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Assessing the influence of climatic variables on electricity demand

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Abstract

The electricity demand is significantly dependent on the weather information. Such weather information is comprised of different climatic variables such as temperature, humidity, wind speed, evaporation, rain fall and solar exposure which constantly change. Therefore, analysing the impacts of these variables on demand is necessary for predicting the future change in demand. In this paper, the cooling and heating degree days are utilised to capture the relationship between the per capita demand to temperature, which is one of the key climatic variables. In addition, Pearson correlation analysis has been employed to investigate the interdependency between different climatic variables and electricity demand. Finally, backward elimination based multiple regression is used to exclude non-significant climatic variables and evaluate the sensitivity of significant variables to the electricity demand. A case study has been reported in this paper by acquiring the data from the state of New South Wales, Australia. The results reveal that the climatic variables such as heating degree days, humidity, evaporation, and wind speed predominantly affect the electricity demand of the state of New South Wales.

Keywords

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Assessing the Influence of Climatic Variables on Electricity Demand

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***Abstract* — The electricity demand is significantly dependent on the weather information. Such weather information is comprised of different climatic variables such as temperature, humidity, wind speed, evaporation, rain fall and solar exposure which constantly change. Therefore, analysing the impacts of these variables on demand is necessary for predicting the future change in demand. In this paper, the cooling and heating degree days are utilised to capture the relationship between the per capita demand to temperature, which is one of the key climatic variables. In addition, Pearson correlation analysis has been employed to investigate the interdependency between different climatic variables and electricity demand. Finally, back-ward elimination based multiple regression is used to exclude non-significant climatic variables and evaluate the sensitivity of significant variables to the electricity demand. A case study has been reported in this paper by acquiring the data from the state of New South Wales, Australia. The results reveal that the climatic variables such as heating degree days, humidity, evaporation, and wind speed predominantly affect the electricity demand of the state of New South Wales.**

***Index Terms*-- Climate Change; Electricity Demand Forecasting; Pearson Correlation; Regression Analysis; Weather Variables.**

I. INTRODUCTION

With strong development of technology and higher living standards, more electrical equipment are being used nowadays to maintain the comforting life styles. Consequently, changing in living environment due to climate change can lead to more or less electricity energy requirement e.g. heating and cooling requirement. This addresses the importance of investigating the impacts of climatic variables on electricity demand.

Numerous studies in the literature highlighted the influences of climatic variable on electricity demand [1], [2]. The authors in [3] illustrated that the global warming can cause up to 6% additional demand consumption required annually in Greece. In [4], the authors showed that the change of the peak electricity demand in Thailand can be increased by more than 15% at the end of the century. While in [3] and [4], only temperature was in the consideration, the authors in [5] believed the other climatic variables such as relative humidity, and wind speed also have strong influence to electricity consumption by analysing the data in eight states of USA. In [6], different dependent patterns of electricity demand on climatic variables in different seasons in the states of NSW, Australia were represented in four different regression models. It was shown that to the end of 21th century, the per capita demand for this state can rise 6.14% in summer season, and 11.3% in the spring season, but decrease 4.11% for winter and 0.45% for autumn season. In [7], the authors reported that the sensitivity of climate change to electricity demand is different for four of the biggest cities of Australia where 7^{0}C rise in temperature may cause 1.5% yearly average demand growth in Sydney and Melbourne, and 10% to 28% growth in yearly average demand of Brisbane and Adelaide. In [8], the authors have revealed that in New Zealand, 1^{0}C rise in temperature will result into 1.4% drop in yearly average electricity demand; however 1^{0}C decrease in temperature will result into 1.6% increase in average yearly electricity demand. In [9], by building the model investigating the air conditioning market saturation to the climate change, the authors indicated that the residential cooling demand is strongly impacted by the change of climatic variables especially, the temperature in USA. It was also found that with the increase of 20% in CDD, this will lead to 1%-9% increase in total residential electricity demand and from 20% to 60% rise of residential AC electricity consumption. In [10], the authors have estimated that a 1.5^{0}C increase in temperature would increase total net expenditure by 4% for the state of California by the year 2100 due to increased cooling and decreased heating demand.

The main objective of this paper is to assess the impact of climatic variables on electricity demand. The assessment is carried out based on the correlation and regression analyses associated with the electricity demand and the climatic variables. However, the results from these analyses do not always translate into good forecasts due to differences in load characteristics. Therefore, the forecasting results should be compared with the results from other methods such as Box-Jenkins [11], Kalman filter [12], neural network [13] for further validation. Time series analysis in conjunction with regression model can be used to forecast the future demand [6].

