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Article

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Customer baseline load models for residential sector in a smart-grid environment

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ABSTRACT

Demand response (DR) can expand the customer participation in the electricity market and lead by changing its pattern from a simple function to an interactive relation. There are various methods to evaluate the successful implementation of DR program, the most important of which is determination of customer baseline load (CBL). In fact, CBL is the expected pattern of customer consumption in the absence of DR programs. Few works have been done in the field of calculation of CBL in residential sector, while most of them have paid little attention to the impact of changes in weather conditions on these calculations.

In this paper, a new method is presented for the calculation of CBL for customers in residential sector in the context of a smart grid, considering the impact of weather changes. The results clearly show the high impact of changes in weather conditions on the calculation of CBL, and also show the extent of effect of buildings' improved insulation on this parameter. It is also indicated that implementing DR programs can increase the willingness of customers in residential sector to improve the insulations of their buildings.

1. Introduction

Until recent years, the activities of wholesale electricity markets were limited to electricity power generation companies, who were competing to gain a higher share of the market and increase their profits. The demand side had little activity due to lack of adaptability to this new environment. This inactivity in demand side led to the greed of supply side which resulted in an increase in prices. This price increase alerted the demand side and caused it to look for strategies to come out of this passivity, which in turn led to the emergence of a broad discussion in electricity markets called the Demand Side Management (DSM).

Demand response program is one of the DSM techniques. Demand response is the process of managing consumers' consumption in response to the supply conditions with the aim of reducing electricity costs and improving system reliability (Yin et al., 2010).

Environmental issues such as increased emission of pollutants along with the rapid growth of energy demand and rising fuel costs have recently diverted more attention to renewable energy sources. But electricity generation through wind or solar energy sources often comes with some degrees of uncertainty. DR programs can help tackling these uncertainties (Brahman et al., 2015).

Demand response is a key component in smart grids (Li and Ho Hong, 2014). Smart grid enables bidirectional flows of energy and uses two-way communication between consumers and suppliers (Pereira et al., 2015).

There are various methods to check the successful implementation of DR programs and customer baseline load (CBL) is the most important method in this regard. In fact, CBL is the pattern of customers' expected consumption in the absence of DR programs. Therefore, CBL must be determined first, and then the amount of consumption is determined after implementing DR programs. Comparing these two values will determine the success rate of DR programs. Determination of the amount of reduced demand compared with CBL is one of the most important issues in DR programs.

So it can be said that CBL is an important measuring criterion for evaluating the performance of load management programs (Gonzalez Cabrera and Gutierrez Alcaraz, 2013). As a result, accurate calculation of CBL is an important step in the

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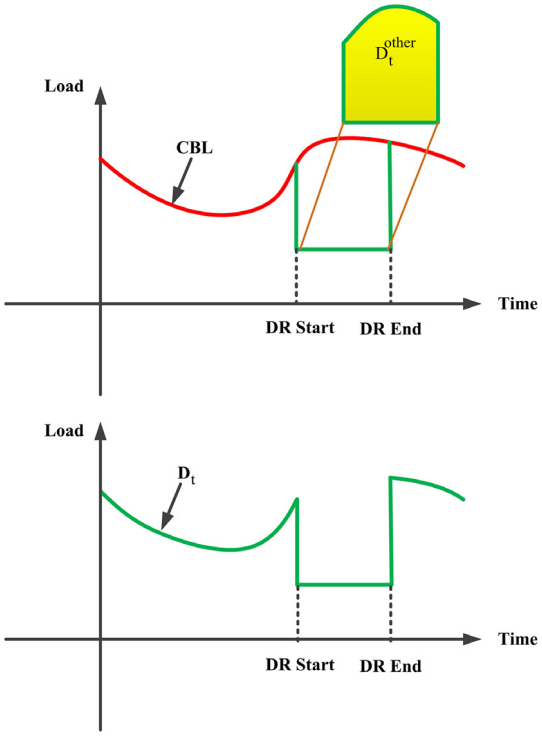

Fig. 1. Load reduction in CBL after the implementation of DR program.

implementation of DR programs. For example, if CBL is obtained lower than its actual value, there will be no incentive for consumers to participate in DR programs.

Overall, there are two different methods to calculate CBL:

1. Day Matching Method.
2. Regression Analysis.

The first one, which is a statistical method, is based on using short historical periods for prediction (Park et al., 2014).

Authors of Ref. Won et al. (2009) have used statistical methods to calculate the value of CBL in South Korea. In Coughlin et al. (2009) a statistical analysis on the performance of different models is performed for the calculation of CBL of buildings that participate in DR programs.

