The Eleventh International Conference on
Engineering Computational Technology
23–25 August, 2022 | Montpellier, France

Proceedings of the Eleventh International Conference on
Engineering Computational Technology
Edited by B.H.V. Topping and P. Iványi
Civil-Comp Conferences, Volume 2, Paper 17.1
Civil-Comp Press, Edinburgh, United Kingdom, 2022, doi: 10.4203/ccc.2.17.1

Application of metaheuristics methods for prediction of electrical energy demand in peninsular Spain

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Abstract

In this paper, a year-ahead electrical energy demand prediction has been performed for the Peninsular region of Spain. Data for electrical energy demand and three other demographic and economic parameters were obtained from the historical records (1990-2021) of Red Eléctrica de Espana (Madrid). For the prediction of future energy demand, metaheuristic algorithms were proposed which utilize data from previous years to predict the electrical energy demand for the coming year. Particularly, the ensemble of Grammatical Evolution (GE) and Differential Evolution (DE) algorithms were used, where GE develops the model form for the equation while DE optimizes the coefficient of the model. Three cases were then studied under the present work where the data from one previous year, three previous years, and five previous years (resulting in three, nine, and fifteen inputs respectively) were used to train the algorithms. For each case, the data were bifurcated into training and test datasets. The accuracy of the algorithmic methods was realized in terms of the objective function (Root Mean Square Error, RMSE). Further, the predicted electrical energy demand

and actual data were also compared with the help of RMSE and other statistical errors. It was found that the least value of RMSE=3.4052 resulted in Case 2 where the inputs for three previous years were used. Further, it was concluded that the ensemble of GE-DE can effectively be used to produce highly accurate electrical energy demand predictions.

Keywords: electrical energy, demand prediction, metaheuristic algorithms, error analysis, Spain.

1 Introduction

The growth of population and economy has led to a major increase in electrical energy demand across the globe [1]. Electrical demand particularly in Spain has been ever-growing and is observed to be much higher between 2008-2015 [2]. Electrical energy demand forecasting is an important problem for the management of power supply and optimizing grid use. As stated by Yu et al. [3], an overestimation of electrical demand can lead to a rush for energy purchase, while an underestimation would lead to a risk in regional loads management.

Therefore, it has become quite essential to find effective ways of forecasting electrical loads [4]. Several forms of models have been proposed including regression/statistical models, time-series, data mining and space methods, etc. Recently, the use of AI techniques, Machine and Deep Learning, and Hybrid models have achieved remarkable progress [5,6]. The main factors that affect the electrical energy demand are deemed to be the economic and demographic variables, such as Gross Domestic Product per capita, consumption, and population.[7]

The main objective here is to analyze the electricity demand data obtained from Red Eléctrica de Espana, (REE, Madrid) for the Peninsular region of Spain in terms of Number of Households, Stock Capital (€), and PIB/capita. The idea here is to apply an effective metaheuristics algorithm to predict a year-ahead energy demand using the data of input variables from previous years. For this, a unique ensemble of Grammatical Evolution (GE) and Differential Evolution (DE) has been employed. Further, we analyze the effect of using even earlier years in training the algorithms. Three particular cases have been studied where the year-ahead electrical energy demand can be predicted using data from (i) a single previous year (ii) three previous years, and (iii) five previous years. The accuracy of these predictions is analyzed in terms of the statistical errors.

2 Methods

2.1 Data

Data for electrical demand was obtained from REE (Madrid) for the Peninsular region of Spain from 1990 to 2021 along with the data for three input variables.
In general, the equation representing the demand prediction for the current year based on the data from up to five previous years is written as:

$$D(t) = f\begin{pmatrix} X1_{(t-1)}, X2_{(t-1)}, X3_{(t-1)}, X1_{(t-2)}, X2_{(t-2)}, X3_{(t-2)}, X1_{(t-3)}, X2_{(t-3)}, X3_{(t-3)}, \\ X1_{(t-4)}, X2_{(t-4)}, X3_{(t-4)}, X1_{(t-5)}, X2_{(t-5)}, X3_{(t-5)} \end{pmatrix} \quad (1)$$

where,
D(t): Electrical demand (current year),
X1: Number of Houses,
X2: Stock Capital (in euros), and
X3: PIB per capita.

With the current approach, we now have three cases where the first case has data from *one previous year* (or 3 inputs), the second case has *three previous years* (or 9 inputs), and finally, the third case has data from *five previous years* (or 15 inputs). Each data was normalized with a respective maximum value of that variable and the data was bifurcated into training and test datasets.