In this paper, impacts of climatic condition on per capita electricity demand are investigated. The regression analysis and Pearson correlation have been employed to reveal the importance of climatic variables. The balance point temperature is estimated based on the temperature and per capita electricity demand data. The degree days are then used to linearise the relationship between temperature and demand.

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The paper is organised as follows: Section II highlights the sensitivity of electricity demand to climatic variables. In section III, results and associated discussion are presented. Section IV gives some concluding remarks.

II. Energy Demand Sensitivity to Weather Variables

Climatic condition comprises of different weather variables, so any change in each of these variables might impact electricity demand; therefore, dependency of the weather variables is necessarily investigated. Pearson correlation is employed to reveal the hidden relationship of temperature to the other weather variables. Regression analysis has been performed using the historical data to investigate the dependency of the different weather variables on electricity demand.

A. Weather Variables

The weather variables such as temperature, rainfall, solar exposure, wind speed and humidity, which may have significant impacts on electricity demand, as there may be a hidden relationship among them. Temperature is one of the key variables that controls atmospheric condition and other weather variables on the earth will be affected by temperature [14].The temperature on the Earth surface is caused by the solar energy and thus, solar exposure and temperature are expected to have close relationship. Any change in temperature will lead to change of water evaporation, and this causes the change in humidity. Furthermore, the differences of temperature lead to the air movement, and change the wind speed. This interdependency between weather variables could be very complex. In all, temperature is the most prevailing climatic variable and has most important impact on electricity demand [15].

In order to estimate the interdependency among different variables, the Pearson correlation technique is commonly used. Using this technique, a correlation coefficient, which is between -1.0 and +1.0, is generated to estimate the degree of correlation between different variables [16]. While +1.0 indicates a perfect positive correlation; -1.0 signifies a perfect inverse correlation; and 0 means no correlation. Commonly used formula of Pearson correlation is given in (1).

$$r_{xy} = \frac{n\sum xy - \sum x \sum y}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \qquad (1)$$

Where r_{xy} is the correlation index between variables x and y, and n is the total number of data points.

B. Balance point Temperature

Balance point temperature is a threshold temperature, at which the per capita electricity demand is minimum. This balance point temperature is commonly considered to be around 18.3^0C for the moderate environment, and at round 21.0^0C for warmer environment [17]. However, the value often varies in different regions due to geographical configuration. In the proposed study, balance point temperature has been estimated based on per capita demand and temperature. Ideally, a "V-shaped" trend curve [18], [19] can be observed as shown in Fig. 1.

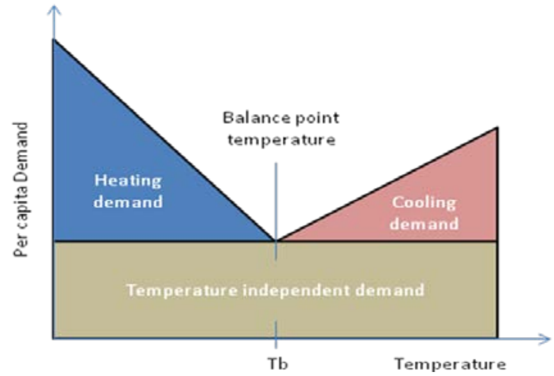

Figure 1. Balance point temperature.

It can be seen from Fig. 1 that the balance point temperature is the point at which demand is at minimum level. When the temperature increases or decreases from this particular point, the demand grows up due to cooling and heating requirement respectively.

C. Degree Days

According to the law of thermodynamics, if a substance weighing m and having specific heat capacity of C requires change in temperature from t_1 to t_2, then the requisite energy E can be expressed as in (2)

$$E = m\,C(t_2 - t_1) \qquad (2)$$

With the same substance, m and C are constant, so the energy needed to change the temperature is proportional to the change of temperature. This implies that there is a strong relationship between the cooling and heating requirement with the change of temperature, and it leads to the use of cooling degree days (CDD) and heating degree days (HDD).

Cooling degree days (CDD) represent the requirement of cooling due to temperature being higher than the balance point temperature, and it is calculated as in (3).

$$CDD_i = \begin{cases} (T_i - T_b) & if\ (T_i > T_b) \\ 0 & if\ (T_i < T_b) \end{cases}, \quad CDD = \sum_{i=1}^{N} CDD_i \quad (3)$$

Where, N is the number of days in a year, T_i is the average temperature of day i, T_b is the balance point temperature.

