecasting in this paper.

3.4. Rolling Forecast

The electricity transaction data used in this paper is time series data, and in the prediction, it is necessary to use the past electricity transaction data to predict the electricity demand in the future time. The characteristic of this time series data is that the closer the date of the training data is to the prediction date, the better the result will be.

For the model to use the latest data, we need to update the training set on time by adding the latest data to the training dataset. This way, when the model is trained, it only needs to take the latest part of the data from the training data set to ensure that the model always uses the latest data. A prediction method such as this, which uses the latest portion of data to retrain before each prediction, is a rolling prediction. The amount of the latest data is called the size of the rolling window. In practice, it is not always necessary to use the latest data for retraining before each prediction, considering the speed and cost of obtaining the latest data, and the time and cost required for retraining. The training set can be updated and retrained after a certain period or after a certain number of predictions, which is called a rolling cycle. The amount of new data that are added to the training set each time is called the moving step. During the prediction process, these parameters can be set to achieve more satisfactory results [41].

4. Materials and Methods

Dynamic pricing, as a demand-side management technique, can achieve equilibrium changes in electricity consumption by influencing customers' electricity consumption, and an asymmetric Stackelberg game can be used in the process of dynamic pricing of electricity to achieve an equilibrium in electricity consumption and improve transaction utility. Therefore, this paper constructs a real-time dynamic pricing model based on an asymmetric Stackelberg game, in which there are two participants in the electricity trading process, i.e., the power company and the customer. The power company is responsible for generating electricity and selling it to its customers. To ensure a stable supply of electricity, the power company issues a certain number of incentives to encourage customers to adjust their electricity consumption. As rational individuals in the trading process, both power companies and customers are selfish.

To improve the trading utility and adjust the distribution of electricity consumption, in this section, we constructed an asymmetric game model based on cost and demand to simulate the process of calculating the optimal price by collaboration between the trading parties. Meanwhile, we divide the day into different periods to develop a dynamic pricing strategy. By solving the Nash equilibrium for each period, the optimal price and optimal trading volume can be obtained. As the input parameters of the model, the electricity demand must be accurately forecasted. To improve the accuracy of the demand forecasting results, in this section, we use the Sarima-Ann hybrid intelligent forecasting model to forecast the electricity demand, which can ensure the accuracy of the electricity forecasting results. After using the collaborative game calculation scheme in this paper, the peak electricity consumption of customers decreases, i.e., the electricity consumption achieves an equilibrium distribution, the utility of electric companies and customers increases, and the total social welfare increases.

4.1. Variable and Parameter Definitions

In this article, we divide the day into N periods and use the subscript k to represent the specific kth period, where $k \in [1, N]$. The variables used in this article are defined as shown in Table 4.

Table 4. Symbol definition.

Symbol	Definition
l_k	Actual electricity consumption in stage k
d_k	Electricity demand on stage k
orl_k	Actual electricity consumption in the stage k before optimization
p_k	The actual sales price of electricity on stage k
r_k	Electricity price in the stage k before optimization
d_{avg}	Average electricity demand in a day
ir	Incentive rate
μ	Load fluctuation coefficient
η	User satisfaction coefficient
z_{max}	The maximum amount of power a user can use
ϖ_1	The weight of the comfort factor in the dissatisfaction function
ϖ_2	The weight of economic factors in the dissatisfaction function
θ	Influence coefficient of demand fluctuation on dissatisfaction function
α	The absolute value of the price elasticity coefficient
eco_k	Dissatisfaction due to economic factors in stage k
com_k	Dissatisfaction due to comfort factor in stage k
$diss_k$	Dissatisfaction in stage k
E_k	Incentive cost in stage k
$\text{flu}(l_k)$	User load fluctuation function in stage k
s_k	User satisfaction function in stage k
C_k	Marginal cost in stage k
l_{min}	Minimum electricity consumption
l_{max}	Highest electricity consumption

4.2. Composition of Electricity Costs

To maximize the utility of both parties, the power company needs to consider the costs paid when setting prices. These costs include marginal cost C_k, load fluctuation cost $\text{flu}(l_k)$ and incentive cost E_k.

Marginal cost C_k: Marginal cost refers to the cost incurred by the power company to meet basic power generation and other needs. The higher the marginal cost, the higher the corresponding electricity price. Additionally, there is a quadratic function relationship between the marginal cost and electricity consumption [42], which can be expressed as:

$$C_k = a_1 l_k^2 + a_2 l_k + a_3 \tag{4}$$

$$a_1 > 0, \quad a_2 \geq 0, \quad a_3 \geq 0 \tag{5}$$

Load fluctuation cost $\mathbf{flu}(l_k)$: Fluctuation cost refers to the extra cost paid by the power company due to the fluctuation of power consumption. This cost is related to the fluctuation of power usage, and the greater the fluctuation of power usage, the greater the cost. The user load fluctuation function $\mathrm{flu}(l_k)$ in stage k shows the extra cost that the power company needs to bear due to the load fluctuation in stage k [16], which should be as low as possible. In this scheme, we calculate the average daily power demand d_{avg} according to the predicted power demand, and d_{avg} can be expressed as:

$$d_{avg} = \frac{1}{N} \sum_{k=1}^{N} d_k \tag{6}$$

Then, the load fluctuation cost is calculated according to the average total power demand of one day, which can be expressed as:

$$flu(l_k) = \mu \sum_{k=1}^{N} \left(l_k - d_{avg}\right)^2 \tag{7}$$

μ represents the load fluctuation coefficient, and different power companies in different regions have different load fluctuation coefficients.

The overall user load fluctuation function can be expressed as:

$$flu(l) = \sum_{k=1}^{N} flu(l_k) \tag{8}$$

The power company wants this function to be as low as possible. In different electricity markets, the coefficient μ will take different values.

Incentive cost $\boldsymbol{E_k}$: The incentive cost E_k represents the expenses paid by the power company to motivate users to participate in peak shaving, and the cost can be expressed as:

$$E_k = \begin{cases} \mathrm{ir}(l_k - \ \mathrm{orl}\ _k) & d_k < d_{avg} \\ \mathrm{ir}(orl_k - l_k) & d_k \geq d_{avg} \end{cases} \tag{9}$$

Among them, ir represents the incentive rate, and orl_k represents the electricity consumption in the kth stage before the dynamic price strategy of this scheme is used. The more obvious the load transfer, the higher the incentive amount obtained by the user.

4.3. Electricity Demand Forecast Based on Sarima-Ann Hybrid Model

In this paper, we assume that all electricity consumers have smart meters through which their electricity transaction data will be uploaded to the power company [43]. After the power company collects the customers' electricity transaction data, it can use the data to forecast the future electricity demand of customers, and the forecast results can guide the generation and pricing process. We regard electricity demand as an input parameter of the dynamic pricing model, and the price is guided by the electricity demand. Understanding the changes in electricity demand can guide power plants to control the amount of electricity generated. By accurately predicting the user demand for a certain period, the output result of the pricing model can be more accurate, and the effect of reducing the power peak and improving the transaction utility of both parties of the power transaction can be better achieved. In this paper, we use the Sarima-Ann hybrid model to forecast the electricity demand and achieve better forecasting accuracy than the traditional Arima forecasting model and Sarima model.

Electricity demand forecasting model Sarima-Ann:

The Sarima-Ann hybrid model in this paper uses the prediction results of the Sarima model and its error as the input of the Ann model training set and uses the widely used BP neural network in Ann to predict the prediction error of the Sarima model. The Sarima prediction error is the nonlinear part of the data, and the Ann model finds the law of the nonlinear part by learning from the data.