New England ISO uses the data related to five similar days prior to the current date to calculate CBL, while California ISO (CAISO) uses the data related to three similar days prior to the current date for this purpose. In South Korea, the data related to four most energy intensive days among last five days is used to calculate CBL (Coughlin et al., 2008).

Ref. Park et al. (2014) has presented a framework for the estimation of CBL in order to be used for DR programs in a smart grid. The method presented in this reference is based on unsupervised learning technique in data mining.

Ref. Avci et al. (2013) has also provided a method for calculating CBL. In that method, CBL characteristics are used to find better matches in previous time periods in terms of power consumption. In Coughlin et al. (2008), regression models have been used to determine CBL. That model has used the relation between electrical loads and temperature. Ref. Gonzalez Cabrera and Gutierrez Alcaraz (2013) has presented a CBL model based on decomposition method.

The procedure employed in the present paper is a new dynamic method based on a combination of statistical and regression methods in the context of a smart grid. In this method, regression model is based on the technique being used for energy audits of the buildings.

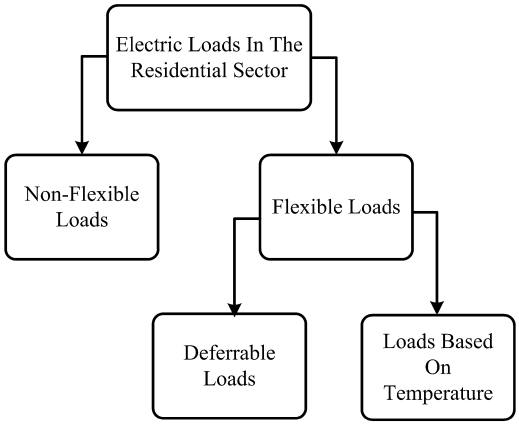

Fig. 2. Electrical loads of residential sector.

The remaining of this paper is organized as follows: problem statement is described in Section 2. Section 3 presents the method of calculating customer baseline load (CBL). In Section 4, the impact of demand response programs on customer incentives to improve quality of the building is investigated. Section 5 provides numerical results and Section 6 outlines conclusions.

2. Problem statement

Retail companies are relatively new elements in the power industry which in fact act as intermediary agent between wholesale markets and consumers. Competition between retail companies results in providing higher flexibility for consumers in choosing their retail company to supply their electrical energy. Therefore, retail companies are constantly looking for increase in their customers' satisfaction. In general, consumers can be divided into two main groups based on their behavior toward electric energy costs. The first group is quite sensitive to the price of electric power, while the other group is less sensitive.

Consumers of the first group impose a higher risk to the retail companies because they are more likely to switch retailers in case of being dissatisfied by the high price of electrical energy. Therefore, retail companies apply various strategies to increase customers' satisfaction. Implementation of DR programs is one of these strategies. As mentioned earlier, for the market to determine the reduction of customer load caused by implementation of DR programs, customer baseline load (CBL) must be constantly calculated and compared with customers' consumption. Overall, consumers' electrical energy consumption, affected by DR programs is as follows:

$$\begin{aligned} &D_t = CBL_t + D_t^{other} \\ &D_t = \text{Consumption at time } t \quad [MW] \\ &D_t^{other} = \text{Increase or decrease relative to} \\ &\qquad\qquad \text{CBL Consumption at time } t \quad [MW]. \end{aligned} \tag{1}$$

The negative values of D^{other} indicate the success of DR programs. This reduction is the basis of monetary benefits. Fig. 1 shows the manner of load reduction in CBL after the implementation of DR programs.

3. Method of calculating customer baseline load

The first step to calculate CBL is to identify and collect appropriate relevant data. The method presented in this paper focuses more on current loads, unlike conventional methods that pay less attention to these loads. As Fig. 2 shows, Electrical loads

