Investigation of Customer Response due to Demand Response

Hung-Ming Chou* Fang-Yu Lin†

Abstract

Demand response (DR) is getting more important in smart grids. To have successful DR implementation, one of the key elements is to be able to forecast the reaction of customer due to the price change. In this work, the challenges of forecasting customer response are discussed. Different ways of modeling the customer response are presented, compared and reviewed. One new statistical model is proposed. To overcome the lack of data, we propose a framework where the customer response due to energy management system (EMS) is simulated and the results are fed into the proposed statistical model. The response of EMS and the statistical model are compared to determine the forecast ability of the statistical model.

Key Words: Demand response, time series analysis

1. Introduction

Demand response, a mechanism to change load consumption, is one of the important features in smart grids. There are several benefits for both customers and utilities [1]. For customers, DR allows customers to save money for their bills and get incentive payments when they adjust their loads smartly. From the market perspective, DR can reduce the price, since it reduces the load in the peak time and avoid using peaking power plants. Also DR can decrease the peak load to normal load ratio and defer or avoid the need to build new power plants. For utilities, especially for load serving entities (LSE), DR allows them to adjust the consumption level so that they can avoid the possible financial losses due to the unexpected high whole sale price. DR provides a financial hedge for the price uncertainty.

Another benefit to have flexible load consumption is to allow more renewable energy integration to the grid. Due to the high penetration level of renewable energy resources, the uncertainty in electricity supply increases. To balance the supply and the load, traditionally generators are controlled so that the load and generation is balanced. However, this kind of generators usually is more expensive to operate due to high ramp rate and higher fuel cost. Because of the continuous ramp up and ramp down, the generator is not operating at its optimal operating point, resulting in lower efficiency and producing more green gas emission. This phenomenon may offset the benefits of using renewable energy resources. Now because of DR, the load is flexible and it can be adjusted based on the system requirement. Even though it may not be possible that DR can get rid of all variation coming from intermittent renewable resources, DR will help to reduce the amount of variation needed for the generators. This will reduce the green house gas emission and lowering overall system operation cost.

Fig.1 shows the DR potential of United States. With more advanced technologist installed, such as smart meter, home energy management system, this DR potential can be achieved.

*Texas A&M University

†Texas A&M University

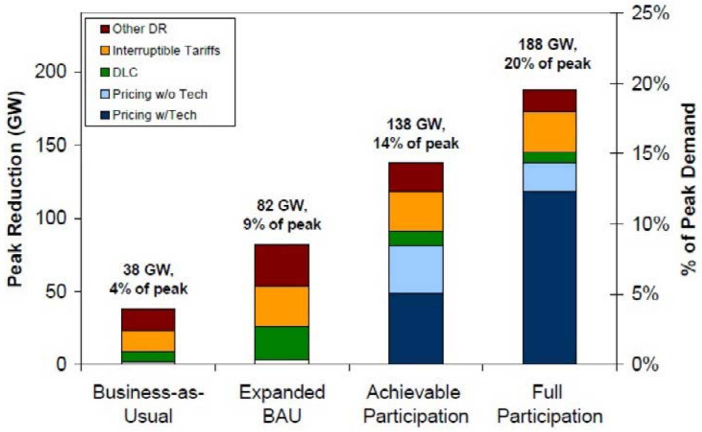


Figure 1: DR potential [1]

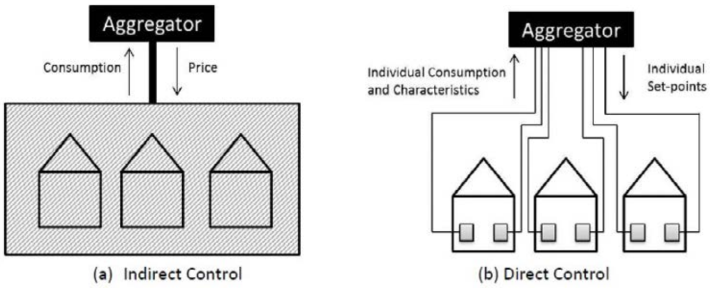


Figure 2: Direct and indirect demand response [2]

In the DR, the communication between customers and utility is important. If the communication exists, the utility can send price information to customers. With price information, customers can determine the optimal consumption and give their scheduled consumption back to the utility. Utility can do the corresponding adjustment so that the system is operated optimally.