The hybrid model can use the actual data of a certain time in the past day (or days) to predict the data of a certain time in the next day. In the hybrid model, Sarima predicts the next day according to the historical actual power demand data, and the linear part of the data can be obtained. Ann can predict the nonlinear part of the data by learning the rules of the prediction results and prediction errors of the Sarima model. That is, first use the Sarima model to make predictions to obtain a prediction result, and then use the Ann model to predict the error of this result. Combining the two can obtain a more accurate prediction result.

To improve the prediction accuracy, in this paper, we use the rolling prediction method, which requires the model to update the latest actual data to the training data set constantly, so we can obtain more accurate results.

The Sarima-Ann algorithm for power trading in this paper is designed as follows.

The process of forecasting power demand by the Sarima model is shown in Algorithm 1.

Algorithm 1: Sarima algorithm for electricity demand forecasting

Input: Historical power actual transaction dataset L
Output: Predicted power demand data D, prediction error E
Initialization: $p=0, d=0, q=0, P=0, D=0, Q=0$, model = Sarima$(0,0,0,0,0,0)$
1: Perform a white noise test on L
2: Perform stationarity test and differentiate on L
3: $bic_0 = bic_$Sarima$(0,0,0,0,0,0)$
4: for p in [0, max_p] : for d in [0, max_d] : for q in [0, max_q] : for P in [0, max_P] :
for D in [0, max_D] : for Q in [0, max_Q] :
5: do
6: $bic_0 = \text{Min}(bic_0, bic\_\text{Sarima}(p,d,q,P,D,Q))$
7: end for
8: Sarima$(p,d,q,P,D,Q) \longleftarrow bic_0$ //Assign the combination of parameters corresponding to bic_0 to the Sarima model
9: Use Sarima(p,d,q,P,D,Q) to predict the electricity demand to obtain the prediction result data set D
10: Subtract the prediction result from the actual power usage value to obtain the prediction error data E
11: save D, E

Step 1: Obtain actual historical electricity transaction data and initialize the model parameters.

Step 2: Preprocess the time series. When using the Sarima model for forecasting, the time series used for forecasting must be a stationary non-white noise time series, so it is necessary to first perform a white noise test and smoothness test on the obtained electricity data. If the series is a white noise series, then the power data are useless and need to be discarded. If the power data form a non-stationary time series, the series is differenced until the series is smooth. When performing the white noise test, this scheme uses the Ljung–Box method, and when the p_value value of the result is less than 0.01, the sequence is proven to be a non-white noise sequence and can be processed subsequently. When conducting the smoothness test, this scheme uses the ADF test, and when the p_value value of the test result is less than 0.01, the series is proved to be smooth; otherwise, the difference is performed until the series is smooth. This procedure corresponds to lines 1–2 of Algorithm 1.

Step 3: Build the Sarima model. The optimal parameters of the Sarima model are determined by calculating the Bayesian information criterion (bic) values. It is known that the smaller the bic value is, the better the model effect is, then this scheme calculates the bic value under different parameter combinations by traversing the parameters, and then finds the most effective parameter combination as the parameters of the final Sarima model to construct the Sarima model. This procedure corresponds to lines 3–8 in Algorithm 1.

Step 4: Model training and prediction. After the Sarima model is built, historical electricity transaction data are used as the training data set to forecast future electricity demand. A rolling forecast method is used here, where the latest acquired data are updated into the training data before each forecast. Since the training data used for each forecast are the most recent, better forecasting results can be achieved. This procedure corresponds to line 9 in Algorithm 1.

Step 5: Save the power demand forecast results and forecast errors. The difference between the power demand forecast result of the Sarima model and the actual power consumption value is taken as the forecast error, and the power demand forecast result and the forecast error of the Sarima model for each period are saved. This procedure corresponds to lines 10–11 in Algorithm 1.

The process of the Ann model predicting the prediction error of the Sarima model is shown in Algorithm 2:

Algorithm 2: Ann algorithm for forecasting the power demand forecasting error of Sarima model

Input: Power demand data set D predicted
by Sarima and prediction error data set E
Output: Future prediction error FE
1: Determine the input x and output y of the training set.
2: Determine the model parameters, including the learning rate number of cycles, activation function,
number of hidden layers, number of hidden layer neurons, number of input features,
the number of output features
and the number of samples.
3: Train the model.
4: Use the trained model to predict the error value to obtain FE.

Step 1: Obtain the power demand forecast result and forecast error of the Sarima model.

Step 2: Determine the training set of the Ann model. In this scheme, the 12 metrics in Table 5 were selected as the input data for the training set of the Ann model, and the prediction error of the prediction day is taken as the output data of the training set.

Step 3: Set the parameters for the Ann model. The main parameters include the learning rate, the number of cycles, the activation function, the number of hidden layers, the number of neurons in the hidden layer, the number of input features, the number of output features, and the number of samples. At the beginning of this scheme, the hyperbolic tangent function tahf() is used as the activation function of the Ann model, the learning rate is set to 0.000348, the number of cycles is set to 90,000, and the number of hidden layers is set to 1, and the number of neurons in the hidden layer is set to 169. The number of input features is 12, the number of output features is 1, and the number of samples is 7 × N. That is, seven days of historical power usage data are selected as samples. In this scheme, the structure diagram of the Ann model can be represented as shown in Figure 3:

Table 5. Definition of input metrics for the training set of the Ann model.

Metrics	Definition
x_1	Forecast result of Sarima power demand at the same time the day before the forecast date
x_2	Forecast error of Sarima power demand at the same time the day before the forecast date
x_3	Forecast result of Sarima power demand one hour after the same time the day before the forecast date
x_4	Forecast error of Sarima power demand one hour after the same time the day before the forecast date
x_5	Forecast result of Sarima power demand one hour before the same time the day before the forecast date
x_6	Forecast error of Sarima power demand one hour before the same time the day before the forecast date
x_7	Forecast results of Sarima power demand at the same time a week before the forecast date
x_8	Forecast error of Sarima power demand at the same time a week before the forecast date
x_9	Forecast result of Sarima power demand one hour after the same time a week before the forecast date
x_{10}	Forecast error of Sarima power demand one hour after the same time a week before the forecast date
x_{11}	Forecast result of Sarima power demand one hour before the same time a week before the forecast date
x_{12}	Forecast error of Sarima power demand one hour before the same time a week before the forecast date

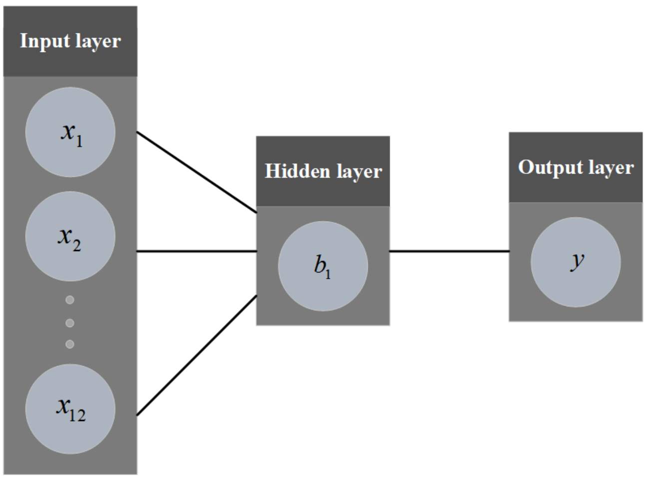

Figure 3. Structure diagram of the Ann model of this scheme.

