LONG-TERM PREDICTIONS OF ELECTRICITY DEMAND: A CHALLENGE FOR COMPUTER ENGINEERING

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NEED AND REPERCUSION OF LONG-TERM PREDICTIONS OF ELECTRICITY DEMAND

Both private companies and public administrations require long-term forecasts of electrical energy demand (EED). Among electric utilities are the carrier and manager of the electrical system, the generation and distribution utilities, and the trading companies; also the fuel supply companies to the generation power plants, and the public administrations responsible for the resource management and land planning, which are in charge of reserving land for placing infrastructures that ensure energy supply to the different activities developed in it. The authors have participated in the Special Territorial Plans of Energy Infrastructure Planning of various islands in the Canary Islands [1-3].

It should be noted that, if the predictions are very low, deficiencies could occur in the power supply, causing inconveniences to different economic sectors, but if they are very high, it could carry a high and unproductive economic investment.

Thermal power plant. Jinámar, Gran Canaria, Canary Islands.

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NEW SCENES

New factors will increasingly influence EED predictions such as overall energy efficiency, self-consumption with the integration of renewable energy in buildings, use of airsource heat pumps, and the introduction of electric vehicles; also social changes such as family type, age of population and number of persons per dwelling, factors that condition the per capita consumption. Climate change and the introduction of smart meters will affect consumption, among other issues, changing social sensitivity. Predict the future evolution of EED will become increasingly complex.

COMPUTER ENGINEERING TO FIND BETTER PREDICTIONS

Various methods of computer engineering (including artificial intelligence, heuristic search, and operations research methods) have been used in order to obtain EED predictions [4-8]. Due to the observation of significant fluctuations of GDP and CPI in the period of the current economic and financial crisis, and searching for better predictions, the results of EED predictions obtained by incorporating the CPI as a new explanatory variable are analyzed in [9].

CASE OF STUDY

An EED adjustment in the Canary Islands is carried out in [9] from historical data of electric energy consumption and population (Instituto Canario de Estadística, ISTAC, http://www.gobiernodecanarias.org/istac/), and GDP and CPI in the Canary Islands (Instituto Nacional de Estadística, INE, http://www.ine.es). Fig. 1 shows a marked linearity of the historical data of electric energy consumption versus GDP until 2007. This trend breaks from 2008.

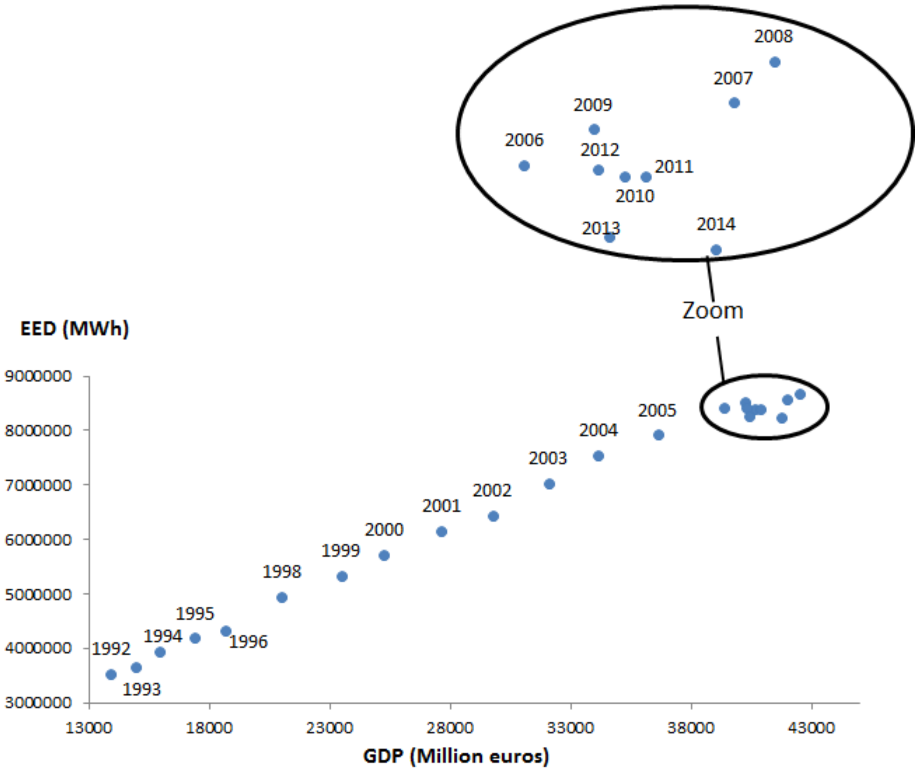

Fig. 1. EED versus GDP (data of the Canary Islands, 1991-2014)

The predictive power of different methods is evaluated in [9]: Multiple Logarithmic and Linear Regression (MLogR and MLR), Support Vector Machines (SVM), Genetic Algorithm (GA), and Artificial Neural Network (ANN); reserving some years to test the fits. These testing years were randomly chosen, but forcing at least one of them was a year of the current economic and financial crisis, and including the last available datum. A comparison of the efficiency

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of the different methods considered is also presented, evaluating the mean absolute percentage error (MAPE) for the test years 1992, 2001, 2004, 2009 and 2014, and for both cases, including CPI variable or not.

