

DEPARTMENT OF ELECTRICAL ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Bawana Road, Delhi-110042

CERTIFICATE

I, KISHAN BHUSHAN SAHAY, Roll No. 2K12/PSY/05 student of M. Tech. (POWER SYSTEM), hereby declare that the dissertation/project titled “**Short Term Load & Price Forecasting of Power Market by Using Artificial Intelligence Tools**” under the supervision of Dr. M.M. Tripathi of Electrical Engineering Department, Delhi Technological University in partial fulfillment of the requirement for the award of the degree of Master of Technology has not been submitted elsewhere for the award of any Degree.

Place: Delhi

(KISHAN BHUSHAN SAHAY)

Date: 31.07.2014

DR. M.M. TRIPATHI

(SUPERVISOR)

Associate Professor (DTU)

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KISHAN BHUSHAN SAHAY

2K12/PSY/05

M. Tech. (Power System)

Delhi Technological University

ABSTRACT

In restructured power markets, forecasting electricity price and load accurately are most essential tasks and basis for any decision making. Short-term load forecasting is an essential instrument in power system planning, operation, and control. Various operating decisions are based on load forecasts like dispatch scheduling of generating capacity, reliability analysis, and maintenance planning for the generators. Also, the accurate day ahead electricity price forecasting provides crucial information for power producers and consumers to develop accurate bidding strategies in order to maximize their profit.

This thesis discusses significant role of artificial intelligence (AI) in short-term load & price forecasting, that is, the day-ahead hourly forecast of the electricity market parameters (load and price). A new artificial neural network (ANN) has been designed to compute the forecasted load & price. The data used in the forecasting are hourly historical data of the temperature, electricity load and natural gas price. The ANN was trained on hourly data from the 2007 to 2011 and tested on out-of-sample data from 2012. The simulation results have shown highly accurate day-ahead forecasts with very small error in load and price forecasting.

However load forecast of ISO New England market is far better than price forecast of ISO New England market. This is because price curves of any electricity market is highly volatile & depends on also many other factors which must also be taken care off. Also, the load forecast is much better with temperature data as input than without taking it. This is due to the fact that temperature and weather data are having high degree of correlation with load of that particular region. This indicates that temperature data is a very important parameter for load forecasting using ANN.

Economic load dispatch (ELD) problem is a common task in the operational planning of a power system, to schedule the connected generating units of plant outputs so as to fulfill load demands at minimum operating cost while satisfying all operational constraints. Optimization is a mathematical technique that is very appropriate to solve the ELD problem. Different optimization techniques like genetic algorithm, pattern search, minimax optimization, hybrid of genetic & pattern search algorithm, hybrid of genetic algorithm & fmincon & particle swarm optimization have been successfully applied to solve the ELD problem & day ahead economic load forecast (DAELF) problems using IEEE 30-bus (06 machine) & standard 26-bus (06 thermal units & 46 transmission line). The results show that particle swarm optimization technique gives the optimum operating cost.

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ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
NN	Neural Network
STLF	Short Term Load Forecasting
LMP	Locational Marginal Price
ELD	Economic Load Dispatch
ELF	Economic Load Forecast
DAELF	Day-Ahead Economic Load Forecast
GA	Genetic Algorithms
PS	Pattern Search Optimization Algorithm
MM	Minimax Optimization
FN	Fmincon Minimization
PSO	Particle Swarm Optimization
HGFN	Hybrid of GA & Fmincon
HGPS	Hybrid of GA & Pattern search