Upgrade of an artificial neural network prediction method for electrical consumption forecasting using an hourly temperature curve model

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Abstract

This paper presents the upgrading of a method for predicting short-term power building consumption that was previously developed by the authors (EUs method). The upgrade uses a time temperature curve (TTC) forecast model. The EUs method involves the use of artificial neural networks (ANN) for predicting each independent process – end-uses (EUs). End-uses consume energy with a specific behaviour in function of certain external variables. The EUs method obtains the total consumption by the addition of the forecasted end-uses.

The inputs required for this method are the parameters that may affect consumption, such as temperature, type of day, etc. Historical data of the total consumption and the consumption of each end-use are also required.

A model for prediction of the time temperature curve has been developed for the new forecast method (TEUs method). The temperature at each moment of the day is obtained using the prediction of the maximum and minimum daytime temperature. This provides various benefits when selecting the training days and in the training and forecasting phases, thus improving the relationship between expected consumption and temperatures.

The method has been tested and validated with the consumption forecast of the Universitat Politècnica de València for an entire year.

Keywords: temperature curve model, building energy consumption forecast, artificial neural networks, building end-uses.

1 Introduction

The current economic situation and the world energy crisis force consumers to use energy more appropriately [1]. It is necessary for large consumers to be aware of their electrical consumption and the dependence of this consumption on external variables. An understanding of how facilities are used may be useful for the implementation of demand response actions [2, 3], for the purchase of energy on the spot market [4], or for the evaluation and verification of energy saving measures [5-7]. Additionally, economic and environmental benefits may be achieved.

Two basic strategies to improve the consumption of a facility are addressed [1, 8-10]. First, *energy efficiency measures* involve reducing energy consumption without reducing production. This causes an increase in the overall performance of the facility that brings economic benefits through a process of measurement and verification. Secondly, *energy management measures* involve a set of actions designed to consume with a lower energy cost. Among these actions are load transfers to valley periods or the control of peak power to avoid consumption higher than the contracted power.

It is important to be able to predict electrical consumption a few days ahead for the verification of the savings achieved when purchasing power on the spot market or participating in demand response programs. For electrical consumption prediction there are different methodologies – including: ARIMA models; multivariate regression models; artificial neural networks (ANN); or linear regression simplified models [11-18]. ANNs have the advantage of being adaptable as more historical data is gathered or when facilities grow [19-22].

End-uses (EUs) are the independent processes that consume energy and can be identified and sometimes measured in a building. Thus, each EU has specific characteristics and a different relationship within the input variables that determine the consumption of the facility.

This approach has various advantages. First, the behaviour of some EUs is monotonous or repetitive, or may be closely linked to just a few input variables, and this enables fewer errors. Secondly, this technique provides detailed information about each EU, so consumer flexibility can be calculated for each EU with greater accuracy and flexible strategies can be independently focused on each EU, thus achieving greater efficiency and better use of energy resources.

The authors previously developed a forecasting method (EUs method) [1] in which ANNs and EUs were used to forecast consumption in medium or low aggregation loads such as a building or a small group of buildings. In this paper, the authors present an upgrade of this method and solve some drawbacks found in the previous method by developing a forecasting model to estimate a time temperature curve for a whole day.

The labour activity parameter (LAP) is defined as a numerical value for each type of day. This enables days with similar consumption profiles to be grouped and separated from other groups. For example, working Mondays can be separated from holiday Mondays, as their consumption is very different.

The temperature time curve (TTC) forecasting model is presented and evaluated. The model shows results that enable the use of these forecasts for other applications.

An application of the proposed method is presented to predict total electrical consumption at the Universitat Politècnica de València (UPV). It is assumed that in the UPV there are two EUs: processes whose consumption is strongly dependent on temperature (STD EUs); and processes that are weakly temperature-dependent (WTD EUs).

The paper is organised as follows. Section 2 describes the proposed TTC prediction model. Section 3 details the modified method for predicting electrical consumption using the TTC model (TEUs method) and an EUs approach. Section 4 presents the application of the proposed method for the prediction of the consumption in the UPV for a whole year and shows the results of the method. A comparison of the results with different methods is also shown. Finally, some conclusions are drawn in Section 5.

2 Model for time temperature curve forecasting

A model for a time temperature curve (TTC) for forecasting has been developed in order to improve the EUs method that was proposed previously by the authors to improve hourly electrical consumption forecasting. A weakness in the EUs method is the fact that the 96 ANN used to predict the 96 quarter-hourly values of a day are trained using the same input variables: maximum temperature (T_{MAX}); minimum temperature (T_{MIN}); average temperature (T_{AVG}) of the day of prediction (DOP); and the average temperature of the day before the DOP (T_{AVG-1}). A temperature curve of the DOP may be used as input to the ANN to improve the prediction obtained by improving the training and prediction phase.

