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Studying Electricity Load Forecasting and Optimizing User Benefits with Smart Metering

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Abstract

Accurate energy projections and optimal utilization of resources require the consideration of real-time variations in demand-side response components. Innovative ultra-short-term power load forecasting approaches such as CNN-BiLSTM-Attention, CNN-LSTM, and GRU models are used to assess the load level and predict daily raw load curve. The study shows that by incorporating predicted raw loads and two types of customer reactions influenced by average reduction rate under different energy efficient classes, wholesale market price fluctuations can be minimized through retail-to-wholesale market connection using demand-side responses. This helps diminish both frequency and amplitude of sudden changes in prices for wholesalers while taking into account an average overall usage pattern based on user class resource consumption rates.

Keywords: Load Forecasting; Attention Mechanisms; Maximum Efficiency; Demand-Side Response; Bidirectional Long-Short Memory Networks; Convolutional Neural Networks

1. Introduction

The advancement of the electrical sector is unavoidable due to new demands arising from both our country's progress and the requirements imposed by modern living. Meeting global goals for energy conservation management and reducing emissions necessitates immediate action, including balancing electricity supply and demand via real-time transactions. Power dispatch management organizations can enhance their operations with short-term load forecasts, allowing them to improve power generation planning and unit scheduling in addition to ensuring grid resilience while decreasing expenses [1][2]. By embracing technological innovations such as electric vehicles, pumped-storage facilities, or integrating storage systems into the grid network like energy storage units - more considerable integration facilitating enhanced responses on-demand-side has led many industrial sectors becoming prospective clients [3][4].

The integration of demand-side management plays a critical role in power market planning. According to Adenso et al.'s a comprehensive analysis, two fundamental aspects are necessary for addressing the challenges encountered by OECD nations in executing demand-side response programs. Through an evaluation of consumer usage patterns and analyzing the characteristics of demand-side behavior, electric energy supply can be seamlessly integrated into the system while refining pricing mechanisms. Hopper et al. [5] study revealed that effective implementation of such strategies is contingent upon ease-of-use, fairness and equal access to information as crucial elements. Revised text:

In the field of demand-side response projects, several models have been developed to consider various factors that affect energy consumption and improve market efficiency. Fell et al. [6] proposed an income-expense model, which takes into account time-of-use electricity prices, subsidy policies, as well as technologies like energy storage and distributed power generation in the smart grid environment. Qadrdan et al. [7] on the other hand, focused on dealing with wind output unpredictability through a two-tier planning model coupled with hourly energy price optimization one day before and an incentive-based demand-side response mechanism for dispatching wind power systems

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effectively. This approach optimizes cost-efficient thermal power generation by utilizing peaked-out peak smoothing along with deep trough filling methods for greater outcomes overall while reducing better-managing the and better managing adoption of sustained pollutions like wind-power efficiently under this framework leading towards more positive outcomes benefiting both producers and consumers alike.

Most historical estimates of short-term load were deterministic and can be further categorized into statistical forecasting techniques or intelligent forecasting techniques based on machine learning, depending on the underlying methodology employed. The models widely used in statistical forecasts include Linear Regression, Recurrent Neural Networks which are a variant of RNNs, and Support Vector Regression. However, these traditional models were not equipped to handle non-linear correlations such as those influenced by climate change and date type; thus their ability to predict accurately was limited. In recent times with the advent of AI technologies, machine learning algorithms have been significantly utilized for accurate predictions using deep-learning approaches. Wu et al. [8] study showed that support vector machines' prediction precision is close to perfect when dealing with small samples but loses effectiveness as data volume increases—hence making neural network models a better alternative for large data sets.

Su et al. [9] opted for the error-based back-propagation model as it is extensively used in short-term load forecasting, is easy to grasp and is applicable in numerous contexts. However, this method's tendency to settle on a local minimum instead of achieving optimal global solutions presented an issue. Zou et al. [10] tackled gradient disappearance when processing massive time series data through their proposed hybrid ant colony optimization algorithm fused with recurrent neural networks. Conversely, Peng et al. [11] employed a long-term and short-term memory-based network model that could consider temporal dynamics along with nonlinear relationships between variables- a feat that allows for accurate predictions though discovering deep associations from feature-dense data appears arduous utilizing this framework.

