Short Term Load Forecasting Using ARIMA, ANN and Hybrid ANN-DWT

4 authors:

Mthulisi Dube
University of Cape Town

Kehinde Awodele
University of Cape Town

Olufemi Olayiwola
University of Cape Town

Kingsley Akpeji
University of Cape Town

SHORT TERM LOAD FORECASTING USING ARIMA, ANN AND HYBRID ANN-DWT

M.M Dube, K. O. Awodele, O. Olayiwola and K.O. Akpeji

Department of Electrical Engineering, University of Cape Town, Private Bag, Rondebosch, 7701, South Africa.

Abstract: A hybrid method comprising artificial neural networks (ANN) and discrete wavelet transform (DWT) for short term load forecasting (STLF) is presented in this paper. For the ANN component of the hybrid model, the Levenberg-Marquardt back-propagation algorithm was used for network training; for the DWT component, the Daubechies mother wavelet was used. The hybrid ANN-DWT technique, the autoregressive integrated moving average (ARIMA) and the artificial neural network (ANN) techniques for STLF were developed in MATLAB 2016a and tested on real historical load data obtained from the City of Cape Town Network Control Centre and the South African Weather Services. All three models were tested and compared for forecasting accuracy. The ranges of MAPE values for ARIMA, ANN, and the ANN-DWT hybrid model show the effectiveness of the hybrid ANN-DWT model in obtaining more accurate forecast results.

Key words: Short term load forecasting, artificial intelligence, ANN, ARIMA, DWT

1. INTRODUCTION

Short-term load forecasting (STLF) is a process of predicting future peak loads with lead times of at least one hour to one week ahead. In a power system, STLF is crucial for short term unit commitment and it also enables power system operators to develop optimal plans for power generation infrastructure [1]. STLF is also helpful in advancing research about integration of renewable resources such as wind and solar [2].

An accurate STLF is paramount as it helps ensure a more efficient and more economic operation of the power system. The efficiency of power system operations is improved by an accurate scheduling which reduces the "out of merit dispatch" caused by a combination of forecast errors, unit ramping limits and reduction in reserves. According to Hodge *et al* [2], power system scheduling processes are performed through unit commitment and the economic dispatch process.

STLF has been deeply researched and a lot of forecasting techniques have been proposed so far. These techniques can be divided into two classifications, namely the traditional forecasting methods and artificial intelligence forecasting methods. Traditional STLF methods are based on statistical theory and the representative prediction methods are the regression analysis method [3], stochastic time series method [4], and similar day approach [5] etc. Computational intelligence techniques rely on rapid development of artificial intelligence technology and the representative prediction methods are expert systems [5], wavelet analysis method [5], artificial neural network [6], fuzzy logic [7], support vector machines method [8] etc.

Hybrid techniques that consist of a combination of at least one artificial intelligence method such as fuzzy logic and artificial neural networks have also been explored in endeavours to achieve better forecasting accuracy [1, 4, 9, 14].

Electrical load demand is stochastic in nature and is heavily influenced by seasonal variation, day types and weather variables such as temperature, wind speed, rainfall, humidity etc. These load affecting factors should therefore be considered when predicting future load; ignoring them would compromise the accuracy of the forecasts. Artificial neural networks have proven to be very effective in predicting short term future load due to their adaptability and ability to learn complex nonlinear relationships between load and other factors [6]. However, hybrid techniques have proved to produce better results compared to ANN models in isolation. Fard *et al* [9] developed a hybrid ARIMA-ANN model using discrete wavelet transforms to utilise the benefits of the ARIMA model in modelling linear components of the load data. This paper presents a hybrid ANN-DWT which improves the already satisfactory accuracy of ANNs for short term load forecasting.

For the purpose of comparative studies, a conventional method (ARIMA), an artificial intelligence method (ANN) and a hybrid of ANN and discrete wavelet transform were developed using MATLAB 2016a software and were then tested on a real South African network data obtained from the City of Cape Town. Although the main focus of this paper is STLF, the ANN and ARIMA models were further tested on medium term historical load data, also obtained from the City of Cape Town for the Philippi/Montague area.