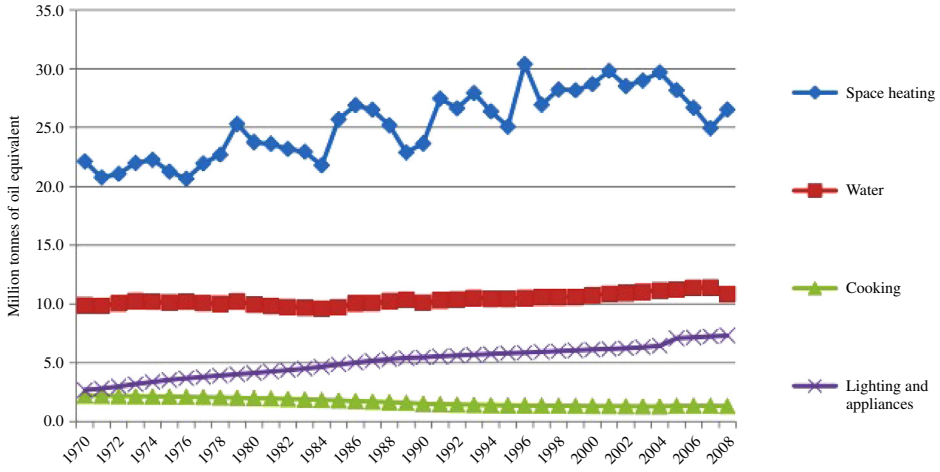

Fig. 3. Energy consumption throughout different years in the UK (Haney et al., 2011).

can be divided into two categories: non-flexible loads (NFL) and flexible loads (FL).

Loads such as lighting, electronic systems, and cooking appliances are non-flexible loads which are largely unchanged in terms of amount and time of consumption. Flexible loads are those, the size and time of which can be controlled to a large extent. These loads can be divided into two categories based on their characteristics: Deferrable loads (DL), and Loads based on temperature (BT). Loads caused by appliances such as washing machines and dishwashers are deferrable loads, and loads caused by HVAC (heating, ventilating, and air conditioning) are based on temperature. Air conditioners compose a large share of total electrical energy consumption in buildings (Pérez-Lombard et al., 2008).

Temperature-based flexible loads have large fluctuations because of their intrinsic characteristics. Fig. 3 shows the electrical power consumption in the residential sector for different years (Haney et al., 2011).

As can be seen in Fig. 3, these loads (unlike the other loads) have large fluctuations and the most important reason behind this issue is the climatic changes throughout different years. But the other loads have a constant rate and time of consumption and the steady increase in the loads of lighting and electronic devices is mainly related to increased use of devices such as mobile phones, computers, etc. in the last two decades. Therefore, determining the pattern of these loads is relatively simple compared with deferrable flexible loads. As a result, these loads pose no problem in this issue.

Also Ref. Haney et al. (2011) has presented the large extent of this share compared with other loads in the residential sector of different countries.

Therefore, given the magnitude and fluctuating nature of these loads, they create many challenges in the process of determining CBL.

According to these discussions, the following equations can be used to calculate CBL per hour:

$$D_t = D_t^{FL} + D_t^{NFL} = D_t^{BT} + D_t^{DL} + D_t^{NFL}$$
$$FL—Flexible\ Loads \qquad NFL—Non\ Flexible\ Loads \qquad (2)$$
$$DL—Deferrable\ loads \qquad BT—Based\ On\ Temperature.$$

And accordingly:

$$D_t^{SR} = D_t^{DL} + D_t^{NFL} = \text{Steady Rhythm (SR)}. \qquad (3)$$

Therefore, D^{SR} has a fixed rate which can be easily obtained through examining historical data. For temperature-based loads, however, the conditions are different, since variations in temperature have significant impact on their values, therefore the temperature-based loads impose the greatest challenge in this field.

3.1. Calculation of D^{BT}

This article has assumed a smart grid where information is exchanged freely between retailer companies and consumers, or in the absence of a smart grid, several different load type buildings are considered in the study network, which are equipped with instruments for recording data about electrical power consumption. Fig. 4 shows an overview of the communications between retailer companies and customers in the context of a smart grid.

In this system, the retailer company acquires the size of electric power consumption (D^{BT}) in HVAC system from smart thermostats installed in the houses with regard to the changes in temperature. These data then will be converted to the form of (ΔT, D^{BT}) and will be plotted in the form of power consumption scatter diagram (Fig. 5). Horizontal axis of this diagram represents the differences between the outside temperature and the desired temperature for indoor environments and its vertical axis shows customers' electric power consumption related to HVAC systems (D^{BT}). In this paper, customers' electric power consumption for HVAC systems (D^{BT}) which is influenced by the temperature difference between indoors and outdoors (ΔT) is called dependent variable (response variable). ΔT variable which affects the response variable is called explanatory variable (independent variable).

Shape of the scatter diagram can indicate a relationship or lack of relationship between two variables. When a variable increases by the increase of other variable there can be a positive correlation between those two variables, and when a variable decreases by the increase of other variable there can be a negative correlation between them. Shape of the scatter diagram cannot definitively show the relationship or lack of relationship between two variables. In other words, if a scatter diagram indicates a correlation between two variables, there may or may not actually be a correlation between those two variables, and both may be increased or decreased by a third factor. Therefore, it is important to note that correlation does not necessarily mean causation.

