



# Analysis and Accurate Prediction of User's Response Behavior in Incentive-Based Demand Response

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**Abstract** - Incentive-based demand response can fully mobilize a variety of demand-side resources to participate in the electricity market, but the uncertainty of user response behavior greatly limits the development of demand response services. This paper first constructed an implementation framework for incentive-based demand response and clarified how load-serving entity aggregates demand-side resources to participate in the power market business. Then, the characteristics of the user's response behavior were analyzed; it is found that the user's response behavior is variable, and it has a strong correlation on the timeline. Based on this, a prediction method of user response behavior based on long short-term memory (LSTM) is proposed after the analysis of the characteristics of the LSTM algorithm. The proposed prediction method was verified by simulation under the simulation environment setup by TensorFlow. The simulation results showed that, compared with the traditional linear or nonlinear regression methods,

the proposed method can significantly improve the accuracy of the prediction. At the same time, it is verified by further experiments that the proposed algorithm has good performance in various environments and has strong robustness.

## 1. INTRODUCTION

As one of the important means for resource scheduling on the demand side, the demand response can fully invoke the resources on the demand side so as to alleviate the problem of decreased flexibility of power system caused by large-scale penetration of renewable energy resource. Incentive based demand response can integrate demand side resources flexibly and extensively, and then participate in the business of the electricity market. Load Serving Entity(LSE) can deliver appropriate incentives for target users based on user's response flexibility, which is obtained by analyzing the user's historical data, so that the profit of LSE can be maximized on the

premise of completing the response goal. In its 2016 report, the International Energy Agency proposed to integrate home users and participate in the electricity market. Coincidentally, in the long-term planning of the PJM power market, it also proposed the need to further expand the scope of demand response to participate in the power market business. Demand response can significantly improve the efficiency and economy of grid operation. Demand response potential typically amounts to around 15% of peak demand. The International Energy Agency (IEA) assessed that the potential could exceed 150 gigawatts (GW) by 2050 in the European Union. Demand response programs could also be an alternative to investment in network capacity upgrades to address congestion. In the case of the United Kingdom, it has been estimated that the cost of network reinforcement could be around one-third less in a system with optimal demand response combined with 100% penetration of electric vehicles and heat pump space heating. In PJM, over 2 million end use customers across almost every segment (residential, commercial, industrial, government, education, agricultural, etc.) participate as Load Management resources.

A large number of distributed residential users have a huge demand response potential. It is able to form a large-scale demand response capacity through the aggregation of a large number of small resident users, and then participate in the demand response business of the electricity market. However, the distributed residents' electricity consumption and response behavior are diversified and distributed, which makes LSE face great uncertainty in implementing demand response services, and it is difficult for LSE to accurately estimate the actual effect of demand response, which greatly limits the ability of demand-side aggregated resources to participate in the power market business. With the development of intelligent information collection technology and the development of user information analysis technology, it is possible to analyze and predict user behavior. Based on this, the recognition and prediction of the response behavior of users under

different incentives have become the primary conditions for LSE to successfully aggregate demand side resources and participate in Electricity market.