Where x_1, $x_2 \ldots x_{12}$ represent input features and y represents output features.

Step 4: Use the training data set to train the model. The specific process is as follows:

(1) Select the training data set. The training data are divided into input data and output data.

(2) Choose an example from the training dataset and feed the input data into the network.

(3) Each layer in the network calculates and outputs the data and uses it as the input of the next layer, and the final data are aggregated to the output layer, which is the prediction result.

(4) Calculate the difference between the predicted result and the actual result. That is the error.

(5) Backpropagation according to the error. Reverse the calculation from the output layer to the first hidden layer and re-adjust the connection weights of each neuron in each layer to make the error develop in a decreasing direction.

(6) Repeat the above steps until the specified number of cycles is reached.

Step 5: Perform power demand prediction on the input test data of the trained Ann model to obtain the error value of the power demand forecast.

Finally, the power demand forecast result of the Sarima model is combined with the error forecast result of the Ann model, and the power demand forecast value of the hybrid model Sarima-Ann is obtained. We use the mean absolute error MAE, mean absolute percentage error MAPE, mean square error MSE, root mean square error RMSE, and R-square to calculate the accuracy of the prediction results of the mixed model.

4.4. Dynamic Pricing Model of Electricity Based on Stackelberg Game

To achieve the peak regulation effect through real-time dynamic pricing and to improve the utility of power companies and customers, this paper constructs a real-time dynamic pricing model for electricity based on the Stackelberg game. The participants in the game model are the power companies and the power users. The power company first determines the power price p_k, and then the user adjusts the power usage l_k according to the power price determined by the power company. The strategy of the power company is the price of each period, and the strategy of the power user is the actual consumption of electricity in each period. Since the behavior of the two participants has a time sequence, the game process is a dynamic game.

4.4.1. Utility of the Electric Company

The power company generates electricity according to the forecasted electricity demand, which incurs a marginal cost C_k. Since load fluctuations will generate a load fluctuation cost $\mathrm{flu}(l_k)$, and to reduce the power peaks and power usage fluctuations, power companies issue incentive allowances to users to motivate users to adjust their power consumption, which generates an incentive cost E_k.

The utility function U_1 of the power company in one day can be expressed as:

$$U_1 = \sum_{k=1}^{N} (l_k p_k - C_k - flu(l_k) - E_k) \tag{10}$$

where

$$flu(l_k) = \mu \sum_{k=1}^{N} \left(l_k - d_{avg}\right)^2 \tag{11}$$

$$E_k = \begin{cases} ir(l_k - orl_k) & d_k < d_{avg} \\ ir(orl_k - l_k) & d_k \geq d_{avg} \end{cases} \tag{12}$$

$$d_{avg} = \frac{1}{N} \sum_{k=1}^{N} d_k \tag{13}$$

$$C_k = a_1 l_k^2 + a_2 l_k + a_3 \tag{14}$$

$$a_1 > 0, \quad a_2 \geq 0, \quad a_3 \geq 0, \quad \text{ir } > 0 \tag{15}$$

where C_k represents the marginal cost, which is described in detail in the electricity cost components of the scenario. $flu(l_k)$ represents the load fluctuation cost, which is measured by the squared sum of the difference between the actual electricity consumption l_k and the average electricity consumption d_{avg}. A larger difference represents a larger fluctuation in power usage, which results in a larger additional load fluctuation cost. μ represents the load fluctuation factor, which can have different values for different scenarios. In addition,

E_k represents the incentive amount, when the predicted user demand d_k is less than the average demand d_{avg}. That is, the electricity consumption may be lower in that period, so the incentive amount will be issued to motivate users to increase the electricity usage l_k, and the greater the difference between the user usage l_k and the original usage orl_k, the more obvious the peak regulation is, and the greater the incentive amount E_k obtained,; conversely, if the predicted user demand d_k is greater than or equal to the average demand d_{avg}, the incentive amount is issued to encourage customers to reduce their electricity usage.

4.4.2. Utility for Electricity Users

When electricity users receive electricity, they will be satisfied, which is related to the amount of electricity used. With the increase of electricity consumption, the degree of satisfaction increases gradually. When the usage is 0, the satisfaction is also 0. According to this feature, the user's satisfaction function can be expressed as a quadratic function [4] as follows:

$$s_k = -\frac{\eta}{2z_{\max}} l_k^2 + \eta l_k \tag{16}$$

$$l_k \le z_{\max} \tag{17}$$

The coefficient η is always greater than 0 and varies according to the user's preference, and z_{max} is the maximum value of the amount of electricity that the user can use.

Due to the new dynamic pricing strategy adopted by the power company, users will be dissatisfied. The dissatisfaction comes from two aspects. Namely, the dissatisfaction caused by economic reasons and the dissatisfaction with the comfort experience caused by load transfer [20]. Different users pay different attention to these two aspects. For some users who value prices, the pricing strategy in this scheme is more likely to cause dissatisfaction among such users for economic reasons. For some users who pay more attention to comfort, the pricing strategy in this scheme is more likely to cause dissatisfaction among such users due to load shifting. This scheme improves based on [20] and sets weights for these two types of dissatisfaction. Different types of users correspond to different weights, and the dissatisfaction function is expressed as:

$$\text{diss}_k = \varpi_1 \text{com}_k + \varpi_2 \text{eco}_k \tag{18}$$

where

$$\varpi_1 > 0, \varpi_2 > 0 \tag{19}$$

$$\varpi_1 + \varpi_2 = 1 \tag{20}$$

$$\text{com}_k = \theta (l_k - \text{orl}_k)^2 \tag{21}$$

$$\text{eco}_k = \frac{\alpha l_k (p_k - r_k)}{r_k} \tag{22}$$

$$\alpha > 0, \theta > 0 \tag{23}$$

ϖ_1 represents the comforting weight, ϖ_2 represents the economic weight, eco_k represents the dissatisfaction caused by the economy in the kth stage, and com_k represents the dissatisfaction caused by the comfort in the kth stage. θ represents the influence coefficient of demand fluctuation on dissatisfaction, and different users correspond to different θ values. α represents the absolute value of the price elasticity coefficient, which reflects the changes in demand caused by price changes. Different regions and different types of users respond differently to the price changes of electricity, which correspond to different price elasticity coefficients. r_k represents the electricity price in the kth stage before using the pricing strategy of this scheme.

Then, the utility function of a power user for one day can be expressed as:

$$U_2 = \sum_{k=1}^{N} (s_k + E_k - p_k l_k - diss_k) \tag{24}$$

4.4.3. Electricity Pricing Game Model

The participants in the game model are power companies and power users. The power company's strategy is $\{p_k\}$, and the power user's strategy is $\{l_k\}$. Under the circumstance that all parties are rational, both parties want to formulate strategies to maximize their utility. The objective function is:

$$\left(p', l'\right) = \arg\max U_1 \tag{25}$$

$$\left(p', l'\right) = \arg\max U_2 \tag{26}$$

Constraints can be expressed as:

$$l_{\min} \le l_k \le l_{\max}, \mathrm{k} = 1, 2, \ldots, \mathrm{N} \tag{27}$$

$$l_{\max} = \min\{d_{\max}, z_{\max}\} \tag{28}$$

$$p_k \ge C_k, \mathrm{k} = 1, 2, \ldots, \mathrm{N} \tag{29}$$

l_{min} represents the minimum power consumption required to ensure the daily life of users, and l_{max} represents the minimum value of the maximum load-bearing capacity of users and the maximum power generation capacity of generators.

In addition, the game model in this paper is feasible and has a unique solution for calculating the optimal price, for which Theorem 1 is proposed and proved in this paper.

