

ADVANCES IN FORECASTING TECHNIQUES IN DEREGULATED POWER MARKET

NITIN ANAND SHRIVASTAVA



**DEPARTMENT OF ELECTRICAL ENGINEERING
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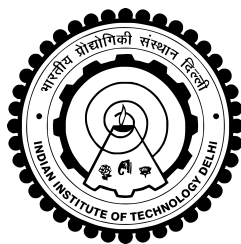
ADVANCES IN FORECASTING TECHNIQUES IN DEREGULATED POWER MARKET

by

NITIN ANAND SHRIVASTAVA
Department of Electrical Engineering

Submitted
in fulfillment of the requirements of the degree of
DOCTOR OF PHILOSOPHY

to the



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Dedicated to Almighty God

CERTIFICATE

This is to certify that the thesis entitled “ADVANCES IN FORECASTING TECHNIQUES IN DEREGULATED POWER MARKET” being submitted by Mr. Nitin Anand Shrivastava to the Indian Institute of Technology Delhi, for the award of the degree of Doctor of Philosophy, is a bonafide record of research work carried out by him under my supervision and guidance. The thesis work, in my opinion, has reached the requisite standard fulfilling the requirements for the degree of Doctor of Philosophy. The results contained in this thesis have not been submitted, in part or full, to any other University or Institute for the award of any degree or diploma.

Dr. B.K. Panigrahi

Associate Professor

Department of Electrical Engineering

Indian Institute of Technology, Delhi

Hauz Khas, New Delhi - 110016

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(NITIN ANAND SHRIVASTAVA)

ABSTRACT

Deregulation of the power markets has made a significant impact on the power generation, transmission and consumption patterns across the globe. In order to ensure higher profits, the market participants rely on accurate forecasting to aid their decision making for profit maximization. Electricity price forecasting is a more challenging task compared to demand forecasting owing to its high volatility and complex nature. Research in price and demand forecasting is in a progressive state and there is a thrust for developing fast and reliable techniques for short and long term applications.

Uncertainty is gradually infiltrating every aspect of power system and is becoming an important concern in efficient planning, operations and control. Consequently, it is imperative to quantify uncertainties related to forecasts which are essential requirement for power system planning and all market related activities. The objective of this thesis is to propose some advances in the techniques of forecasting which will cater to the needs of the deregulated power market participants. The highlights of thesis are as follows:

In order to overcome the limitations imposed by conventional neural networks based techniques and also advanced optimization based techniques for short term applications, a novel and reliable technique based on extreme learning machines and wavelet transforms is proposed in this work. The technique is validated us-

ing data from some existing and emerging markets across the globe and superior performance is observed compared to existing techniques.

The uncertainty related to forecasts is quantified using statistical tools like prediction interval and confidence interval. An attempt is made to investigate the application of conventional bootstrapping technique for uncertainty quantification. Conventional way of data resampling is replaced with an alternate method for better estimation of the actual conditional distribution of the predicted value for a given data set. The inefficiency of the conventional method in improving the forecasts from coverage aspects was observed in this study. In order to overcome the limitations of the conventional methods, a new technique is developed to directly estimate the prediction intervals using support vector machines in an unsupervised manner. Suitable parameters for support vector machines are obtained by particle swarm optimization technique. A modification in the existing performance index for prediction intervals is also proposed in order to obtain reliable intervals using an optimization technique. The efficiency of the proposed technique is confirmed using several case studies based on artificial as well market data sets.

One of the goals of this work is to supply the decision makers with a wide range of reliable options with respect to forecasts. This is achieved by framing the prediction interval generation as a multi-objective problem and generating a range of pareto-optimal solutions. The proposed technique involves support vector machine as a learning technique aided with a multi-objective differential evolution algorithm. The technique is applied on a number of test cases involving electricity price and

demands and reliable performance is observed.

In the upcoming smart grid scenario, the market participants will have the ability to respond to price signals below and above certain price thresholds. Such requirements of the market participants are met by supplying them with the information about the expected class of the future electricity price based on thresholds determined by market operators and utilities. An attempt is made to investigate into this matter using novel extreme learning machine technique. Some customer specific methodologies are also developed and performance is evaluated using actual market data.

Finally, an attempt is made to address some fundamental issues related to price forecasts and their application by the market participants. Keeping in view the limitations of commonly used MAPE index and a number of alternate choices, extensive experiments are performed to come up with a most suitable choice for all situations. Detailed case studies are also performed to evaluate the impact of forecasting errors on the economics of the market participants and some insightful conclusions are drawn from them.

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Notation and Abbreviations

The following symbols are used in this thesis:

ACE : Absolute coverage error

ACF : Auto correlation function

ANN : Artificial Neural Network

$BEMC$: Bulk electricity market consumer

BP : Back propagation

C : Cost parameter for SVM

$C1$: Cognitive coefficient for PSO

$C2$: Social coefficient for PSO

CI : Confidence interval

CWC : Coverage width criterion

DE : Differential evolution

E : Number of Ensembles

EI : Economic impact

ELM : Extreme Learning Machines

$FIEI$: Forecast inaccuracy economic impact

FT : Fourier Transform

$g(x)$: Activation function

g_best : Global best position in PSO

H : Hidden layer output matrix

$H^\dagger$: Moore Pensrose generalized inverse of H

<i>HOEP</i>	: Hourly Ontario Electricity Price
<i>IESO</i>	: Independent Electricity System Operator
<i>IW</i>	: Weight matrix from input layer to hidden neurons
<i>LUBE</i>	: Lower upper bound estimation
<i>MAE</i>	: Mean absolute error
<i>MAPE</i>	: Mean absolute percentage error
<i>MDE</i>	: Mean deviation error
<i>MeDE</i>	: Median deviation error
<i>MODE</i>	: Multi-objective differential evolution
<i>LS</i>	: Least square
<i>ML</i>	: Machine learning
<i>MLP</i>	: Multilayer perceptron
<i>MP</i>	: Moore-Penrose
<i>N</i>	: Data samples
$\tilde{N}$	: Number of hidden nodes
N_{Pareto}	: Number of members in pareto-optimal front
<i>PCC</i>	: Percentage correct classification
<i>PI</i>	: Prediction interval

$PICP$	: Prediction interval coverage probability
$PINAW$	: Prediction interval normalized average width
$PINC$	: Prediction interval nominal confidence
PSO	: Particle Swarm Optimization
P_t	: Actual Price value at hour t
$\hat{P}_t$	: Forecast price at hour t
p_best	: Personal best position of the particle in PSO
RBF	: Radial basis function
$RMSE$	: Root mean square error
RTO	: Regional transmission organization
$SLFN$	: Single-hidden-layer feedforward neural networks
$sMAPE$	: Symmetric mean absolute percentage error
SVM	: Support vector machine
SVR	: Support vector regression
Y	: Target Matrix
W	: Input weight matrix
v_i	: PSO particle velocity vector
$WELM$	: Wavelet based ELM
$WRMSE$	: Weekly root mean square error
WT	: Wavelet Transform
α_i, α_i^*	: SVM dual variables
β	: output weight matrix

γ : RBF kernel function parameter

ϵ : Error tolerance range

μ : Nominal confidence level

θ : Threshold

ψ : Mother wavelet function

φ : Father wavelet function

ω : Inertia weight