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Multi-Objective Optimization for Electrical Demand Forecasting

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Abstract

Electrical load forecasting is a key component of energy management system, playing a critical role in power scheduling, peak reduction, and power system management. The accuracy of the load forecast has a significant effect on the efficiency of energy management systems in terms of making optimal control decisions. In this paper, our contribution is the proposal of a Multi-Objective Optimization approach to improve the accuracy of an Artificial Neural Network-based electricity demand forecasting model.

Keywords: Multi-Objective Optimization, Artificial Neural Network, NSGA II, TOPSIS, Electrical Demand Forecasting

1 Introduction

Load forecasting is defined as the prediction of electrical power over a pre-defined period. In terms of the time horizon, the prediction of the energy consumption can be classified as Long-, Medium and Short-Term Load Forecast (STLF) [1]. STLF considers predictions ranging from a few minutes to a few hours, Medium-Term Load Forecast (MTLF) deals with forecasting load from weeks to several months, while Long-Term Load Forecast (LTLF) is used for load forecast over one year. In terms of practical application, STLFs are crucial for daily operations of the energy plants, evaluation of net interchange, unit commitment, scheduling and other system security analysis. Usually, MTLF is

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used for fuel scheduling, maintenance planning etc. LTLF is used for effective management of grid and expansion planning, future investments and revenue analysis. In terms of methodology, electrical load forecasting techniques can be divided into two broadly defined categories parametric or non-parametric models. Parametric models consist of time series and dynamic programming methods, while non-parametric models comprise artificial intelligence methods such as Artificial Neural Networks (ANN) [2][3], which have recently been receiving a lot of attention in the literature. Among the advantages that make them so popular is their ability to provide better accuracy in highly nonlinear problems and complex relationships. The main difficulty in using ANNs is parameter tuning necessary during the training stage, which significantly affects the power of generalization of the model to new data, because there is no definite and explicit method for selecting optimal parameters for the ANN [4]. Optimizing these parameters is an important prerequisite to enhancing forecasting performance. This paper is organized as follows: An introduction of ANN method is presented in Section 2. Section 3 and 4 deal with the problem formulation and the ANN-based multi-objective optimization methodology. Then, Section 5 presents further discussion and prospects of the study. The last section concludes the paper.

2 Artificial Neural Network

The ANN is a mathematical model inspired by biological neural networks. Like the human brain, the ANN contains a set of artificial neurons spread over three or more layers with many connections between them, this interconnection being called weights. The transition from one layer to another is done by a calculation of a weighted sum of inputs and the result is used as the argument of the nonlinear function f called activation function. Equation 1 summarizes this mathematical formulation.

$$y_j = f_a\left(\sum_{i=1}^n e_i W_{i,j} - b_j\right) \quad (1)$$

Where n is the number of inputs, f_a is the activation function, e_i is the i^{th} input, y_j is the output at iteration j , $W_{i,j}$ is the weights vector and b_j is the bias.

The first step in designing an ANN-based forecasting model is to select an appropriate architecture. Generally, the ANN model is built based on a Multi-layer Perceptron (MLP) [1], which is a feed-forward type of ANN. The MLP architecture is characterized by a multi layers structure with an input and an output layer, as well as one or more hidden layers. In our preceding our study [5], we proceeded to define an adequate architecture of the ANN giving a best forecasting performance by acting to two parameters: number of layers and the number of neurons per layer. The MLP used has three layers: The first one is the input layer consisting of the number of neurons depending

on the number of inputs variables. The optimal inputs data was selected by considering the most influential parameters of the power consumption pattern. The second one is the hidden layer. The choice of one hidden layer is based on various research studies [6] which show that just one hidden layer is adequate to forecast electrical demand whereas the number of neurons in the hidden layer can be chosen according to the case study. The selection of the number of neurons was determined based on a parametric approach [5]. The last layer is the output corresponding to the consumption forecast one hour ahead. In order to improve the performance of the ANN, the MLP structure must be driven by optimal parameters. In this context, special attention is given in this work to the use of an MOO based approach to improve the accuracy of the electricity demand forecasting model.

