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Résumé

Nous proposons, dans ce papier, un modèle de prévision tenant compte de l'effet de la climatisation sur la consommation d'électricité[1]. Cette modélisation a nécessité une analyse spécifique de l'élasticité de la consommation journalière par rapport à la température. Ainsi, l'étude de l'évolution de la part estimée liée à la température (chaud/froid), nous a permis, de prévoir l'évolution du parc d'appareils de climatisation. Ce résultat était particulièrement utile, dans la prévision à moyen terme surtout en absence d'une quantification directe du parc de climatiseurs.
Mots-clés : Principal : Ingénierie-industrie, secondaire : Econométrie

Abstract

Recently, the Tunisian electric load has shown qualitative and quantitative modifications. These changes are relating to the highly increase in the cooling and heating needs. Under this situation, mid-term load forecasting must take into account weather impact and especially the equipment rates increase on heating and cooling devices. In this paper, we propose a mid-term load modeling under lack of information about equipment rates. For this purpose, method for weather-sensitive load estimation, based on temperature consumption sensitivity analysis is presented.
Keywords: Principal: Engineering-industry, secondary: Econometrics.

1 Introduction

The electric power mid-term loads forecasting, such as the daily consumption and the annual daily peak values are essential to the operating and planning of utility company. However, the prediction of these electric variables is increasingly difficult, because of their dependence to the economic cycles and recently to the weather changes. Thus, due to the highly increase in air-conditioning load, univariate time series modeling becomes

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insufficient. Indeed the field of low voltage represents 45% of the total Tunisian electricity consumption (the residential sector represents 68% of this class of consumers) and the use of central air conditioner units in the tourism sector which represents 12% of average level voltage consumption (47% of the global consumption). In this case, models which take account weather factors are suitable, e.g Mirasgedis et al. (2006), Ning Lu et al. (2010), Chen et al. (2001). Nevertheless, with the Tunisian electricity consumption context, models elaborating which take account weather factors is not a trivial task. The related difficulties are listed as follows:

- There are no consensus about how to estimate the evolution of weather impact on the daily electricity consumption. Indeed, prediction is being a complicated task because of the lack of immediately available useful information about the consumers's classes consumption structures and their equipment rates on heating and cooling devices
- Only available climatic time series are the minimum and maximum values of the observed Tunis area daily temperatures. Moreover, many studies have founded that the temperature is the most commonly used load predictors, e.g Hippert (2001), Valenzuela et al. (2002).

The mid-term forecasting model of the daily electric consumption is given by[2]:

$$DE(a,i,j) = \frac{DE_a^f \times PJ(i,j) \times S(i)}{NJE(i)} \quad (1)$$

where *DE(a,i,j)* is the power forecasted for the j day and the i week in the considered year a. DE_a^f represents the total consumption forecasted for the considered year a. *PJ(i,j)* (resp. *S(i)*) is daily (resp. weekly) power weights. *NJE* is the number of equivalent days. Since 2000, the Absolute Percentage Errors (APE) observed for the yearly peak load forecasting is being greater than 3% and reaches 6% in 2004. This result is related to qualitative and quantitative modification on load curve characteristics generated by the greater consumption of the air conditioning observed during last decade. A more complex load forecasting models which take account weather factors are then necessary even for mid-term forecasting.

The outline of the paper is as follows: Section 2, recalls the utility of the weather sensitive component analyzing. A short description of the proposed annual air conditioning share estimation method was also presented. The proposed mid-term load forecasting method is presented in Section 3.

2 Annual air-conditioning share estimation

Isolating electric air-conditioning share from the total aggregated electric consumption is a difficult task. e.g Contaxi (2004), Mirasgedis et al. (2006). We propose to make preprocessing of the daily electric consumption (DE_j) in order to extract the non sensitive

[2]This model is derived from the Model for Analysis of Energy Demand (MAED). The latter, was developed by the International Atomic Energy Agency (IAEA) and adapted to Tunisian electricity consumption context.

electricity load component (holidays and industrial seasonality).
In Tunisia, high sensitivity with climatic changes is observed in the fields of low and average voltage consumptions composed primarily of tourism, residential and administration sectors. Based on this hypothesis, the preprocessed load component is given by:

$$DE_j^* = DE_j - \sum_s \frac{DE_{s,m,j}}{NJE_m^s}. \quad (2)$$

Where, $DE_{s,m,j}$ is the monthly consumption of the sector $s \in \{industry,\ agriculture,\ transport\}$. Note that different numbers of equivalent day NJE_m^s for the m month related to the s sectors are evaluated.[3]