Theorem 1. *There is a unique (p', l') that maximizes the utility of the two participants in one day; that is, the Nash equilibrium solution is unique.*

Proof of Theorem 1. This scheme uses the reverse induction method to solve the Nash equilibrium (p', l'), and obtains the optimal price and optimal power consumption for each period of the day. The detailed proof process can be viewed in the Appendix A. □

5. Simulation Settings and Results

In this section, simulation experiments are set up to demonstrate the effectiveness of the Sarima-Ann algorithm of this scheme in terms of prediction accuracy and excellence of our game pricing model in terms of peak regulation and utility improvement. In particular, the Sarima and Ann algorithms and the game model of this scheme are run under PyCharm, using the programming language Python.

5.1. Experimental Data Set

This simulation experiment uses transaction data published by a U.S. energy authority as the dataset. The dataset contains hourly electricity consumption, hourly forecasted demand, hourly electricity generation, and hourly total interchange, which can be downloaded at the end of the paper under Data Availability. This dataset is used in this proposal because it contains hourly electricity consumption information, which facilitates the simulation experiments of real-time dynamic pricing strategies. The hourly electricity consumption in the dataset is used in the electricity demand forecasting experiments and the dynamic pricing model simulations, and the forecasted hourly demand is used in the dynamic pricing model simulations for convenience.

5.2. Electricity Demand Forecast

In this experimental section, we use the historical hourly electricity consumption from the transaction data as the dataset and update the newly obtained data into the training data using the rolling prediction method before each prediction. The simulation is performed following the prediction steps of Sarima's algorithm and Ann's algorithm in the scheme. The forecasting is first performed with the Sarima model, which finally outputs the demand forecasting results and the forecasting error. The output result and its error are sorted and used as the input of the Ann model to obtain the prediction result of the error. Finally, the demand prediction result of the Sarima model and the error prediction result of the Ann model are combined to obtain the final electricity demand prediction result. The prediction effect is compared with the prediction effect of the traditional Ariam model and Sarima model.

5.2.1. Data Preprocessing

This experiment uses the hourly electricity transaction data of a power bureau in the United States as a dataset. The data is normalized to the maximum and minimum values, and the data is mapped to the range of -1 to 1. This operation can improve the convergence speed of the model.

5.2.2. Prediction Results of the Sarima-Ann Hybrid Model

In this part, we use the Sarima-Ann hybrid model to forecast electricity demand according to the forecasting process in the Algorithms 1 and 2. The final forecast effect of the hybrid model Sarima-Ann is shown in Figure 4. It can be seen that it is close to real power usage.

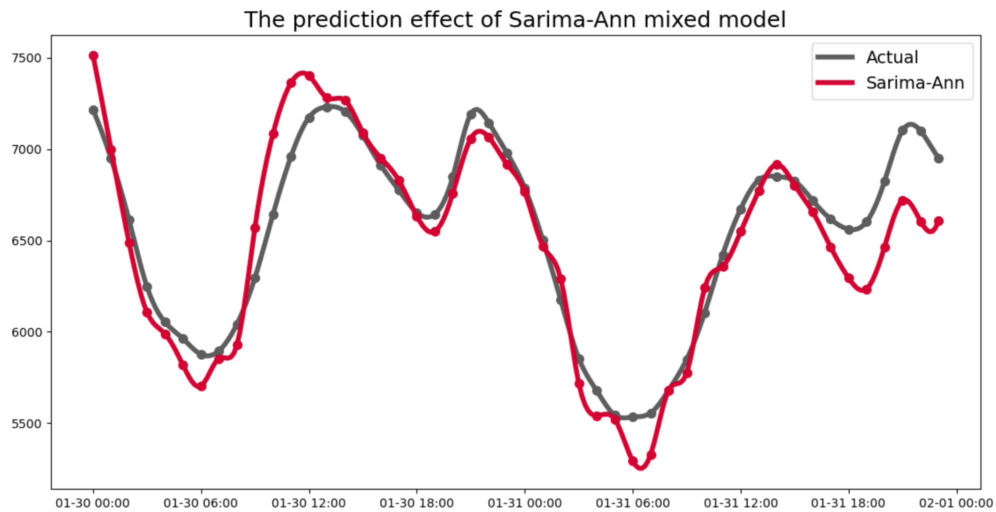

Figure 4. The prediction effect of Sarima-Ann mixed model.

5.2.3. Comparison of Prediction Effects

To verify the prediction effect of this hybrid model, this part compares the prediction accuracy of the traditional Ariama model, Sarima model, and Sarima-Ann model.

Figure 5 shows the comparison of the Arima model, Sarima model, and hybrid model Sarima-Ann. The blue curve shows the prediction effect of the Arima model, the yellow curve shows the prediction effect of the Sarima model and the red curve shows the prediction effect of the hybrid model. It can be seen that using the Arima model to forecast the power demand can already predict the general trend, and it has a good forecasting effect most of the time. After adding seasonal factors to the Arima model, the forecasting accuracy of the obtained Sarima model is slightly improved, but there is still a slight gap compared with the real power demand. After combining the Sarima model with the Ann model, the problem that the nonlinear part of the data is difficult to deal with is solved, and a better prediction effect is obtained. It can be seen that, compared with the traditional Arima and Sarima models, the prediction effect of the hybrid model is more in line with the actual situation and has better prediction accuracy.

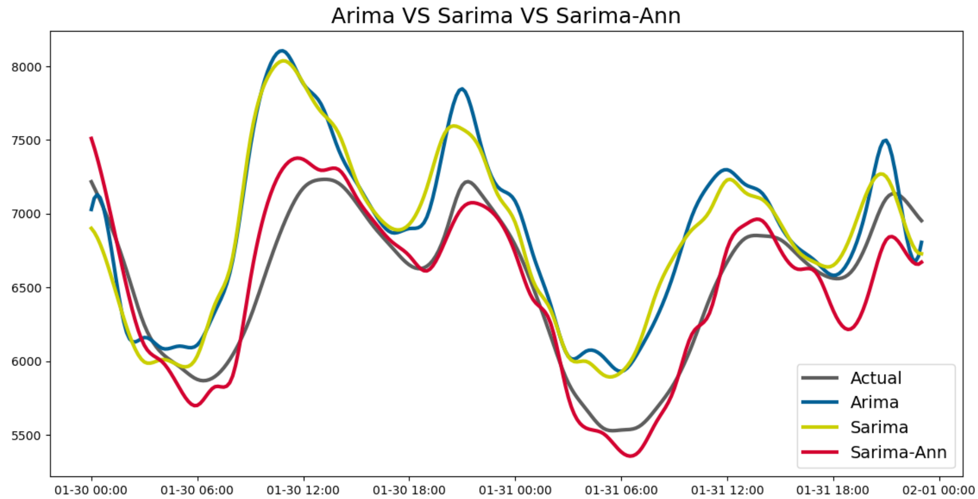

Figure 5. Comparison of prediction results of three models.

5.2.4. Error Analysis and Method Evaluation

In this scheme, the average absolute error MAE, average absolute percentage error MAPE, mean square error MSE, root mean square error RMSE, and R-square R2 are used to evaluate the power demand forecasting effect of the Arima model, Sarima model, and Sarima-Ann mixed model. The smaller the average absolute error MAE, average absolute percentage error MAPE, mean square error MSE, and root mean square error RMSE, the better the forecasting result is, and the closer R2 is to 1, the better the forecasting effect is. The evaluation results of the three models are shown in Table 6 below.

