KJMS 2022 VOL.4 (1): 106-116

KDU Journal of Multidisciplinary Studies (KJMS)

Volume 4. Issue 1 July 2022

DOI: http://doi.org/10.4038/kjms.v4i1.44

APPLICATION OF ARTIFICIAL NEURAL NETWORK FOR SHORT TERM ELECTRICITY DEMAND FORECASTING

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ABSTRACT

Many researchers around the world work on short term electricity demand forecasting (STLF) in order to establish an accurate power planning and generation system in their countries. This research, with its focus on short-term load forecasting, aims to fill this gap by implementing two methodologies based on Artificial Neural Network (ANN) and Autoregressive Integrated Moving Average (ARIMA) applied on a set of half an hourly load demand data of six years, provided by Ceylon Electricity Board in Sri Lanka. The data of first five years (~70% of the dataset) were used to train the algorithms and those of the last year (~30% of the dataset) were used for testing. The effect of historical load demand patterns on making the prediction of the next 24 hours were studied. Moreover, with the historical data, unlike in most literature which forecasts only one value (either peak load demand of the day or only the load demand of the next half an hour), the demand of the entire day (48 values for each half an hour) is forecasted at once. The predictions obtained by the application of ANN were compared with those of ARIMA methodology which is a benchmark of comparing predictions in STLF. None of the applications provided deviated predictions compared to each other and ANN can be used to predict the next day half-hourly electricity demand since the application was successful in grasping the periodic patterns that exist in half hourly series.

KEYWORDS *ANN, ARIMA, Half Hourly Electricity Demand, STLF*

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1. INTRODUCTION

In electrical generation, short term electricity demand forecasting plays a supreme role as the main target of power generation sector of a country is to provide a continuous and uninterrupted power supply to the people. Demand forecasting has been studied since the 1960's. A demand forecasting strategy with higher accuracy is vital in order to establish an accurate power planning and generation procedure in a country. In addition to that, demand forecasting for a short time period is very essential. In order to utilize the above sources efficiently to meet the load demand, scheduling of power generation is essential as generators cannot be started up and shut down instantly and some types of plants (e.g. thermal) involve a startup and shutdown cost. Therefore, it is essential to forecast the load demand for a short period of time (e.g. 24 hours) and to prepare a power generation plan for that period.

Many researchers around the world have investigated load forecasting models based on various forecasting techniques to prepare a better generation plan. They have classified load forecasting into three or four categories according to the time span. Singh et al. (2013) have divided load forecasting into three categories, i.e. short-term forecasts which are usually from one hour to one-week, medium forecasts which are usually from a week to a year, and long-term forecasts which are longer than a year. According to Zor et al. (2017), there are four categories of electric load forecasting with respect to time span, i.e. long-term where 3-year and 50-year electric load is predicted, medium-term where the forecast ranges from 2 weeks to 3 years, and short-term electric load forecasting (or short-term load forecasting, generally abbreviated as STLF in the literature), which refers to hour, day or week ahead predictions, and very short-term electric load forecasting which includes few minutes to an hour ahead forecasting of electric loads Yang (1974), Lee et al. (1992) and Al-Hamadi and Soliman (2004).

For strategic planning of the development of the electric power systems, both long-term and medium-term forecasts have significant advantages which include scheduling of construction of new generation and transmission capacity, maintenance scheduling, as well as long-term demand side measurement and management planning (Amjadi 2001). However, an accurate STLF technique can reduce operating costs, keep energy markets efficient, and provide a better understanding of the dynamics of the monitored system. Out of the load forecasting systems, STLF is a method where historical data are fine-tuned using more recent data. In addition to that, main requirements of the STLF process are accuracy and reliability. Further, it is preferred if the forecasting process can be automated (Yang 1974). Therefore, it is very important to maintain an error-reduced forecasting plan for the next 24 hours and to prepare a power generation plan for that period since there is not a well-planned strategy to forecast load for the next day yet.