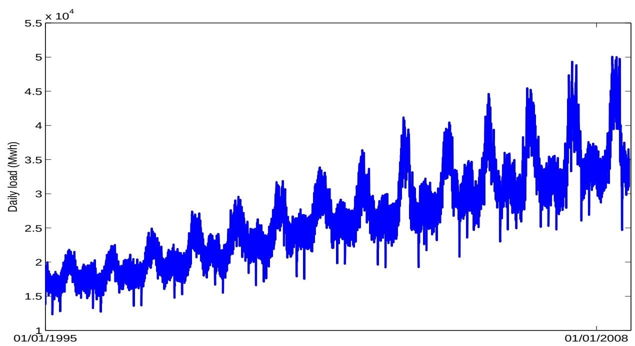
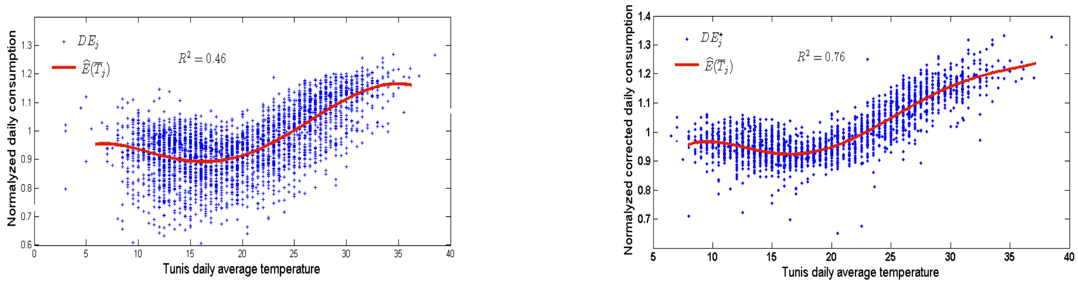


Figure 1: Daily electric load consumption 1995-2008 from STEG utility

The proposed annual air conditioning estimation is based on the analysis of the Tunisian daily corrected consumption DE_j^* with daily temperature indicator T_j elasticity analysis. Preliminary results established from the analysis of a weighted average temperature ($\overline{T} = \frac{\alpha T_{min} + \beta T_{max}}{\alpha+\beta}$) and consumption correlation shows that the more significant daily temperature indicator is obtained for $\alpha = \beta = 1$. In this case, The temperature consumption elasticity is defined as $\frac{d(\widehat{E}(\overline{T}_j))}{d(\overline{T}_j)}$, where $\widehat{E}(\overline{T}_j)$ is the non linear model fitting of the scatter diagram of the daily consumption DE_j^* versus average temperature $\overline{T}_j$ (see Fig.2).

Generally, electric time series have known seasonal components (weekly, monthly). In addition, The Tunisian electric daily load consumption, recorded during the period 1995 to 2008, shows linear long-term trend component and high increasing asymmetric fluctuations (see $Fig.1$). This means that the growth rates in high and low temperature intervals of cooling and heating needs are not the same which is due to the existence of other heating sources than electricity. We then differentiate the effects of high and low temperature (P_{HT}^a and P_{LT}^a). The annual temperature effects estimation are :

[3] Note that STEG does not has daily sectors electricity consumption (only monthly values are available) which have different sensitivity with the climatic changes, e.g Sailor (2001), Yang et al. (1996), Chico et al. (2005).



(a) (b)

Figure 2: Scatter diagrams: (2.a) Normalized total daily consumption DE_j vs daily average temperature $\overline{T}_j$, (2.b) Normalized corrected daily consumption DE_j^* vs $\overline{T}_j$

$P_{LT}^a = \sum_{min(\overline{T}_j)}^{T_{ref}} \eta_{\overline{T}_j} \times [\widehat{E}^a(\overline{T}_j) - \widehat{E}^a(T_{ref})]$ and $P_{HT}^a = \sum_{T_{ref}}^{\max(\overline{T}_j)} \eta_{\overline{T}_j} \times [\widehat{E}^a(\overline{T}_j) - \widehat{E}^a(T_{ref})]$ for high and low temperature (Fig.3).

Where $\eta_{\overline{T}_j}$ is the number of days where the observed average temperature is equal to $\overline{T}_j$. T_{ref} is the reference temperature derived from the daily Tunisian consumption and daily average temperature elasticity analysis (Fig.2). Note that the reference temperature meaning is close to comfort temperature estimation. The study of the evolution of the normalized temperature consumption share can gives information about the increase on the total equipment rate $\rho_a^{HT} = \frac{P_{HT}^a}{CDD_a}$ and $\rho_a^{LT} = \frac{P_{HT}^a}{HDD_a}$ of heating and cooling devices.