According to Lin et al. [12] the SVR approach exhibits limited efficacy, leading to binary forecast output, high errors of prediction and delayed effects in data with excessive spurious interference. In contemporary studies on speech recognition, image recognition, machine translation etc., scholars have shown rising interest in attention mechanisms due to their resource allocation efficiency. To enhance the accuracy of electric load forecasting, some researchers have also investigated incorporating an attention mechanism. Long Short-Term Memory Networks are frequently utilized in power load forecasting due to their distinctive memory features and gate designs, enabling them to take into account both the temporal and nonlinear nature of load data simultaneously. The research implemented LSTM neural networks for electrical demand prediction and experimentally demonstrated that compared with feedforward neural networks, the LSTM model performed better in terms of both practicality and predictive ability [13]. Sima Siami-Namini's investigation on time series analysis and power load forecast indicated that Bi-directional LSTMs outperformed uni-directional LSTMs models [14].

The conventional unidirectional long and short-term memory network was improved to a bi-directional LSTM structure, the BiLSTM. This method learns data from both directions of a time series, increasing the predictive power of models with higher accuracy which can be employed in electric demand prediction. In 2020, Wang suggested applying CNN and BiLSTM techniques together into one hybrid model named CNN-BiLSTM creating an improvement over a single structured LSTM model or combined CNN-LSTMs' performance [14].

This research initiates a distinctive approach using the AC-BiLSTM tech for ultra-short-term electricity load forecasting by augmenting on advantages from Attention Mechanisms inscribed within specific features of non-linear/time-series nature characterized as electrical load data while making use of vivid characteristics embedded only in convoluted neural networks; hence upgrading this technology than previous generations [15].

This research delves into the subject of demand-side response by focusing on power load forecasting and maximizing total benefits for power customers. The integration of active distribution systems and customer-generated demand responses can lead to a substantial enhancement in the overall efficiency of the power system [16]. Furthermore, this innovation creates opportunities for dynamic real-time rates along with cost-cutting measures in energy markets. The study uses an advanced forecasting model named CNN-BiLSTM-Attention, where convolutional neural network, bidirectional long- and short-term memory network coupled with attention mechanism generate high prediction accuracy via cognitive processing through CNN layering approach. This new AC-BILSTM serves as an effective tool to predict variations in system loads accurately over time. To achieve an accurate load projection, a thorough analysis of the demand-side response potential in the region must be conducted. This will entail superimposing the initial load with demand-side resources that factor in responsive loads. A model for demand-side responsiveness is then established to optimize benefits resulting from these policies and investigate how tariffs influence electricity consumption using a specific case study. During periods of high energy consumption, clients can adopt various measures such as pricing signals which prompt them to reduce their usage or shift their power hours consequently addressing peak demands while contributing towards promoting market stability through curbed power consumption during peak times.

2. Methodology

This article presents a novel approach to predict extremely short-term power load utilizing AC-BiLSTM, CNN-LSTM, and GRU. The methodology incorporates the nonlinear and time-series characteristics of power load data. To effectively capture the sequence data's temporal properties in both directions, Bidirectional Long Short-Term Memory layer is utilized in which its hidden output features are fed into an Attention mechanism. This enables us to reduce undesired variables' impact through applying weights on the recovered temporal information from BiLSTM layer.

2.1. Convolutional Neural Network CNN

The majority of layers in a CNN consist of the input layer, convolutional layer, ReLU layer, pooling layer and fully connected layers which are similar to those utilized in a standard neural network. The key components of a CNN include the convolutional and pooling layers [17]. CNNs adopt convolution kernels to extract nonlinear localized features from energy consumption data efficiently which has proven beneficial for studying power systems. By arranging these stacked layers appropriately within the network architecture generates an effective functioning CNNS capable for load forecasting purposes.

2.2. LSTM Neural Network

Conventional neural networks pay little mind to the data that will be available from one processing instant to the next, focusing instead simply on the data that is available at the moment. The LSTM neural network is a viable option for fixing this issue [18]. The LSTM neural network, developed by Hochreiter et al., was a novel recurrent network design. By incorporating forgetting gates, input gates, and output gates into logical control units, LSTM is able to increase the storage capacity of long-term memories. These gates are responsible for keeping the cell in a constant state of change.

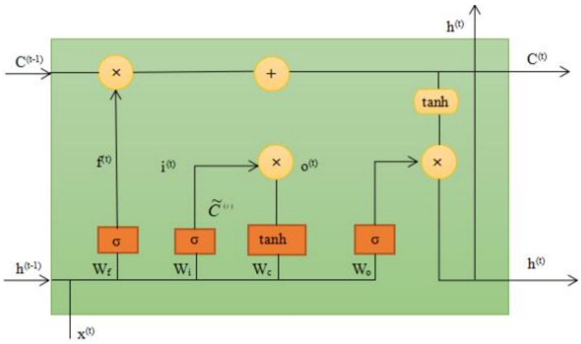

Figure 1. Structure of LSTM

In order to decide which parts of the cell state C(t-1) from the previous time step should be ignored, the equation used by the forgetting gate employs information about both current input x(t) and hidden state h(t-1). The output produced by this gate is a value between 0 and 1 that determines whether certain bits in C(t-1) are kept (if closer to 1), or discarded (if closer to 0).