In Sri Lanka, the electricity generation authorities forecast the next day demand based on the demand history. First, the electricity demand pattern during the 24 hours' period, prior to the required time slot, is manually matched with the load demand pattern in history. Then the best match is found and the pattern following that best match will be considered as the forecasted pattern for the next 24 hours. However, this technique leaves room for forecasting errors according to the study carried out by Somarathne et al. (2020). Accordingly, there is a necessity of more research to study the interrelationships among daily patterns in forecasting the demand for next 24 hours.

In implementations of STLF, Autoregressive Integrated Moving Average (ARIMA) modelling has been used as a sophisticated benchmark and exponential smoothing techniques including Holt Winters method have been used in many research investigations; Taylor (2003), Taylor et al. (2006) and Taylor (2010). With the use of computing technologies for load forecasting fuzzy logic systems and neural network systems are used to model the complexity and nonlinear behaviour of load data by Abraham et al. (2001) and Liu et al. (1996). Some researchers pay their attention on artificial neural networks and a great number of papers reported successful investigations with them (e.g. Hippert et al., 2001), but it is still not clear whether neural networks and more complex non-linear models outperform simpler and more standard forecasting procedures such as ARIMA modelling and exponential smoothing techniques. When considering multivariate nonlinear techniques, artificial neural network methods have been used by using weather variables in some research papers as in Taylor et al. (2002), and Khan et al. (2004).

In this study, short term load forecasting for 24 hours ahead based on half hourly electricity demand in Sri Lanka will be investigated by using Seasonal ARIMA modelling and Artificial Neural Network modelling. Then the accuracy measures of both models were compared to each other by considering forecasts of the selected two weeks.

2. METHODOLOGY

2.1 Data collection

Half hourly electricity load demand (in MW) in Sri Lanka from 01/01/2009 to 31/12/2014 was considered for the analysis by assuming that the demand is equal to the generation.

The data of 2009-2013 (~70% of the dataset) were used to train the algorithm and data of 2014 (~30% of the dataset) were used for testing as given in Fig. 1.

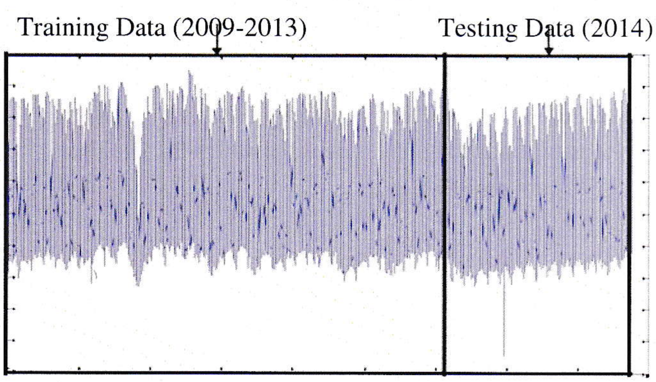

Figure 1: Data allocation for Training and Testing

The next day load will be predicted using, ARMA methodology and Artificial Neural Network. So, the load series was divided into 48 numbers of individual time series (based on half hours) and the proposed methodologies were applied to each series.

E.g.

Let $\{L_{n,m,o}\}$ is the load of n^{th} half an hour of m^{th} day of the o^{th} year ; $n = 1,2,\ldots,48$, $m = 1,2,\ldots,365$ and o=1,2,3,4,5

Half hourly electricity demands of five years =

$$\begin{bmatrix} L_{1,1,1} & L_{1,2,1} & L_{1,3,1} & \cdots & L_{1,364,1} & L_{1,365,1} \\ L_{2,1,2} & \cdot & \cdot & \cdots & \cdot & L_{2,365,2} \\ L_{3,1,3} & \cdot & \cdot & \cdots & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdots & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdots & \cdot & \cdot \\ L_{48,1,5} & L_{48,2,5} & \cdot & \cdots & \cdot & L_{48,365,5} \end{bmatrix} = \begin{bmatrix} L_1 \\ L_2 \\ \cdot \\ L_n \\ \cdot \\ L_{48} \end{bmatrix}$$

Proposed techniques were applied to each half hourly series

Accordingly, half hourly electricity demands were predicted for the weeks *01st –07th January 2014, 1st-7th February 2014 and 01st – 07th October 2014.*

2.2 Technology

Seasonal ARIMA Technology

The each half hourly series were checked for stationary and if so, the series was differenced to make it stationary before applying ARIMA.