2.2 Development of Metaheuristics Methods

Electrical demand prediction can be described as an optimization problem that can be tackled with the help of metaheuristic algorithms to minimize the error. Currently, an *ensemble of two metaheuristic algorithms* i.e. Grammatical Evolution (GE) and Differential Evolution (DE) has been utilized to solve the Electrical Demand prediction problem [8]. The advantage of using GE is its ability to guide the search of an algorithm using grammar [9]. While, DE, represents a metaheuristic algorithm better suited for problems where some parameter values need to be found [10].

3 Results

The three cases show good agreement between the prediction and actual values. Error analysis carried out in terms of the objective function and the other four statistical errors has been shown in Table 1. It can be observed that Case 2 has the minimum RMSE = 0. 0145 on the test dataset followed by Case 3 with an RMSE of 0.0178 and lastly Case 1 with an RMSE of 0.0306.

Case	Case 1		Case 2		Case 3	
Error	*Training*	*Test*	*Training*	*Test*	*Training*	*Test*
RMSE	0.0210	0.0306	0.0111	*0.0145*	0.0107	0.0178
Average Error	-0.0001	-0.0018	0.0001	-0.0055	-0.0001	-0.0032
R^2	0.9917	0.9842	0.9972	0.9962	0.9966	0.9911
Absolute Error	0.0178	0.0192	0.0095	0.0112	0.0084	0.0125
Relative Error	0.0231	0.0252	0.0114	0.0129	0.0095	0.0146

Table 1: Performance of algorithms on normalized datasets under different cases.

Figures 1(a)-(f) represent the prediction results (normalized electrical demand) for the three cases under study. For each case, the performance of algorithms has been demonstrated separately on training as well as test dataset.

