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An approach for Short-Term Load Forecasting Using RBFNN in the Smart Grid

Satheesh Kumar[1], Saravana Kumar Gurusamy[2], B. Subathra[1], Seshadhri Srinivasan[3]

Abstract: Accurate demand forecasts are important for managing energy efficiently in electric grids. However, building models for demand forecasting is a challenging task as it depends on numerous factors that are both intrinsic and external to the grid. Furthermore, these factors are time-varying and non-linear as well. This makes demand forecasting a cumbersome task. This investigation proposes a simple model for short-term load forecasting in smart grids that uses the radial basis function neural networks and time-series data to provide short-term demand forecasts. The proposed method is simple as it just uses the time-series to data in forecasting. The use of RBFNN is motivated by its ability to model non-linear and time-varying entities. The modelling approach consists of four phases: data-collection, pre-processing, modelling and validation. The time-series data of the demand is collected during the data-collection phase. As the data obtained has numerous outliers, missing information and bad-data, the pre-processing approaches are used to eliminate them. The modelling step consists of tuning the RBFNN and finally in the validation step, the forecasting model is validated using test data-set. The proposed forecasting approach is illustrated using data obtained from Delhi load dispatch centre and an Australian energy grid data. Our results show that the proposed approach provides reasonably accurate forecasts and is simple compared to existing methods in literature.

1. INTRODUCTION

Load forecasting is a vital component for building energy management systems and predictive controllers in the smart grid paradigm [1]. It has been widely used for many energy management application such as optimal power flow [2], district energy management [3], building energy management [4, 20], and distributed hierarchical control [5]. Accuracy of load forecasts are important to design reliable energy management systems. Usually demand on the grid depends on meteorological (season, day of the week etc.), social (For example, population growth), environmental factors (such as ambient air temperature, relative humidity), demographic factors (tropics, arid, humid, hot etc.), political factors (e.g. regulations, financial policies) influence the demand. Furthermore, with the de-regulation of electricity markets presence of renewable energy sources, flexible loads, and storage systems that provide bi-directional energy flow, demand forecasting is becoming more and more complex. In particular, the short-term forecasting that aims to predict future demand changes for a time-frame ranging from a few minutes up to one-day is more challenging. The computation resources and time-frame required for energy management systems complicates this task further.

The tight-coupling between energy demand and prices has forced researchers to study the demand forecasting models in good detail. The available methods can be categorized as: statistical, machine learning and hybrid. The most common statistical methods are exponential smoothing, regression models and so on

[1] Department of Electrical and Electronics Engineering, Kalasalingam University, Krishnankoil, India, *Email: {msk1901}@yahoo.com, {clk0602}@gmail.com*

[2] Electrical and Computer Engineering, University of Gondar, Ethiopia, *Email: {saravana.control}@gmail.com*

[3] International Research centre, Kalasalingam University, Krishnankoil, India, Email: *{cpscourse}@klu.ac.in*

[6, 7]. Machine learning tools such as artificial neural networks [8], support vector regression [9] and other methods have been proposed. Hybrid methods combine more than one forecasting method within a model. The hybrid methods can either be sequential or parallel [10]. Although, hybrid methods have proven to provide good accuracy than other methods, the scarce computation and timing resources make their adaptation in energy management systems difficult. The statistical methods provide good results for linear and time-invariant systems. However, accuracy of their forecasts for complex and non-linear behaviours is quite low. Machine learning tools provide a good trade-off between computation and accuracy; therefore, are emerging as a promising forecasting tool. There are several ANN models studied in literature. Traditionally, the ANN is trained using back propagation methods [11] have been widely employed. However, it has been found in many applications that RBFNN exhibit good model fidelity while modelling non-linear and time-varying behaviours [12]-[14]. The authors in [15] and [16] studied the combined use of fuzzy and RBFNN for short-term forecasting. Similarly, in [17] short-term forecasting combining ANFIS and RBFNN was proposed; the method showed good forecasting accuracy. The authors in [4] used a hybrid model that combined particle swarm optimization and RBFNN. The role of genetic algorithms and RBFNN for forecasting load forecasting. Other investigations have also studied the use of RBF for short-term forecasting [18]-[19]. However, these methods use various input information as inputs and are computationally intensive. Our objective in this investigation is to propose a simple model for demand forecasting that uses just the time-series data of the demand to predict future demand in the grid. The main contribution of the investigation are simple RBFNN based model for load forecasting in energy grids that is simple and easy to realize in dedicated automation hardware. The proposed forecasting tool is illustrated using demand data from Delhi load centre and an Australian power grid.