The autocorrelation function of each series was plotted to observe non-stationary.

E.g. consider the series of electricity demand during the half an hour 7.00pm-7.30pm in Figure 2(a) and Figure 2(b).

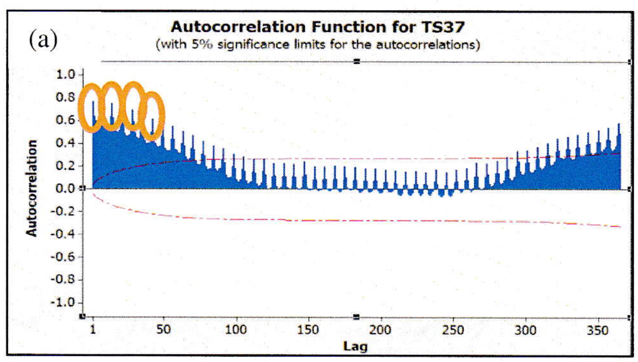

Figure 2(a)

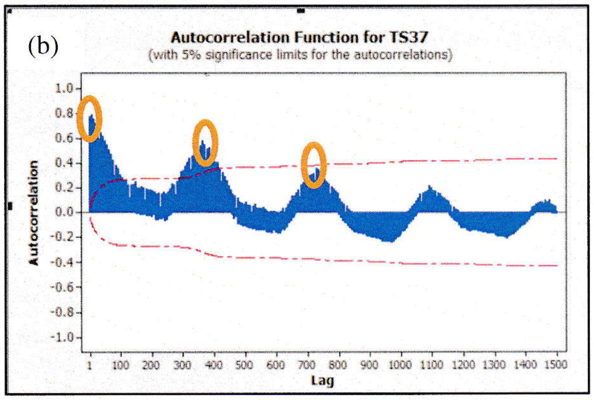

Figure 2(b)

Figure 2: Plots of Autocorrelation functions with respect to 37th half an hour (Lag in days)

Figure 2(a) and 2(b) show annual, weekly and daily periodic patterns in the series, and it is seen that the first few lags do not decay to zero immediately. This reveals that the series is stationary. Therefore, differencing of the series is needed to make the series stationary.

Based on the patterns exhibited in ACF, each of $\{L_n\}$ was differenced at lags 1, 7 and 365 according to the annual and weekly patterns that exist in load as follows. Then, 48 ARMA models were developed to forecast load of each half an hour for one week ahead. The model formats which were shown by the models were stored separately.

Considering the load demand series of each n up to *31st December 2013,* the load demand of the weeks *01st - 07th January 2014. 01st - 07th February 2014 and 01st - 07th October 2014* with respect to each n were forecasted.

Identification of tentative models is the first step of ARIMA methodology. Identification consists of specifying the appropriate structure (AR, MA or ARMA) and order of model. It is sometimes done by looking at plots of the sample autocorrelation (acf) and the sample partial autocorrelation function (pacf). Tentative models under each case will be identified. Then, the accuracy measures will be compared between each tentative models under each case and two models will be finalized under each case. The coefficients which are obtained by the models were considered, will be estimated and then diagnostic checking or verification will be performed. In this step, two important elements of checking are to test that the residuals of the model are random, and to ensure that the estimated parameters are statistically significant. Usually, the fitting process is guided by the principle of parsimony, by which the best model is the simplest possible model – the model with the fewest parameters and reduced error that adequately describes the data.

Artificial Neural Network

In this method, artificial neural networks were built with the intention to provide a better forecast of load demand of electricity for the next 24 hours. Here, the load demand of electricity of nth half hour of the next day was predicted using the load demand of the same half hour of history through an artificial neural network. Thus, 48 neural networks were developed with respect to each half hourly series. This can be illustrated using the following diagramme (Figure 3).