$$f^{(t)} = \sigma(W_f \bullet [h^{(t-1)}, x^{(t)}] + b_f) \tag{1}$$

In order to compute the forgetting gate state f(t) at a specific moment t, one can utilize the weights and biases (bf) of said state along with the bipolar sigmoid activation function, σ. By processing input x(t), the input gate is capable of determining relevant stored information within a neuron. Subsequently, utilizing equation, an updated input gate is generated which results in obtaining temporal memory cell state C(t). The newly acquired cell-state C(t) may be obtained by further implementing equations 3 to 4.

$$\mathrm{i}^{(\mathrm{t})} = \sigma(W_{\mathrm{i}} \bullet [\mathrm{h}^{(\mathrm{t}-1)}, x^{(\mathrm{t})}] + \mathrm{b}_{\mathrm{i}}) \tag{2}$$

$$\tilde{C}^{(t)} = \tanh(W_c \bullet [h^{(t-1)}, x^{(t)}] + b_c) \tag{3}$$

$$C^{(t)} = \mathrm{f}^{(t)} \otimes C^{(t-1)} + i^{(t)} \otimes \tilde{C}^{(\mathrm{t})} \tag{4}$$

In the context of recurrent neural networks, a key component is the input gate state at each time step. The amount of information transferred from control x(t) to C(t) is determined by variables such as weight matrix Wi and bias vector bi associated with the input gate. In addition, Wc represents the weight matrix responsible for regulating cell states while bc denotes its respective bias term. The activation function of the hyperbolic tangent, denoted by tanh, is the Hadamard product.

The most important data from the present state is picked by the output gate. To calculate the output value h(t), the tanh layer multiplies the neuron state by the sigmoid layer's output, which is then used as input to the next hidden layer. The output gate can be found by solving for x in both Eq. (5) and Eq. (6).

$$O^{(t)} = \sigma(W_o \bullet [h(^{t-1)}, x^{(t)}] + b_o) \tag{5}$$

$$\mathrm{h}^{(t)} = o^{(t)} \otimes tahnC^{(t)} \tag{6}$$

where: O(t) is the state of the output gate at time t, Wo is the output gate's weight matrix, and bo is its bias term.

2.3. BiLSTM Neural Network

The model only takes into account top-down data because LSTM is a unidirectional recurrent neural network. Since the final output may depend on a long series of inputs in a practical application, it is important to record all of those inputs. The use of BiLSTM neural networks, which incorporate forward and backward LSTM layers for prediction, have been found to perform better than traditional unidirectional LSTMs due to their ability to utilize both past and future information. However, it is important to note that the unidirectional LSTM model may be advantageous as it relies less on external factors and places more emphasis on the internal history of load data in generating predictions.

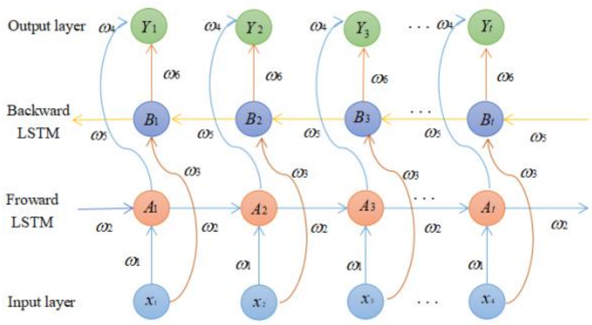

Figure 2. Bilateral long short-term memory network architecture

2.4. Gated Recurrent Unit (GRU)

Recurrent neural networks (RNNs) include GRU networks because their inter-neuron connection topology includes at least one cycle8. Since their introduction in 1997, they have undergone further refinement. When trying to train long-term dependencies with conventional RNNs, difficulties with vanishing and ballooning gradients are typical. The GRU

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is a type of gated RNN that can handle such issues. The model seen in Figure 3 is made up of a number of neurons. Third, the ideal number of neurons is established by the size of the feature space. The output space is proportional to the number of neurons in the output layer.

The GRU networks' core functionality is represented by a hidden layer(s) made up of memory cells. The cell requires two gates, the reset gate (t r) and the update gate (u p), to facilitate status updates and maintenance (t u). The circuit diagram of a memory cell is shown in Figure 4.

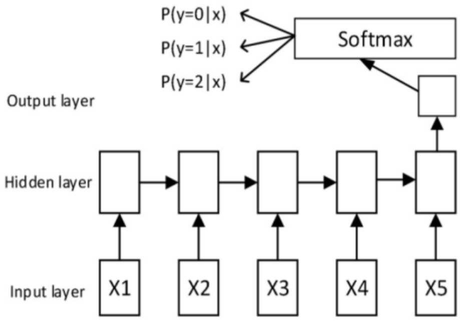

Figure 3. Structure of GRU-based model.