The rest of this paper is organised as follows: Section 2 presents a brief theoretical overview about the ARIMA model and also discusses how it was developed and tested in MATLAB. Section 3 briefly discusses the ANN theory. Section 4 focuses on the hybrid ANN-DWT model development as well as a brief theory on wavelets. In section 5, simulation results for both short term and medium term load forecasting are presented and discussed. Conclusions are then presented in section 6.

2. THE AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (ARIMA)

The autoregressive integrated moving average (ARIMA) is a statistical time series technique that has been widely used for STLF. However, like other statistical methods, it produces substandard results when modelling complex nonlinear variables. The ARIMA model development and testing is discussed in the following subsections.

2.1 Stationarity and differencing

A stationary time series is one whose statistical properties such as mean, variance and autocorrelation, etc. are all constant over time [10]. Most statistical forecasting methods are based on the assumption that the time series can be rendered approximately stationary or can be made stationary through the use of mathematical transformations.

The autocorrelation function (ACF) plot can be used to identify stationarity of the time series data. The ACF of a stationary time series drops off to zero relatively quickly while the ACF of non-stationary time series decreases slowly. Thus the first difference of the data was computed in order to make it stationary.

The differenced time series is the change between each observation in the original time series as shown in equation (1) below:

$$y'_t = y_t - y_{t-1} \quad (1)$$

The time series was differenced once, because it exhibited a non-stationary behaviour due to a slightly increasing trend. After the first differencing, it became stationary. The differenced time series has no trend and its statistical properties (mean, variance, etc.) are constant over time. The ACF and the partial autocorrelation function (PACF) graphs for both the original time series and the differenced time series are shown in Figure 1 below.

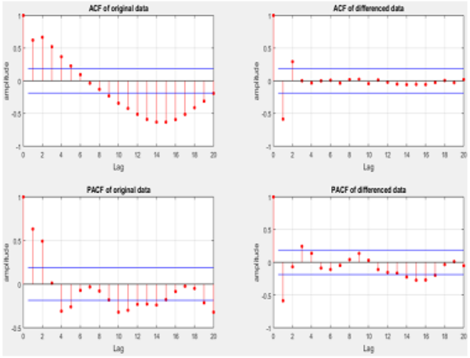

Figure 1: ACF and PACF graphs of both the original and differenced time series data

2.2 ARIMA model selection and AIC computation

After differencing the time series to make it stationary, the ACF and PACF plots of the differenced time series were further used to identify candidate parameters for the ARIMA model. The last significant spike (above the significance range) of the ACF represents the *q* parameter in the ARIMA model while the last significant spike of the PACF plot represents the *p* parameter and the value of *d* is 1 since the times series was differenced once.

Various models were selected and parameters estimated using the least squares method. The estimated parameters were then tested for goodness of fit using Akaike's information criterion (AIC). The model with the least AIC (ignoring absolute values) was the one selected. After an appropriate ARIMA model was selected, the Box-Ljung test was conducted to test the validity of the null hypothesis which says: the residuals of the ARIMA model are not significantly autocorrelated. The null hypothesis test was not rejected implying that the ARIMA (20, 1, 2) model chosen was appropriate. In the ARIMA (20, 1, 2) model chosen, the "20" is the autoregressive term, the "1" is the differencing term and the "2" is the moving average term.

3. ARTIFICIAL NEURAL NETWORKS

The artificial neural network model was selected as an alternative design because it is one of the most effective artificial intelligence techniques for short term load forecasting. The ANN model has the ability to model nonlinear input variables and produce more accurate predictions compared to statistical methods.

3.1 The artificial neural network architecture

The ANN architecture used is shown in Figure 2 below. The multilayer perceptron feedforward backpropagation algorithm was used to train the network. It consisted of one input layer, one hidden layer (with 10 neurons) and one output layer. The input and output layers were both $[29 \times 1]$ matrices. The log-sigmoid transfer function was used for the hidden layer.