For an artificial neural network, several parameters are to be selected appropriately to come up with the best architecture. They are the number of layers, the number of nodes in each layer and the number of arcs which interconnect with the nodes. Other network design decisions include the selection of activation functions of the hidden and output nodes, the training algorithm, data transformation or normalization methods, training and test datasets, and performance measures. Initially, the first five years of the original dataset were taken as the training dataset in creating the neural network, and it was tested for the last year (of the original dataset).

Figure 4 illustrates the neural network designed for the load demand prediction for the next 24 hours. Let d= no of historical demands and m=no of neurons in the hidden layer.

Consider the load demand series of nth Half hour $\{L_n\}$ in Figure 4.

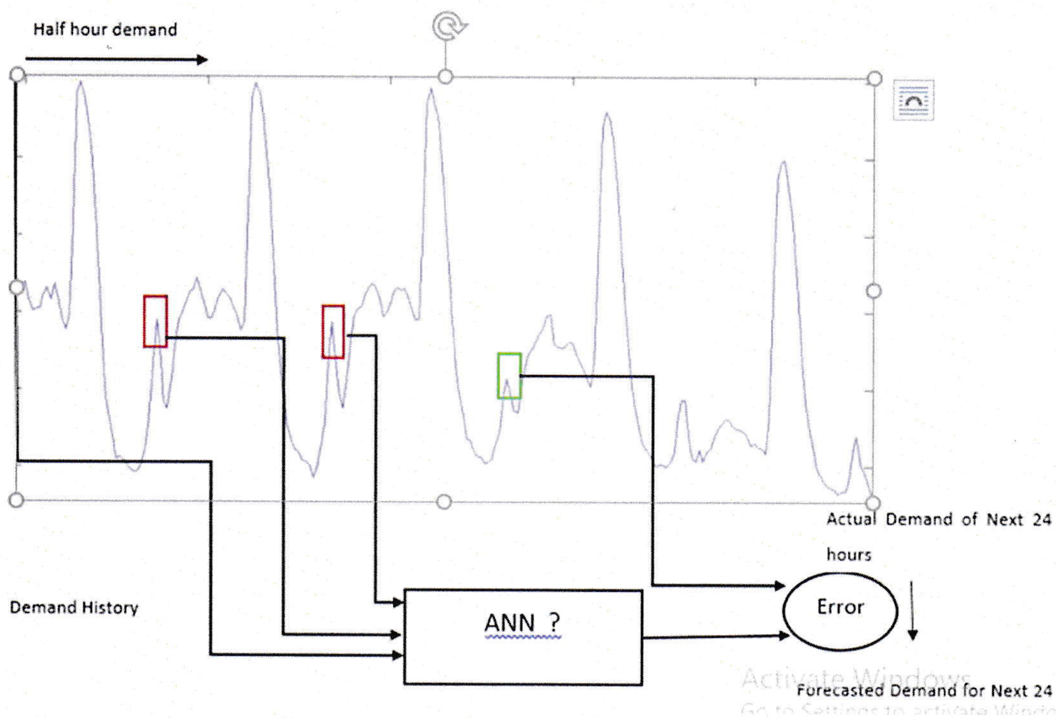

Figure 3: Illustration of Neural Network model

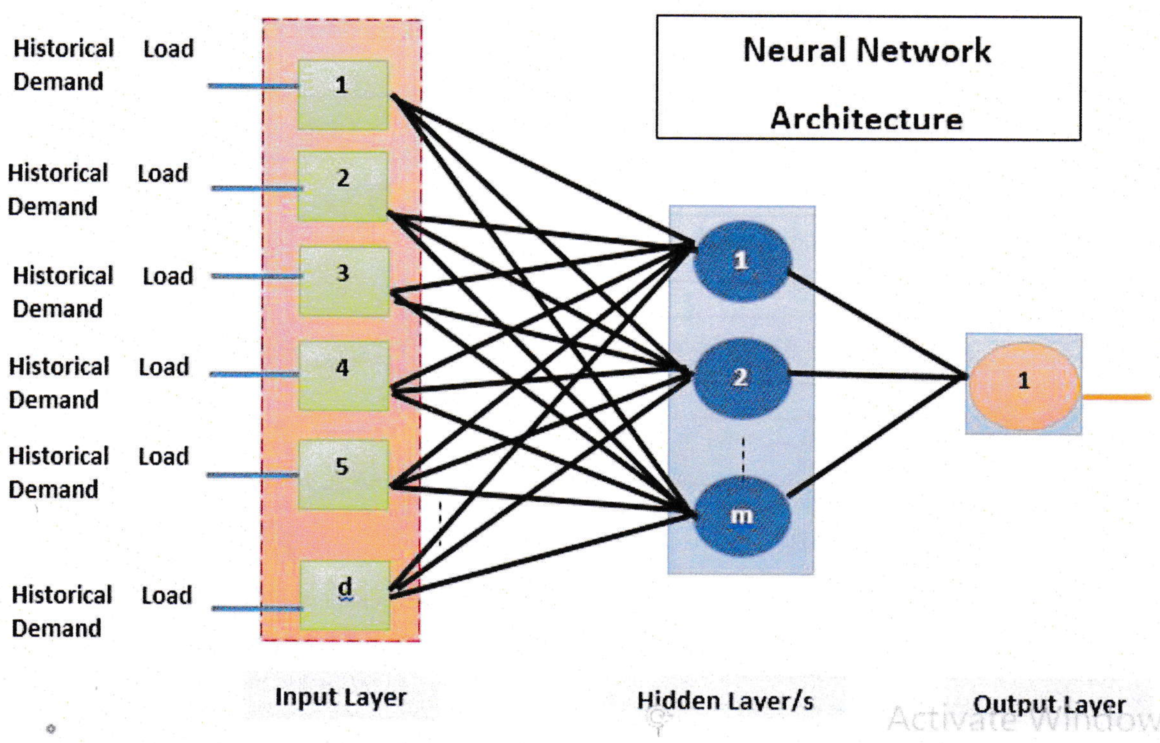

Figure 4: Architecture of Neural Network

48 numbers of neural network models were developed with the use of the following inputs. Suppose we need to forecast the demand of i[th] half an hour of the day – D , year- Y $X_{i,D,Y}$
Following Inputs were considered.

- $X_{i,D-1,Y}$
- $X_{i,D-7,Y}$
- $X_{i-1,D-1,Y}$
- $X_{i,D,Y-1}$
- $X_{i,D-1,Y-1}$