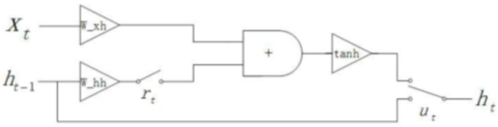

Figure 4. Structure of GRU memory cell

2.5. Attention mechanism

Initially, attention was implemented in image processing to explore how machines could imitate the selective focus of human brain. With regards to deep learning, it is assumed that the relative significance of various factors alters at discrete levels within the network and through this mechanism, higher-level detectors can emphasize pertinent information while disregarding less crucial aspects. A visual representation of Attention unit's architecture has been depicted in Figure 5.

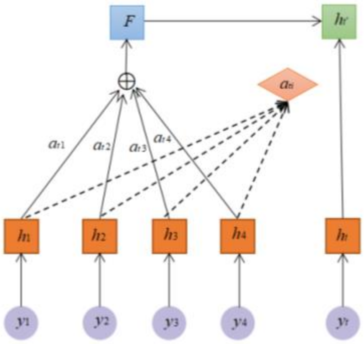

Figure 5. Attentional Organization

$$S_{ti} = V \tanh(W_{h_t} + U_{h_i} + b) \tag{7}$$

$$a_{ti} = \frac{\exp(S_{ti})}{\sum_{i=1}^{t} \exp(S_{tk})}, i = 1,2,3,\dots,t-1 \tag{8}$$

$$F = \sum_{i=1}^{t} a_{ti} \times h_i, i = 1,2,3,\dots,t-1 \tag{9}$$

$$h'_t = f(F, h_t, y_t) \tag{10}$$

In this equation, "au" represents the weight assigned to the BiLSTM attention layer output for a given input. The inputs are represented by y1,y2,y3,...,yt and their corresponding hidden layer states are h1,h2,h3,... ,ht where ht corresponds to input yt. Ultimately, we obtain the final feature vector denoted as F. The neural network model's real-time training involves evolving parameters V,W,U, and B in response to improvements made during refinement of the model.

2.6. AC-BiLSTM Model Architecture for Prediction

This study suggests three approaches. One strategy for predicting future power consumption is an AC-BiLSTM-based method (shown in Figure 6). The first step is to create a training set and a test set from the processed load data. After that, we create the AC-BiLSTM model. To algorithmically identify the innate characteristics of load data, our research implements a CNN system that comprises only one convolutional layer and pooling layer. By exploring the intrinsic dynamics of local features obtained through CNN, complex global features can be decrypted using BiLSTM hidden layer modeling. The attention mechanism leverages BiLSTM-generated attributes as input to discern time-based information's importance recovered by said model with little human intervention. This allows for a more efficient means of probing the robust temporal association by utilizing the load data's inherent time series features. The attention mechanism aids in mitigating the consequences of load forecasting outcomes by preventing unnecessary data loss and drawing attention to pivotal moments in the past. To mitigate the impact of superfluous data on load prediction outcomes, attention mechanism effectively reduces the loss of past information while highlighting significant historical events. By using this approach, the Attention layer generates an output that is later directed to a fully connected layer; subsequently providing precise energy demand forecasts with better accuracy. Overfitting can be avoided in a BiLSTM network by inserting dropout layers after each hidden layer. The model's training duration can be shortened and its generalizability improved without resorting to overfitting with this approach. In this research, we optimize the network parameters at each layer using the Adam (Adaptive Moment Estimation) algorithm, with mean squared error (MSE) as the loss function. After completing the training of the AC-BiLSTM model, it is saved and then evaluated against a test set. The prediction results are thoroughly analyzed to pinpoint where enhancements can be made. Three techniques were used in this study: one utilizing BI-LSTM, another with LSTM, and the third implementing GRU. All three approaches tackled similar scenarios but varied slightly in their modifications.