The paper is organized as follows. Section 2 presents the preliminaries of the RBFNN based short-term forecasting. The proposed forecasting approach is presented in Section 3. Results obtained using the proposed approach on two data sets are presented in Section 4. Conclusions and future course of the investigation is presented in Section 5.

2. PRELIMINARIES

The procedure for forecasting consists of four phases: data-collection, pre-processing, modelling and validation. In the data-collection phase, the demand data is collected from the energy grid. Here it is worth to mention that the data collection step in this investigation is performed using web services that collect data from dedicated webpages. The collected data is converted into a format that is easier for processing.

2.1. Data-Preprocessing

This data usually contains bad-data, noise, missing measurements and outliers. The data needs to be pre-processed for building the model. This data uses bad data uses ÷-squared test for bad data(outlier) elimination. To remove the outliers sigma test is used, data lying beyond 3-sigma values are removed from the data set. Then the bias of the data is removed by computing the mean. Finally, the data is normalized to provide the input/output data that will be used for modelling. The time-series typically consists of the hours and the demand.

2.2. Modelling

The pre-processed data is the input to the modelling phase wherein the RBFNN is used for demand forecasting using the time-series data. As stated earlier the motivation to use RBFNN stems from its ability to model complex non-linear and time-varying phenomenon. The RBFNN essentially consists of three layers: input, hidden and output as shown in Fig 1. The input data is split into two parts, one for learning and other for training. An analysis of the input data revealed the presence of a pattern that consists of 24 hours of data. In order to perform short-term load forecasting, the input sequence (training data) is split into three parts each separated by one time-step. The input sequence 1 is the input to the RBF network, while the input sequence 2 is the output. Similarly, the input sequence 2 is the input and the third sequence separated by one time step is the input. The input 1 is the input and input 2 is the output during the training phase. Similarly, during the validation phase, input 2 is first provided as input and validated against the third data segment of the input. The input layer maps these inputs to the hidden layer which consists of the Gaussian function and the hidden layer is linearly mapped to the output. The output of the RBFNN can be viewed as a linear combination of the Gaussians and hence can be used to map non-linearly varying functions.

Consider now that there are n inputs and m outputs, the hidden layer has s neurons, the connection weight between the input layer and the hidden layer is wij, and the connection weight between the hidden layer and output layer is wjk. The training process of RBF network can be divided into two steps, the first step is to learn to identify the weight wij without teacher, and the second step is to identify the weight wjk with teacher. The weights, mean and variance of the Gaussian as well as the number of neurons in the hidden layer are the parameters that needs to be tuned for RBFNN. The number of layers in the hidden layer needs to be selected using trial-and-error approach or an optimization driven approach. In this investigation we use the dichotomous search to find the optimal number of neurons that reduces the mean square of the error.

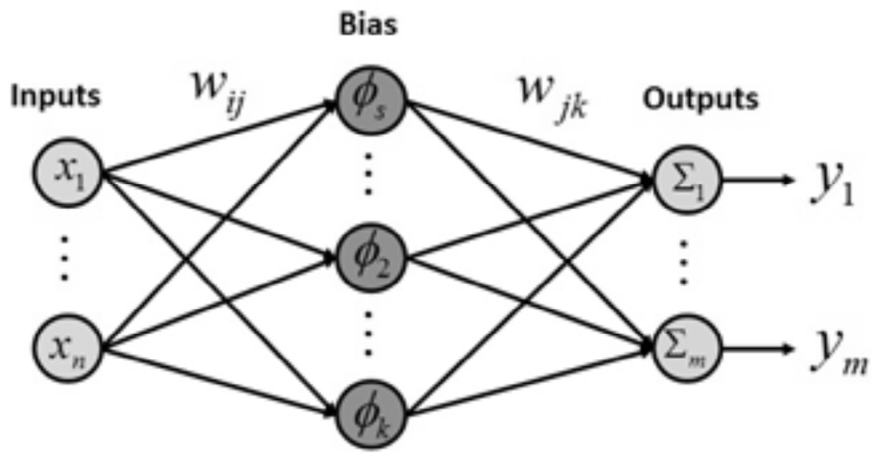

Figure 1: The topology structure of RBF neural network.

