



Ain Shams University
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**An Economical stochastic Study of Electrical Load Pattern
For Energy Management**

Ph.D. Thesis
By

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Dedication

Dedicated to the soul of my father, my beloved mother, and my lovely sisters; Reham, Radwa, and Reem

Also, dedicated to everyone tried to help me, all my teachers, professors, my friends,...

STATEMENT

This thesis is submitted to Ain Shams University in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Electrical Engineering (Power and Machines).

The work included in this thesis is carried out by the author at Electrical Power and Machines Department, Ain Shams University. No part of this thesis has been submitted for a degree or a qualification at any other university or institute.

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Abstract

Deregulation in power systems has been applied mainly from an economical point of view. Deregulation also supports the technical performance by introducing the competition among suppliers. Initially, the idea was using tariff continually changing with time instead of fixed one. From economical point of view, this means that if the price at a certain hour is high, the consumption will be minimized and vice versa. Technically, this will lead to re-plan and re-distribute the demand to shift the loads from the peak hours with higher prices to the lower demand hours with lower prices. Thus, the previous knowledge of both load and price values are critical for short term, long term planning strategies, and security studies. Under The new construction of electricity power markets, the new markets must announce their prices 24 hours ahead and every 5 minutes to facilitate the demand response plans, unit commitment, and price determination. It is clear that different suggested strategies need insight knowledge about the load and price relationship or values. Therefore, the need for forecasting studies turned to be crucial.

Many factors are effecting on load forecasting studies such as previous loading, temperature, weather condition, prices ...etc. As an impact of the deregulated market, the role of the prices is dominantly effects on load. Other factors are also inherently involved in both load and price time series. Therefore, to build a load forecasting model, estimated prices algorithm is also needed to predict the price of the foreseen load value. Hence, it is convenient to build a load-price forecasting model. Due to the difficulties in attaining the other factors affecting load and price time series, it is suitable to build load and price forecasting models depend on load and price time series, which are inherently including other factors such as temperature, weather conditions.

Different techniques have studied load forecasting such as classical time series techniques, regression techniques, and machine learning techniques. Support vector machine is one of the novel machine learning techniques, which is recently implemented in power system studies. Support vector machine as a forecasting technique, its performance is directly related to the input data. Thus, preprocessing techniques are functionalized to reduce the number of input data, and help in parameters selection. These techniques are the well known; normalization, principal component analysis, K nearest neighbor points, and cross validation technique.

The suggested models procedure will work as follows: the proposed load and price models will forecast load and price values, which will be used as initial values to the load-price model to find the final load and price values. These models are only based on the load and price time series, and their alternatives such as load differences, price differences, load-price product, load-price division, square values of load.....etc. After gaining some experience, two alternatives have proven their adequate role in the forecasting process, and they have implemented in the proposed models. The suggested load, price, load-price algorithms work as follows:

- Model 1 is a new proposed model forecasts load values based on previous load time series, and the difference between each two successive points in the time series. This model has been tested using the data of the second competition from EUropean Network on Intelligent TEchnologies for Smart Adaptive Systems. The proposed model shows promising results.
- Model 2 is based on price time series only. The anticipated model forecasts price values based on the previous time series, and the difference between each two successive points in the time series. This model has been tested, compared using data from California Electricity Market, and compared with other pre-published studies.
- Model 3 is based on both load, and price time series. In this model, a proposed algorithm is utilized to forecast both load and price values independent of other factors based on their values and the product of each load and its price. The results have been compared with other algorithms using samples taken from National Electricity Market Management Company, 2003.

Models which are based on time series data are sensitive to noise effects. So, the proposed models sensitivity required to be tested. Four types of noises have been added to the load and price time series to test whether the models would stand or not. The results have revealed a satisfactory operation.

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