Fig. 5 indicates that D^{BT} increases with the increase of ΔT variable. With the help of regression, we will seek to obtain a pattern or mathematical relation between these variables, so that we can determine the quantity of an unknown variable (D^{BT}) with the help of the known variable (ΔT). To start, we must estimate

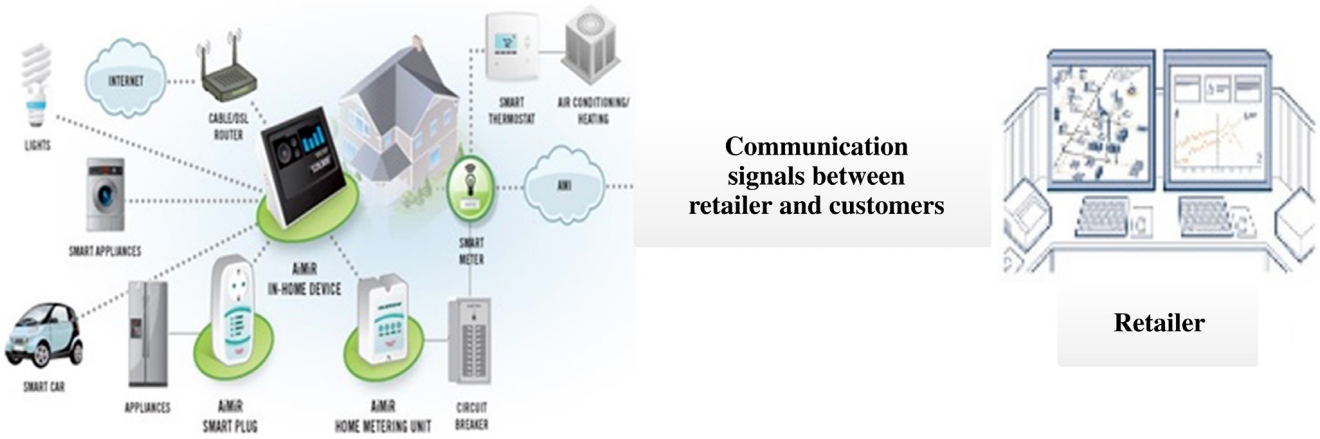

Fig. 4. Communications between retailer companies and customers.

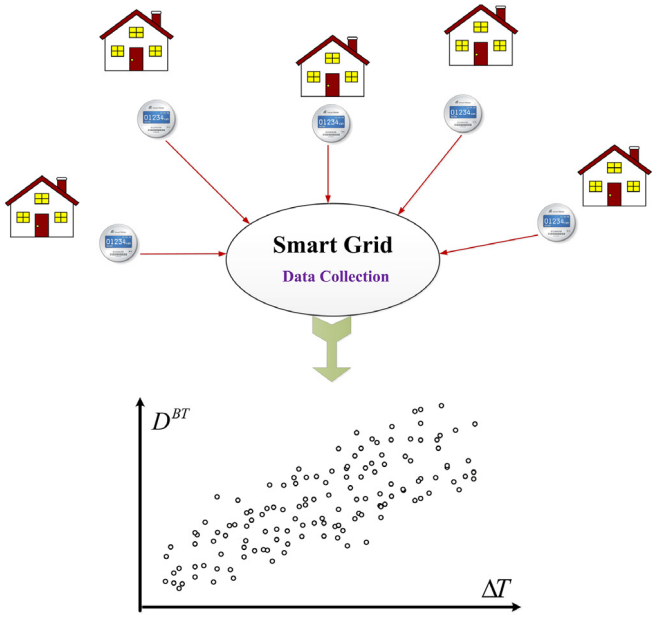

Fig. 5. Scatter diagram of recorded power consumptions related to air conditioners (D^{BT}) versus the temperature difference (ΔT).

a linear relationship between these two variables, and scatter diagram can give us an initial idea in this regard. The estimated equation can be written as follows:

$$D_t^{BT} = \beta_1 \Delta T_t + \beta_0. \tag{4}$$

In this equation, β_0 and β_1 are the intercept and slope respectively. In regression applications these variable are called regression coefficients. The most common way for estimating these values is the least-squares regression method. We use this method to estimate regression coefficients. As shown in Fig. 6, this method gives us a line in which the sum of the squares of vertical distances from the points to the regression line is minimized.