2.3. Tuning of the RBF network

Since now the weights of the RBFNN is fixed, there are three parameters that can be adjusted: mean and variance of the neurons in the hidden layer and the weights of the output layer. In order to construct the RBFNN, first the mean of the basis function are selected using prior experience or clustering algorithm. To select the basis function, C-means clustering is sued. The center of each of these cluster is used as the mean of the basis function. As the hidden layer to output mapping is a linear weight, batch least squares implemented using a pseudo inverse command can be used for computing the output for a set of over-constrained equations.

2.4. Validation Phase

During the final phase of the modelling, the actual and estimated data are compared to compute performance metrics. In our analysis we use three metrics, mean square error, means absolute error, and mean absolute percentage error to validate the results.

3. PROPOSED RESEARCH

3.1 Data Partitioning

A close inspection into demand data reveals patterns for 24 hours. Usually time-series data contains time and the actual value of the variable to be estimated. Departing from the regular approach, we divide the data-sets into three each separated by one hours (or one time step). The first among the data-set is used for predicting the second set of data. Similarly, the second 24 hours data is used for predicting the next 24 hours and so on. This sort of partitioning allows for accurate prediction. A time-span separation of one hour is used when the estimation is used. This makes it possible to forecast even for short duration of intervals of time.

3.2. Implementation of RBFNN based load forecasting

To implement the RBFNN based forecasting we use batch least squares. The objective is to reduce the square of the error between the actual and predicted value. During the training phase the input is the demand separated by one time-step (one hour in our case) and the output values to be obtained is the demand delayed by one hour. This means the demand at the instant k+1 is affected by the demand at time epoch k. The learning proceeds for 70% of the data. Once trained, the network is validated during the validation phase by partitioning the validation data similar to the input data space. The RBFNN forecasts are validated using error measures that compute the fitness of the identified data. The various steps involved in the implementation of the RBFNN is shown in Fig. 2.

4. RESULTS

The proposed load forecasting approach is validated for two data-sets collected at different conditions. The first set of data is collected from the Delhi load dispatch center, New Delhi, India. The historical information

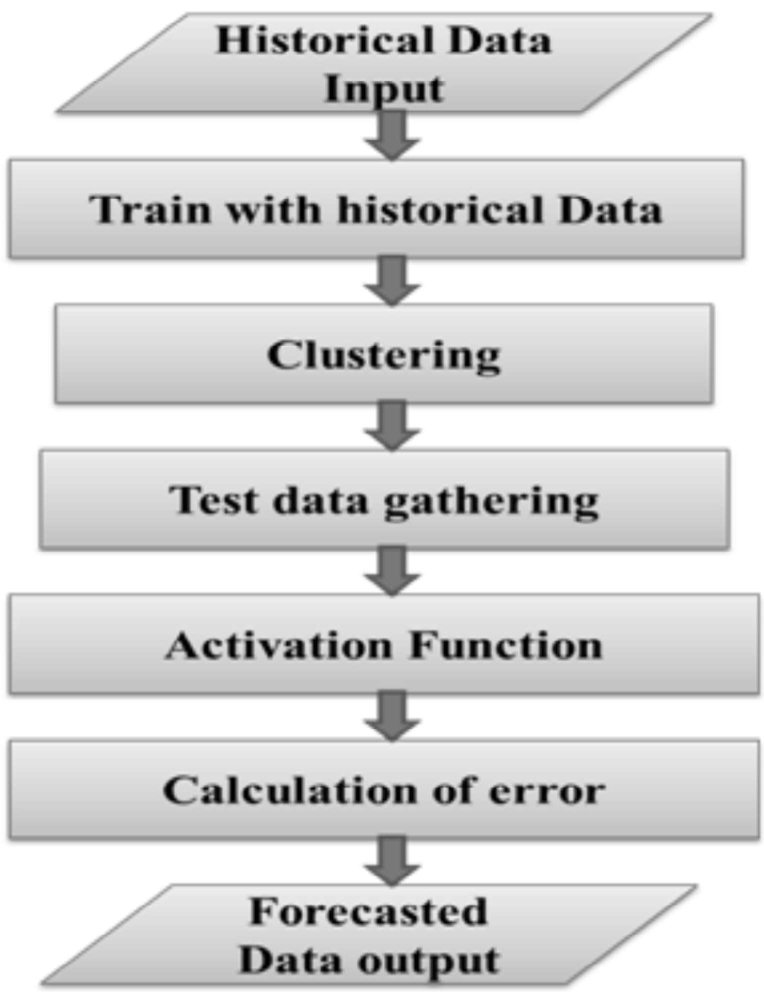

Figure 2: Steps involved in RBF training

can be found from the web link and services can be written to load the data into the data-base. The procedure is illustrated in Fig 3. The actual power data is collected from www.delhisldc.org/daily availability reports. The details of the data collected are shown in Table 1.