The model presented in this section enables the creation of an hourly TTC (or any other desired time interval) for a day using the minimum and maximum temperatures of the DOP and surrounding days. The main advantage of this model is that it produces different temperature input data for each hour, which will provide better results because the consumption of HVAC systems and other temperature-dependent EUs varies significantly with temperature.

To perform the forecast of the TTC, expected minimum and maximum temperatures of three consecutive days are required. This data is available at most weather stations [23, 24]. Geographic location data (latitude and longitude) and the date of the DOP are also required. From this data, the steps of the methodology to develop the model to obtain the TTC are described below.

First, data for the DOP and for the adjacent days is calculated.

dn denotes a value equal to the day number of the year (Julian day number) for the DOP (1 to 365, taking February 29 as equal to February 28, as the variation in the calculation is negligible). Thus, θ denotes the daily angle and is calculated as:

$$\theta = \frac{2 \cdot \pi}{365} \cdot (dn - 1) \tag{1}$$

The equation of time (et) denotes the difference between true solar time and mean solar time expressed as:

$$et = (0.000075 + 0.001868 \cdot \cos(\theta) + 0.032077 \cdot \sin(\theta) - 0.014615 \cdot \cos(2\theta) - 0.04089 \cdot \sin(2\theta))229.18 \tag{2}$$

The 229.18 factor is used to convert radians to minutes.

Solar declination (δ) is the angle in radians between the equatorial plane and the line connecting the centres of the Sun and Earth and can be calculated by the Expression 3:

$$\delta = 23.45^{\circ} \cdot \cos\left(2 \cdot \pi \cdot \frac{dn - 173}{365}\right) \cdot \frac{\pi}{180} \tag{3}$$

The 173 value corresponds to Julian day number for June 22 (vernal equinox).

Solar angular hour (h) is calculated as:

$$h = \cos^{-1}\left(\frac{\sin\left(\frac{-0.833 \cdot \pi}{180}\right) \cdot \sin(\delta)}{\cos(\varphi) \cdot \cos(\delta)}\right) \tag{4}$$

The number of hours of daylight (n_d) is calculated in function of the h:

$$n_d = \frac{h}{7.5} \cdot \frac{180}{\pi} \tag{5}$$

The sunrise (t_{sr}) and sunset time (t_{ss}) are calculated using the following expressions:

$$t_{sr} = 12 - \frac{n_d}{2} - \frac{et}{60} \tag{6}$$

$$t_{ss} = 12 + \frac{n_d}{2} - \frac{et}{60} \tag{7}$$

Finally, the hours of difference (h_d) to the meridian for the location and date of the DOP must be known. For example, in Valencia, a value of +1 hour during the winter and +2 hours during summer time (from the last Sunday in March to last Sunday in October) should be used.

All these parameters are calculated for the DOP; for the day before the DOP (superscript a); and the day following the DOP (superscript p).

φ denotes the latitude in radians, λ is the longitude in radians, *t* is the time of forecast (which is iteratively calculated from t = 0 to t = 23 with an increment of 1 hour for an hourly curve (or from time t = 0 to t = 23.75 for a quarter hourly curve).

The model fixes significant temperatures at specific times and then performs the interpolation in the remaining hours of the day using a sinusoidal segment and an exponential segment (Figure 1).

Figure 1. Theoretical curve for prediction of temperature for a full day.

The specific times in which maximum (subscript *max*) and minimum (subscript *min*) temperature occur in a day are calculated using the following expression for the DOP, the day before, and the day after the DOP:

$$t^a_{\min} = t^a_{sr} + h^a_d - \lambda \cdot \frac{24}{360} - \frac{et^a}{60} \tag{8}$$

$$t^a_{\max} = \frac{t^a_{\min} + t^a_{ss} + h^a_d - \lambda \cdot \frac{24}{360} - \frac{et^a}{60}}{2} + 1.5 \tag{9}$$

$$t_{\min} = t_{sr} + h_d - \lambda \cdot \frac{24}{360} - \frac{et}{60} \tag{10}$$

$$t_{\max} = \frac{t_{\min} + t_{ss} + h_d - \lambda \cdot \frac{24}{360} - \frac{et}{60}}{2} + 1.5 \quad (11)$$

$$t_{\min}^{p} = t_{sr}^{p} + h_d^{p} - \lambda \cdot \frac{24}{360} - \frac{et^{p}}{60} \quad (12)$$

The 1.5h parameter in Expression 9 and 11 is fixed in the model as the estimated time that the maximum temperature moment is delayed at the moment of maximum radiation due to thermal inertia.