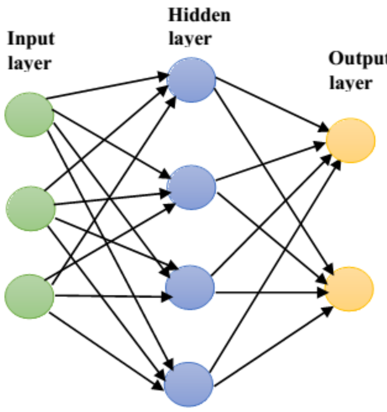

Figure 2: The ANN architecture

The input layer is responsible for reception and activation of data from input files. It typically has a transfer function of 1 so that it does not alter the inputs. The hidden layer receives signals from all of the neurons in the input layer, applies the transfer function to the input signals and passes the outputs of the transfer function to the output layer [11]. The output layer makes these outputs available for display, further computation or use in another program.

4. THE ANN-DWT HYBRID MODEL

This paper focuses on the application of DWT in time series analysis for STLF. The ANN-DWT hybrid method has been proposed and implemented by other researchers [12, 13, 14] in previous studies, but they all had the same approach, which was to decompose the historical load time series, forecast the decomposition components on separate neural networks, then sum up the forecasts of all approximate and detailed components to reconstruct the ultimate forecast signal.

In this paper, a different DWT algorithm was used. The time series (made up of historical load and weather data) was forecasted by the ANN before decomposition by DWT. The output of the ANN forecast was then decomposed into approximate and detailed components, which are then independently fed to separate neural networks for retraining. The output signals of these individual ANN forecasts were then summed up to reconstruct the final output forecast. This method utilised the benefits of both neural networks and wavelets to improve load forecasting results. For the ANN component of the model, the Levenberg-Marquardt back-propagation algorithm was used, while the Daubechies mother wavelet was used in the DWT component. The db6 Daubechies family member was used to perform 3 level decomposition on ANN output signals.

4.1 A brief introduction to wavelets

Wavelets are mathematical functions whose operations are similar to Fourier analysis. They are used for various applications such as time series analysis and signal processing. Wavelets are the basic operating units of wavelet transforms which breakdown an input signal into separate low and high frequency components and analyse those components separately [12].

Generally, wavelet transforms can be categorised into two types: continuous wavelet transform (CWT) and DWT. The former was developed to operate on functions that are defined over the entire real number system while the latter is only suitable to operate on functions defined over a wide range of integers. The discrete wavelet transform is a discretized CWT, meaning that it breaks down the time series signal into integer number of samples for analysis, the data need not be integers but it is decomposed to discrete integer number of samples or pixels (in image processing). The DWT is advantageous because it results in the same number of coefficients as the original signal before decomposition hence more accurate.

The formula for DWT computation is as in (2) [9]:

$$f(t) = \sum_{k} C_{j0,k} \emptyset_{j0,k}(t) + \sum_{j>j0} \sum_{k} \omega_{j,k} 2^{j/2} \Psi(2^j t - k) \quad (2)$$

Where:

- $f(t)$ is a discrete wavelet transform function
- Ψ is the mother wavelet function.
- j is the dilation or level index.
- k is the translation or scaling index.
- $\emptyset_{j0,k}$ is the scaling function of the course scale coefficients.
- and $C_{j0,k}$ and $\omega_{j0,k}$ are the scaling functions of detail (fine scale) coefficients

The Daubechies mother wavelet family was chosen for the design due to its orthogonality which enables it to retain key information of the original signal in the frequency domain.

4.2 Data selection for the ANN component

Table 1 illustrates how input variables were selected for ANN training and testing.

After training the network, the outputs of the ANN forecast were decomposed into approximate and detailed parts using the discrete wavelet transform. The decomposition components were then forecasted independently on separate neural networks. Their forecast outputs were all summed up to reconstruct the original signal.