There are many different kinds of demand response. One categorization is by how the load is controlled, shown in Fig.2. In the direct load control DR, the utility and the customer has a contract. This contract specifies how much load will be cut and at what time if the system needs to do so. Therefore, the amount of load reduction is pre-determined. In the indirect load control, the utility sends signals to customer, such as price or other kind of incentives. Based on the information, the customer makes the optimal decision and adjust their consumption accordingly. In this mechanism, the amount of load change is not deterministic.

The relationship between the price and the consumption, shown in Fig.3 is important, especially when the DR is becoming popular and the amount of DR is high in smart grids. One reason is that this relationship will help utility to figure out the suitable incentive for customers to adjust their consumption. If the incentive is not enough, customers is not willing to adjust their loads and DR cannot fulfill their purpose. Secondly, this relationship will help utility to figure out the amount of incentive required to achieve the desired consumption change. In some DR application, especially in the real-time market, it is important for utility to quickly figure out the amount of incentives so that the customers can achieve the

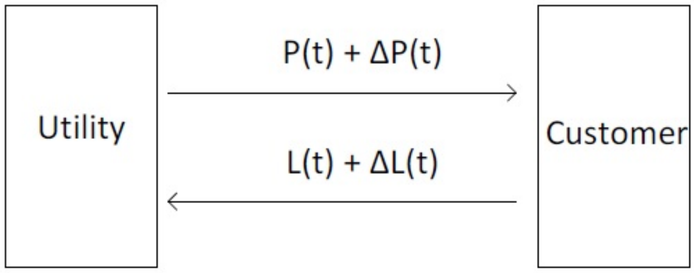


Figure 3: Interaction between the utility and customer

desired consumption change. Even though utilities can send multiple incentives to customers and continue to send if the consumption change is not achieved, as done in [3], the speed will be slow and may not suitable for real-time market operation. The third reason is that the DR will increase the uncertainty of consumer consumption. A system with DR is like a closed-loop system. The price and the consumption interact with each other and they form a closed-loop system. With the uncertainty in consumer consumption, the price will have more uncertainty and in some cases, the price will become unstable [4]. Therefore, the ability to forecast the consumption change due to DR is important, especially when the DR level is high.

In this work, we will discuss several challenges in forecasting the customer reaction due to DR. Moreover, we will review several current methods and propose a new statistical model for this purpose. A framework of simulation is proposed to get the customer consumption response, and the proposed statistical model is implemented based on the data of customer consumption response.

2. Challenges in modeling customer response to DR

There are several challenges in forecasting the consumption change due to DR, especially the price variation. Firstly, there is not much data available. Right now, most consumers have a fixed rate electricity price. Their consumption does not depend on the price information. Even though there are some pilots that implement DR, most of them implement critical peaking power (CPP) or time of use (TOU) [5], [6], which cannot be used for the real time pricing (RTP) scheme.

The second challenge is that each customer is different. They have different characteristics. Their house size is different, the habits of electricity consumption is different, their schedule is different. The appliance, include whether they have EV or other type of loads is different.

The third challenge is the privacy issue. As the smart meter data is available to the utility, it is possible to get information about the customer by data mining techniques. Some information, such as the users living style, schedule, etc can be inferred from the smart meter data [7]. Therefore, in the near future, due to the privacy issues, some of the smart meter data will not be available, or be available with certain restriction.

The fourth challenge is that the customer behavior may not be rational. Some customer may not be responsive to the price information [2]. For example, if the customer is rich, they may not care about the electricity price at all. Or in some case, if the customer need to have some appliance running, such as charging the EV at a specific time, the consumption wont change due to the price increment.

Outside the engineering field, several fields, such as economics and social study, investigate the customer behavior under different environments and situations [8], [9]. Customer behavior is too complicated to predict accurately. However, there is a silver lining. With the energy management system (EMS) installed in the house in the future, the customer response may be more rational. EMS can help customers to find the optimal consumption schedule to achieve their maximum benefits, which will make the reaction of customers easier to model and forecast.

When forecasting the customer reaction to price change, it is important to consider several factors, such as the current price, the customer utility function, customer status, the weather, social factors, etc. It is a complicated task and it is almost impossible to build a perfect model to do the forecast. Several approximations and assumption are needed to do the forecasting.