Table 1
Data set of Delhi SLDC

Historic depth	Not consecutive days are available for whole year
Starting date	01-03-2014 at 0:00
Finishing date	30-03-2014 at 23:00
Frequency	24h forecast specifying the hourly load.
Input data	Unrestricted demand of the State Load Despatch Centre Delhi, India(data provided by SLDC, Delhi www.delhisldc.org/daily availability report).

The second set of data is collected from the Australian grid. The data is collected every 30 minutes for a period of one year is used for the forecasting from AEMO from NSW, Australia through http://mathworks.com as shown in Table 2.

Table 2
Data set of Australian power industry

Historic depth	Consecutive days are available for whole year
Starting date	01-01-2006 at 0:30
Finishing date	31-12-2006 at 23:30
Frequency	24h forecast specifying the0.5hourly load.
Input data	system load data of one year are used for this forecasting model from AEMO on NSW, Australia through http://mathworks.com

As stated earlier, the number of neurons in the hidden layer affect the accuracy of the forecasts. Therefore, in our approach we use dichotomous search a brute force optimization technique to compute the number of neurons that are required for providing accurate forecasts. The actual demand and forecasted values of the demand for the data obtained from Delhi load dispatch center with the number of hidden layer neurons equal to 15 is shown in Fig 4. It can be seen that the RBFNN provides accurate forecasts even with the smaller set of data-set using the data portioning method mentioned in the paper. Furthermore, only the time-series data is used in forecasting, the influences of the external factors are completely neglected. In spite of these factors, the proposed method provides good forecasts. As the method is simple and easier to build in dedicated embedded platforms the proposed approach can be easily adapted to EMS systems in power stations. It can be observed that with the M = 15, a mean square error of 9.89% and a mean absolute percentage error of 2.52% was observed.

4.1. Results of Delhi SLDC data

Similarly, the performance of the proposed RBFNN based forecasting approach for M=18 neurons with the data collected from SLDC was tested. Our results showed that, with the proposed RBFNN, the MAPE and MSE values were reduced as illustrated in Table 3. Therefore, in our analysis, we select, 18 hidden neurons for estimating the demand in SLDC.

4.2. Results of Australian Energy Grid

To validate the proposed RBFNN based forecasting approach, one year consumption data of the network for 30 minutes duration is used for training and validation. During training 70% of the data is used, whereas 30% of the data is used for validation.

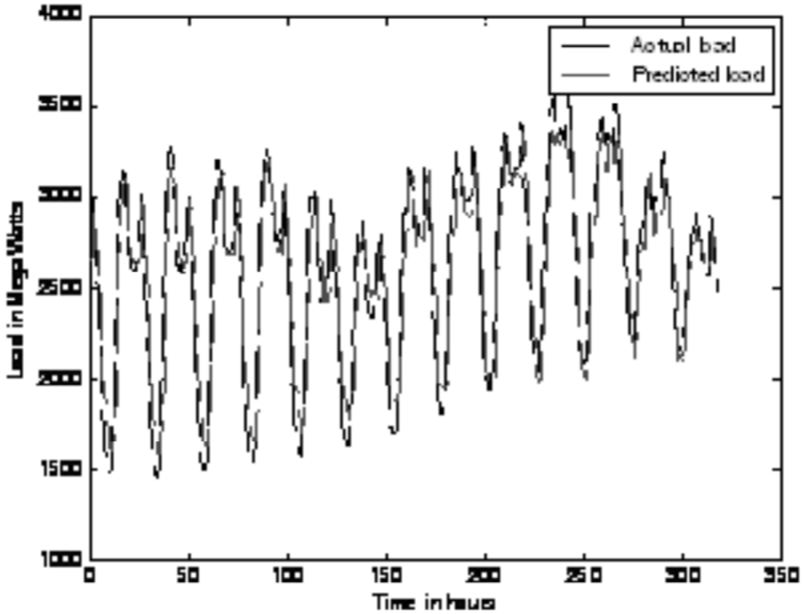

Figure 3: Plot for Actual load of vs Predicted load for M = 15MSE = 9.89%; MAPE = 2.521%