- $X_{i,D-7,Y-1}$

After several trials with the aforesaid inputs, the following inputs have been identified as the most effective inputs in order to increase the model accuracy.

Inputs
- $X_{i,D-1,Y}$
- $X_{i,D-7,Y}$
- $X_{i-1,D-1,Y}$
- $X_{i,D,Y-1}$

After several trials, the most appropriate structures were selected. Table 1 provides a description for the created artificial neural networks for each case

Table 1: Informative Neural Network

Parameter	**Value**
No of hidden layers	2
Input Variables	4
No of input patterns	1826
No of outputs	1
Transfer function	Hyperbolic tangent sigmoid transfer function
training function	training function that uses Levenberg-Marquardt optimization

Then, the load demand of the weeks *01st -07th January 2014. 01st -07th February 2014 and 01st - 07th October 2014* with respect to each *n* were forecasted.

Checking Model Accuracy

The electricity demands of selected weeks were forecasted using ARIMA modelling technique and ANN.

Then, the below mentioned accuracy measures RMSE- Root Mean Square Error, NRMSE- Normalized Root Mean Square

Error, MAE – Mean Absolute Error, MAPE –Mean Absolute Percentage Error, Coefficient of Determination (R^2) and ME-Mean Error of the finalized ARIMA models and ANN models will be compared to find the applicability of ANN as a better technique to forecast the electricity demand one day ahead.