Table 1: Selected inputs for ANN training

MODEL	INPUT COMPONENT	DESCRIPTION
ANN (Levenberg-Marquardt)	1 – 24	Hourly historical load data for a chosen week day or weekend day
	25	Average wind speed for that day
	26	Day type for that chosen day
	27	Average humidity for that day
	28	Minimum temperature for that day
	29	Maximum temperature for that day

5. SIMULATION AND DISCUSSION OF RESULTS

A comparative study of the forecasting accuracies of the three models was conducted using the mean absolute percentage error (MAPE), the mean absolute deviation (MAD) and the mean square error (MSE). The MAPE (3) is the commonly used technique for evaluating forecasting accuracies, because it determines the errors in percentage terms.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|Actual_i - forecast_i|}{|Actual_i|}\right) \times 100 \qquad (3)$$

5.1 Simulation results for short term load forecasting

A day ahead forecast for a summer weekday

A day ahead load forecast for Thursday, 30 January, 2014 was conducted using the three models discussed. Forecast results are depicted in Figure 3.

The MAPE, MAD and MSE for all three forecasting models are presented in Table 2.

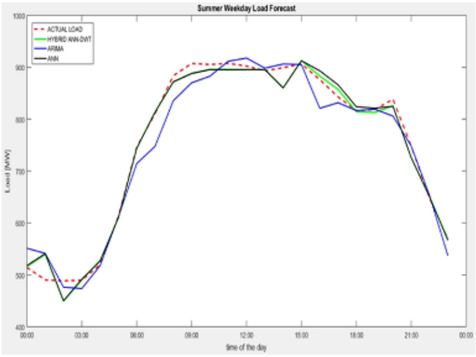

Figure 3: Forecast for Thursday 30 January, 2014.

Table 2: MAPE, MAD and MSE values of load forecasts for Thursday 30 January 2014

	ARIMA	ANN	HYBRID ANN-DWT
MAPE (%)	2.92	1.89	1.75
MAD	20.59	12.94	11.84
MSE	804.50	338.23	307.10

A day ahead forecast for a winter weekday

A day ahead load forecast for Thursday 26 June 2014 was conducted and the forecast results are shown in Figure 4. The corresponding MAPE, MAD and MSE for all three models are presented in Table 3.

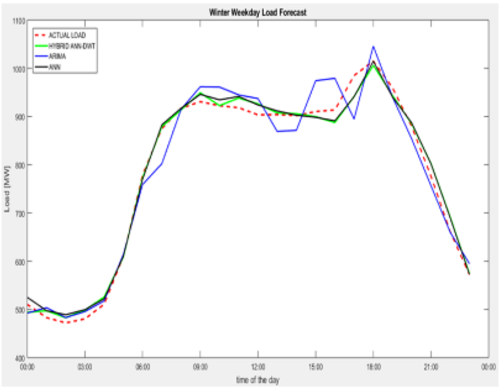

Figure 4: Forecast for Thursday 26 June, 2014.

Table 3: MAPE, MAD and MSE values for ARIMA, ANN and ANN-DWT load forecasts for Thursday 26 June 2014

	ARIMA	ANN	HYBRID ANN-DWT
MAPE %)	3,58	1,89	1,85
MAD	29,41	13,94	13,61
MSE	1364	301,38	297,31

5.2 Simulation results for medium term load forecasting

To further investigate the forecast accuracy of ANN vis-à-vis ARIMA, medium term load forecasting was carried out using the duo. Using load data spanning 2005 - 2015 for Philippi/Montague area of Cape Town, the area's load profile for 2015 was predicted. Results thus obtained are shown in Figure 5. The corresponding MAPE, MAD and MSE for both models are presented in Table 4.