Table 6. Comparison results of various indicators of the model.

Model/Index	MAE	MAPE	MSE	RMSE	R2
Arima	383.4	6.0	241,212	491.1	0.3
Sarima	378.3	5.9	234,637	484.4	0.3
Our work	134.4	2.1	28,475	168.7	0.9

Through numerical comparison and analysis, it can be seen more intuitively that, compared with Arima, the prediction accuracy of Sarima is slightly improved. Compared with the two methods, our hybrid Sarima-Ann in this paper has a great improvement in prediction accuracy.

5.2.5. Parameter Selection for the Sarima-Ann Hybrid Model

Learning rate and the number of cycles are two parameters in the model. Using different learning rates and the number of cycles will make the model achieve different prediction results. In this experimental section, we compared the prediction results of the Sarima-Ann hybrid model with different learning rates and different numbers of cycles, selected the three parameter values with better results, respectively, and showed their prediction results.

Figure 6 shows the predicted results corresponding to the three learning rates with good results. When the learning rates are 0.000348, 0.00033, and 0.000324, the predicted results are close to the actual values.

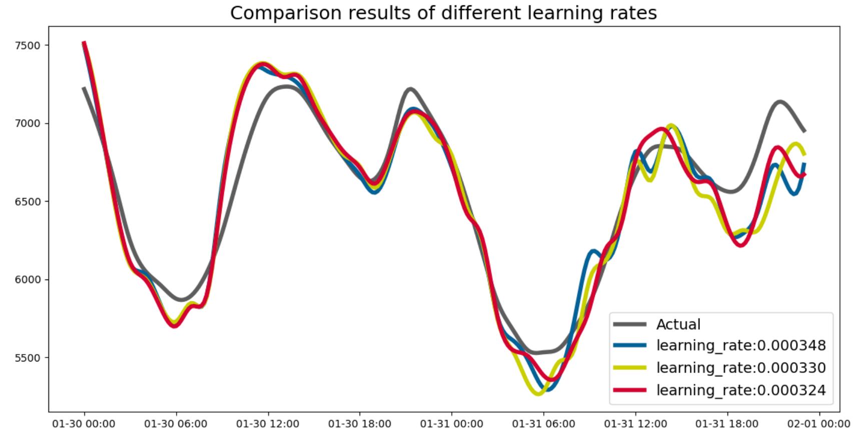

Figure 6. Comparison results of different learning rates.

Figure 7 shows the prediction results corresponding to three cycles with good prediction results. When the cycles are 60,000, 80,000, and 90,000, the prediction results are close to the actual values.

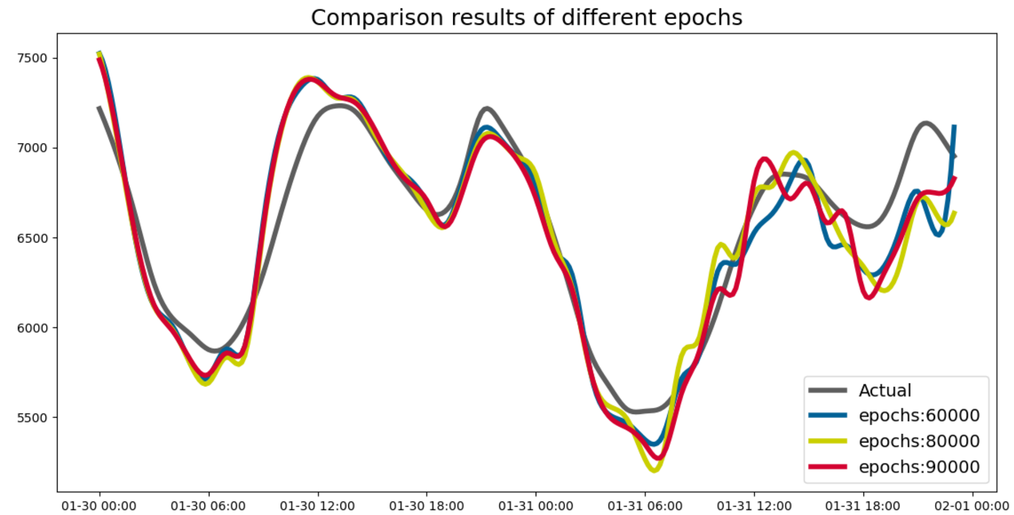

Figure 7. Comparison results of different cycle times.

5.3. Simulation of Dynamic Pricing Model Effect

In this experiment, the value of N is set to 24, and the actual hourly transaction volumes in the energy dataset introduced at the beginning of this chapter are also used as the experimental dataset to validate the results achieved using the one-hour pricing model in this scheme. To simplify the experimental process, this part directly uses the power demand forecast results in the data set. In practice, the Sarima-Ann model of this scheme can be used to forecast the power demand, and then the forecast results are used as input parameters of the pricing model. In the experiment, we set a_1 = 0.01, a_2 = 0.02, a_3 = 0, μ = 10,ϖ_1 = 0.7,ϖ_2 = 0.3, α = 10, z_{max} = 10,000, η=195, θ = 0.015, and the electricity price is 100. In practice, these values can be selected according to different situations.

Figure 8 shows the comparison between the electricity usage within one day after using our pricing model and the original electricity usage. It can be seen that after using our pricing model, a good peak shaving effect is achieved, and the fluctuation of electricity usage is weakened. This effect is achieved through the pricing of electric power companies. In the pricing process, electric power companies not only consider the influence of prices on users' electricity usage, but also the influence of incentive amounts on electricity usage.

The comparison chart between the price and the actual electricity consumption of users is shown in Figure 9.

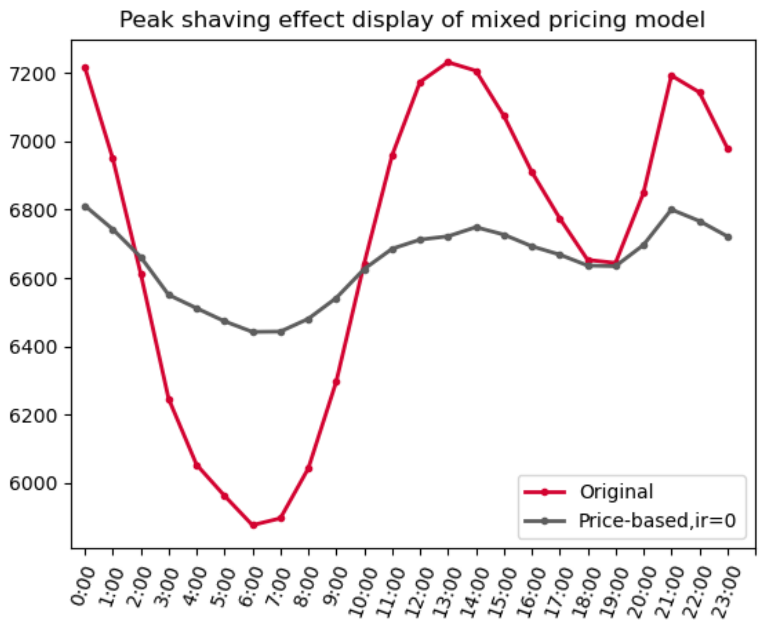

Figure 8. Peak adjustment effect of a mixed pricing model.

As shown in Figure 9, the price and the actual electricity consumption have the same trend. In the low peak period, the power company will lower the price to encourage users to use electricity. During the peak period, the power company will raise the prices to encourage users to reduce electricity consumption, thus achieving a peak shaving effect.