Let the accuracy measures,

RMSE

$$\sqrt{\frac{\sum_{i=1}^{r}(x_{obs,i}-x_{model,i})^2}{r}}$$

NRMSE

$$\sqrt{\frac{\sum_{i=1}^{r}(x_{obs,i}-x_{model,i})^2}{\sum_{i=1}^{r}\left(x_{obs,i}-\bar{x}_{obs}\right)^2}}$$

MAE

$$\frac{1}{r}\sum_{i=1}^{r}\left|x_{obs,i}-x_{model,i}\right|$$

MAPE

$$\frac{1}{r}\sum_{i=1}^{r}\frac{\left|x_{obs,i}-x_{model,i}\right|}{x_{obs,i}}*100$$

Coefficient of Determination (R^2) $1-(NRNMSE)^2$

where, $x_{obs,i}$ is the observed/actual demand for i[th] half an hour, $x_{model,I}$ is the modeled/predicted value for i[th] half an hour, $\bar{x}_{obs}$ is the mean of observed demand, and r is the number of demand values in the series.

Table 2: Model Formats Observed for each half our demand serie

TS	MODEL	
1	$(1-\phi_1 B)(1-\phi_2 B^7)\psi_{dD}x_t = (1-0_1 B)(1-0_2 B^7)(1-0_3 B^{365})e_t$	A
2		
3		
4		
5		
6		
7		
8		
9	$(1-\phi_1 B)\psi_{dD}x_t = (1-0_1 B)(1-0_2 B^7)(1-0_3 B^{365})e_t$	B
10		
11	$(1-\phi_1 B)(1-\phi_2 B^7)\psi_{dD}x_t = (1-0_1 B)(1-0_2 B^7)(1-0_3 B^{365})e_t$	C
12		
13	$(1-\phi_1 B)\psi_{dD}x_t = (1-0_1 B)(1-0_2 B^7)(1-0_3 B^{365})e_t$	B
14		
15		
16		
17		
18		
19		
20		
21		
22		
23	$(1-\phi_1 B)(1-\phi_2 B^7)\psi_{dD}x_t = (1-\theta_1 B)(1-\theta_2 B^7)(1-\theta_3 B^{365})e_t$	C
24	$(1-\phi_1 B)\psi_{dD}x_t = (1-0_1 B)(1-0_2 B^7)(1-0_3 B^{365})e_t$	B
25		
26		
27		
28		
29		
30	$(1-\phi_1 B)(1-\phi_2 B^7)\psi_{dD}x_t = (1-0_1 B)(1-0_2 B^7)(1-0_3 B^{365})e_t$	A
31	$(1-\phi_1 B)(1-\phi_2 B^2)(1-\phi_3 B^3)\psi_{dD}x_t = (1-\theta_1 B)(1-\theta_2 B^7)(1-\theta_3 B^{365})e_t$	D
32	$(1-\phi_1 B)(1-\phi_2 B^2)(1-\phi_3 B^3)(1-\phi_4 B^4)\psi_{dD}x_t = (1-\theta_1 B)$ $(1-\theta_2 B^7)(1-\theta_3 B^{365})e_t$	E
33	$(1-\phi_1 B)\psi_{dD}x_t = (1-0_1 B)(1-0_2 B^7)(1-0_3 B^{365})e_t$	B
34		
35	$(1-\phi_1 B)(1-\phi_2 B^7)\psi_{dD}x_t = (1-0_1 B)(1-0_2 B^7)(1-0_3 B^{365})e_t$	C
36	$(1-\phi_1 B)\psi_{dD}x_t = (1-\theta_1 B)(1-\theta_2 B^7)(1-\theta_3 B^{365})e_t$	B
37		
38		
39	$(1-\phi_1 B^2)(1-\phi_2 B^4)(1-\phi_3 B^7)(1-B)(1-B^7)(1-B^{365})x_t = (1-0_1 B)(1-0_2 B^7)(1-0_3 B^{365})e_t$	F
40	$(1-\phi_1 B)\psi_{dD}x_t = (1-\theta_1 B)(1-\theta_2 B^7)(1-\theta_3 B^{365})e_t$	B
41	$(1-\phi_1 B)(1-\phi_2 B^2)(1-\phi_3 B^4)(1-\phi_4 B^7)(1-B)(1-B^7)(1-B^{365})x_t = (1-\theta_1 B^7)(1-\theta_3 B^{365})e_t$	G
42	$(1-\phi_1 B)(1-\phi_2 B^2)(1-B)(1-B^7)(1-B^{365})x_t = (1-\theta_1 B)(1-\theta_2 B^7)(1-\theta_3 B^{365})e_t$	A
43	$(1-\phi_1 B)(1-\phi_2 B^7)\psi_{dD}x_t = (1-\theta_1 B)(1-0_2 B^7)(1-0_3 B^{365})e_t$	C
44		
45	$(1-B)(1-B^7)(1-B^{365})x_t = (1-0_1 B)(1-0_2 B^7)(1-\theta_3 B^{365})e_t$	H
46	$(1-\phi_1 B)\psi_{dD}x_t = (1-\theta_1 B)(1-\theta_2 B^7)(1-\theta_3 B^{365})e_t$	B
47	$(1-B)(1-B^7)(1-B^{365})x_t = (1-\theta_1 B)(1-\theta_2 B^7)(1-\theta_3 B^{365})e_t$	H
48		