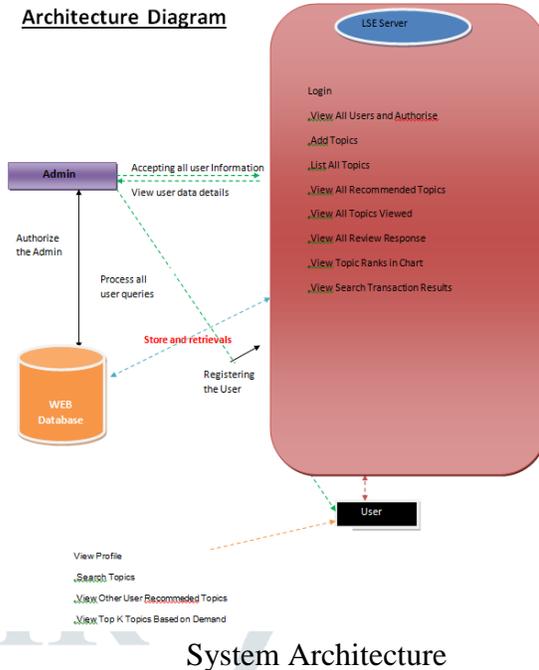
## 2. LITERATURE SURVEY

There has been a lot of research on the prediction and optimization of user behavior. Gao *et al.* propose a novel cross-domain recommendation model for the information processing and computing in CPS (Cyber-physical systems), alleviated the sparsity problems in individual domain and improved across recommendation accuracy. Qiao *et al.* studied domain-independent prediction algorithms and spatio-temporal based prediction method, searching for low cost and simple location/place prediction methods that can be implemented on mobile device. Xie *et al.* [21] proposed a combined model STL-ENN-ARIMA (SEA), based on the combination of the Elman neural network (ENN) and the autoregressive integrated moving average (ARIMA) model, improved the performance of heat demand prediction. Zeng *et al.* propose a new methodological framework to assess the potential reliability value of DR in smart grids, to deal with the the uncertainty on the demand side. Liu *et al.* optimized the incentive function of the traditional Elman neural network model, introduced the influence factors of demand response, and improved the accuracy of short-term power load forecasting. Zhang *et al.* proposed an effective model predictive control method that can minimize the operating cost of residential microgrid and is robust to the uncertainty of the prediction. Garulli *et al.* compared the prediction performance of several linear and nonlinear load forecasting models, including the black box model that does not require preprocessing of the original data, and the gray box model that is applied after a certain preprocessing of the original input signal. Li *et al.* abstracted the user's response cost into a quadratic function and uses a leastsquares method to train the user's cost function. Fei *et al.* proposed a synchronous pattern matching principle based

residential customer baseline load estimation approach without historical data requirement. Campos and Wei formed a mixed-integer linear programming model for short-term decisions of power retailers and solved the model to maximize profits, the user's response under different incentives is reported by the user beforehand. Jindal *et al.* proposed a novel data analytical demand response management scheme for residential load with an aim to reduce the peak load demand after analyzing the smart user's home load data. Yu *et al.* viewed DR as a multi-interest game process and used game theory to analyze the coordination among decision makers. The user's response cost function was abstracted to a quadratic function. Dadkhah and Vahidi provided demand-side flexibility by using an optimal real-time pricing scheme. Different levels of rationality are given by extending demand-price elasticity matrices for different types of consumers. Paterakis *et al.* predicted the load curve of residential load under the price signal based on artificial neural network and wavelet transform methods.

From the analysis of the above literatures, it can be seen that most of the behavioral analysis of users in demand response focuses on the prediction of user load, and lack of analysis and prediction of the user's response behavior under different environments and incentive signals. Therefore, this paper analyzed this issue

### 3. SYSTEM ANALYSIS:



### EXISTING SYSTEM

- ❖ Gao *et al.* [19] propose a novel cross-domain recommendation model for the information processing and computing in CPS (Cyber-physical systems), alleviated the sparsity problems in individual domain and improved across recommendation accuracy. Qiao *et al.* studied domain-independent prediction algorithms and spatiotemporal based prediction method, searching for low cost and simple location/place prediction methods that can be implemented on mobile device. Xie *et al.* proposed a combined model STL-ENN-ARIMA (SEA), based on the combination of the Elman neural network (ENN) and the autoregressive integrated moving average (ARIMA) model, improved the performance of heat demand prediction.
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- ❖ Garulli *et al.* compared the prediction performance of several linear and nonlinear load forecasting models, including the black box model that does not require preprocessing of the original data, and the gray box model that is applied after a certain preprocessing of the original input signal. Li *et al.* abstracted the user's response cost into a quadratic function and uses a least squares method to train the user's cost function. Fei *et al.* proposed a synchronous pattern matching principle based residential customer baseline load estimation approach without historical data requirement.
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### Disadvantages

- In the existing work, the entire business process of incentive-based demand response, the user's response to different incentives is affected by many factors.
- The system is less effective due to lack of user's activity recognition.