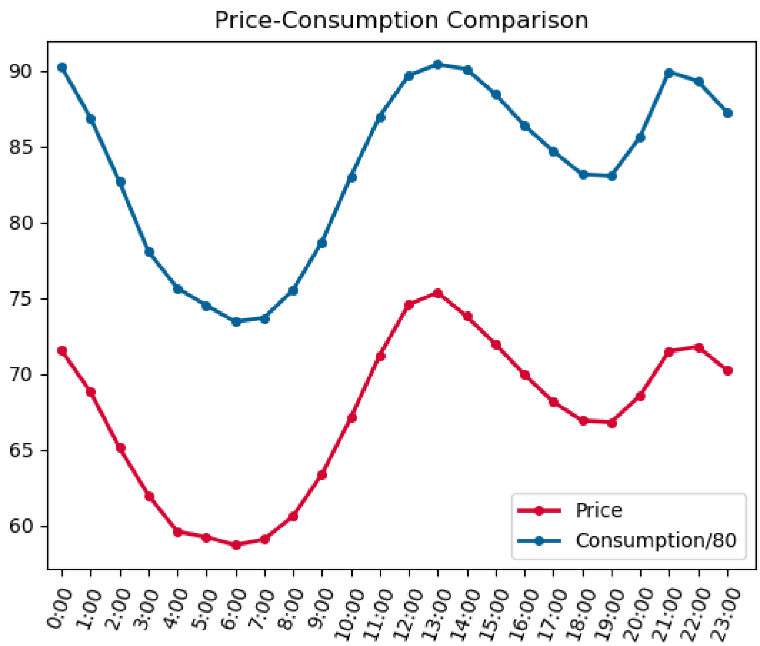

Figure 9. Comparison of price and electricity usage.

In this part of the experiment, the incentive rate is adjusted to different values, and the effect achieved only based on pricing and the effect achieved by the mixed strategy based on the pricing and incentive amount are compared. For the convenience of the display, we only compare the effects of incentive rates of 0, 1, 2, and 3. The peak shaving effect comparison chart is shown in Figure 10.

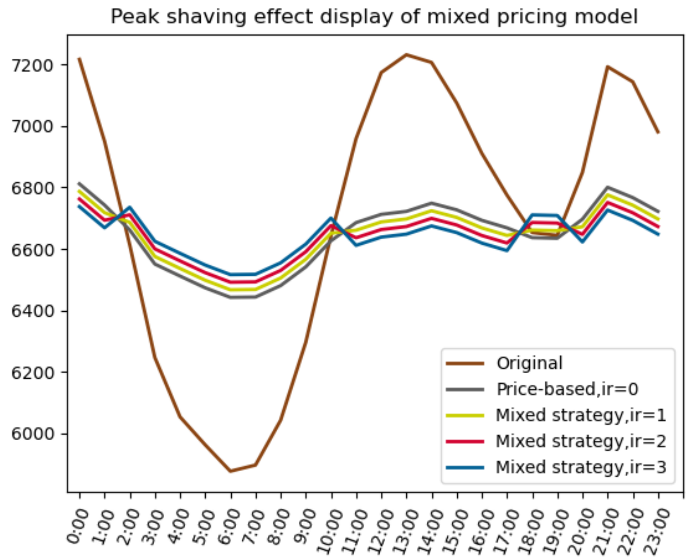

Figure 10. Comparison of peak shaving effect under different ir.

As shown in Figure 10, the gray curve is the power usage under the price-based model, the brown curve is the original power usage, and the other color curves are the power usage under the mixed model with different ir values. It can be seen that, under the pricing strategy of this scheme, even if the incentive rate is adjusted to 0 without considering the incentive effect, a good peak shaving effect is achieved, and the peak shaving effect can be better after the incentive effect is added.

In addition, this experiment compares the effects of the model with the incentive rate of 0, that is, only based on the price, and the mixed pricing model of this scheme when the incentive rate is adjusted to 1, 2, and 3, respectively. The comparison results are shown in Tables 7–9.

Table 7. Peak shaving effect display under different ir.

ir/Index	Fluctuation/Ten Thousand	Original Fluctuation/Ten Thousand	Peak Drop Ratio
ir = 0	29.42387153	499.91185	94.11%
ir = 1	19.98781504	499.91185	96%
ir = 2	13.45781961	499.91185	97.3%
ir = 3	9.833885252	499.91185	98%

Table 8. Electricity consumption display under different ir.

ir/Index	Original Consumption	Consumption Reduction	Consumption Reduction Rate
ir = 0	160,590	1092.4074	0.68%
ir = 1	160,590	1141.7901	0.71%
ir = 2	160,590	1191.1728	0.74%
ir = 3	160,590	1240.5556	0.77%

Table 9. Effect display of utility improvement under different ir.

ir/Index	Cost Reductions	Company Utility Increase	User Utility Increase	Social Welfare Increase
ir = 0	45,653,061.9	40,347,836.9	5,404,811.1	45,752,648.0
ir = 1	46,502,239.1	41,191,116.5	5,412,354.9	46,603,471.4
ir = 2	47,057,592.7	41,740,572.6	5,420,491.3	47,161,063.9
ir = 3	47,319,122.8	41,996,205.2	5,429,220.2	47,425,425.4

The cost in Table 9 refers to the extra cost incurred by power companies due to fluctuations in electricity consumption and incentives. As can be seen from Table 7, both the price-based model and the hybrid price-and-incentive-based model in this scheme can greatly reduce the fluctuation of trading volume, and the reduction ratio can reach more than 90%. As can be seen from Table 8, this scheme does not have much impact on the total electricity consumption, and the total electricity consumption can be reduced by less than 1% by adjusting the incentive rate. That is, this scheme can greatly reduce the peak of electricity usage while guaranteeing the total electricity usage is almost unchanged; through Table 9, it can be seen that both the price-based model and the hybrid pricing model in this scheme can reduce the additional costs incurred by the power companies due to fluctuations in electricity usage and incentives, and increase the utility of the power companies and customers as well as the total social welfare. In addition, by comparison, the hybrid model obtained by adding incentives to the utility function has better results in reducing the peak and increasing the utility of both parties and the total social welfare.

The above results prove that when the incentive rate is 1, 2, and 3, it can achieve a better effect than the single price-based model. That is, the existence of an incentive rate makes the pricing model proposed in this paper better realize peak shaving, increase the utility of power companies and users, and improve the total social welfare. Next, taking the step of 0.1 as a step, comparing the peak shaving effect achieved by different incentive rates in the interval (0, 8) and the effect of improving the utility of both parties and the total social welfare achieved by different incentive rates in the interval (0, 7), we can find the appropriate incentive rate for this model.

As shown in Figure 11, the fluctuation of power consumption first decreases and then increases with the increase of the incentive rate, and the peak adjustment effect is better in the interval (3, 5). There is an incentive rate in the interval (7.4, 7.5), which makes our pricing strategy have the same peak-shaving effect as that based on single pricing. Additionally, in the interval (0, 7.4), compared with single pricing, our pricing strategy has a better peak shaving effect.

As shown in Figure 12, the utility increase of power companies first increases and then decreases with the increase in the incentive rate, and the utility increase is higher in the interval (3, 4). There is an incentive rate in the interval (6.7, 6.8), which makes the mixed strategy have the same effect of increasing the utility of power companies as that based on single pricing. Additionally, in the interval (0, 6.7), our pricing model has a better effect on increasing the utility of power companies than the single price-based model.

As shown in Figure 13, the increase in the user's utility increases with the increase in the incentive rate, and the higher the incentive rate, the greater the increase in the user's utility.