3. RESULTS & DISCUSSION

Seasonal ARIMA

Each half-hourly series were converted into stationary by differencing in order to apply Seasonal ARIMA.

The finalized 48 numbers of seasonal ARIMA models with respect to each half an hour were stored in Table 2.

Let $\psi_{dD} = (1-B)(1-B^7)(1-B^{365})$.

Table 2 consists of the ARIMA models obtained for each half hourly series. According to the model formats in Table 2, model format B is the most frequently resulting model among 48 numbers of half hourly demand series. Most of the half hourly demand series recorded during the day time demonstrate the model format B. According to the obtained models, the demand of the same half an hour in the previous day is highly correlated with that of the next day. Also, the demand of the same half an hour is highly correlated with that of the day before the previous day and the same day of the last week according to the other models such as A, C and G.

Artificial neural network

The following parameters were considered as the inputs to 48 numbers of neural networks by trialing several sets of inputs.

Forecast the demand of i[th] half an hour of the day – D, year- Y $X_{i,D,Y}$

Inputs $-X_{i,D-1,Y}$, $X_{i,D-7,Y}$, $X_{i-1,D-1,Y}$, $X_{i,D,Y-1}$

Table 3: Accuracy measures of all techniques for the week 1-1-2014 to 7-1-2014

Model	NRMSE	RMSE	MAPE	MAE	Coefficient of Determination
ARIMA	0.2904	87.8026	4.7280	60.0652	0.9157
ANN	0.3212	97.1261	5.8009	73.3915	0.8968

According to the accuracy measures in Table 3, ARIMA approach resulted in better forecasting during the week 1-1-2014 to 7-1-2014.

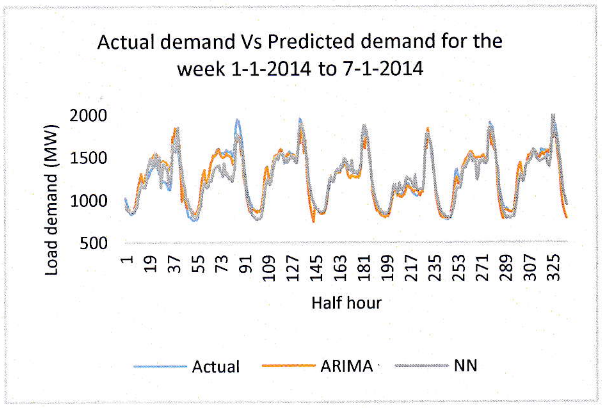

Figure 5: Actual Demand Vs Predicted Demand obtained by models during 1-1-2014 to 7-1-2014

Table 4: Accuracy measures of all techniques for the week 1-2-2014 to 7-2-2014

Model	NRMSE	RMSE	MAPE	MAE	Coefficient of Determination
ARIMA	0.3684	111.324	5.9100	72.486	0.8642
ANN	0.4332	130.919	7.3951	87.547	0.8123