3. Methods to model customer reaction to DR

Currently, there are several ways to model the customer reaction to the price change: EMS optimization method, elasticity method and statistical method. In the following subsections, we will describe these three methods and have some assessment of their pros and cons.

3.1 EMS optimization

Energy Management System (EMS) performs the optimization so that the trade-off between the minimum electricity payment and maximum customer utility can be achieved. Much literature has proposed different kinds of formulation with different kind of objective functions and constraints. Here we will lists several literature to show different formulations.

[10] maximizes the utility of the consumer subject to a minimum daily energy-consumption level, maximum and minimum hourly load levels and ramping limits on each load. Also the price uncertainty is modeled through robust optimization techniques.

[11] minimizes the electricity consumption based on the day-ahead price. The consumption at each hour is determined. The consumption at each hour is shifted to other hour within the day or to other hour with the same period. The limitation of how much amount of consumption to be shifted in each hour is pre-specified. The amount of consumption reduction is not modeled in this work.

[12] uses mixed integer linear programming (MILP) optimization technique to minimize the energy consumption, total cost of electricity and gas, emission, peak load and any combination of these objectives, while considering end-user preferences. End-user preference include the desired room temperature and the hours of operation of each device. The maximum deviations that the customers is willing to accept for each device such as maximum temperature deviations and the latest acceptable time to complete a task are incorporated. This paper considers very detailed formulation for each devices and the corresponding constraints. The price considered is the dayahead price.

[13] uses multi-agent concept. For each house, a similar MILP is solved to determine the optimum consumption level. Q-Learning algorithm is used to solve the Markov Decision Problems with incomplete information, such as the information on other participants. This paper divides the consumption into three type: consumption that depends on the current time, consumption that depends not only the

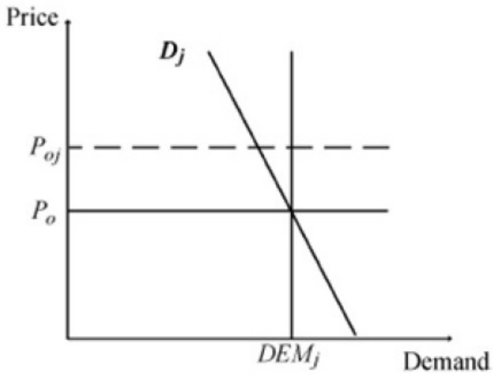


Figure 4: Demand variation due to the price variation [14]

situation and operating status in current time, but also those in neighboring time, and consumption independent of the time.

EMS optimization techniques can determine the customers response to price change quite accurately. However, there are some drawbacks. Firstly, some information about customers are required, such as customers schedule, customers priority, occupancy states, appliances rating, etc. Generally this information is not available to utility. Even if there is some methods to get this information based on smart meter data, due to the privacy protection of customers, this set of customer data may not available. Secondly, to run the optimization of each customer to get the customer response is quite time consuming. It is almost impossible to do this. Therefore, some kinds of aggregation and approximation are needed. Lastly, even if we can do the optimization of each individual customer, it is hard to define the utility functions of customer. Even for customers themselves, it is hard to define their utility function. With the customer utility function not available, the optimization cannot accurately determine the customers response to the price change.

3.2 Elasticity Model

Elasticity of consumption with price is the relationship between the consumption change and the price change, shown in Fig.4. In [14], [15], the elasticity is used to forecast shortterm customer load. Two types of elasticity is used: self and cross. Self elasticity ϵ_{ii} is used for the load variation at time i due the the price at the same time slot, while the cross elasticity ϵ_{ij} is used for the load variation at time i due to the price change at time slot j.

The elasticity is determined based on the historical data of customer consumption and price. Statistical methods are used to find the parameters.

[16] proposes the concept of conditional dynamic consumer elasticity. Elasticity is conditional because with the DR, elasticity will be changed with price, since customers reaction to price change will change if the price is different. It is dynamic because some type of loads cannot be deferred indefinitely, such as charging electric vehicle. Therefore, the elasticity also depend on the task and the schedule of customer. This number will evolve with time and need bottom up approach, meaning the model is obtained from each customer to get the aggregated elasticity. The empirical data is used to identify appropriate models. Some type of adaptive estimation of parameter should be used to consider the time varying nature of the elasticity under DR.

