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Short term load forecasting using particle swarm optimization neural network

Ozgur Cemal Ozerdem[a]*, Ebenezer O. Olaniyi[b], Oyebade K. Oyedotun[b]

[a]Electrical&Electronics Engineering, European University of Lefke, Gemikonagi-Lefke, via Mersin 10, Turkey

Abstract

Energy is very important in many areas of life. Moreover, humans seem to be almost totally reliant on electrical energy in the last few decades. Although, huge efforts are invested in electronic devices which consume lesser energy or rely on alternative power sources, many emerging devices continue to rely on some sort of electrical power. Energy companies are tasked with supplying sufficient energy to consumers; hence, such companies should be able to project the amount of energy to be made available to consumers at different times. It is undesirable that lesser energy than demanded is supplied at any particular time, as this may lead to system collapse or compulsory shedding of load (some consumers experience power interruption). In this work, we model the problem of short term load forecasting using particle swarm optimized feedforward neural network. The described system is capable of predicting hourly load supplied by an energy company. Also, we investigate modeling load forecasting with conventional feedforward neural network, trained with the back propagation learning algorithm. The results obtained show that the both particle swarm and back propagation optimized feedforward networks are suitable regressors for modeling energy demand. Although, the back propagation optimized networks slightly edge on achieved mean absolute error (MAE) and mean square (MSE), the particle swarm optimized networks boasts of faster convergence. Training is roughly twice fast in particle swarm optimized networks, since error gradients computations are not required for optimization. The database used within this work is obtained from a North Cyprus based energy company.

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Keywords: Load forecasting; energy demand; regression; neural networks; particle swarm optimization.

* Corresponding author:
E-mail address: oozerdem@eul.edu.tr

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1. Introduction

Energy is vital to all living beings on earth. Modern lifestyle has further increased its importance, since population growth and the nearly inevitable haste with which we want things done meant faster and reliable transport, communication, manufacturing processes and 'everything'. It is apparent that all these cannot be separated from sufficient and reliable energy, hence the pace of electrical technology did not disappoint the engineering world.
The challenges that the field of engineeringis faced with over the years in order to introduce sufficient, economic and environmental friendly power generationschemes cannot be overemphasized. It is therefore necessary that energy delivery be optimally achieved. In many situations, energy companies have to supply some required amount of energy to consumers at different times; and of course, energy demand is subject to fluctuations from expected values. Common reasons for this include rapidweather changes, festive periods, holidays, etc.

Generally, energy companies projectenergy demands at various times so that it can be adequatelyinjected into transmission lines, this energy is referred to as the *based load*. Since, energy demand is subject to fluctuations, it is common practice that many energy companies inject little more than is exactly required into transmission lines. In other scenarios, energy companies generate some additional energy in addition to the projected energy demand; this energy (*referred to the as spinning reserve*) is only made available in the advent of unforeseen huge surges in energy demand (Longlong, and Dongmei, 2013; Chen, et al. 2013) . From an economic point of view, energy companies bare the cost of unused spinning reserves, unless in situations where such energy is delivered to consumers as discussed above. Hence, ability of energy companies to forecast loads accurately great impacts on energy economics and therefore business. i.e. with more accuracy in load forecast, tighter constraints can be introduced on power injection into transmission lines and spinning reserves (Jiang, 2015).

This work presents the modelling of short term load forecasting (hourly load) using learning systems. Such complex relationship between expected loads and factors described to affect load forecasting is modelled using neural networks. The factors considered within this work to affect expected hourly loads include time of the day(in hours), day of the week (Monday to Sunday), hourly load of previous week (L_{pw}), hourly load of two weeks back (L_{p2w}), and average of L_{pw} and L_{p2w}, L_{av}.

In this work, we propose the optimization of designed feedforward neural networks using the particle swarm optimization (PSO) algorithm. PSO allows the global optimization of the feedforward networks, since, the entire weights space can be stochastically searched; in contrast to feedforward networks which rely on back propagations of local error gradients and often get stuck in local minima. We investigate both approaches to training the designed networks, and performances are presented in consideration of achieved MeanAbsoluteError (MAE) and Mean Square Error (MSE) and training time.The remaining sections present related works, brief introduction of neural networks and PSO algorithm, training and testing of networks, and conclusion.