In this method, parameters are obtained by minimizing the following function:

$$SSE = \sum_{i=1}^{N} (D_i^{BT} - \hat{D_i}^{BT})$$
$$SSE = \text{Sum of } \textit{Squared Errors} \tag{5}$$
$$N = \textit{number of observerd observed data } (D_i^{BT}, \Delta T).$$

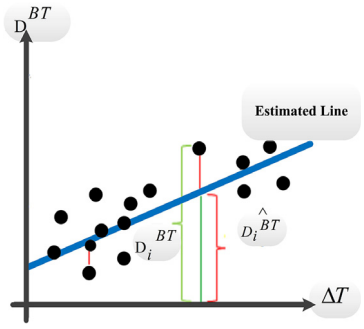

Fig. 6. The least squares method for calculation of regression line.

It is obvious that coefficients should be estimated in a way that would result in minimum SSE for all points of (ΔT, D^{BT}). Calculating the derivative of that equation will result in following formula:

$$\beta_1 = \frac{SS_{xy}}{SS_{xx}} \quad \text{and} \quad \beta_0 = \overline{D_i^{BT}} - \beta_1 \overline{\Delta T_i}$$

where

$$SS_{\Delta T \Delta T} = \sum (\Delta T_i - \overline{\Delta T_i})^2 = \sum \Delta T_i^2 - \frac{1}{N} \left(\sum \Delta T_i \right)^2$$
$$SS_{xy} = \sum (\Delta T_i - \overline{\Delta T_i})(D_i^{BT} - \overline{D_i^{BT}}) \tag{6}$$
$$= \sum \Delta T_i D_i^{BT} - \frac{1}{N} \left(\sum \Delta T_i \right) \left(\sum D_i^{BT} \right).$$

Regression can also be calculated with the help of softwares such as SPSS.

As a result, these equations can help us obtain baseline load and are also useful in predicting the future load and purchasing electrical energy.

3.2. Proposed method for calculating CBL

As mentioned earlier, to determine the reduction of customer load caused by implementation of DR programs, customer baseline load (CBL) must be constantly calculated and compared with customers' consumption. In many markets, the calculation of customer base load (CBL) is based on the average consumption of customers in the last 2, 4, 5, 8, or 10 similar days (Faria et al., 2013; Yamaguchi et al., 2009). In this study, we use the average consumption of last 5 similar days. The method presented in this paper is based on modification of values obtained from conventional methods with regard to weather conditions.

This method has six steps. The first three steps are common in most conventional methods (Faria et al., 2013) and the only difference of this method is the number of considered days. But the last three steps are the innovative approach of the presented method. This approach is the modification of CBL with regard to weather conditions which play an important role because of the power consumption of air conditioning equipment.

According to the above discussion, the algorithm of method presented in this paper for the working days are as follows:

Step one: the data of last 10 days will be collected for the calculation of customers baseline load.

Step two: 5 days will be selected from the 10 days mentioned above. These 5 days will be selected by eliminating 5 days including holidays and days with lower consumption.

Step three: For each hour of the day, power consumption of 5 selected days will be averaged. This average value will represent the customers' baseline load in working days.

$$D_t^{Ave} = \frac{D_t^1 + D_t^2 + D_t^3 + D_t^4 + D_t^5}{5}. \tag{7}$$

Step four: For each hour of the day, temperature of 5 selected days will be averaged.

$$T_t^{Ave} = \frac{T_t^1 + T_t^2 + T_t^3 + T_t^4 + T_t^5}{5}. \tag{8}$$

Step five (modification): in this step, power consumption values will be modified with respect to temperature values. This modification will be performed according to Eq. (4). It can be said that, for each degree of temperature change, the size of air conditioning loads will change by β_1.

Step six (calculation of CBL): According to the previous five steps, CBL can be obtained as follows:

$$\begin{aligned} &CBL_t = D_t^{Ave} + (T_t - T_t^{Ave})\beta_1 \\ &CBL_t = \textit{Customer Baseline Load for } t \\ &T_t = \textit{Air temperature for } t. \end{aligned} \tag{9}$$

The process of calculating CBL for holidays is similar to that for working days, except that only last four holidays will be considered and the one with lower consumption will be eliminated.

4. Quality of the building thermal insulation and demand response programs

With help of the obtained model (Eq. (9)), It is shown that the size of electrical power consumption related to changes in weather conditions depends on the size of $\beta_1 * \Delta T$, and the increase or decrease in these two parameters has a significant impact on the increase or decrease of electric power consumption. In the case of ΔT, this factor is dependent on weather conditions.

