## **USE OF SUPPORT VECTOR MACHINES TO FORECAST ENERGY PRODUCTION**

## C. K. WALGAMPAYA<sup>1</sup>, M. KANTARZDIC<sup>2</sup>

<sup>1</sup>Department of Engineering Mathematics, Faculty of Engineering, University of Peradeniya <sup>2</sup>Department of Computer Engineering and Computer Science, Speed School of Engineering, University of Louisville, USA

This paper deals with the application of a novel neural network technique and support vector machine (SVM), in forecasting of the energy production as it has always been an important issue in the power industry. Recently, the SVM technique has attracted many researchers. This is largely due to the structural risk minimization (SRM) principle in SVM that has greater generalization ability and is superior to the empirical risk minimization (ERM) principle as adopted in neural networks. In SVM, the results guarantee global minima whereas ERM can only locate local minima. Also, SVM is adaptive to complex systems and robust in dealing with corrupted data.

Our research is based on data collected through a network of 200 energy plants, which are dispersed geographically in United States. These energy plants operate through out the year continuously. Sensors in each plant keep record of vital information including real-time power production. These measures are taken at specific intervals. This interval can vary from a fraction of a second to a day. The data for our analysis comprises energy production readings of sensors at 200 distributed energy plants, and the cumulative variable, that correspond to the total energy production of those 200 energy plants. These data are available from year 2002 to year 2004. As most of the machine learning techniques such as ANN and SVM require that all data to be normalized we have normalized the data between [-1, 1]. The data between year 2002 and 2003 are used as training data and year 2004 data are used as testing data. We have built separate training and testing data sets by varying the number of sensor inputs. Prediction models are built with ANN and SVM techniques with those selected number of sensor data.

We used a feed forward neural network with backpropagation learning with one hidden layer. The algorithm was implemented in MATLAB. We have experimented the ANN model with different combinations of the parameters and found out that values 0.001 for accuracy and 0.04 for learning rate with Tangent-Sigmoid activation function give the best prediction results. The LIBSVM toolbox was used for SVM methodology. In this study we have used a nonlinear SVM with polynomial kernel,  $K(x, y) = (x^*y+1)^d$  and Gaussian radial basis function,  $K(x, y) = \exp(-1/\delta^2 (x-y)^2)$ . We experimentally determined parameters C = 100, and  $\delta^2 = 10$  giving best prediction performances.

Prediction results are compared and analyzed. We have seen that prediction accuracy increases with the increase of number of sensors that was used. Until 70 sensor inputs SVM performs much better than ANN in terms of required number of sensors for a given prediction accuracy. Both SVM and ANN results saturate around 130 input sensors. The results may be attributable to the fact that SVM implements the SRM principle and this leads to better generalization than conventional techniques.