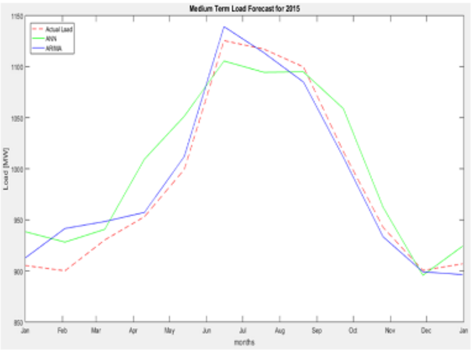

Figure 5: Medium term load forecast for the year 2015

Table 4: Table showing MAPE, MAD and MSE values for medium term load forecast for the year 2015

	ARIMA	ANN
MAPE (%)	1,23	2,66
MAD	11,89	25,95
MSE	243,90	941,64

5.3 Discussion of results for short term load forecasting

The results of the STLF show that the forecast – actual load mismatch was greatest using the ARIMA model. This can be attributed to its weakness in modelling non-linear variables. However, it was able to pick up the shape of the actual load. The performance of the ARIMA compares favourably with other accepted standards in practice. Some ARIMA models with MAPEs around 10% have been reported [13, 14].

In this study, more accurate results were obtained with ANN and the ANN-DWT hybrid models. The improved performance of the ANN model over the ARIMA can be attributed to the ANN's ability to model stochastic loads having non-linear relationship with weather variables as stated in literature.

Referring to Table 2, the significantly high MAD in the ARIMA forecast was reduced by 37.2% with the ANN model. Of all three models, the ANN-DWT hybrid model produced the best forecast accuracy: Compared to the ARIMA model, the percentage reduction in MAPE, MAD, and MSE were 40.1%, 42.5%, and 61.8% respectively; compared to the ANN model, the percentage reduction in MAPE, MAD and MSE were 7.4%, 8.5% and 9.2% respectively. With the ANN-DWT hybrid model, the fairly accurate results of the ANN were further improved by the DWT through decomposition and network retraining.

5.4 Discussion of results for medium term load forecasting

As seen from Figure 5, the ARIMA model performed much better than the ANN model when applied to medium term historical load data. This can be attributed to the fact that medium term time series data had no weather variables and only historical load was considered for forecasting.

Historical load exhibited a more linear characteristic and thus favoured a statistical time series method (ARIMA). For this reason, the ANN-DWT was not applied for medium term data since its requisite model (ANN) came second best to ARIMA. In Table 4, one can see that the values of MAPE, MAD and MSE of the ARIMA model are much lower than those of ANN model. This resonates with what was stated in other studies [9] that the ANN is not so good a model for data that exhibits a more linear characteristic.

6. CONCLUSIONS

Accurate STLF is pivotal to electrical utilities and independent power producers. It enables them to plan and control the power system operations efficiently and economically. In this paper, three models - ANN, ARIMA and the hybrid ANN-DWT - were investigated for STLF. The same number and type of input variables were applied to all three models in order to compare their forecasting abilities. Results of the short term load forecasts for all three models were presented and compared using metrics such as MAPE, MAD and MSE.

The results obtained showed that ANNs are better suited to model short term load than ARIMA. Thus, for historical load with exogenous variables, the ANN model is preferable for STLF. However, with load data exhibiting linear characteristics (like the medium term data used in this study), the ARIMA model is preferable for performing load forecasts.

Furthermore, the accuracy of ANN models in predicting non-linear short term load, can be improved using hybrid techniques. In this paper, ANN-DWT hybrid model was presented for improving the forecast accuracy of ANN models. Results obtained show the effectiveness of the proposed model in obtaining more accurate forecast results.

7. ACKNOWLEDGEMENT

The authors are grateful to Mr Peter Jaeger of the City of Cape Town Network Control Centre for providing the historical load data used in this study. We would also like to thank the South African Weather services for their assistance with weather information.

8. REFERENCES

[1] Y.-j. He, Y.-c. Zhu, D.-x. Duan and W. Sun, "Application of neural network model based on fuzzy classification and input selection in short term load forecasting," in *Proceedings of the Fifth International Conference on Machine Learning and Cybernetics*, Dalian, 2006.