On the other hand, the size of heat loss Q is proportional to the temperature difference between indoors and outdoors. This loss mainly depends on the thermal insulation quality of buildings, and can be calculated using the following equation for walls and windows (Rautiainen et al., 2009):

$$Q = UA * \Delta T \tag{10}$$

where U is the heat transfer coefficient and A is the area of the wall. So power loss is proportional to the multiplication of UA and temperature difference. This equation for the ground floor is equal to multiplying coefficient of proportionality F by floor area P. For natural ventilation and air conditioning, multiplication of mass flow rate and specific heat of the air gives the power loss. The amount of power required for heating of flow with mass flow rate $\dot{m}$ and with specific heat capacity of C_P is equal to $\dot{m}\ C_p \Delta T$. So the total heat loss is:

$$\begin{aligned} Q &= UA * \Delta T + \mathrm{FP} * \Delta T + \dot{m}\ C_P * \Delta T \\ &= (UA + \mathrm{FP} + \dot{m}\ C_P) * \Delta T. \end{aligned} \tag{11}$$

Here, a factor called Building Load Coefficient (BLC) is defined as:

$$\begin{aligned} &BLC = \sum UA + \sum \mathrm{FP} + \dot{m}\ C_P \\ &BLC = \textit{Building Load Coefficient}. \end{aligned} \tag{12}$$

In fact, the building load coefficient is the amount of heat load for each degree of temperature difference between indoor and outdoor. Then we can write:

$$Q = BLC * \Delta T. \tag{13}$$

Comparing Eqs. (4) and (13) shows that β_1 is equivalent to BLC, except that β_1 is related to all buildings in the studied network, but BLC is for a specific building. BLC value is unique for each building and depends on the quality of thermal insulation and other specifications. β_1 value can be obtained by the following equation.

$$\begin{aligned} &\beta_1 = \sum_{i=1}^{N} BLC_i \\ &N = \text{the number of residential customers} \\ &BLC_i = BLC \textit{ for } i\text{th residential customers}. \end{aligned} \tag{14}$$

According to the above equation, it can be concluded that β_1 somehow represents an overall assessment on the quality of insulations in all costumers' building in that certain network.

So the impact of building insulation quality on the electric power consumed by air conditioning systems is formulated. Higher quality of insulation in buildings reduces BLC value and consequently reduces β_1. Therefore, implementing demand response programs and its benefits for consumers, will encourage them to take actions such as using double glazed windows to improve the insulation quality of their buildings.

5. Numerical results

Nord Pool is the northern Europe electricity market shared by Norway, Denmark, Sweden and Finland. This market is the first multinational electrical energy trade market in the world. It includes different regions, and NO1 is one of its most important regions which is tasked with supplying electric power to the Norwegian capital Oslo.

In this study, it is to perform load management programs for the city of Oslo from the start of August 2014. So as mentioned in the previous sections, Customer Baseline Load (CBL) must be calculated for each hour to determine the success rate of this program. Therefore, According to the first step of the proposed method, the data related to power consumption and weather conditions in last ten days should be collected to calculate CBL.

The data related to NO1 region required for this part of paper are acquired from Nord Pool Spot (2014) and Weather service (2014). These data, which are related to the time interval from July 22 to July 31, 2014 (summer) for the hour between 17 and 18 o'clock, are shown in Table 1.

According to the second step, 5 days of these 10 days must be eliminated. These 5 days should be July 26–27 for being holidays and July 29–31 for their lower consumption compared to the other days. Data related to the remaining five days are shown in Table 2.

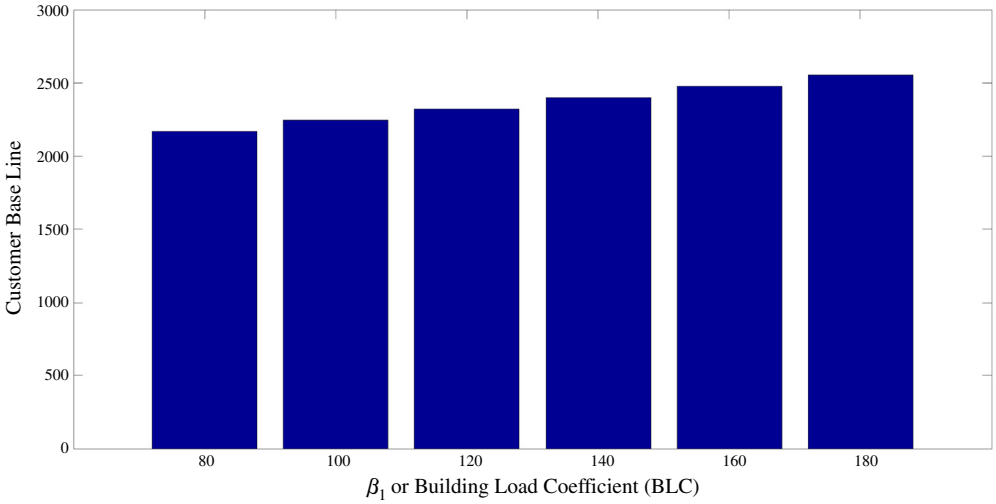

Fig. 7. Sensitivity analysis based on the first scenario.