There are several drawbacks of using elasticity model to forecast the consumption variation. First, from the historical data, it is not easy to estimate the cross elasticity ϵ_{ij} How to decompose the consumption variation due to price at time i and price at time j is quite challenging. Since price is always changing, it is hard to have the data where only the price at time j is changed and the consumption variation at time i is available. It is a convoluted problem. Second drawback is that the elasticity model cannot consider the saturation effect. In most cases, the customers have maximum and minimum consumption level. Once the consumption is at one of these two levels, the consumption wont change even if the price is changed. Thirdly, the elasticity model assumes that the relationship between price and consumption is linear. However, according to [17], the relationship is not always linear.

3.3 Statistical Model

Statistical model is widely used, especially in the load forecast [18], [19] and price [20] forecast. However, there are only several statistical models used in the literature to model the response of customer due to price change. The main reason could be the lack of data so that it is hard to verify the result.

3.3.1 Regression Model

Regression model to model the customer response is used in [21], [22]. Given a set of data points (x_1, y_1), ..., (x_t, y_t), where y is the consumption while x are the price and other related factors, the linear regression model between y and x can be found as

$$y_t = x_t^T \theta + \epsilon_t \tag{1}$$

The set of parameters θ is estimated by

$$\hat{\theta} = (X^T X)^{-1} x_t^T y \tag{2}$$

To predict y_{t+1},

$$\hat{y}_{t+1} = x_{t+1}^T \theta \tag{3}$$

The parameter θ can be updated every time when the new data x_t and y_t are available:

$$\mathbf{R_t} = \alpha \mathbf{R_{t-1}} + \mathbf{x_t x_t^T} \tag{4}$$
$$\theta_{\mathbf{t}} = \theta_{\mathbf{t-1}} + \mathbf{R_t}^{-1} \mathbf{x_t} (\mathbf{y_t} - \mathbf{x_t}^T \theta_{\mathbf{t-1}}) \tag{5}$$

However, in this method, one big assumption is that the data point (x_1, y_1), ..., (x_t, y_t) are independent. Therefore, the consumption at the neighboring time slots do not influence with one another. However, as seen from various literature, the consumption at time t is dependent on the consumption at time t_1. The regression model cannot deal with the load shifting effect in the DR event.

To consider the relationship of the data point at different time slots, time series model can be used. One of the basic time series model is AR model. In the load forecast, the consumption at time t is yt, which can be expressed as:

$$y_t = \rho_1 y_{t-1} + \rho_2 y_{t-2} + \ldots + \rho_p y_{t-p} + \epsilon_t \tag{6}$$

The parameters ρ are estimated based on the time series data $(y_1, y_2, \ldots, y_{t-1})$.

To consider the effects of price and other factors to the consumption, ARX(p) model is used and these effects are modeled through x_t. [21]

$$\begin{aligned} y_t &= \rho_1 y_{t-1} + \rho_2 y_{t-2} + \ldots + \rho_p y_{t-p} \\ &+ \theta_1 x_{t-1} + \theta_2 x_{t-2} + \ldots + \theta_q x_{t-q} + \epsilon_t \end{aligned} \tag{7}$$

In some cases, to find time series data into ARX model, the value of p may be very large. Large p will make the cost higher and may have some numerical stability issue. (ref: time series book) Therefore, we propose to use ARMA with covariate. Original ARMA(p,q) model can be expressed as

$$\begin{aligned} y_t &= \rho_1 y_{t-1} + \rho_2 y_{t-2} + \ldots + \rho_p y_{t-p} \\ &+ \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \ldots + \theta_q \epsilon_{t-q} \end{aligned} \tag{8}$$

The covariate x_t includes the price information and other factors at time$t$ that influence the consumption. ARMA model with covariate can be expressed as:

$$\begin{aligned} y_t &= \rho_1 y_{t-1} + \rho_2 y_{t-2} + \ldots + \rho_p y_{t-p} \\ &+ \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \ldots + \theta_q \epsilon_{t-q} \\ &+ \gamma x_t \end{aligned} \tag{9}$$

where $\epsilon_t = y_t - \hat{y}_t$, the prediction error at time t.