Here a method of Differential Evolution (DE) is incorporated. This method was chosen for its proven effectiveness in resolving various complex test cases [10]. The parameters involved in all methods considered were adjusted in order to achieve the best fit (see Table I). The DE method adjusted the same nonlinear exponential function that the GA [9], and the best results were obtained with a variable mutation parameter (*F*):

$$F(n) = F_{ini} - \frac{(F_{ini} - F_{fin})}{1 + e^{2\ln(S) - \frac{4}{N_{max}} n \ln(S)}} \qquad (1)$$

where n is the number of iterations, F_{ini} and F_{fin} are the values of the ordinates of the horizontal asymptotes of the function $F(n)$, N_{max} is the maximum number of iterations, and S is a form factor.

	MAPE % (testing years)	
Method	Population, GDP and CPI	Population and GDP
MLR	3.41	3.04
MLogR	2.46	1.66
SVM (Linear)	3.63 (C=3)	3.42 (C=30)
SVM (Gaussian)	2.09 (C=10, σ=0.05)	2.38 (C=5, σ=0.5)
DE	1.76 (CR=0.4, F_{ini}=0.7 ,F_{fin}=0.1, S=100)	2.51 (CR=0.1, F_{ini}=0.7, F_{fin}=0.1, S=10)
GA	1.71	2,77
ANN	1.22	1.58

Table I. Error of the different methods for the cases of including or not the CPI variable.

Fig. 2 shows the best fit obtained, which corresponds to the use of ANN.

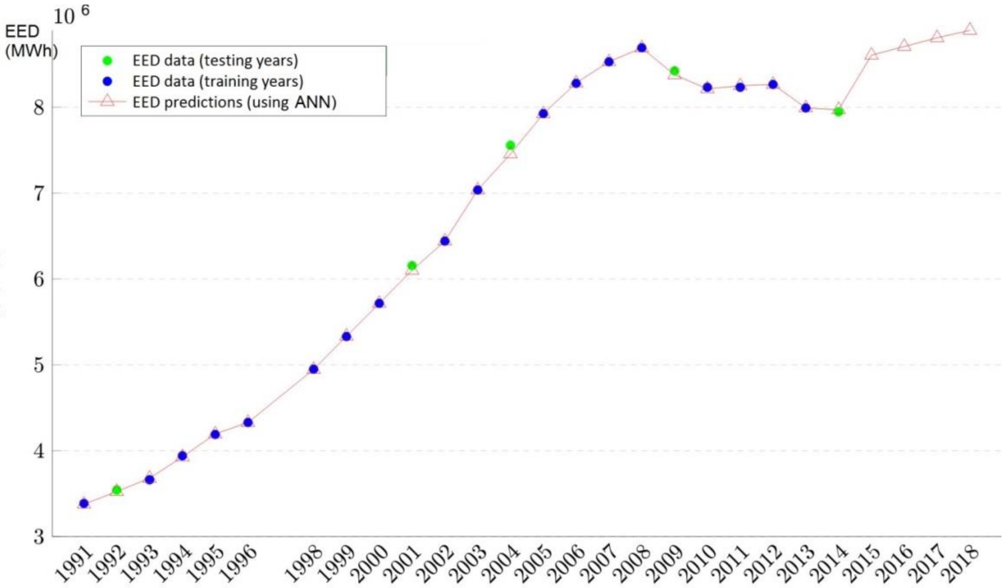

Fig. 2. Actual data (testing and training years) and EED predictions using ANN (Canary Islands, 1991-2014)

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CONCLUSIONS

In the case of study considered, the incorporation of variable CPI improved the predictions obtained with all nonlinear methods (as shown in Table I), and contributed to get the best result of DEE prediction. Energy efficiency, self-consumption, the use of airsource heat pumps, the introduction of electric vehicles are, among others, new factors which leads to need new explanatory variables in forecasting electrical energy demand. In the context of the emerging new scenes, the design of new methods for predicting the EED, which are efficient in dealing with the level of uncertainties that exist in the time evolution of these new variables, is a challenge for computer engineering.

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