Similarly, heating degree days (HDD) represent the heating energy requirement because of the temperature being lower than the balance point temperature, and it is calculated as in (4).

$$HDD_i = \begin{cases} (T_b - T_i) & if\ (T_i < T_b) \\ 0 & if\ (T_i > T_b) \end{cases}, \quad HDD = \sum_{i=1}^{N} HDD_i \quad (4)$$

D. Regression Analysis

Regression analysis helps to establish the connection between independent and dependent variables and the degree of their dependency. In this proposed study, multiple linear regression analysis is employed to express demand dependency in terms of linear combination of different weather variables. Fig. 2 shows conceptual framework of correlation among different weather variables and regression analysis to obtain electricity demand.

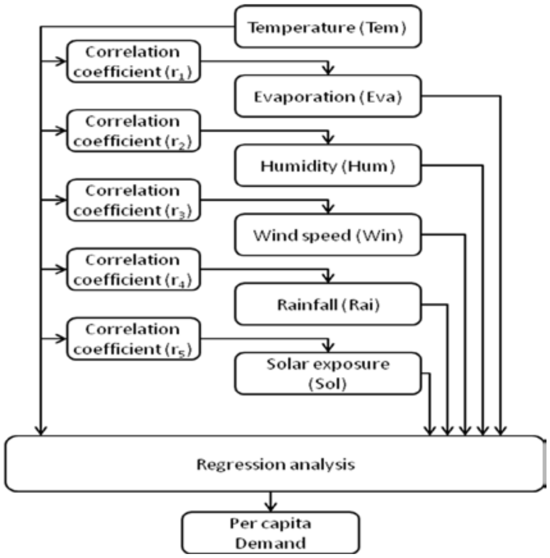

Figure 2. Conceptual framework to derive electricity demand using regression analysis.

The regression equation for electricity demand can be written as in (5).

$$D = c_0 + \sum_{j=1}^{m} c_j x_j + \varepsilon \quad (5)$$

Where D is the per capita demand expressed in kW-h, c_0 is a constant term, x_j is the weather variables, c_j is the coefficients of the variables, and ε is the error term.

With the important weather variables such as temperature (represented in terms of 2 variables, *CDD* and *HDD*), wind speed *(Win)*, rainfall *(Rai)*, humidity *(Hum)*, solar exposure *(Sol)* and evaporation *(Eva)*, the regression equation can be rewritten as in (6).

$$\begin{aligned} D &= c_0 + c_1 CDD + c_2 HDD + c_3 Hum + c_4 Rai \\ &+ c_5 Eva + c_6 Win + c_7 Sol + \varepsilon \end{aligned} \quad (6)$$

The back-ward elimination regression method has been employed in this study to exclude the insignificant variables. At the beginning, all the variables are included into the model and then the least significant variables are excluded from that model one by one with the application of back-ward elimination regression analysis. In this analysis, the probability criterion to exclude a variable from the model has been set as $F \geq 0.05$. This means that in the regression analysis, the least significant variable which has 'sig' value being maximum and greater than 0.05, is eliminated from the model, and another model is formed after excluding that variable. This process continues until all the variables in the model have 'sig' value less than 0.05, and the remaining variables are considered as the most significant variables affecting electricity demand.

III. Results and Discussion

A case study has been reported with the aid of historical data collected from the state of NSW, Australia for the years 1999 to 2010. The electricity demand data including all sectors, were collected from Australian energy market operator (AEMO) [20]. These datasets are available for every half an hour and has been collated on daily and yearly basis for the proposed studies. The annual data of population are accessible from Australian Bureau of Statistics [21] for calculating the per capita demand. The climatic parameters at Sydney airport station [22] are assumed to be representing the entire state of NSW as around 75% of population of NSW are in Sydney and the surrounding areas.

A. *Selection of Weather Variables*

With the temperature is the key climatic variable, which controls most of other climatic variable, investigating the correlation between temperature and other weather variable is necessarily for appropriate selection of weather variables. Pearson correlation has been employed in this study to evaluate such correlation. Higher value of correlation coefficient indicates possible existence of multicolinearity in the regression analysis, which signifies interdependency between two significantly impacting variables [23]. Fig. 3 shows correlation between temperature and other weather variables. From Fig. 3, it is observed that rainfall, wind speed and humidity have inconsistently correlated with temperature. However, evaporation and solar exposure show high correlation with temperature.

