# ELECTRICITY DEMAND PREDICTION OF LARGE COMMERCIAL BUILDINGS USING SUPPORT VECTOR MACHINE

Indika Sujeewa Samarawickrama

(108863K)



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N.G. Indika Sujeewa Samarawickrama

(108863K)



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#### DECLARATION

I declare that this is my own work and this thesis does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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The above candidate has carried out research for the Masters thesis under my supervision.

Signature of the supervisors:

Dr. K.T.M. Udayanga Hemapala

Date:

Dr. Buddhika Jayasekara

Date:

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#### ABSTRACT

In an ideal competitive commercial world, having accurate energy forecasting tool becomes a Key Performance Indicator (KPI) for the building owners. Energy forecasting plays a crucial role for any building when it undergoes the retrofitting works in order to maximize the benefits and utilities. This thesis elaborates accurate energy forecasting tools based on Support Vector Machine Regression (SVMR). SVM is one of the most important methods which is widely applied in different literatures, in forecasting and regression of random data sets. It estimates the regression using kernel function, which is composed of a set of linear functions that is defined in a high-dimensional feature space while, inputs having nonlinear performance.

In the case study, four commercial buildings in Colombo, Sri Lanka, are randomly selected and the models were developed and tested using monthly landlord utility bills. Careful analysis of data identified three important parameters, (Dry-bulb temperature (T), Solar Radiation (SR) and Relative humidity (RH)), which have significant contribution to the model, which is under consideration. Stepwise searching method is used to investigate the performance of SVM with respect to the three tunable parameters, C,  $\gamma$  and  $\varepsilon$ ; and thereby to develop the radial-basis function (RBF) kernel.

The results showed that the structure of the training set has significant effect to the accuracy of the prediction. The analysis of the experimental results reveal that all the forecasting models give an acceptable result for all four commercials buildings with low coefficient of variance & a low percentage error (% error).



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