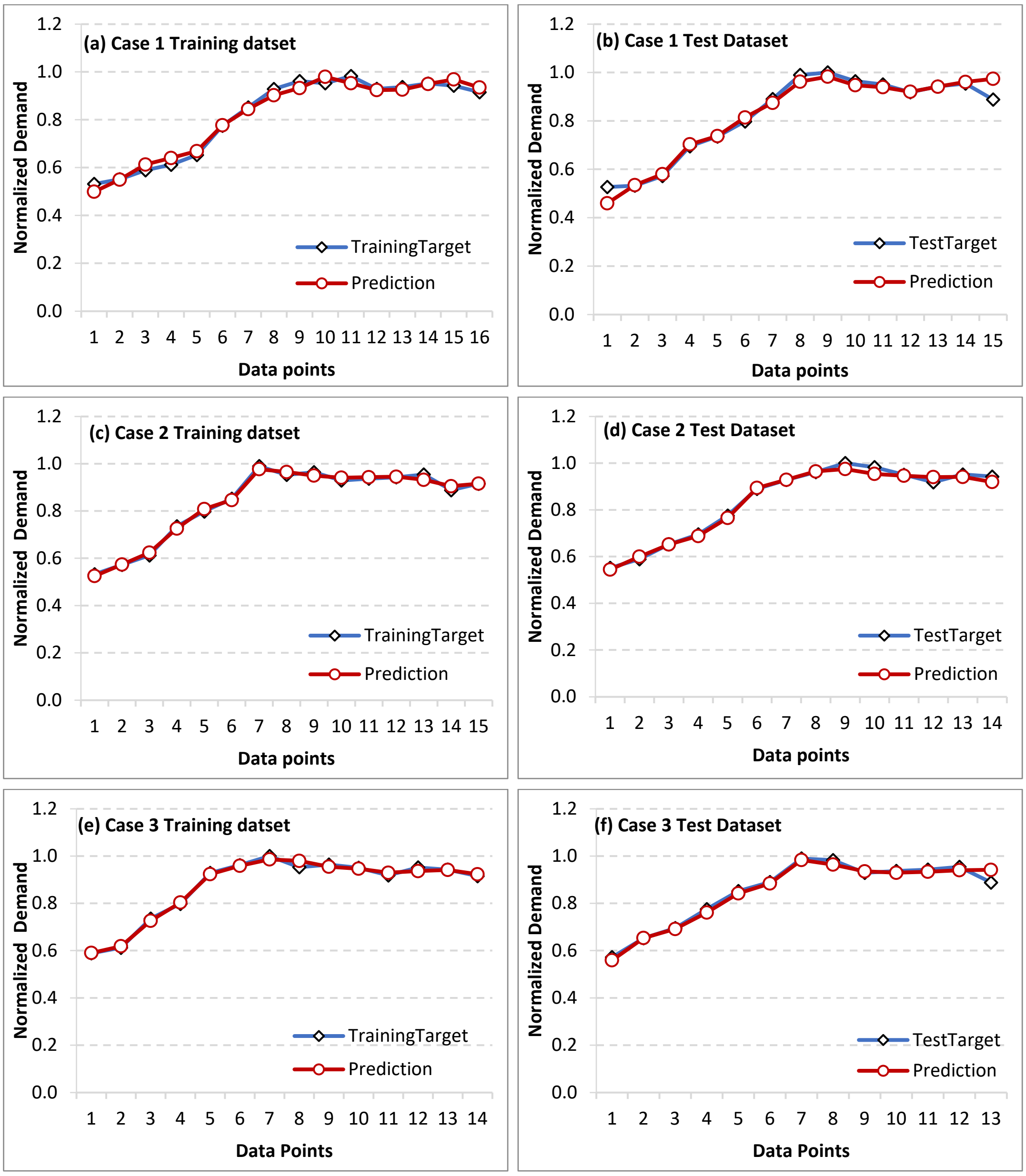

Figure 1: Predicted electrical demand (normalized) for the three cases.

This confirms that including the data from the last three years to predict the electrical energy demand for the coming year has the least error.

Further, the total values of predicted electrical energy demand are calculated for the three cases as shown in Fig. 2 (a)-(c). It is observed that the predicted values of electrical energy demand are quite close to the actual data and thus the algorithms work well.