To find the value of p and q, the autocorrelation function (ACF) and partial autocorrelation function (PACF) need to be used, respectively. Once p and q are determined, several methods are used to estimate the parameters of ρ, ϵ and γ, such as moment estimation, least square estimation and maximum likelihood.

Several extension of this model can be made, such as consideration of consumer status, the nonlinear effect of factors on consumption, which can be model in the vector x_t. Moreover, the nonlinear term can be incorporate in (9).

4. Implementation Framework and Case Studies

Due to the lack of data, especially the consumer consumption data with respect to real time price, we have to simulate the customer behavior under different values of electricity price. The framework we use to simulate the customer response is shown in Fig.5. The price signal series can be generated by statistic model or from historical price data. The customers EMS system is implemented to simulate the customer response. Based on the price and customer response, the statistical model of customer response is built, including the determination of model order as well as statistical model parameters. At the final stage, the results from the EMS and the statistical model are compared to check whether the statistical model can forecast the customer response accurately.

For the implementation of EMS, as mentioned in section III-A, there are many ways to perform EMS. We select the method described in [11]. The formulation of the optimization is

$$\min_{x_t, y_t} \sum_{t \in T_d} \bar{P}_t (x_t + y_t) \tag{10}$$

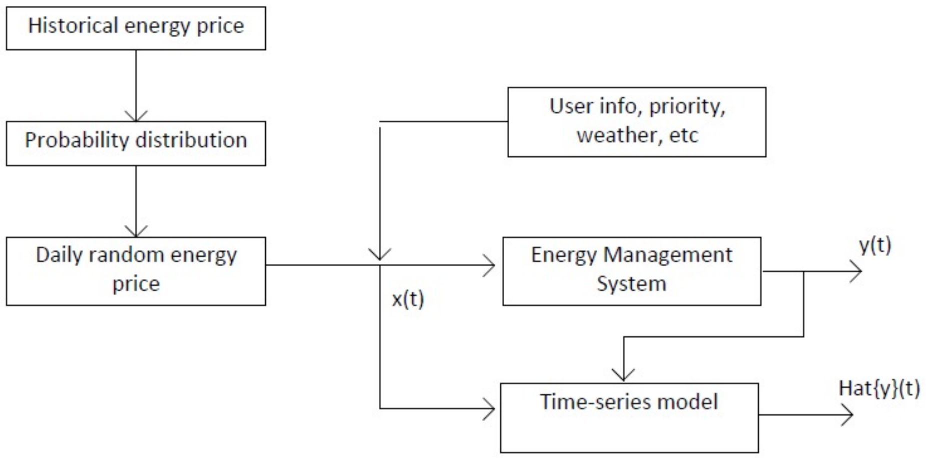


Figure 5: Implementation framework

subject to

$$\sum_{t\in T_d} x_t = 0 \tag{11}$$

$$\sum_{t\in \Omega_k} y_t = 0 \quad \text{for } k = 1{,}2{,}3 \tag{12}$$

$$x_t + y_t \leq A_t(L^{\text{peak}} - \bar{L}_t) \quad \text{for } t \in T_d \tag{13}$$