As shown in Figure 14, the increase in the total social welfare first increases and then decreases with the increase in the incentive rate, and the increase in social welfare is higher in the interval (3, 4). There is an incentive rate in the interval (6.8, 6.9), which makes the mixed strategy have the same effect of increasing social welfare as that based on single pricing. Additionally, in the interval (0, 6.8), our pricing model has a better effect on increasing the utility of power companies than the single price-based model.

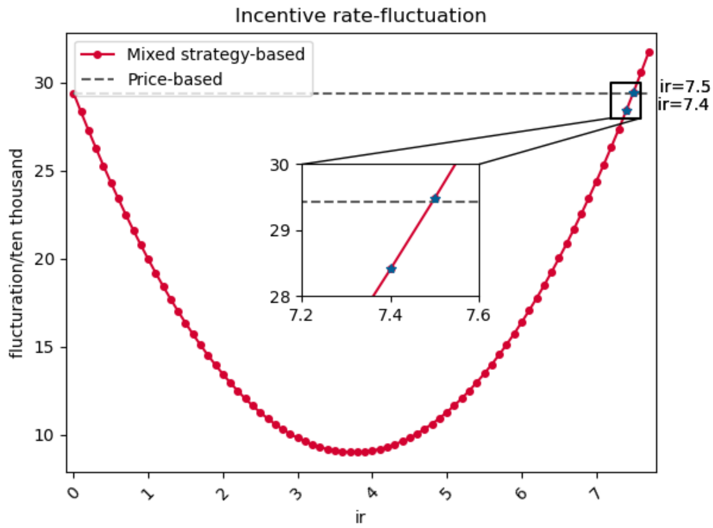

Figure 11. Influence of incentive rate on fluctuation of power usage.

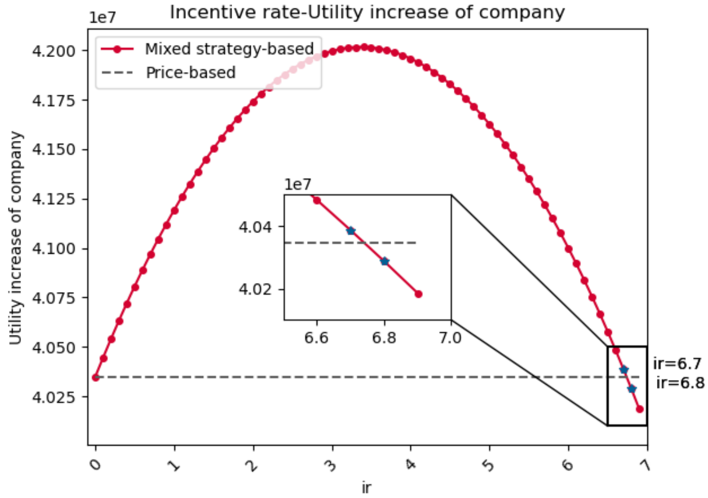

Figure 12. Influence of incentive rate on utility of power companies.

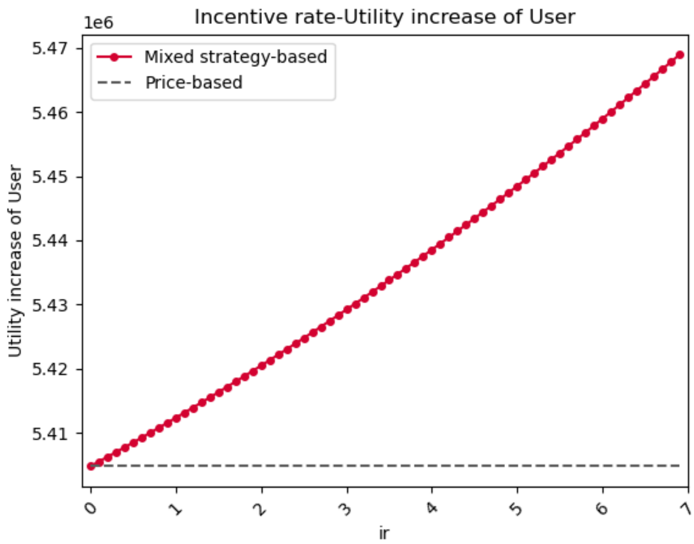

Figure 13. Influence of incentive rate on user utility.

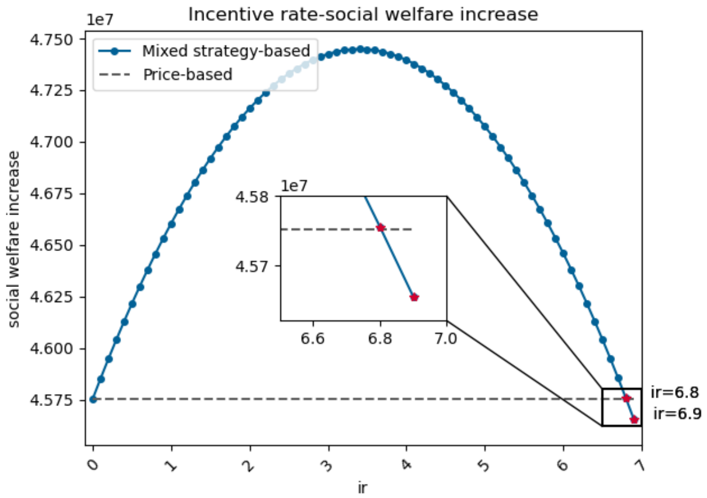

Figure 14. Influence of incentive rate on total social welfare.

Therefore, under comprehensive consideration, the incentive rates in the interval (3, 4) are more effective for peak adjustment and improving social welfare. In practice, the incentive rate can be set in this interval.

6. Discussion

For the prediction algorithm proposed in this paper, it can be seen from the simulation experiments and results that after adding seasonal factors to the traditional Arima model, the prediction accuracy is improved, and if measured by the MAE index, the accuracy can be obtained with a 1.3% improvement compared to the original and considering the non-linear factors in the data, the effect achieved using the Sarima-Ann hybrid model is significantly improved after the Ann model is introduced, and if MAE is still used as the measure, a 64.5% improvement in accuracy is obtained compared to the original. It can be proved that the hybrid forecasting model of this scheme does have better forecasting accuracy for electricity demand. In future research, other hybrid methods can be explored to achieve the results.

For the pricing model in this paper, the simulation and experimental results show that the peak electricity consumption can be reduced by more than 90% under the model with a guaranteed reduction of less than 1% in total electricity consumption. That is, the scheme can significantly reduce peak electricity consumption while guaranteeing that the total electricity consumption remains essentially unchanged. In addition, the transaction utility is significantly higher under this model, and the total transaction utility improvement can be up to 4.6×10^7. The peak regulation and trading utility improvement achieved after the introduction of the incentive amount are both better than those before the introduction. By adjusting the incentive rate to compare the peak regulation effect and the utility improvement effect, an interval with good peak regulation and total transaction utility improvement could be found. In practical applications, a suitable incentive rate can be chosen within this interval to make the model obtain better results. In future research, the existing scheme could be extended to consider multiple participants, and new game models can be constructed to solve problems in more application scenarios.

7. Conclusions

In this paper, we propose a new collaborative energy price calculation scheme, which designs a new utility function for both electric utilities and customers. By adding the incentive amount to the original price-based pricing strategy, it can better balance the electricity demand and improve the transaction utility. In this paper, the Sarima-An intelligent forecasting model is used to forecast the electricity demand. Compared with the traditional Arima and Sarima models, this forecasting model has better forecasting accuracy, which improves the accuracy of pricing results under this scheme and alleviates the problem of low service quality caused by information asymmetry.