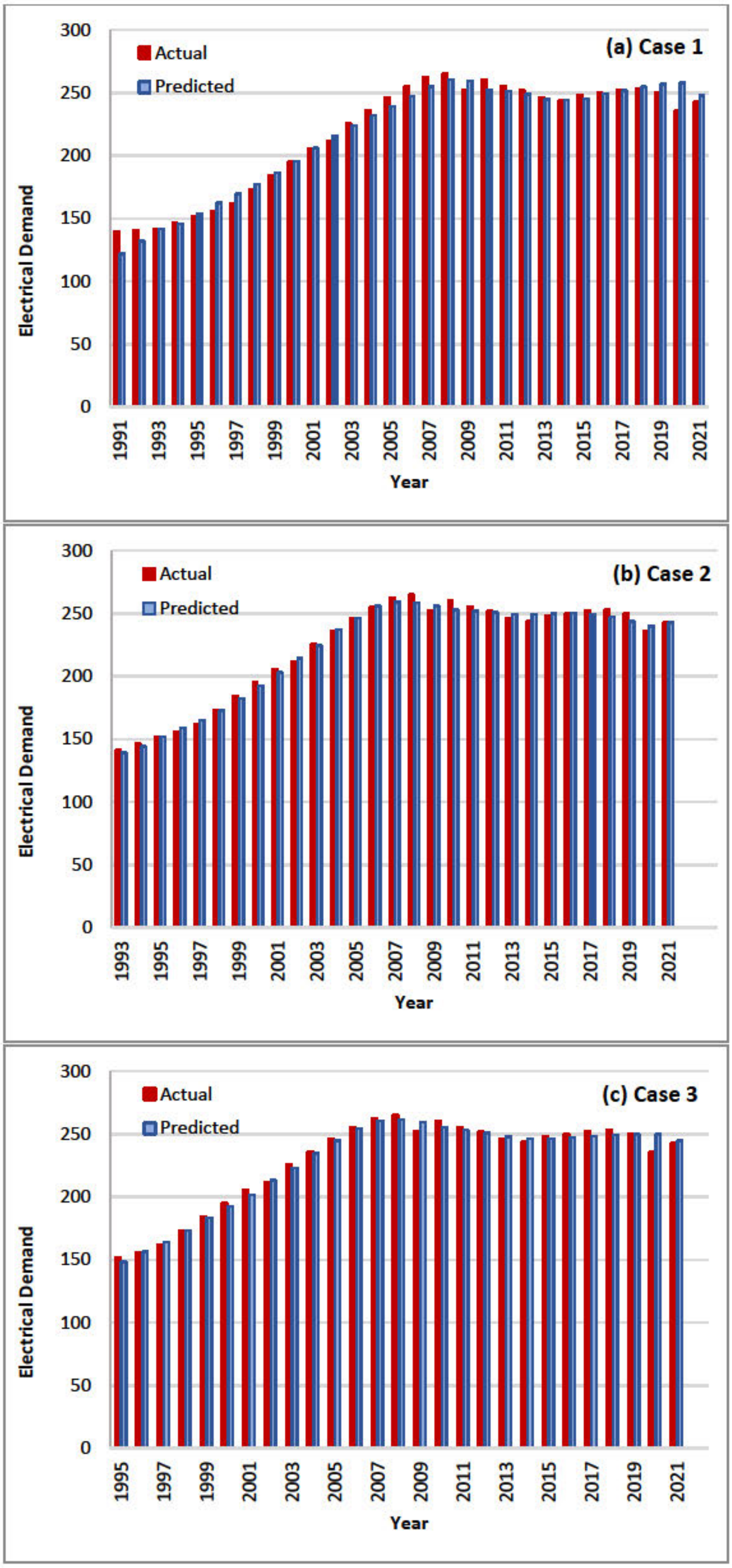

Figure 2: Actual and predicted electrical demand for the three cases.

Table 2 represents the values of the objective function (RMSE) together with other errors for the different cases under study.

Error	Case 1	Case 2	Case 3
RMSE	6.9198	*3.4052*	3.9299
Average Error	*-0.2454*	-0.6937	-0.3757
R^2	0.9875	*0.9965*	0.9938
Absolute Error	4.9006	*2.7375*	2.7942
Relative Error	0.0241	*0.0121*	0.0121

Table 2: Performance of algorithms under different cases for electrical energy demand prediction.

It is observed that RMSE is the lowest for Case 2, while R^2, absolute error, and relative error are also the minimum for Case 2. However, the average error is lowest for Case 1. Since the judgment mainly relies based on the objective function (RMSE), it is deemed that Case 2 has the best performance.

Finally, Fig. 3 shows the evolution of electrical energy demand for the best case and indicates the range of prediction based on the *runs* of the algorithm. It is observed that the span of prediction for each data point is small and thus the uncertainty in predictions is very low with an overall relative error of 1.21%.

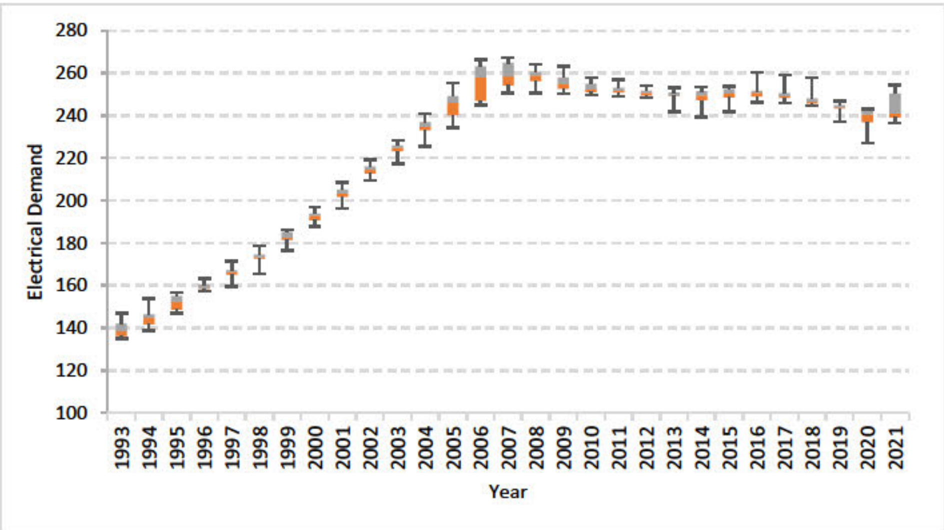

Figure 3: Electrical demand evolution for the best case.

4 Conclusions and Contributions

The following conclusions are drawn:

a) The ensemble of GE-DE can be effectively utilized to forecast the electrical demand based on the selected input variables.
b) Among the cases considered, Case 2 most accurately predicted the year-ahead electrical demand i.e. the case with input data from *three* previous years.

c) Further, the algorithms can be trained to predict more years-ahead for medium to long terms demand prediction.

The main contribution of this research approach is the use of an ensemble of two metaheuristic algorithms GE produces flexible models based on the type of algorithm used and DE optimizes the coefficients of the model equation, which resulted in a highly accurate electrical demand prediction with error as low as 1.21%.

Acknowledgments

The work reported under the manuscript has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 754382. The authors would like to thank Prof. Abraham Duarte and Dr. José Manuel Colmenar for extending their support towards the research work.

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