Table 1
Data collected from NO1 region.

Date		Hour	Consumption (MWh)	Temp (°C)
22-Jul	Tue	17–18	1758.3	30
23-Jul	Wed	17–18	1932.9	30
24-Jul	Thu	17–18	1848.5	30
25-Jul	Fri	17–18	1895.3	30
26-Jul	Sat	17–18	1826.4	29
27-Jul	Sun	17–18	1957.4	18
28-Jul	Mon	17–18	1907.4	26
29-Jul	Tue	17–18	1747.6	26
30-Jul	Wed	17–18	1732.7	24
31-Jul	Thu	17–18	1696.2	21

Table 2
Data gathered from the second step.

Date		Consumption (MWh)	Temp (°C)
22-Jul	Tue	1758.3	30
23-Jul	Wed	1932.9	30
24-Jul	Thu	18.48.5	30
25-Jul	Fri	1895.3	30
28-Jul	Mon	1907.4	26
	Average	$D_t^{Ave} = 1868.48$	$T_t^{Ave} = 29.2$ °C

According to the third step, D_t^{Ave} must be calculated:

$$D_t^{Ave} = \frac{D_t^1 + D_t^2 + D_t^3 + D_t^4 + D_t^5}{5} = \frac{1758.3 + 1932.9 + 1848.5 + 1895.3 + 1907.4}{5} = 1868.48. \quad (15)$$

Now as the fourth step, the average temperature for the selected days must be obtained:

$$T_t^{Ave} = \frac{T_t^1 + T_t^2 + T_t^3 + T_t^4 + T_t^5}{5} = \frac{30 + 30 + 30 + 30 + 26}{5} = 29.2\ ^\circ\text{C}. \quad (16)$$

In the fifth step, value of third step must be modified with respect to the air temperature. Finally as the last step, the average power consumption is obtained as follows:

$$CBL_t = D_t^{Ave} + (T_t - T_t^{Ave})\beta_1 = 1868.48 + (T_t - 29.2)\beta_1. \quad (17)$$

Customer Baseline Load Models for residential sector in a smart-grid is a new subject of research and to the best of the authors' knowledge; few papers have been presented in this area. The literature review shows that in the last few years, growing number of researchers have shown interest in this topic, but unfortunately, there is still no other work whose results can be compared with those obtained here. On the other hand, validating the model with experimental data requires us to implement a model-sized smart grid that would possess the characteristics and requirements stated in the paper, something that is currently impossible due to novelty subject of smart grid and lack of proper infrastructure to implement this model at this time. This paper aims to provide an infrastructure study for smart grids, which considering their rapid growth (Lyons Hardcastle, 2012), will be certainly achievable in the next few years.

Validity of the proposed model was assessed by a sensitivity analysis (SA). Sensitivity analysis is the study of how the variation (uncertainty) in the output of a statistical model can be attributed to different variations in the inputs of the model (Saltelli et al., 2008). In the other words, it is a method for systematically changing variables in a model to correctly predict the resulting impact on the outputs.

To validate the presented model via sensitivity analysis, two following scenarios are assumed. In the first scenario of sensitivity analysis, we check the how the variation in the output CBL with respect to variations of input $\beta 1$ at the constant temperature of $T_t = 35$ °C. It is clear that the value of β_1 increases with the decrease of insulation quality. On the other hand, a decrease in insulation quality increases the energy loss and consequently the increased power consumption, which in turn increases the customer baseline load (CBL). So it is reasonable to expect the proposed model in this paper to correctly predict this behavior. Validity of this argument is proved by sensitivity analysis conducted on the model; results of this analysis is shown in Fig. 7.

In the second scenario of sensitivity analysis, we check the how the variation in the output CBL with respect to variations of temperature for a fixed $\beta 1 = 120$. As temperature increases, the cooling system is expected to require more power, which in turn leads to an increased baseline load. The proposed model is expected to adequately predict this behavior and Fig. 8, which shows the results of sensitivity analysis, demonstrates the validity of this argument.