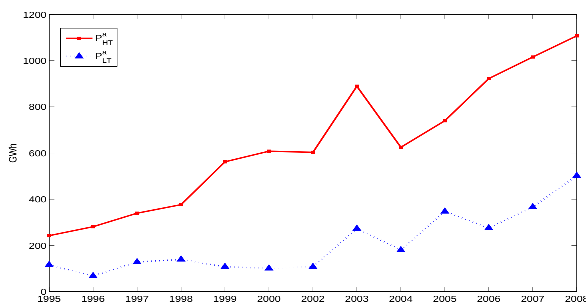


Figure 3: Estimated annual temperature sensitive electricity load components

3 Mid-term load forecasting

Statistical techniques such as regression are broadly used for mid-term load forecasting. These approaches usually require an additive model which decomposes the total load DE at different time scales (eq.3), on base load DE^b (which takes into account trend, day of the week, seasonal monthly component), special event component DE^s (related to calendar), completely random term DE^r and Weather sensitive load DE^w, e.g Mirasgedis et al. (2006), as follows:

$$DE = DE^b + DE^s + DE^w + DE^r \tag{3}$$

where equations of the components are:

$$DE^b + DE^s = c + at + \sum_{i=1}^{6} \alpha_i 1_{\{j=i\}} + \sum_{k=1}^{11} \beta_k 1_{\{m=k\}} + \gamma 1_{\{j=JF\}} + \theta 1_{\{j=J_{RAM}\}} \tag{4}$$

$$DE_j^r = \sum_{j=1}^{2} \alpha_i DE_{j-i}^r + \varepsilon_j \ \ ; \varepsilon_j \text{ is a white noise distributed error.} \tag{5}$$

where c, a are trend coefficients. $\sum_{i=1}^{6} \alpha_i 1_{\{j=i\}}$ and $\sum_{k=1}^{11} \beta_k 1_{\{m=k\}}$ are dummies which represents, respectively, the seasonal weekly and seasonal annual load components. $1_{\{j=JF\}}$ and $1_{\{j=J_{RAM}\}}$ denote the particular consumption structure observed in holidays and Ramadan.

The proposed daily load forecasting method is based on multiple regression modeling which integrates two traditional explanatory variables reflecting temperature effects: the Cooling Degree Days $CDD_j = max(0, (\overline{T}_j - T_{ref})$ and the Heating Degree Days $HDD_j = max(0, (T_{ref} - \overline{T}_j))$, Mirasgedis et al. (2006), Sailor (2001), Contaxi (2004).
The introduction of climatic variables in forecasting models is not trivial for two reasons. The first is that it is difficult to extract nonlinear impact of temperature on load and memory effect characterizing the behavior of the consumers towards the variations of the temperature. The second is connected to the asymmetry of the impact of high and low temperatures: elasticity is different according to the zones of temperature and one observes, also a saturation phenomenon of the consumption with regard to the temperature. This phenomenon is observed in two branches relatives to cooling and heating devices and is due to the exhaustion of the air conditioning park.
A Particular care must be given to the impact of the level of saturation of heating or cooling devices, eg Sailor (2003). As a consequence, we propose to modify the expressions of the CDD_j and HDD_j as follows: $CDD_j^{NL} = CDD_j . \frac{\widehat{E}(\overline{T}_j)}{\widehat{E}(T_{ref})}$ and $HDD_j^{NL} = CDD_j . \frac{\widehat{E}(\overline{T}_j)}{\widehat{E}(T_{ref})}$, which takes into account the nonlinear impact of temperature on load. As results, based on the significatively test we have determined lags of the memory effect.

Moreover, we integrate into the model forecasting of the logarithmic daily consumption $\log(DE_j)$, the annual indicator of the increase usage of cooling and heating devices ρ_a^{HT} and ρ_a^{LT}. We assume the additive expression model given in $eq.1$ for $log(DE_j)$ forecasting model.

$$DE_j^w = \rho_a^{HT} \sum_{i=0}^{2} \sigma_i CDD_{j-i}^{NL} + \rho_a^{LT} \sum_{i=0}^{2} \mu_i HDD_{j-i}^{NL} \tag{6}$$

Then we were able to build a model of mid-term forecasting, by scenarios of daily consumption of electricity based on scenarios of weather evolution.

4 Conclusion

In this paper, equipment rates increasing on cooling and heating devices is analyzed. Through this study of weather-sensitive load estimation, based on consumption temperature sensitivity analysis, a mid-term daily load forecasting is proposed. The method was tested on the daily consumption forecasting for three years and has given accurate interval confidence. These last ones were chosen to allowing the STEG to plan adequately sized generation.

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