Chapter 10

Hybrid Particle Swarm Optimization With Genetic Algorithm to Train Artificial Neural Networks for Short-Term Load Forecasting

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ABSTRACT

This research proposes a new training algorithm for artificial neural networks (ANNs) to improve the short-term load forecasting (STLF) performance. The proposed algorithm overcomes the so-called training issue in ANNs, where it traps in local minima, by applying genetic algorithm operations in particle swarm optimization when it converges to local minima. The training ability of the hybridized training algorithm is evaluated using load data gathered by Electricity Generating Authority of Thailand. The ANN is trained using the new training algorithm with one-year data to forecast equal 48 periods of each day in 2013. During the testing phase, a mean absolute percentage error (MAPE) is used to evaluate performance of the hybridized training algorithm and compare them with MAPEs from Backpropagation, GA, and PSO. Yearly average MAPE and the average MAPEs for weekdays, Mondays, weekends, Holidays, and Bridging holidays show that PSO+GA algorithm outperforms other training algorithms for STLF.

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INTRODUCTION

STLF is vital for many utility activities: security analysis, fuel purchasing, generator scheduling, and maintenance scheduling (Rana & Koprinska, 2016). Forecasting errors can negatively affect the monetary savings regardless of whether its positive or negative. Over forecasting causes producing or purchasing extra electricity. Under forecasting causes revenue reduction by not having of enough electricity to cover the customer demand (Ismail, Yahya, & Mahpol, 2009). However, STLF is difficult due to the nonlinear behavior of the load consumption. Load consumption depends on many factors such as weather conditions, human behavior, and commercial and social activities (Singh & Singh, 2001). Therefore, contemplating the significance and the difficulty of STLF, a number of Artificial Intelligence (AI) and statistical based techniques have been suggested by researchers (Hassan, Khosravi, & Jaafar, 2015). Even though, statistical based forecasting techniques such as Regression Analysis (Dudek, 2016) and Stochastic Time Series (Clements, Hurn, & Li, 2016) abound in STLF, these are good at forecasting linear time series. Since electricity load consumption is highly nonlinear, AI based forecasting techniques such as Deep Learning (Coelho et al., 2016; Dedinec, Filiposka, Dedinec, & Kocarev, 2016; Qiu, Ren, Suganthan, & Amaratunga, 2017), Fuzzy Logic (Hassan, Khosravi, Jaafar, & Khanesar, 2016), machine learning based models (Jurado, Nebot, Mugica, & Avellana, 2015), and Artificial Neural Networks (ANNs) (Chae, Horesh, Hwang, & Lee, 2016; Ding, Benoit, Foggia, Bésanger, & Wurtz, 2016) are better for STLF.

ANN is introduced to STLF as a pattern matching technique. Recognizing and learning nonlinear patterns in data and adjusting its weights based on them to work with unseen data is the principal operation of ANN. Due to its continues accuracy for STLF, use of ANN is ample in the field. However, forecasting capabilities of ANN have been proved by comparing it with other forecasting techniques: Gajowniczek and Ząbkowski (Gajowniczek & Ząbkowski, 2014) use Multi-Layer Perceptron (MLP) and Support Vector Machines (SVM) in their research for electricity forecasting and show that MLP performs better compared to SVM. ANN and Box-Jenkins methods for electricity forecasting are compared by (Ramakrishna, Boiroju, & Reddy, 2011). Results of their research show that ANN performs better in electricity demand forecasting than Box-Jenkins method. Ringwood et et., (Ringwood, Bofelli, & Murray, 2001) also use ANN for forecasting Irish electricity demand. They find that ANN is better for forecasting all three time horizons: Short-Term Load Forecasting (STLF) for next hour to one week, Medium-Term Load Forecasting (MTLF) for one week to one month, and Long-Term Load Forecasting (LTLF) for one months to several years.

However, ANN has some limitations and continues monitoring is required to minimize their effect on forecasting outcomes (Singh & Singh, 2001): ANN takes large computational times as it requires many training cycles to learn the patterns in large datasets, forecasts depend on the random initial values, difficulty of selecting inputs and targets, and determining the number of hidden units (layers and neurons). One of the most highlighted limitations with ANN is, training likely to stops at local minima. The standard training algorithm to adjust the weights and bias of ANNs is Backpropagation (Shayeghi, Shayanfar, & Azimi, 2009). Nevertheless, Backpropagation is a gradient search algorithm and these kind of training algorithms tend to get trapped at local minima (Sarangi, Singh, Swain, Chauhan, & Singh, 2009; Shayeghi et al., 2009) and are sensitive to the random initial parameters (Bashir & El-Hawary, 2007).

To overcome the above limitations, meta-heuristic optimization techniques are used to train ANNs: Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). GA and PSO are population-based global optimization techniques which are used to solve complex nonlinear objective functions (Subbaraj & Rajasekaran, 2008). The ability of training ANNs with GA and PSO for electricity forecasting has

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