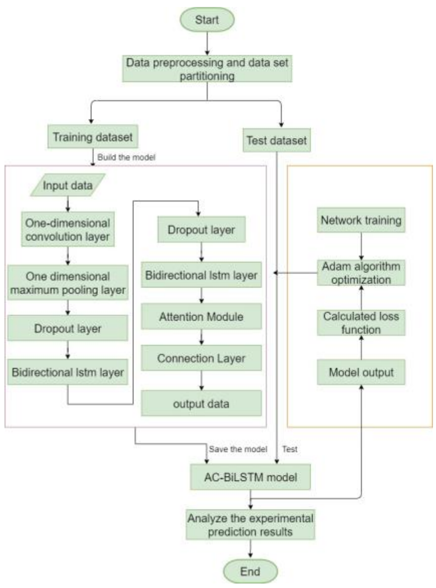

Figure 6. Structure of Attention Incorporating demand-side response resources into load forecasting

As active power distribution systems and user-side demand response evolve, new power grid companies along with a diverse set of resources for response are emerging. Consumers with differing patterns of energy consumption demonstrate various responses during the operation of an active distribution network. To prevent unnecessary expenses on expansion projects, more accurate load forecasting is required. This requires consideration of both the capacity and effect of demand-side resources on loads. To achieve this goal, the process follows three stages: load forecasting that includes assessing the capability to respond and determining impact from demand side resources.

Load management is crucial for anticipating the impact of energy-efficient resources on power consumers and avoiding excessive strain on power usage. To achieve this, it is essential to quantify the potential reduction in electricity consumption by end-users resulting from energy-saving measures during a specific period. Symbolically, we represent the initial amount of energy used by consumers before implementing any measure as Q_{it} . In addition, h_i and $\varphi_{er,i}$ are representing the total rate of load reduction after deploying an efficient resource through its penetration level and technology adoption rate coefficient respectively. This helps describe whether such a resource exists or not; having an indicator value of either 0 or 1 accordingly. Therefore, integration advances in efficiency can effectively reduce overall user demand at periods when supply falls short due to external factors like unexpected natural calamities interfering with normal operations within power grids thereby maintaining electric continuity while enhancing economies towards sustainability initiatives.

$$\Delta Q_{it} = Q_{it,0} h_i \varphi_{er,i} \tag{11}$$

Hence, it can be inferred that the total electricity conserved by consumers through the combined utilization of distinct energy-saving resources is calculated at a specific time I to be:

$$\Delta Q_t = \Delta Q_{1t} + \Delta Q_{2t} + \ldots + \Delta Q_{mt} \tag{12}$$

A common oversight is to underestimate the multitude of unique energy-saving technologies available today. As a result, determining power consumption at time t after implementing energy efficiency measures requires factoring in both the initial electricity usage and subsequent changes in consumption that occur due to these resources being utilized by the user.

$$Q_{er,t} = Q_{t,0} - \Delta Q_t \tag{13}$$

2.7. The Influence of Load Resources on User Load

Load resources can be classified into administrative and economic measures. Demand response users often rely on modifying their electricity usage voluntarily by either shifting consumption time or reducing energy use in order to achieve the goal of load shifting. Direct load control and systematic power management are two types of administrative actions, while an example of an economic measure is electricity price plans that involve changing rates from peak to valley or from season to season. The effect of implementing administrative initiatives typically results in a decreased trend in the load curve with the corresponding model for load reduction being:

$$\Delta P_{i,t} = P_{t,er,0} - Q_{er,t} \mu_i \frac{1}{\eta_{lo,i} t} \tag{14}$$

The formula involves the load reduction impacted by the availability of the load resource at a particular time, denoted as $\Delta P_{i,t}$. The resulting load after implementing energy efficiency measures is represented as $Q_{er,t}$. A state coefficient describes whether or not the specific load resource exists; its value of 1 indicates existence while that of zero implies it does not exist. Furthermore, $\eta_{lo,i}$ stands for electric power user's rate under influence from said resources at time . Finally, multiplying both average and penetration rates gives us the overall lightening capability achievable when multiple loads combine their efforts in conjunction with established procedures.

$$\Delta P_t = (\Delta P_{t,1} + \Delta P_{t,2} + \ldots + \Delta P_{t,n}) \sigma_t \tag{15}$$

The given expression pertains to the summation of total load resources utilized concurrently, presented as ΔP_t in the formula. The number of available load resources for consumers is represented by 'n.' By combining both energy-efficient and load resources, it creates a resultant load during time t.

$$P_t = P_{t,0} - \Delta P_t \tag{16}$$

One of the concepts relevant to this discussion is the original power load of a user, which does not take into account any demand-side response resources.

load stacking: To obtain an accurate load forecast and estimate the forecasting error, it is necessary to measure and calculate how much impact was made by any demand-side response resources on the user's overall load during a given period. These values are then added onto the original power load in order to create a more complete picture of energy usage.

2.8. Demand-side response load model

Time-of-use pricing and emergency demand response, two of the most common types of demand-side response, are now part of the energy infrastructure in the Baghdad area. In order to smooth out the load curve and prevent spikes and troughs, utilities often use time-of-use energy pricing policies that encourage consumers to reduce power use during peak hours and shift to lower-demand times. When implementing emergency demand response, however, the incentive payment price is set in advance by the power system operator. Power users may reduce their load requirements during emergencies if the stability and reliability of the power grid are threatened. A response model is being created and tested to examine load shifting by electricity consumers and the effect of fluctuating energy costs and incentive payments on demand.