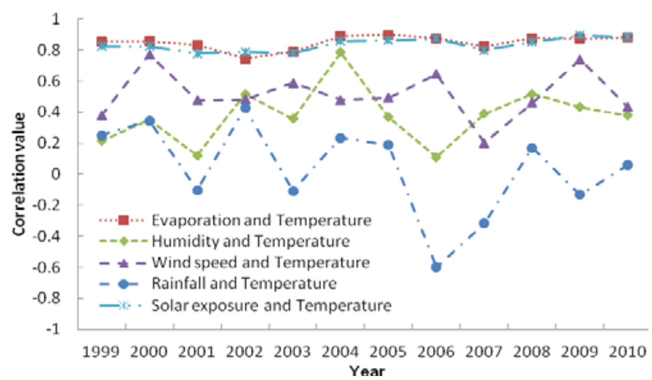

Figure 3. Correlation between temperature and other weather variables.

B. *Correlation between Demand and Climatic Variables*

The Pearson correlation has been applied to calculate the correlation between per capita electricity demand and weather variables. If there exists a correlation of +1.0 or -1.0 between demand and a single weather, then simple linear regression is sufficient instead of multiple regression analysis. Table I illustrates the Pearson correlation matrix, where interrelationships among different variables can be observed in terms of different correlation coefficients. From Table I, it is seen that more than one variable have potential to establish a relationship with the electricity demand. Multiple regression analysis will help to relate only significant variables with the demand and exclude non-significant variables. It will also help to quantify the extent to the influence of individual variables on the demand pattern.

TABLE I. PEARSON CORRELATION BETWEEN DEMAND AND CLIMATIC VARIABLES

	D	*CDD*	*HDD*	*Rai*	*Eva*	*Hum*	*Win*	*Sol*
D	1.0	0.3	-0.1	-0.3	0.2	-0.4	0.9	0.3
CDD	0.3	1.0	-0.3	-0.2	0.3	-0.3	0.3	0.4
HDD	-0.1	-0.3	1.0	0.3	-0.7	0.4	-0.2	-0.3
Rai	-0.3	-0.2	0.3	1.0	-0.6	0.7	-0.1	0.0
Eva	0.2	0.3	-0.7	-0.6	1.0	-0.9	0.3	0.3
Hum	-0.4	-0.3	0.4	0.7	-0.9	1.0	-0.4	-0.3
Win	0.9	0.3	-0.2	-0.1	0.3	-0.4	1.0	0.5
Sol	0.3	0.4	-0.3	0.0	0.3	-0.3	0.5	1.0

C. Identification of Balance Point Temperature and Degree Days

In practice, the relationship between electricity demand and temperature is not perfectly smooth like the ideal case. The balance point temperature T_b, however, can be estimated by using the trend-lines. In Fig. 4, the daily average per capita demand and temperature data for 12 years from 1999 to year 2010 for the state of New South Wales (NSW), Australia were used to plot the scatter and trend-line to evaluate the balance point temperature for every year, and also for the whole period of 12 years.

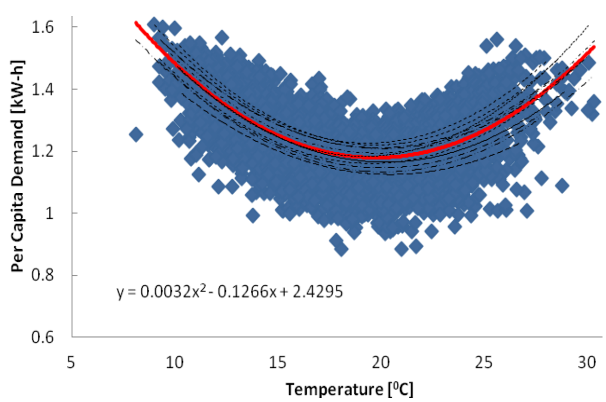

Figure 4. Actual relationship between per capita electricity demand and temperature in NSW, Australia from year 1999 to 2010.

From Fig. 4, it can be seen that the trend-line is shifted up in different year. This shifting-up trend can be explained with more consumption of the electricity demand at the same temperature. Also, the trend-line for whole period has the same shape with the individual yearly trend-line. This confirms that the dependency pattern of demand on temperature is robust in different time scale. Based on the trend-line equation for the whole period, balance point temperature for Sydney has been calculated and found to be 19.8 ^{0}C.

It was expected that threshold level for individual years and the whole period would be the same but in reality they are slightly different. This may be due to the small error in calculation. For more detail of view, year-wise analysis results are given in table II. It can be seen from this table that the threshold level of balance point temperature varies from 19.0 to 20.3 in the past 12 years (1999-2010). This again confirms the balance point temperature of the whole period is 19.8^{0}C.