3 Problem Formulation

The generalization performance of a neural network is defined by its ability to learn from a data set while minimizing the influence of noise once tested on new data presented to network. This performance can be measured by the the error value of the validation set compared to the training set. This suggests that the fit of the neurons to the data can be controlled by achieving a good trade-off between the error and the norm of the weight vectors. In fact, three objective functions are considered in this paper to optimize the ANN architecture : (1) sum of squared errors, (2) norm of the weights vector and, (3) number of hidden neurons . The three objectives functions are described by Equations 2, 3 and 4.

$$f_1(w) = \frac{1}{N} \sum_{j=1}^N (d_j - y_j)^2 \quad (2)$$

$$f_2(w) = \|W\| \quad (3)$$

$$f_3(w) = \text{Min}(N_h) \quad (4)$$

Where, W is the ANN weights norm vector, N is the training set size, N_h is the number of hidden neurons, d_j and y_j are respectively desired and current outputs at iteration j . For ANN forecasting evaluation, Mean Absolute Percentage Error (MAPE) metric is used. MAPE is defined in Equation 5:

$$MAPE\% = \frac{1}{N} \sum_{j=1}^N \left| \frac{d_j - y_j}{d_j} \right| \times 100 \quad (5)$$

4 Proposed Method

In order to find optimum values of the problem defined in section 3 a MOO evolutionary algorithm is used. The first step consists of generation of Pareto

front by NSGA-II algorithm [7]. The advantage of this algorithm is the assignment of fitness according to non-dominated sets. Then, for the second stage a Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [8] is employed to find the best solution with a good trade-off. The proposed approach is represented on the Figure 1.

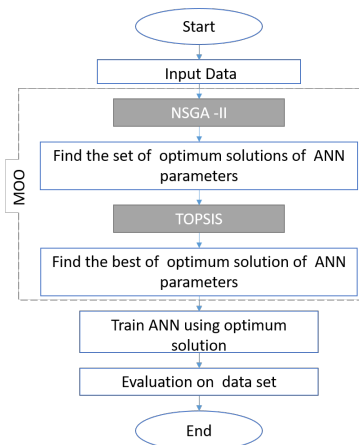


Fig. 1 Flowchart of the proposed methodology.

5 Discussion and Prospects

The dataset used in this study (collected at the French transmission system operator RTE) contains historical energy demanded from the year 2017. The dataset data from May 1st to July 23rd 2017, was used to train the network, while data from 24th to 30th July 2017 was used for the validation process.

The ANN model used in our tests is composed by a three layers perception feed forward neural network. The first layer receives as inputs:

- Days of the week encoded as (current day = 1), otherwise (0).
- Time of the day expressed in hours.
- Meteorological parameters: temperature, humidity, wind speed and radiation.
- Historical data : $P_t, P_{(t-1h)}, P_{(t-2h)}, P_{(t-22h)}, P_{(t-23h)}$.

The second layer is the hidden layer composed of 20 neurons. The last layer is the output corresponding to the consumption forecast one hour ahead $P_{(t+1h)}$.

Figure 2 display the power consumption pattern using the ANN model. It shows both the real power demand and the predicted one. The comparison of both load curves reveals a good match between the current and predicted power consumption with a satisfactory detection of the peak load periods. The

quality of the forecasting process is evaluated in Figure 3 where the MAPE has been calculated for the whole week.

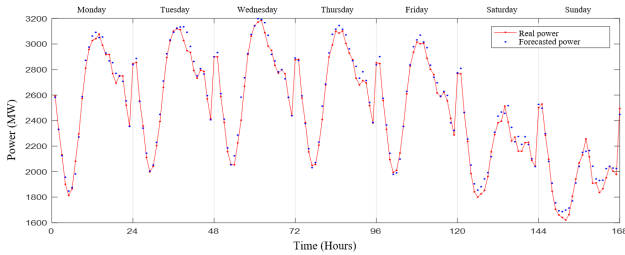


Fig. 2 Load forecasting on week using ANN.

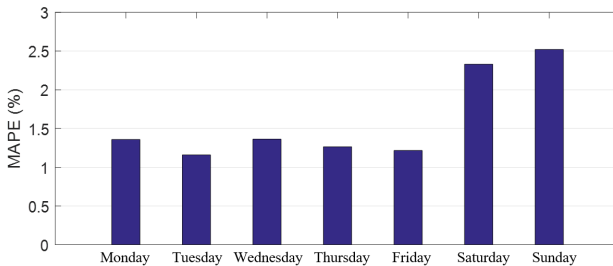


Fig. 3 Evaluation metric using MAPE.

6 Conclusion

This paper proposes an approach to electric load forecasting using MOO algorithm applied to ANN parameters optimization. First, the MOO algorithm is used to find a set of optimal solutions for the ANN parameters, then a TOPSIS-based approach is used to select the optimized solution. Based on a comparative study, our conclusions on the benefits of the MOO approach to the forecasting performance will be presented in the full paper, in order to illustrate the advantages of MOO for ANN architecture optimization over a conventional approach based on manual tuning.

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