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CHAPTER 1

INTRODUCTION

This chapter covers the introduction, background and the motivation to develop NNs ensemble. It also illustrates the aims and objectives to be accomplished during this work and proposed method. Finally the chapter concludes with the organization of the thesis.

1.1 Introduction

Power load forecasting is of great importance in planning and managing the resources of power systems. The utilization of load forecasting is to guarantee that unexpected demands are taken care of. System operators also make it assure to match the demands to the appropriate system's resources that the generators provide in order to sustain the balance. It is vital that load forecasting be reliable so that operational plans can be developed for power stations and generators, as well as for the implementation of better plant scheduling. In general, power load forecasting may be long-term, medium-term or short-term. Long-term load forecasts (one month to several years ahead) are needed for capacity planning and maintenance [1]. Medium-term load forecasts (one week to several months ahead) are required for power system maintenance operation and scheduling of fuel supplies [2]. A short-term load forecast (one hour to one week ahead) is required for unit commitment and to provide a method of energy transfer scheduling and load dispatch which has an increased efficiency as well as more security [3]. Development of an accurate, fast and reliable short-term load forecasting model is needed to address supply and demand fluctuations and to maximize the short-term system's operation performance. Besides, several other managerial tasks can be arranged based on forecasts.

Numerous investigations have been proposed during the last few decades to improve the accuracy of power load forecasting. These techniques symbolize the journey that begins with the rather basic more common techniques up to the more complex forms found in the present times. The conventional methods commonly use various regression models [4], Box-Jenkins time series models [5], the Bayesian estimation model [6] and the state space and Kalman filtering approach [7]. These methods fail to produce accurate load forecasts due to their theoretical and practical limitations in terms of computational effort, amount of historical data required and identification capacity [8]. Weather (wind, humidity, and temperature) and calendar (day of the week, month of the year, season, and holiday) information are relevant independent variables that are used for building regression models. It is well known that these factors affect the system's load. It is already known that multivariate modeling is practically unreliable [1] for short-term load forecasting. Moreover, the linear regression models can not generate acceptable forecasts as the electric loads are known to be nonlinear [9]. An

accurate and thorough evaluation of these models has been reported in [1] for short-term load forecasts.

In the last decade, reports have been made for load forecasts regarding techniques of computational intelligence like fuzzy systems, neural networks (NNs) and evolutionary algorithms. A comprehensive survey of these techniques for short-term load forecasting can be found in [10]. An expert system using a fuzzy set approach is used to imbed heuristic rules in the knowledge base for short-term load forecasting [11]. Applications of NNs [12], [13], fuzzy logic system [14], neuro-fuzzy [15], and support vector machines [9] have increased quickly for load forecasting. Techniques for quantification of uncertainties associated with forecasts have also been proposed in recent years [16], [17]. Amongst artificial intelligence methods, NNs have gained huge popularity in the last two decades [18].

NN techniques have the ability to learn and construct a flexible non-linear input-output mapping. However, the training procedure in an expert system approach uses a lot of time and for NN models, a significant disadvantage is over-fitting. NN shows perfect performance for training data but much poorer performance for future data prediction (not a good generalization power) [19]. There is no need for NN models to adopt completely a particular functional relationship between forecasted load and historical data. This is because the training process allows NN to learn the functional relationship between the outputs and inputs of the particular network. However, minor adjustment in the training set and/or choice of parameters result in enormous differences in the predicted output of NNs. The supposed diversity of NNs is the consequence of inherent non-identifiability of the model. Moreover, the performance of the NN models is not good with scarce data or data having random errors [?].

It is practically possible to combine forecasts generated by different techniques to achieve more accurate results. There is a rich literature about combinations of forecasts, where it is often claimed that combined forecasts are more accurate than individual forecasts. After the pioneering work on forecast combinations [20], they have been extensively adopted by many researchers with different techniques. The NN field has also enjoyed the taste of forecast combinations. Ensemble modeling [21] and thick modeling [22] are two other parallel techniques applied to NNs to improve the forecasting performance.

This paper proposes and implements a simple yet powerful method for generating accurate combined forecasts. The key idea is that the generalization power for combined models is much better than the generalization power of individual NN models. The best models for combination of forecasts are selected based on their performance for a validation set, where an error-based performance measure is used to rank trained NN models. NN models are diversified through their random initialization in the training stage and changing their structure (number of neurons per layer). The diversification is applied with the purpose of maximizing the generalization power of combined forecasts. Performance of the proposed method is examined for a daily load forecasting problem in a real world energy.

1.2 Proposed Method

NNs are universal approximators with excellent learning capabilities. It is proven that they can approximate any nonlinear relationship to any arbitrary degree of accuracy.

Among various NNs types, feed-forward NNs are preferred for the complex task of classification and regression [23]. This class of NNs consists mainly of three sets of neuron layers, namely, the input layer, hidden layer(s), and an output layer. Such a fully connected network is trained in a supervised manner through minimization of an error-based cost function such as mean squared error (MSE). In this section, we propose a practically efficient and effective algorithm for enhancing the generalization power of a group of NNs used for in forecasting problems.

1.2.1 Data split

The set of samples are divided into three subsets: training (D_{train}), validation (D_{vald}), and test (D_{test}) sets. D_{train} and D_{vald} are used in the training stage of NN models and selecting their best performing ones. The (D_{test}) is used for the examination of performance of the proposed method for generating combined forecasts.

1.2.2 NN initialization and parameter selection

Consider that n_{total} and n_{Best} indicate the number of NN models used in analysis and the number of best performing NN models, respectively. n_{total} NN models with a different number of neurons in their hidden layer are generated in this stage. Parameters of these NN models are randomly initialized. All these are done to maximize the diversification of NN models used for forecasting task.

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