### Proposed System

- ❖ Firstly, the architecture of the incentive-based demand response is constructed and analyzed, providing a reference for the implementation of incentive-based demand response business.
- ❖ Secondly, the user's response behavior is analyzed economically. Based on the existing user's response cost abstract formula, the user's response elasticity is analyzed to provide support for the user's response behavior identification.
- ❖ Finally, the characteristics of the Long Short-Term Memory (LSTM) algorithm are analyzed, and the LSTM based user's response behavior identification method is proposed. Through simulation experiments, it is verified that the method can accurately predict the user's response behavior. At the same time, it has good performance in different environments and has strong robustness.

### Advantages

- The system is able to form a large-scale demand response capacity through the aggregation of a large number of small resident users, and then participate in the demand response business of the electricity market.
- An effective user behavior measurement.

### MODULES:

- **LSE Server**

In this module, the server has to login by using valid user name and password. After login successful he can perform some operations such as View All Users and Authorize, Add Topics,List All Topics,View All Recommended Topics View All Topics Viewed,View All Review Response,View

Topic Ranks in Chart,View Search Transaction Results

### Viewing and Authorizing Users

In this module, the Server views all users details and authorize them for login permission. User Details such as User Name, Address, Email Id and Mobile Number.

- **User**

In this module, there are n numbers of users are present. User should register before performing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user can perform some operations like View Profile,View Other User Recommended Topics ,View Top K Topics Based on Demand Search topics.

### Viewing Profile Details

In this module, the user can see their own profile details, such as their address, email, mobile number, profile Image.

## 4. OUTPUT RESULTS:



Fig 4.1: Home Page

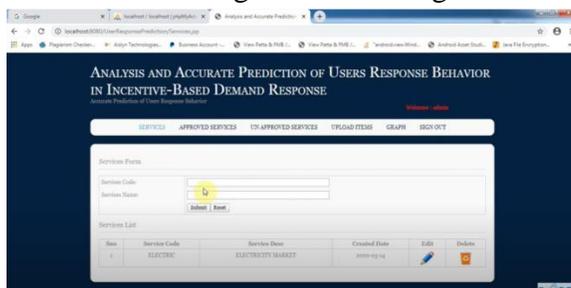


Fig 4.2: Services Form Page

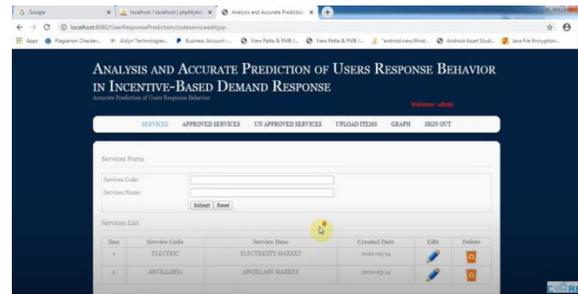


Fig 4.3: Approved Services Page

## 5. CONCLUSION

In the incentive-based demand response, the current research lacks accurate prediction of user response behavior, and it is difficult for LSE to aggregate the demand-side users into the regular business of the electricity market. In this study, the user demand response characteristics and influencing factors are deeply analyzed, and the applicability of the LSTM algorithm is analyzed theoretically. Then the user response behavior prediction method based on LSTM network is designed and tested by Tensor Flow. Through simulation experiments, it can be seen that compared with the linear regression method, the proposed algorithm in this paper can improve the prediction accuracy of the response behavior of a single user, and can accurately predict the response behavior of user group. Also, the proposed algorithm in this paper has a strong adaptability, even if the user group behavior is volatile, it can also accurately predict its behavior. The work of this paper can advance the precise process of demand response and provide support for LSE to aggregate the demand-side resources to participate in the regular business of the electricity market.

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