$$x_t \geq -F_t^{\text{D}} \bar{L}_t \tag{14}$$

$$y_t \geq -F_t^{\text{P}} \bar{L}_t \tag{15}$$

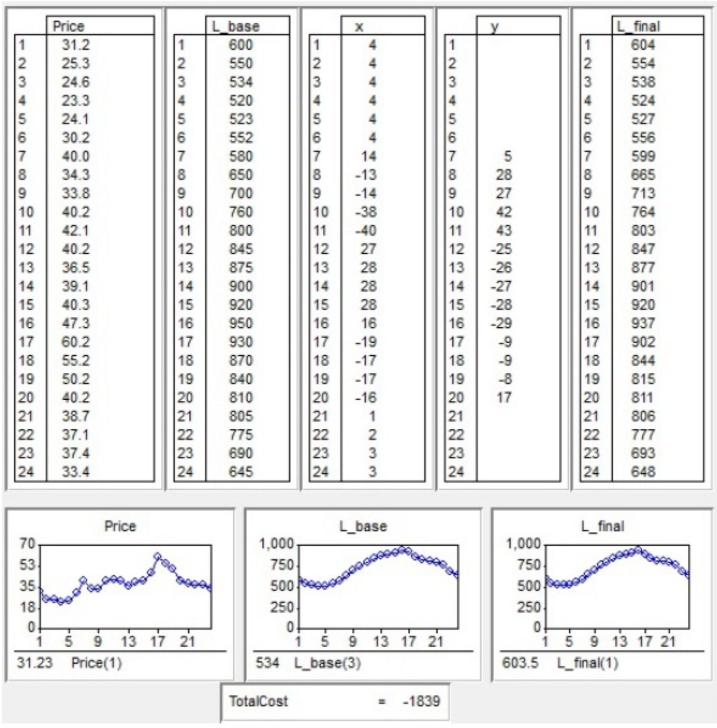
where the decision variables x_t and y_t are the amount of energy shifted to hour t from any other hour and from any other hour within the same period, respectively. $\bar{P}_t$ is the day-ahead price at hour t, A_t is the faction of $L^{\text{peak}} - \bar{L}_t$ that can be shifted at this hour from another hour, F_t^{D} is the faction of $\bar{L}_t$ that can be shifted at any other hour, while F_t^{P} is the faction of $\bar{L}_t$ that can be shifted within the same period. The parameters are given in [11].

The load profile determined by the EMS is

$$L_t = \bar{L}_t + x_t + y_t \quad \text{for } t \in T_d \tag{16}$$

This optimization formulation is implemented and solved in AIMMS, an optimization tool that is available for students and able to solve different kind of optimization problem. The interface is easy to use and a page that can take input and show output is easy to built. Moreover, several companies, including Alstom Grid, use this tool as the optimization tool inside their products. It is free for academic usage and there is no limitations for free version. The interface built in AIMMS for EMS implementation is shown in Fig. 6. The price data and the base load data can be entered in this interface and the calculated x_t, y_t and L_t are shown in this interface as well.

The price $\bar{P}_t$ is from the ERCOT whole sale real time price. The original load without the EMS $\bar{L}_t$ is given in [11]. The price of several days are entered into the EMS system with the same base load for different days. Based on the price and base load information, EMS generates the optimized output for each day corresponding to different price. As soon as the consumption of the user is determined



	Price	L_base	x	y	L_final
1	31.2	600	4		604
2	25.3	550	4		554
3	24.6	534	4		538
4	23.3	520	4		524
5	24.1	523	4		527
6	30.2	552	4		556
7	40.0	580	14	5	599
8	34.3	650	-13	28	665
9	33.8	700	-14	27	713
10	40.2	760	-38	42	764
11	42.1	800	-40	43	803
12	40.2	845	27	-25	847
13	36.5	875	28	-26	877
14	39.1	900	28	-27	901
15	40.3	920	28	-28	920
16	47.3	950	16	-29	937
17	60.2	930	-19	-9	902
18	55.2	870	-17	-9	844
19	50.2	840	-17	-8	815
20	40.2	810	-16	17	811
21	38.7	805	1		806
22	37.1	775	2		777
23	37.4	690	3		693
24	33.4	645	3		648

Figure 6: AIMMS user interface

corresponding to different price, these pairs of data are fed into the statistic model implemented in R. We build the user model based on 4-day data, including price information and consumption. Then we input the 5th day price information into AIMMS EMS as well as the statistical model. We can compare the calculated consumption output from EMS as well as from statistical model so that the forecast ability of the statistical model can be determined.

Fig.7 and Fig.8 show the ACF and PACF. Based on the information, p value is selected to be 2 based on PACF, while q value is selected to be 4 based on ACF. The resulting statistic model is

$$\begin{aligned} y_t = {} & 1.9235y_{t-1} - 0.9926y_{t-2} - 1.0673\epsilon_{t-1} \\ & + 0.1392\epsilon_{t-2} - 0.2827\epsilon_{t-3} + 0.2133\epsilon_{t-4} + 0.0003p_t \end{aligned} \tag{17}$$

The estimation error of the model based on the 4-day data is: AIC=-401.25, AICc=-399.16 and BIC=-378.17, which shows the estimation error is quite small.

Fig.9 shows the consumption from the EMS (black color) and from the statistical model (red color). The statistical model is built based on the information of hour 0 to hour 96 (4 days). The statistical model forecast the consumption of hour 97 to hour 120 (5th day). As seen from the figure, the forecast value from the statistical model is quite close to the value from the EMS model.