According to the obtained results, the effect of β_1 on changes in customers baseline load is successfully determined. Fig. 9 shows variation of CBL with respect to the variations in the temperature,

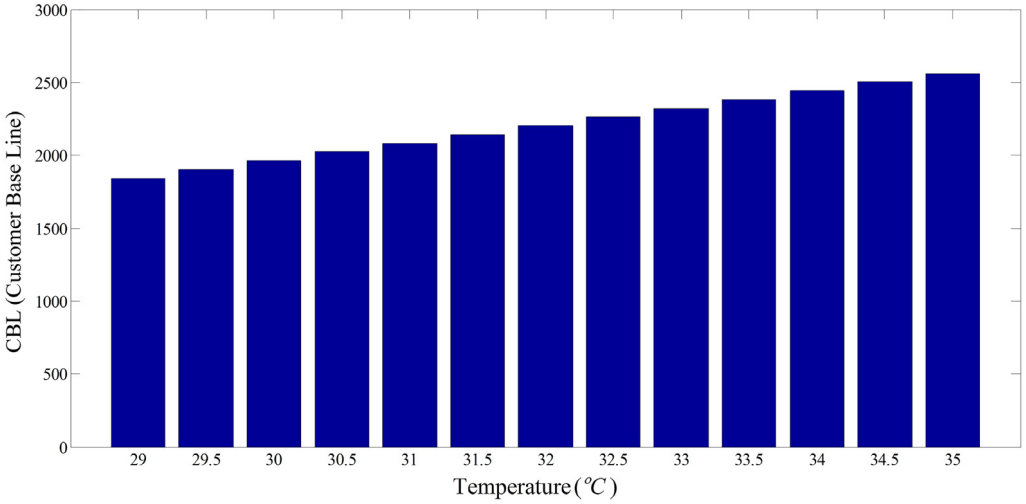

Fig. 8. Sensitivity analysis based on the second scenario.

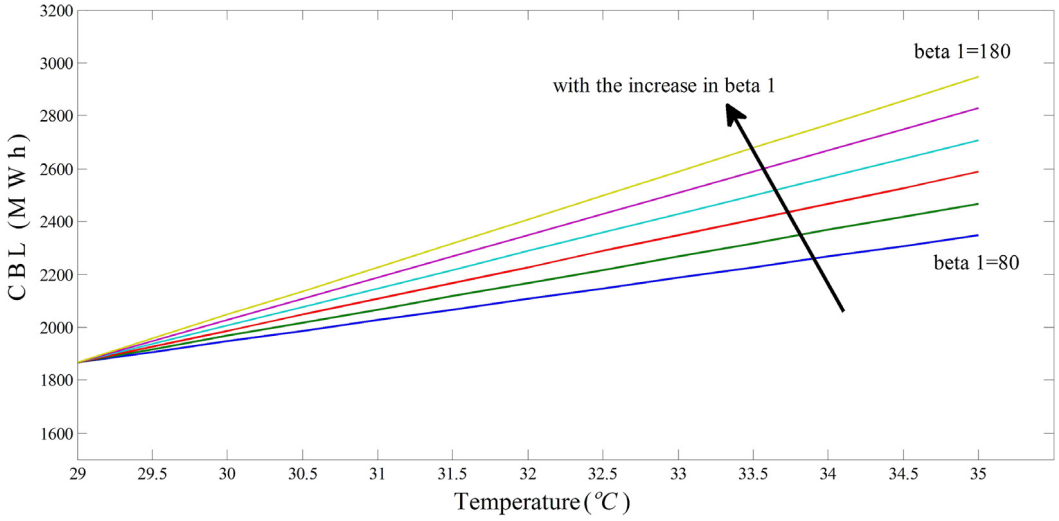

Fig. 9. Changes in CBL with respect to changes in temperature and β_1.

for different values of β_1, from 80 to 180 megawatt hours per degree centigrade. Therefore, based on these results one can say that using conventional methods of CBL calculation, without considering weather changes, greatly reduces the accuracy of calculation and can cause problems in the implementation of DR programs.

6. Conclusion and future work

In this paper, a dynamic method was presented for calculating CBL for customers of residential sector by considering the impact of weather conditions on power consumption. Unlike the most common models, that use statistical methods such as the average consumption of the last few days to determine CBL, the proposed method uses a dynamic model based on a combination of linear regression and statistical models for this purpose.

The results clearly indicated the high impact of changes in weather conditions on the calculation of CBL, and also showed the extent of effect of improved insulation in the buildings on this parameter.

As mentioned in the paper, average of demand values is used here which can reduce the model accuracy. Although this is a common method of CBL calculating in most of the electricity markets but however it cannot return a completely accurate and error-free result. Working on this issue is considered as the future work.

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