Two more significant time points should be calculated, which correspond to the link section between the sinusoidal temperature segment with the exponential segment, called t_c. These two instants (one for the day before the DOP curve, which will set the temperature at the beginning of the DOP; and another for the DOP curve, setting the temperature at the end of the DOP) are calculated as follows:

$$t_c^{a} = \left(t_{ss}^{a} + h_d^{a} - \lambda \cdot \frac{24}{360} - \frac{et^{a}}{60} - 2 \right) - 24 \quad (13)$$

$$t_c = \left(t_{ss} + h_d - \lambda \cdot \frac{24}{360} - \frac{et}{60} - 2 \right) \quad (14)$$

The value 2h is fixed in the model as the number of hours before sunset in which to perform the change of the sinusoidal function to the exponential function, since the height of the sun is no longer considered sufficient to provide a radiation level that avoids the exponential decay of the temperature.

The sinusoidal segment of the temperature must pass through the maximum and minimum temperature, and is defined: as

$$Tavg_{\sin}^{a} = \frac{T_{\max}^{a} + T_{\min}^{a}}{2} \quad (15)$$

$$Tavg_{\sin} = \frac{T_{\max} + T_{\min}}{2} \quad (16)$$

With this data a value of the temperature may be calculated for each hour t=0, …, 23 as follows:

For $t<t_{min}$

$$P_{\sin}^{a} = 2 \cdot \left(t_{\max}^{a} - t_{\min}^{a} \right) \quad (17)$$

$$A_{\sin}^{a} = T_{\max}^{a} - T_{\min}^{a} \quad (18)$$

$$T_c^a = Tavg_{\sin}^a + \frac{A_{\sin}^a}{2} \cdot \cos\left(\left(t_c^a - t_{\max}^a\right) \cdot \frac{2 \cdot \pi}{P_{\sin}^a} \right) \tag{19}$$

$$B = \frac{\ln\left(T_c^a\right) - \ln\left(T_{\min}\right)}{t_c^a - t_{\min}} \tag{20}$$

$$A = \frac{T_c^a}{e^{B \cdot t_c^a}} \tag{21}$$

$$T(t) = A \cdot e^{B \cdot t} \tag{22}$$

For $t_{min} \leq t < t_c$

$$P_{\sin} = 2 \cdot \left(t_{\max} - t_{\min}\right) \tag{23}$$

$$A_{\sin} = T_{\max} - T_{\min} \tag{24}$$

$$T(t) = Tavg_{\sin} + \frac{A_{\sin}}{2} \cdot \cos\left(\left(t - t_{\max}\right) \cdot \frac{2 \cdot \pi}{P_{\sin}} \right) \tag{25}$$

For $t \geq t_c$

$$P_{\sin} = 2 \cdot \left(t_{\max} - t_{\min}\right) \tag{26}$$

$$A_{\sin} = T_{\max} - T_{\min} \tag{27}$$

$$T_c = Tavg_{\sin} + \frac{A_{\sin}}{2} \cdot \cos\left(\left(t_c - t_{\max}\right) \cdot \frac{2 \cdot \pi}{P_{\sin}} \right) \tag{28}$$

$$B = \frac{\ln\left(T_c\right) - \ln\left(T_{\min}^p\right)}{t_c - t_{\min}^p} \tag{29}$$

$$A = \frac{T_c}{e^{B \cdot t_c}} \tag{30}$$

$$T(t) = A \cdot e^{B \cdot t} \tag{31}$$

Kelvin units in temperature values (T) are mandatory to avoid null temperature values that do not enable certain operations.

With this procedure, giving values for t ($0 \leq t < 24$) a prediction of temperature for any time of day may be calculated. Figure 1 explains the stages used in the TTC of an entire day. Figure 2 shows the temperature curves of two weeks of 2010 compared with the forecast obtained by the proposed model.

Figure 2. Comparison between the actual temperature and the temperature prediction model from 3/4/2010 until 17/4/2010.

The forecasting model to obtain a TTC was tested for the whole year 2010. A maximum error of 6.6 ° C and a MAPE error of 0.28 and an EME error [1] of 2.47 with temperature expressed in Kelvin (MAPE cannot be calculated with the value 0º Celsius). Results are very accurate and may be used to obtain better forecasts of consumption for each moment of the day.