TABLE II. BALANCE POINT TEMPERATURE IN DIFFERNT YEARS

Year	Equation	Balance point temperature
1999	$y = 0.0026x^2 - 0.1045x + 2.1935$	20.1
2000	$y = 0.003x^2 - 0.1203x + 2.3451$	20.1
2001	$y = 0.0029x^2 - 0.1166x + 2.3145$	20.1
2002	$y = 0.003x^2 - 0.1218x + 2.3953$	20.3
2003	$y = 0.0026x^2 - 0.1045x + 2.1935$	20.1
2004	$y = 0.0026x^2 - 0.1045x + 2.1935$	20.1
2005	$y = 0.003x^2 - 0.1211x + 2.425$	20.2
2006	$y = 0.0035x^2 - 0.1397x + 2.5987$	20.0
2007	$y = 0.0035x^2 - 0.1373x + 2.556$	19.6
2008	$y = 0.0031x^2 - 0.1246x + 2.4496$	20.1
2009	$y = 0.0036x^2 - 0.1366x + 2.492$	19.0
2010	$y = 0.0032x^2 - 0.1265x + 2.3945$	19.8

D. Regression Analysis

Electricity demand sensitivity to the model variables is examined in this paper. Initially, CDD, HDD, rainfall, wind speed, humidity, solar exposure, and evaporation have been included in the regression model. Using SPSS statistical tool, regression analysis has been performed and associated coefficients have been investigated. The 'sig' value of a variable less than 0.05 implies a significant effect of the

TABLE III. BACK-WARD ELIMINATION REGRESSION ANALYSIS

Model no.	Model summary			Significance level of predictors							
	R	R2	Adjusted R2	Constant	*Hum*	*Eva*	*Win*	*HDD*	*Sol*	*Rai*	*CDD*
1	0.981	0.962	0.894	0.028	0.085	0.030	0.004	0.112	0.391	0.466	0.597
2	0.979	0.958	0.909	0.010	0.040	0.012	0.002	0.059	0.414	0.461	Removed
3	0.976	0.953	0.914	0.001	0.004	0.004	0.001	0.026	0.409	Removed	Removed
4	0.973	0.947	0.917	0.001	0.002	0.002	0.000	0.020	Removed	Removed	Removed

related variable on the demand. In the first step, the variable *CDD* with the highest p-value of 0.59 is removed from the mod 1, and then mod 2 is formed based on the remaining variables. In the second step, the *Rai* is excluded because of highest p-value of 0.461. In the third step, *Sol* is elimated due to the highest p-value of 0.409, and the obtained model after this step is considered to be the final model, where all the p-values are found to be less than 0.05. The remaining variables which are *HDD*, *Win*, *Eva*, and *Hum* can be considered as the most significant variables impacting on electricity demand. The modelled demand is compared with the actual demand as in Fig. 5. It can be seen from this figure that the correspondence between modelled and actual demand is very close. This confirms the ability of the selected climatic variables to quantify the electricity demand.

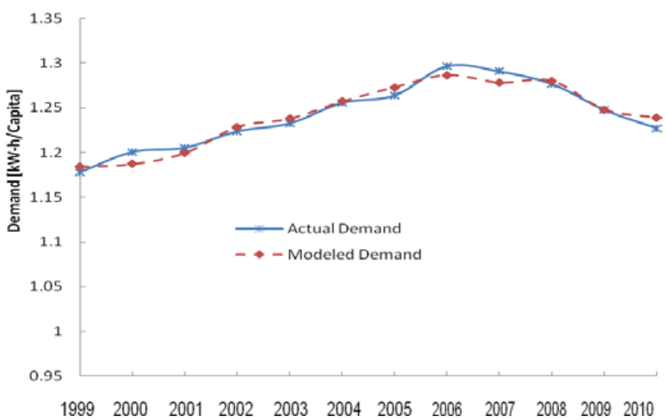

Figure 5. Actual and model demand

IV. Conclusions

In this paper, the impacts of climatic variables on electricity demand have been analysed. The cooling and heating degree days have been employed to capture the relationship between per capita demand and temperature. The Pearson correlation and multiple regression analysis have been used to determine the significant weather variables impacting on electricity demand, and estimate the degree of significance of these variables in the demand forecasting. The proposed method has been tested on the electricity demand data for the state of NSW, Australia and the impacts of the associated climatic variables are determined. The results show that the per capita electricity demand in this state predominantly depends on the HDD, wind speed, evaporation and humidity. In other words, these climatic variables greatly influence the energy demand. In future research, a robust forecasting model will be developed using these variables to predict electricity demand. Furthermore, the impact of the change in load nature, such as the type of load in different sectors, on the model will be thoroughly investigated. In addition, the influence of distributed generation will be comprehensively considered.

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