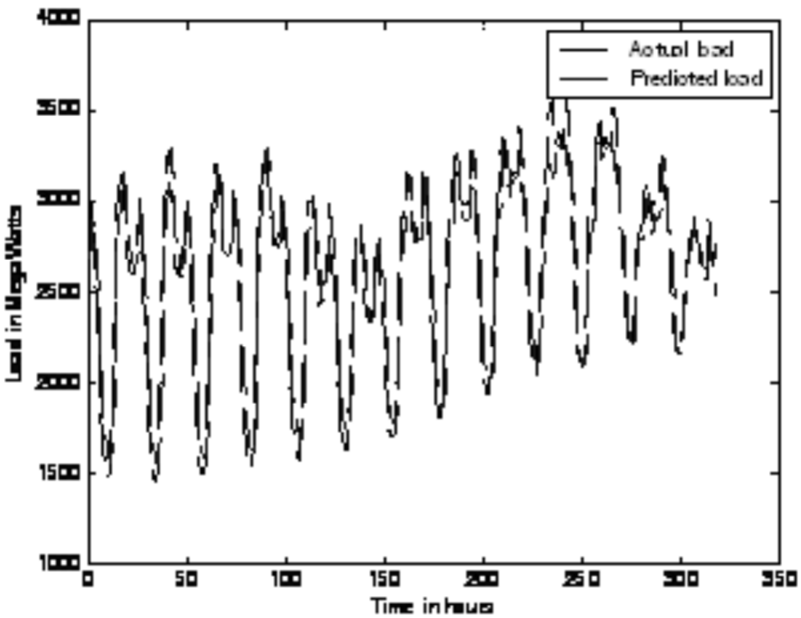

Figure 4: Plot for Actual load of vs Predicted load for M = 18; MSE = 9.302%; MAPE = 2.433%

Table 3
Error for different value of M of Delhi SLDC data

Sl. No	*Value of M*	*MAPE*	*MSE*
1	15	2.521	9.890
2	18	2.433	9.302

The actual and estimated values of the demand for the Australian energy grid with the proposed approach and RBFNN using 15 neurons in the hidden layer is shown in Fig 5. It is observed that the proposed approach gives a minimum square error of 1.4% and MAPE value of 3.782%.

Similarly the validation results for the demand forecasting for the Australian energy grid data with 18 hidden layer neurons is shown in Fig 6. Our results show that, the proposed approach can be used for forecasting even with small time intervals say 30 minutes.

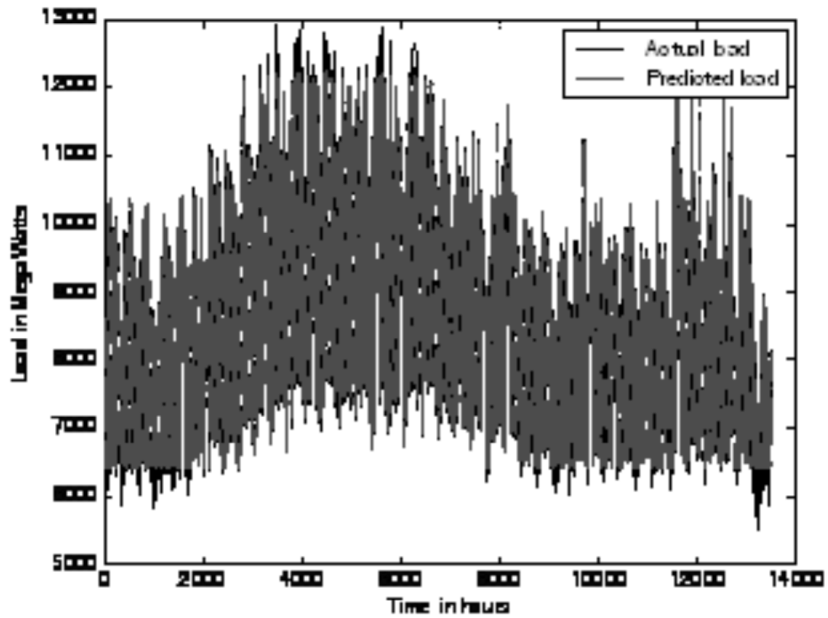

Figure 5: Plot for Actual load of vs Predicted load for M = 15; MSE = 1.406; MAPE = 3.7842

