

Abstract

Time series forecasting has obtained significant academic and industrial interests nowadays, which finds its significance in various application fields, including power system related applications (electric load, wind power and solar irradiance forecasting, etc.), as well as financial market related applications (stock price, exchange rate and electricity price forecasting, etc.). Many statistics based machine learning models have been proposed to obtain accurate results for time series forecasting up to present. The methods can be divided into two categories: linear models (such as auto-regressive moving average) and non-linear models (such as artificial neural network and support vector machine). However, due to the highly nonlinear characteristics of real world time series signals which caused by various influencing factors, it is very difficult to ensure the performance of machine learning models. Deep learning and ensemble methods are possible solutions to this problem.

This thesis mainly focuses on the state-of-the-art ensemble learning methods and deep learning models for both power system and financial market related time series forecasting. The development of time series forecasting is introduced, and a brief review of existing algorithms is also given. Motivated by the attractive advantages of ensemble learning, two deep learning based ensemble methods are presented: (i) ensemble method composed of deep belief networks and support vector machines, (ii) empirical mode decomposition (EMD) based ensemble deep learning model. The performance of the proposed methods is evaluated by real world time series datasets. On the other hand, the ensemble methods based on fast learning models are also investigated in this thesis, such as decision tree ensembles and random vector functional link (RVFL) neural network based ensemble models. Specifically, a novel decomposition method composed of discrete wavelet transform and EMD is combined with incremental RVFL for electric load forecasting. Finally, the advantages and potential future developments of deep learning and ensemble methods are discussed.