However, the current scheme proposed in this paper is only for the case of two participants in the transaction process, and in future work, more participants can be considered, and a new utility function can be built based on this scheme to enable the scheme to be applied in more scenarios. In addition, this scheme does not consider the problem of user privacy leakage during the calculation process. The data generated in the energy trading process is likely to leak user privacy in the centralized calculation process, so how to safeguard user privacy in the price calculation process will be a direction of future research. In the future, cryptographic techniques such as homomorphic encryption [44] could be used in this price calculation scheme to solve the privacy leakage problem in the calculation.

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Appendix A

Proof of Theorem 1. The solution process of the Nash equilibrium and the proof process of Theorem 1 in the article are as follows.

Step 1: For the user's utility function U_2, consider l_k as an independent variable, and use the Hessian matrix to find l' that maximizes U_2.

First, solve the first derivative concerning l_k for U_2:

When $d_k < d_{avg}$:

$$\frac{\partial U_2}{\partial l_k} = -\frac{\eta}{z_{\max}} l_k + \eta - p_k + ir - 2\varpi_1 \theta (l_k - orl_k) - \frac{\varpi_2 \alpha (p_k - r_k)}{r_k} \tag{A1}$$

Let $\frac{\partial U_2}{\partial l_k} = 0$, the optimal power consumption when U_2 is maximized can be expressed as follows:

$$l' = \frac{(2\varpi_1 \theta orl_k + \varpi_2 \alpha + \eta + ir) z_{\max} r_k}{\eta r_k + 2\varpi_1 z_{\max} \theta r_k} - \frac{(\varpi_2 \alpha z_{\max} + z_{\max} r_k) p_k}{\eta r_k + 2\varpi_1 z_{\max} \theta r_k} \tag{A2}$$

For simplicity, we will abbreviate the above formula as follows:

$$A_k = \frac{(2\varpi_1 \theta or_k + \varpi_2 \alpha + \eta + ir) z_{\max} r_k}{\eta r_k + 2\varpi_1 \theta z_{\max} r_k} \tag{A3}$$

$$B_k = -\frac{(\omega_2 \alpha z_{\max} + z_{\max} r_k)}{\eta r_k + 2\varpi_1 \theta z_{\max} r_k} \tag{A4}$$

where

$$A_k > 0, B_k < 0 \tag{A5}$$

Then, l' can be simplified to the following formula:

$$l' = A_k + B_k p_k \tag{A6}$$

When $d_k >= d_{avg}$:

$$\frac{\partial U_2}{\partial l_k} = -\frac{\eta}{z_{\max}} l_k + \eta - p_k - ir - 2\varpi_1 \theta (l_k - orl_k) - \frac{\varpi_2 \alpha (p_k - r_k)}{r_k} \tag{A7}$$

Let $\frac{\partial U_2}{\partial l_k} = 0$, the optimal power consumption when U_2 is maximized can be expressed as follows:

$$l' = \frac{(2\varpi_1 \theta orl_k + \varpi_2 \alpha + \eta - ir) z_{\max} r_k}{\eta r_k + 2\varpi_1 \theta z_{\max} r_k} - \frac{(\varpi_2 \alpha z_{\max} + z_{\max} r_k) p_k}{\eta r_k + 2\varpi_1 \theta z_{\max} r_k} \tag{A8}$$

For simplicity, we will abbreviate the above formula as follows:

$$A_k = \frac{(2\varpi_1 \theta orl_k + \varpi_2 \alpha + \eta - ir) z_{\max} r_k}{\eta r_k + 2\varpi_1 \theta z_{\max} r_k} \tag{A9}$$

$$B_k = -\frac{(\varpi_2 \alpha z_{\max} + z_{\max} r_k)}{\eta r_k + 2\varpi_1 \theta z_{\max} r_k} \tag{A10}$$

where

$$B_k < 0 \tag{A11}$$

Similarly, l' can be simplified to the following formula:

$$l' = A_k + B_k p_k \tag{A12}$$

Then, solve the second derivative of l_k with respect to U_2, whether $d_k < d_{avg}$ or $d_k >= d_{avg}$, there are:

$$\frac{\partial^2 U_2}{\partial l_k \partial l_i} = \begin{cases} -\frac{\eta}{z_{\max}} - 2\varpi_1 \theta, i = k \\ 0, \mathrm{i} \neq \mathrm{k} \end{cases} \tag{A13}$$

Since η,z_{max} and θ are always positive, the diagonal elements of the Hessian matrix are all negative, the other position elements are always 0, and the matrix is negative definite. Therefore, the obtained l' is the optimal power usage when U_2 is maximized.

Step 2: Substitute the obtained l' into the utility function U_1 of the power company, regard p_k as an independent variable, and use the Hessian matrix to obtain the p' value when U_1 is maximized.

Substituting the resulting l' into the utility function U_1 of the power company, we can obtain:

$$U_1 = \sum_{k=1}^{N}\left(B_k p_k^2 + A_k p_k - C_k\right) \pm ir\sum_{k=1}^{N}(A_k + B_k p_k - orl_k) - \sum_{k=1}^{N}\left(\mu\left(A_k + B_k p_k - d_{avg}\right)^2\right) \tag{A14}$$

Solve the first derivative with respect to p_k for U_1:

When $d_k < d_{avg}$:

$$\frac{\partial U_1}{\partial p_k} = 2B_k p_k + A_k - 2a_1 B_k^2 p_k - 2a_1 A_k B_k - a_2 B_k - 2\mu B_k^2 p_k + 2B_k\left(A_k - d_{\text{avg}}\right) - irB_k \tag{A15}$$

Let $\frac{\partial U_1}{\partial p_k} = 0$, the optimal power consumption when U_1 is maximized can be expressed as follows:

$$p' = \frac{2a_1 A_k B_k + a_2 B_k + B_k ir - A_k - 2B_k\left(A_k - d_{avg}\right)}{2B_k - 2a_1 B_k^2 - 2\mu B_k^2} \tag{A16}$$

When $d_k >= d_{avg}$:

$$\frac{\partial U_1}{\partial p_k} = 2B_k p_k + A_k - 2a_1 B_k^2 p_k - 2a_1 A_k B_k - a_2 B_k - 2\mu {B_k}^2 p_k + 2B_k\left(A_k - d_{\text{avg}}\right) + irB_k \tag{A17}$$

Let $\frac{\partial U_1}{\partial p_k} = 0$, the optimal power consumption when U_1 is maximized can be expressed as follows:

$$p' = \frac{2a_1 A_k B_k + a_2 B_k - B_k ir - A_k - 2B_k\left(A_k - d_{\text{avg}}\right)}{2B_k - 2a_1 B_k^2 - 2\mu B_k^2} \tag{A18}$$

Then, solve the second derivative of p_k with respect to U_1, whether $d_k < d_{avg}$ or $d_k >= d_{avg}$, there are:

$$\frac{\partial^2 U_1}{\partial p_k \partial p_i} = \begin{cases} 2B_k - 2\mu B_k^2 - 2a_1 B_k^2, i = k \\ 0, \mathrm{i} \neq \mathrm{k} \end{cases} \tag{A19}$$

Since B_k is always negative, and μ and a_1 are always positive, the diagonal elements of the Hessian matrix are all negative, and the other elements are 0, so the matrix is negative. Therefore, the obtained p' is the optimal electricity price when U_1 is maximized.

Therefore, it can be proved that the Nash equilibrium solution is unique, and different periods and different demands correspond to different Nash equilibrium solutions. □

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