2.9. Avoidable load model

The avoidable load model, which argues that consumers can reduce their power use by stressing moderation or better management, is related to the self-elasticity coefficient of the price elasticity of demand. Consumers haven't paid much attention to this form of electricity consumption because it's often fairly tiny. Once the policy's incentive is strong enough, however, customers will take steps to reduce their excessive electricity consumption. As a result, researchers and policymakers have been paying special attention to issues like electricity price grading and incentive systems, as well as the connection between basic user wants and overall demand. This is how a model is constructed.

The remuneration for motivation is denoted as I(t), wherein t denotes the specific time of the day and D(t) indicates the magnitude of power consumption by users. Additionally, P(t) characterizes the expense corresponding to a single unit of electricity. In instances where consumers enroll for urgent demand scheme, their electrical energy utilization will exhibit akin traits:

$$\Delta D(t) = D_0(t) - D(t) \tag{17}$$

The power requirement that is independent of the demand-side response is referred to as the D(t) initial energy demand. The user gets incentive compensation TI and revenue B at time t.

$$TI(\Delta D(t)) = I(t) \times \Delta D(t) \tag{18}$$

$$B(t) - \underline{B}(D(t)) - D(t) \times P(t) + TI(\Delta D(t)) \tag{19}$$

Of these, one variable stands for the revenue received by the user prior to being compensated at time t for electricity demand equaling X. This function denoting revenue can be articulated as follows:

$$B(D(t)) = B_0(t) + P_0(t) \times \Delta D(t) \times \left[1 + \frac{\Delta D(t)}{2E(t) \times D_0(t)} \right] \tag{20}$$

Where $B_0(t)$ income when user demand is at its highest is $D_0(t)$; E(t) is the time-t elastic response coefficient. According to Equation (12) and Equation (15):

$$P(t) + I(t) = P_0(t) \times \left[\frac{D(t) - D_0(t)}{E(t) \times D_0(t)} + 1 \right] \tag{21}$$

Among them, $P_0(t)$ is the original cost of a unit of electricity. The preceding formula proves that if $I(t) = 0$, then $D(t) = D_0(t)$. It demonstrates that the price of power does not vary when there is no motivation to pay.and $E(t)$ is zero.

2.10. Academic paraphrase

The relationship between the coefficient of cross-elasticity of demand and transferable load is evident, as industries continue to progress, causing a shift in maximum allowable loads. Time-of-use electricity pricing affects users more if they consume higher energy levels; hence, limiting expenses by utilizing the load transfer period is common. To reduce electrical loads, policymakers suggest options such as substituting hot water or gas boilers for electric heating boilers and shifting usage during peak power times. Policymakers primarily address concerns including basic power demands, transfer potential assessments, electricity price tiers' structure and incentivizing policies which are crucial elements that must be considered carefully when discussing cross-elasticity coefficients of energy consumers at different time periods (t) and scenarios (j).

$$E(t,j) = \frac{P_0(t)}{D_0(t)} \times \frac{\partial D(t)}{\partial P(t)} \tag{22}$$

The demand model dependent on the time-of-use pricing is as follows:

$$D(t) = D_0(t) + \sum_{t=0}^{23} E(t,j) \times (P(j) - P_0(j)) \times \frac{D_0(t)}{P_0(j)} \tag{23}$$

Taking into account the power price and the incentive compensation I(j). at this time is necessary if emergency demand measures are performed simultaneously at timej.

$$\Delta P(j) = P(j) - P_0(j) + I(j) \tag{24}$$

Upon a thorough examination of the time-of-use electricity tariff and incentive remuneration, it is possible to express the electrical energy consumption behavior exhibited by consumers at any given moment t.

$$D(t) = D_0(t) + \frac{D_0(t)}{P_0(j)} \times \sum_{t=0}^{23} E(t,j) \times \Delta P(j) \tag{25}$$

Ultimately, the avoidable load model was combined with the transferable load model in order to deduce the hourly consumption pattern of power users. This is exemplified through equation (26).

$$D(t) = \left[D_0(t) + \frac{D_0(t)}{P_0(j)} \times \sum_{t=0}^{23} E(t,j) \times \Delta P(j) \right] \times \left[1 + \frac{E(t) \times \Delta P(t)}{P_0(t)} \right] \tag{26}$$

3. Experimental Results

3.1. Experimentation Environment

This study's experiment makes use of an Intel(R) core (TM) i5-5200CUP2.20GHz processor, together with 8GB of RAM. One month's worth of data from an area's power grid's asynchronous operation is used as the training set database for the load model, and weather data from that time period is collected as the feature used to determine the day's peak demand. The test sample is divided into two parts: the characteristic set, which consists of data from the first 30 minutes of the day and the target set, which consists of data from the remaining period. Additionally, we process outliers and missing data as missing data and fill in the gaps with an average value (18).