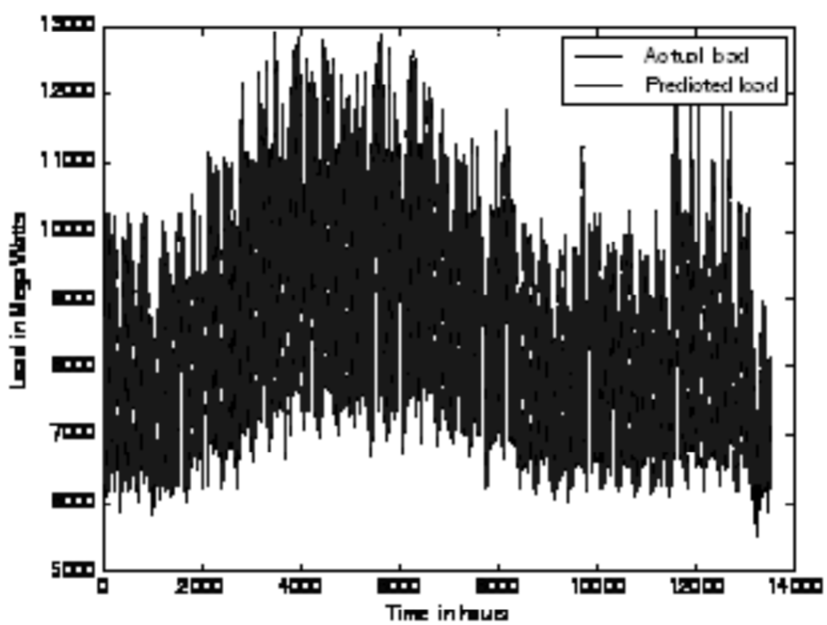

Figure 6: Plot for Actual load of vs Predicted load for M = 18; MSE = 0.1326; MAPE = 3.5306; M = 18

Table 4
Error for different value of M of Australian power industry data

Sl. no	*Value of M*	*MAPE*	*MSE*
1	15	3.7842	1.406
2	18	3.5306	1.326

The proposed RBFNN approach has been implemented on two data-sets in different conditions and time-frames. Our results demonstrate the proposed approach works equally well for both the data-sets. Further, the proposed approach is well suited for providing accurate forecasts on short-time intervals. This can be understood from the Australian energy grid results that provides forecasts for every 30 minutes (< than one hour duration). Since the method uses linear input and output mapping with Gaussian hidden layer neurons. It can be easily realized in dedicated hardware used in power automation.

5. CONCLUSION

This paper presented a RBFNN based short-term forecasting model for demand in energy grids. The proposed approach used time-series data of the demand and RBFNN to predict the future load. The main idea behind the approach is to use the patterns of data and then partition it considering the time-frame. Then use one set of data temporally one step ahead to predict the data delayed by one step. This sort of input-output pair makes it possible to perform short-term forecasting. The proposed forecasting model was illustrated on demand data collected from two different conditions and time-frames. The proposed approach works equally well for both the data-sets. Our investigation shows that the proposed approach achieves an accuracy as close as less than 10% only using the time-series information. The proposed approach is simple and can be easily built into energy management systems where computation and time constraints are very strict. Optimizing the network parameters and deciding the number of neurons using an optimization driven approach is the future course of this investigation.

References

[1] Srinivasan, Sudarshan, Ulle Kotta, and Srini Ramaswamy. “A layered architecture for control functionality implementation in smart grids.” Networking, Sensing and Control (ICNSC), 2013 10th IEEE International Conference on. IEEE, 2013.

[2] A. Maffei, S. Srinivasan, L. Iannelli, and L. Glielmo, “A receding horizon approach for the power flow management with renewable energy and energy storage systems”, Proceedings of the AEIT 2015, Naples, Italy.

[3] G. Gambino, F. Verrilli, M. Canelli, A. Russo, M. Himanka, M. Sasso, Seshadhri Sriniavsan, C.D. Vecchio, and Luigi Glielmo, “Optimal Operation of the district heating power plant with thermal energy storage”, Proceedings of the American Control Conference (ACC 2016), 2016.