4.1 Discussion

As seen from (17), the contribution to the consumption y_t due to the price p_t is quite small, compared to the contribution of previous consumption y_{t-1} and y_{t-2} . Does it mean that the price has little impact on the consumption? On the surface, it is the case. However, one of the possible reason is that since the previous consumption

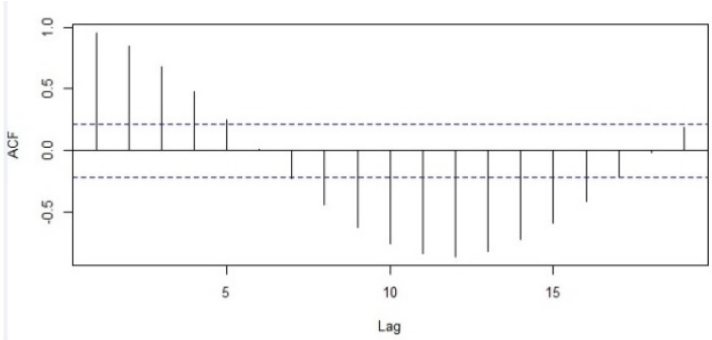


Figure 7: ACF

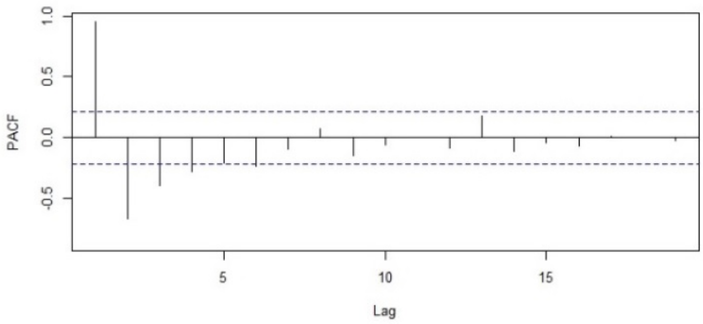


Figure 8: PACF

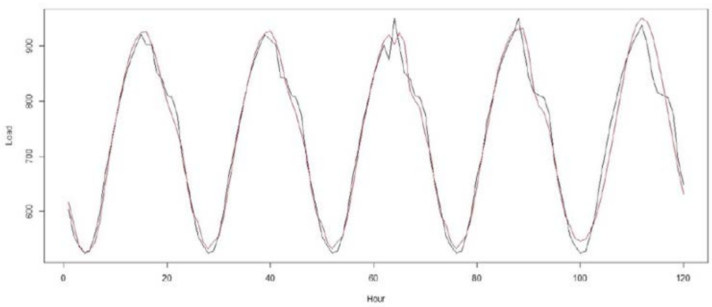


Figure 9: Comparison for the results from EMS and statistical model

is also influenced by price, in some sense, they already contain some information and some impact of the price. Another reason is the price fluctuation is not severe in our data. If the price fluctuation is high and the resulting consumption change is large, then the contribution of price may be larger. In the EMS optimization, the load consumption can only be shifted to other time slots with certain ratio. If the ratio can be increased or the consumption can be increased/decreased, then the influence of price will be higher.

5. Conclusion and Future Works

In this work, the challenges of forecasting customer response are discussed and different ways to model the customer response are presented, compared and reviewed. We also propose a framework where the customers response due to energy management system (EMS) is simulated and the results are fed into the statistic model. The responses of EMS and the statistical model are compared to determine the forecast ability of the statistical model.

It is complicated to forecast the customer response, since it is related not only the engineering aspects, but also customer behavior science. As for now, due to the fact that not so many real-time price based DR, the data is not much. But in the near future, with the higher adoption of smart meter and the implementation of real-time pricing demand response, the data will be more abundant.

In the future work, other factors will be included, such as temperature and customers status and preference. More several price fluctuation will be considered. Also different kinds of EMS optimization formulation will be implemented so that we can check whether the statistical model can forecast the consumption accurately for different EMS algorithms. Lastly, we will try to figure out the relationship between, instead of price and consumption, price change and consumption change. The method will be similar, but some implementations and case studies need to be done. This relationship can be used in the coupon-based DR [3].

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