3.2. AC-BiLSTM model analysis for short-term load prediction

The forecasting outcomes and the absolute deviation (defined as the variation between projected values and actual measurements) of short-term energy load estimation for AC-BiLSTM modeled dataset are exhibited by Figure 7.

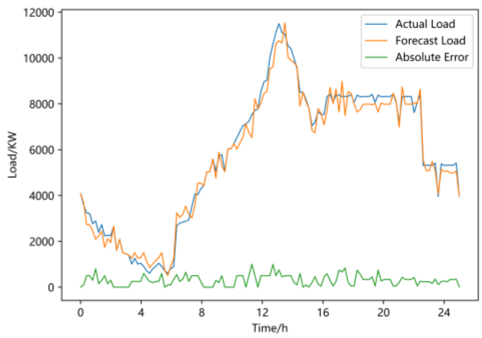

Figure 7. Modeling the short-term load with AC-BiLSTM and comparing it to the real value

Figure 7 depicts the forecast mistakes that occur after a specific amount of time, despite the fact that the load forecasting model can prevent being stuck in the local ideal, enlarge the search space, and boost the likelihood of finding the global optimal value. Possible explanations include anomalous observations and missing data. Application of the AC-LSTM with the AC-GRU is depicted in Figures 8 and 9.

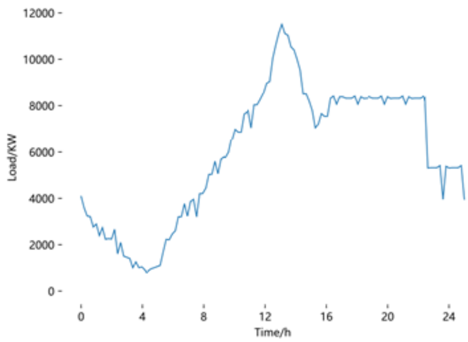

Figure 8. Modeling the short-term load with AC-LSTM and comparing it to the real value

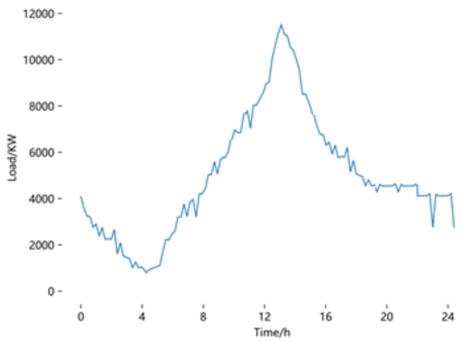

Figure 9. AC-GRU models for checking predicted and measured short-term loads

3.3. Load prediction outcomes considering demand response

In order to gain insight from the past and create better predictions right now. We improve the major power consumption infrastructure for a variety of users by considering the impact of both load class resources and energy efficiency class resources as shown in Table 1.Collect data on how people are cutting back on their electricity use, then apply that information as a superposition to the load forecast values for each moment generated by the AC-BiLSTM, AC-LSTM, and AC-GRU models, then run the numbers.

The integration of demand-side resources has undoubtedly enhanced the efficacy of node impact. The projected deviation is now more reasonable and aligns with reality in general. Moreover, to ensure precision in the prediction

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model, three prominent short-term load forecasting algorithms- Long Short-Term Memory, Bidirectional LSTM, and Support Vector Machine- are chosen for experimental comparison. Figure 7 depicts the outcomes obtained from applying these selected algorithms on daily load estimation test data while Table 2 presents an evaluation index used to assess prediction errors.

Table 1. The foundational information for load forecasting

User Type	Energy efficiency resources avg	Load resources avg
Industry	0. 0243	0.6220
Construction	0. 0325	0.6691
Transport	0. 0365	0.3358
IT	0. 1235	0.9025
Business	0. 1349	0.5236
Accommodation and meals	0. 1267	0.6326
Finance	0. 0885	0.6911
Agency	0. 1475	0.5433
Resident	0. 1565	0.3366

Table 2. Analyzing algorithmic failure rates

Algorithm	E_{MAE}/(kW·h)	ER_{MSE}/(kW·h)
AC-BiLSTM	485.82	713.66
Bi-LSTM	553.35	905.22
AC-LSTM	482.02	780.35
AC-GRU	497.72	735.65

The findings of our assessment and analysis on average annual power utilization and maximum electricity demand among different clients prior to and after the introduction of demand-side resources are presented in Tables 3 and 4. Our results provide further evidence that employing measures for reducing energy usage through responsive management at the user end can be effective. It is observed that both peak load as well as individual energy consumption exhibit a substantial decline, by over 20 percent, due to such resources. Consequently, there is strong confirmation regarding the achievement of desired outcomes from implementing demand-driven responses through lowered need for new lines or substations resulting in significant cost savings.