[4] F. Verrilli, G. Gambino, S. Srimnivasan, G. Palmieri, C.D. Vecchio, and L. Glielmo, “Demand Side Management for heating controls in microgrids”, Proceedings of the 4rth International Conference of Advances in Control and Optimization of Dynamical Systems (ACODS 2016), Tiruchirappalli, India.

[5] Srinivasan, Sudarshan, Ravindra Kumar, and Juri Vain. “Integration of IEC 61850 and OPC UA for Smart Grid automation.” Innovative Smart Grid Technologies-Asia (ISGT Asia), 2013 IEEE. IEEE, 2013.

[6] J. W. Taylor, Short-term load forecasting with exponentially weighted methods, IEEE Transactions on Power Systems 27 (1) (2012) 458–464.

[7] J. W. Taylor, P. E. McSharry, Short-term load forecasting methods: An evaluation based on European data, IEEE Transactions on Power Systems 22 (4) (2007) 2213–2219.

[8] Landa-Torres, Itziar, et al. “The application of the data mining in the integration of RES in the smart grid: Consumption and generation forecast in the I3RES project.” Power Engineering, Energy and Electrical Drives (POWERENG), 2015 IEEE 5th International Conference on. IEEE, 2015.

[9] A. Kavousi-Fard, H. Samet, F. Marzbani, A new hybrid modified firefly algorithm and support vector regression model for accurate short term load forecasting, Expert Systems with Applications 41 (2014) 6047–6056.

[10] Ren, Y., Suganthan, P. N., Srikanth, N., & Amaratunga, G. (2016). Random vector functional link network for short-term electricity load demand forecasting. Information Sciences.

[11] K. Hornik, M. Stinchcombe, H. White, Multilayer feed forward networks are universal approximators, Neural Networks 2 (5) (1989) 359–366.

[12] Srinivasan, S., Buonopane, F., Saravanakumar, G., Subathra, B., & Ramaswamy, S. (2015, August). Modelling time-varying delays in networked automation systems with heterogeneous networks using machine learning techniques. In Automation Science and Engineering (CASE), 2015 IEEE International Conference on (pp. 362-368). IEEE.

[13] Yu-Jian Chang; Shuo-He Wang; Hai-Yan Sun, “Research of short-term load forecasting algorithm based on wavelet analysis and radial basis function neural network,” in Power Electronics and Intelligent Transportation System (PEITS), 2009 2nd International Conference on , vol. 1, no., pp. 81-84, 19-20 Dec. 2009.

[14] Singh, N.K.; Tripathy, M.; Singh, A.K., “A radial basis function neural network approach for multi-hour short term load-price forecasting with type of day parameter,” in Industrial and Information Systems (ICIIS), 2011 6th IEEE International Conference on , vol., no., pp. 316-321, 16-19 Aug. 2011.

[15] Feng Liu; Zhifang Wang, “Electric load forecasting using parallel RBF neural network,” in Global Conference on Signal and Information Processing (GlobalSIP), 2013 IEEE , vol., no., pp. 531-534, 3-5 Dec. 2013.

[16] Campbell, P.R.J., “A Hybrid Modelling Technique for Load Forecasting,” in Electrical Power Conference, 2007. EPC 2007. IEEE Canada , vol., no., pp. 435-439, 25-26 Oct. 2007.

[17] Zhang Yun; Zhou Quan; Sun Caixin; Lei Shaolan; Liu Yuming; Song Yang, “RBF Neural Network and ANFIS-Based Short-Term Load Forecasting Approach in Real-Time Price Environment,” in Power Systems, IEEE Transactions on, vol. 23, no. 3, pp. 853-858, Aug. 2008.

[18] Dongxiao, Niu; Ling, Ji; Tian Jie, “Improved RBF network applied to short-term load forecasting,” in Software Engineering and Service Science (ICSESS), 2011 IEEE 2nd International Conference on , vol., no., pp. 864-867, 15-17 July 2011.

[19] Xiaolei Hu; Ferrera, E.; Tomasi, R.; Pastrone, C., “Short-term load forecasting with Radial Basis Functions and Singular Spectrum Analysis for residential Electric Vehicles recharging control,” in Environment and Electrical Engineering (EEEIC), 2015 IEEE 15th International Conference on , vol., no., pp. 1783-1788, 10-13 June 2015

[20] S. Mallikarjun, Seshadhri Srinivasan, B. Subathra, J. Vain and U. Kotta, “Learning based personalized energy management systems for residential buildings”, Energy and Buildings, 2016.