3 Prediction method for electrical consumption forecast

The prediction method for electrical consumption forecasting presented in this paper using a TTC model (TEUs method) is based in the EUs method previously presented by the authors [1]. Some modifications have been introduced to solve some drawbacks such as modifying the inputs in the model which were constant for a day (T_{MAX}, T_{AVG}, T_{MIN} and T_{AVG-1}). In the EUs method the ANNs are trained with the minimum number of days, with features as similar as possible to the DOP. Random and uncontrolled training data may be introduced when using many measures in the training phase.

In STD EUs the authors consider that consumption depends on the energy consumed during the days immediately preceding the DOP with similar external temperatures and with the same LAP. In this sense, in the TEUs method the days are similar when the curves of temperatures are similar.

The TTC model obtained as presented in Section 2.0 is used in the TEUs method to obtain different input data for each value forecast (24 values in an hourly consumption prediction curve for a day).

- The selection of training days for the STD EUs is performed on days with a temperature curve similar to the DOP. From this set of days, the four days with the most similar thermal requirements (according to Table 1 using XDD to consider system inertia) are selected. For example, in the first column for selection criteria (1), in a day with higher HDD (heating degree days) than CDD (cooling degree days) the selected days are the four days closest to the DOP; two days with higher HDD parameters (namely, XDD+1, XDD+2) and two days with lower HDD parameters (XDD-1, XDD-2). The days selected must have the same LAP and are taken from the 30 immediately preceding days. If no data meets this criterion, then the selection criteria labelled as 2 is chosen, and so on. If the selected day has higher CDD than HDD parameters, for selection criteria (1), the selected days are the four days closest to the DOP, two days with higher CDD parameters (namely, XDD+1, XDD+2) and two days with lower CDD parameters (XDD-1, XDD-2).

Table 1. Selection criteria in STD EUs.

- The inputs to the ANN used for the prediction of each hour differ in order to improve training of the ANNs and forecasting phases.
- The estimated consumption curve is calculated for each hour instead of each quarter hour and so provides greater stability. An hour-long period has been chosen because this period is the interval used in the purchase of energy in electricity markets. Using this methodology it is possible to obtain a prediction of consumption for each hour of the next day 24 hours in advance.

The proposed prediction method mainly consists of the same steps as the EU method. First, the selection of similar days to the DOP is carried out, and the selected days are used as inputs to the ANNs for training. Secondly, ANNs are used to predict each EU separately, and finally, the partial predictions of each EU are added to obtain total consumption.

The ANN architecture in the TEUs method is a multilayer perceptron with three neurons in the hidden layer used to predict consumption for each hour of the day.

The proposed ANNs architecture (Figure 3), is similar to architecture defined in the EUs method, and is composed of three layers: one input; one hidden; and one output layer.

However the input variables differ. Four neurons are considered in the input layer:

- T_t^{AVG3}: average temperature of the three hours before the time of prediction (TP). Consumption is very sensitive to the closest previous hours.
- CDD_t: cooling degree days from the beginning of the DOP until the TP. The reference temperature considered in this study is 21 °C.
- HDD_t: heating degree days from the beginning of the DOP until the TP. The reference temperature considered in this study is 18 °C.
- P_{t-1}: the expected consumption in the previous hour, which provides smooth shifts and reduces consumption independence compared to the previous hour. For 0:00 am this input is not used for two reasons: first; because a prediction of the previous day is required; and secondly, because there is very little nocturnal consumption variability.

Considering the number of inputs, three neurons were chosen in the hidden layer.

The output of the neural network has only one neuron, which represents the prediction of the consumption of the plant as hourly active energy consumption for a given moment ($\hat{L}_t$).

Figure 3. ANN architecture used in the proposed method.

5000 cycles are used for the training phase of the ANNs. The momentum and learning parameter descends throughout the training, thus facilitating convergence to a minimum error. The initial value used for the learning parameter is 1 and the initial value for the momentum parameter is 0.5 during the first 500 cycles. A learning parameter of 0.9 and a momentum of 0.2 to 1500 cycles are then used; and a learning parameter of 0.7 and a momentum of 0.2 are used for the other cycles.

The days selected to train the STD EUs are those with temperature curves similar to the DOP and with thermal requirements more similar to the DOP in accordance with Table 1. To assess the goodness of the temperature curve the mean squared error (MSE) is used as in Expression 32 with the TTC of the selected day and the expected TTC for the DOP.

$$MSE = \frac{\sum_{h=0}^{23} \left(T(h) - T_{DOP}(h)\right)^2}{24} \tag{32}$$

Thus, the four days with the same LAP with the least MSE of temperature are ordered from smallest to the largest error and selected – following the criteria explained in Table 1.