[2] B. Hodge, D. Lew and M. Milligan, "Short-Term Load Forecasting Error Distributions and Implications for Renewable Integration Studies," in *IEEE Green Technologies Conference*, Colorado, 2013.

[3] M. M. Ismail and M. M. Hassan, "Artificial Neural Network Based Approach Compared With Stochastic Modelling For Electrical Load Forecasting," in *U2013 Proceedings of International Conference on Modelling, Identification & Control (ICMIC)*, Cairo, 2013.

[4] H. Li, Y. Zhao, Z. Zhang and X. Hu, "Short-Term Load Forecasting Based on the Grid Method and the Time Series Fuzzy Logic Forecasting Method," in *International Conference on Renewable Power Generation (RPG 2015)*, Beijing, 2015.

[5] M.Kalantar and L.Ghods, "Different Methods of Long-Term Electric Load Demand Forecasting; A Comprehensive Review," *Iranian Journal of Electrical & Electronic Engineering,* vol. 7, no. 4, pp. 249-259, 2011.

[6] H. S. Hippert, C. E. Pedreira and &. R. C. Souza, "Neural Networks for Short-Term Load Forecasting: A Review and Evaluation," *IEEE Transactions on Power Systems,* vol. 16, no. 1, pp. 44-53, 2001.

[7] S. Ahmadi, H. Bevrani and H. Jannaty, "A fuzzy inference model for short-term load forecasting," in *2012 Second Iranian Conference on Renewable Energy and Distributed Generation*, Tehran, 2012.

[8] N. Ye, Y. Liu and Y. Wang, "Short-Term Power Load Forecasting Based on SVM," in *Proceedings of 2010 Conference on Dependable Computing (CDC'2010)*, Yinchang, 2010.

[9] Akbari-Zadeh, A. K. Fard and Mohammad-Reza, "A hybrid method based on wavelet, ANN and ARIMA model for short-term load forecasting," *Journal of Experimental & Theoretical Artificial Intelligence,* vol. 26, no. 2, pp. 168-181, 2014.

[10] R. Nau, "Statistical forecasting," Fuqua School of Business, 1 May 2016. [Online]. Available: https://people.duke.edu/~rnau/411home.htm. [Accessed 25 October 2016].

[11] G. McNeill and D. Anderson, "Artificial Neural Network Technology," Kaman Sciences Corporation, New York, 1992.

[12] I. Daubechies, Ten Lectures of Wavelets, Philadelphia: Society for Industrial and Applied Mathematics, 1992.

[13] I. Khandelwal, R. Adhikari and G. Verma, "Time Series Forecasting Using Hybrid ARIMA and ANN Models Based on DWT Decomposition," in *International Conference on Computer, Communication and Convergence (ICCC 2015)*, Odisha, 2015.

[14] K. M. U. Ahmed, M. Ampatzis, P. H. Nguyen and W. L. Kling, "Application of time-series and Artificial Neural Network models in short term load forecasting for scheduling of storage devices," in *Power Engineering Conference (UPEC), 2014 49th International Universities*, Cluj-Napoca, 2014.

[15] D. K. Chaturvedi and S. A. Premdayal, "Neural-Wavelet Based Hybrid Model for Short-Term Load Forecasting," *Control Theory and Informatics ,* vol. 3, no. 2, pp. 42-45, 2013.

[16] M.Ulagammai, "Short Term Load Forecasting Using ANN and WNN," *International Journal of Computer Trends and Technology (IJCTT),* vol. 1, no. 1, pp. 123-128, 2011.

[17] D.A.Kapgate and Dr.S.W.Mohod, " Short-Term Load Forecasting using Hybrid Neuro-Wavelet Model," *International Journal of Electronics and Communication Engineering & Technology (IJECET),* vol. 4, no. 2, pp. 280-289, 2013.

[18] Q. Luthuli and K. Folly, "Undergraduate Thesis for Short term Load Forecasting using Artificial Neural Networks," University of Cape Town, Cape Town, 2013.