Table 3. Annual electricity outcomes before and after taking demand-side resources into account are compared.

User Type	Unconsider demand side resources (MW·h)	Consider demand side resources (MW·h)
Industry	9133. 262	8766. 565
Construction	547. 355	516. 266
Transport	5698. 561	5986. 365
IT	310. 256	298. 362
Business	16523. 154	13950. 845
Accommodation and meals	705. 264	703. 265
Finance	129. 656	126. 325
Agency	225. 365	300.562
Resident	1221. 689	1119. 986

Table 4. Results from calculating the maximum load without and with

User Type	Unconsider demand side resources (MW·h)	Consider demand side resources (MW·h)
Industry	4401.562	4090.326
Construction	213. 325	200. 236
Transport	1595. 564	1501. 369
IT	99. 265	88. 639
Business	3684. 856	3416. 691
Accommodation and meals	88. 336	90. 226
Finance	12. 302	9. 365
Agency	3. 396	3. 698
Resident	345. 264	309. 566

3.4. Emergency demand response and time-of-use power pricing's effect on the load curve

The dataset was built on a month's worth of historical load data collected when the regional power system switched to asynchronous operation. The model presented in this study is based on the maximization of user benefits, therefore it may be used to predict how much power a user will need at any given time. After time-of-use energy pricing and emergency demand response are put into place, the regional peak-valley price mechanism predicts that peak electricity pricing will be (1.26 RMB/KWh) and low electricity pricing will be (0.42 RMB/KWh), with an equilibrium price of (0.84 RMB/KWh). Assume that the remuneration for participating power users is (1.3 RMB/KWh). If, for example, the incentive payment is reduced to 0.4 RMB per kilowatt-hour (KWh).

It is reasonable to predict that the level of user engagement will decrease along with the amount of incentive payment received. Some users will even resort to dishonest methods in order to decrease the strain placed on the system in order to receive money rewards. In order to circumvent this problem, the power system operating agency typically specifies the lower limit of load utilization as the standard for determining the least amount of electricity that users of the power grid are required to consume under normal power consumption conditions. With the implementation of demand-side response measures during peak power consumption period in the energy market, consumers can modify their electricity usage patterns according to pricing signals. This responsiveness from the consumer end has a significant potential to enhance system reliability by decreasing frequency and magnitude of wholesale price fluctuations over an entire supply cycle. One proposed solution is connecting both retail and wholesale markets for better results.

4. Conclusion

The problem of demand-side response is investigated in this paper, with the assumptions of load forecasting and maximizing the comprehensive benefits to electricity users. The paper is grounded in the growing body of literature on the demand-side response in China and its evolution over time. We employ the time sliding window to compile the multidimensional data into a continuous feature map, which we then use to extract spatial characteristics for load forecasting. persistent association. The AC-BiLSTM model is used to reliably predict the load on the system. Superimposing the initial load on top of the response load that takes into consideration demand-side resources after a comprehensive analysis of the region's capacity for reaction. In order to maximize customer benefits, a load response model was constructed by employing two demand-side response approaches: time-of-use tariff that is based on price and an emergency demand response system that provides incentives. After these two steps have been implemented, we will analyze the correlation between electricity demand and pricing. The studies showed that by adjusting electricity use in response to market price signals during peak demand in the electrical market, customers might save money through demand-side response. Through the use of demand-side response during peak demand times, power system balance adjustment costs can be lowered and power-related societal resources can be maintained. Potential exists for enhancing the consistency of the power supply cycle by implementing demand-side response measures in both short

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and long run. Achieving this would involve mitigating price fluctuations within the wholesale market to curtail adverse effects through understanding interconnections between retail and wholesale markets among other strategies.

5. Declaration

5.1. Author Contribution

Conducted conception and methodology and employed academic methods: S.S.J.; Resource utilization, data curation, and original draft production: S.S.J.; Reviewed, drafted, and revised the work: S.S.J.; Author has read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data given in this study may be found in the publication and the data collected by the authors.

5.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

5.4. Institutional Review Board Statement

Not applicable

5.5. Informed Consent Statement

Not applicable

5.6. Declaration of Competing Interest

The authors stated that there are no conflicts of interest in the publication of this paper. Furthermore, the ethical concerns encompass other aspects such as plagiarism, informed consent, research misconduct, data fabrication, data falsification, adherence to proper authorship guidelines for publishing and submission, and redundancy avoidance.

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