For WTD EUs, the selection is made by taking the four days closest to the DOP with the same LAP. Since there is a slight dependence on external temperature, the ANNs architecture employed is the same as in the STD EUs.

This process results in a forecast for each EU. A prediction of total consumption is then obtained by the addition of the obtained prediction for each EU.

4 Application and results

The proposed method for predicting hourly electrical consumption has been applied to obtain the total electrical consumption of the UPV. The method has been applied for an entire year from 1 August 2010 until 31 July 2011.

The UPV is considered a large commercial consumer with a contracted power of 13.5 MW and an annual consumption of around 50 GWh. Among the more than 70 buildings on the UPV campus consumption varies depending on external variables. This is one of the reasons why the prediction of consumption by EUs produces better results than a method based on the total consumption, since the relationship between total consumption and the input variables is more difficult to determine.

UPV consumption is dependent on two variables: weather and working patterns.

Working patterns in the UPV depend on the type of day and the season. The LAP is used and values are assigned accordingly for each day [1].

Consumption forecast is calculated by using two EUs. STD EU, that denotes all consumption that is strongly temperature-dependent, such as HVAC systems, ventilation systems, and so on, and WTD EU that denotes the remaining consumption facilities. LAP values are the same for both EUs, since both depend on the type of day (there is a higher consumption of air-conditioning and other devices such as lights and PCs when there are more people in the university).

More than 280 power meters have been installed to obtain electrical consumption. STD EU data is obtained by considering the 20 meters that measure consumption that is strongly dependent on temperature (panels that feed exclusively HVAC systems), and WTD EU data is obtained using the remaining meters.

In this work, an electrical consumption forecast and a comparison between three methods is made:

- TEUs method: the proposed new method that includes the prediction of TTC and EUs.
- EUs method: the prediction method that uses EUs and constant values of temperature.
- TC method: previous method that only uses the total electrical consumption.

Figure 4 shows the result of electrical consumption prediction for 15/2/11 made using the proposed TEUs method for each EU and the actual total consumption.

Figure 4. UPV consumption forecast for 15/2/11 using TEUs method.

The MSE of the temperature curve compared with the forecast for the selected training days for STD EU are 6.27 for 10/1/2011, 9.84 for 18/11/2010, 23.29 for 9/12/2010 and 19.81 for 11/1/2011.

The errors of the prediction are MAPE = 2.58 and EME 2.79.

Additionally, Figure 5 presents results for the prediction for an entire week (from 21 February to 27 February 2011) using the TEUs method.

Figure 5. Forecast of consumption for the week of 21/2/11 to 27/2/11 using the TEUs method.

Table 2 shows the errors broken down by day for the analysed period. The errors for the entire period are MAPE = 3.71 and EME = 3.77.

Table 2. Forecast errors for UPV consumption forecast from 21/2/11 to 27/2/11 using TEUs method.

Table 3. Results of multiple simulations at the UPV.

To compare the different methods an entire year has been analysed. Results are presented in Table 3. The number of days in which it is possible to obtain predictions depends on the availability of input data. Using the TEUs method, results are improved by using detailed temperature data obtained with the proposed TTC model during training and prediction phases in the ANNs.

Finally, Figure 6 graphically compares the MAPE error for each day using the TEUs method and the EUs method for all the predicted days. By defining a dead band of ± 2% of MAPE within which both methods are similar, it is shown that errors are lower for the TEUs method.

Figure 6. Result comparison for TEUs and EUs methods.

5 Conclusion

This paper presents the upgrade of a method for predicting short-term power building consumption that was previously developed by the authors (EUs method). The upgrade uses a time temperature curve (TTC) forecast model. The EUs method consists of applying an algorithm of artificial neural networks (ANN) for the prediction of each independent process – end-uses (EUs). EUs consume energy with a specific behaviour in function of certain external variables. The EUs method consists of obtaining the total consumption by the addition of the forecasted EUs.

A model for prediction of the TTC has been developed for the new consumption prediction method (TEUs method). The temperature at each moment of the day is obtained using only the prediction of the maximum and minimum daytime temperature of the DOP and the maximum and minimum temperature of the surrounding days. This provides different benefits in the selection of the training days and in the training and forecasting phases, thus improving the relationship between expected consumption and temperatures. Cooling and heating degree day values of the training days and the day of prediction (DOP) are used to characterise thermal requirements.

An additional advantage of this method is that each EU may be defined by the user with the desired input variables.

The method has been tested with a consumption forecast for the Universitat Politècnica de València for an entire year and successful results were obtained.

Acknowledgement

This research work has been possible with the support of the Universitat Politècnica de València (Spain) with grant #CE 19990032.

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