

## **SHORT TERM ELECTRIC POWER CONSUMPTION FORECASTING USING LINEAR PROGRAMMING SUPPORT VECTOR REGRESSION**

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### ABSTRACT

Accurate forecasting of electric power consumption by the national electric power grid is critical for short term operations and long term utilities planning. The power load prediction impacts a number of decisions (*e.g.*, which generators to commit for a given period of time) and broadly affects wholesale electricity market prices. Load prediction algorithms also feature prominently in reduced-form hybrid models for electricity pricing which are some of the most accurate models for simulating markets and modeling energy derivatives.

Within the realm of short term power load prediction, we propose a large-scale linear programming support vector regression (LP-SVR) model. The LP-SVR is compared with other two non-linear regression models: Feed Forward Neural Networks (FFNN) and Bagged Regression Trees (BRT). The three models are trained to predict hourly day-ahead loads given temperature predictions, holiday information and historical loads. The models are trained on hourly data from the New England Power Pool (NEPOOL) region (courtesy ISO New England) from 2004 to 2007 and tested on out-of-sample data from 2008.

Experimental results indicate that the proposed LP-SVR method gives the smallest error when compared against the other approaches. The LP-SVR shows a mean absolute percent error of 1.58% while the FFNN approach has a 1.61%. Similarly, the FFNN method shows a 330MWh (Megawatts-hour) mean absolute error, whereas the LP-SVR approach gives a 238MWh mean absolute error. This is a significant difference in terms of the extra power that would need to be produced if FFNN was used.

The proposed LP-SVR model can be utilized for predicting power loads to a very low error, and it is comparable to FFNN and over-performs other state of the art methods such as: Bagged Regression Trees, and Large-Scale SVRs.

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