Table 5: Accuracy measure of all techniques for the week 1-10-2014 to 7-10-2014

Model	NRMSE	RMSE	MAPE	MAE	Coefficient of Determination
ARIMA	0.2554	75.4554	4.6329	60.2893	0.9348
ANN	0.2220	65.7278	4.1177	51.8170	0.9507

Table 6: Accuracy Measures Day-wise during 1-1-2014 to 7-1-2014

Day	ARIMA				ANN			
	NRMSE	RMSE	MAPE	MAE	NRMSE	RMSE	MAPE	MAE
1.1.2014	0.5126	128.637	8.5420	105.5981	0.4478	112.3715	7.5387	91.1397
2.-1.2014	0.2873	99.7026	6.3674	79.3276	0.4745	164.6483	9.9451	140.2511
3-1-2014	0.3042	93.0170	4.1728	54.4379	0.2214	67.6919	4.6069	55.2543
4-1-2014	0.2306	61.2703	3.4607	45.3574	0.1570	41.7246	2.5219	32.5148
5-1-2014	0.1121	34.7181	2.1199	24.7236	0.2363	73.2026	5.7980	62.1438
6-1-2014	0.2523	80.3157	4.2706	54.8496	0.2732	86.9649	4.9581	62.6595
7-1-2014	0.2745	86.1093	4.1627	56.1619	0.2677	83.9838	5.2373	69.7774

Table 7: Accuracy Measures Day-wise during 1-2-2014 to 7-2-2014

Day	ARIMA				ANN			
	NRMSE	RMSE	MAPE	MAE	NRMSE	RMSE	MAPE	MAE
1-2-2014	0.1383	35.9172	2.3072	28.2262	0.1758	45.6365	2.7554	35.2660
2-2-2014	0.0933	26.4792	1.8326	20.0127	0.2646	74.7748	5.6888	62.8215
3-2-2014	0.3967	122.0826	7.2145	103.4017	0.2238	68.8617	4.2126	55.4857
4-2-2014	0.7771	234.2617	18.6603	198.176	0.9228	278.1671	22.2259	236.835
5-2-2014	0.2773	97.0562	5.5811	78.21	0.3693	129.2624	8.3389	108.9475
6-2-2014	0.2206	66.0051	3.5164	49.8776	0.3052	91.3287	5.6196	70.4719
7-2-2014	0.1113	34.6488	2.2581	29.4977	0.2302	71.6631	2.9258	43.0051

Table 8: Accuracy Measures Day-wise during 1-10-2014 to 7-10-2014

Day	ARIMA				ANN			
	NRMSE	RMSE	MAPE	MAE	NRMSE	RMSE	MAPE	MAE
1-10-2014	0.3689	113.7863	6.8430	94.9607	0.2235	68.9450	4.7882	56.5008
2-10-2014	0.2505	78.8657	4.4911	58.9610	0.2192	69.0095	4.0802	55.3816
3-10-2014	0.2985	91.5506	4.6333	59.2600	0.1137	34.8568	2.1290	28.6940
4-10-2014	0.2506	64.4021	4.1949	54.6840	0.2561	65.7861	4.3141	55.5242
5-10-2014	0.2072	57.7893	4.4896	50.2103	0.2583	72.0291	4.6428	52.8097
6-10-2014	0.2845	91.1579	4.9718	62.8256	0.2288	73.3096	4.3952	58.7150
7-10-2014	0.2820	78.0188	5.4007	68.2925	0.2457	67.9701	4.4741	55.0932

In the predictions of 1st and 2nd January 2014, deviations from the regular daily pattern can be diagnosed in both ARIMA and ANN predictions. This is owing to the holidays of the previous week which sets within Christmas vacation because the demand of the same time slot on the previous week is one of the inputs in ANN methodology. However, the predictions have captured the daily and weekly patterns of electricity demand as shown in Figure 5

Table 4 illustrates that ARIMA modelling results a better accuracy compared to the ANN for the first week of February 2014.

Comparison of actual demand and predicted demand for the first week of February 2014 shows that (Table 4 and Figure 6) application of ARIMA indicates a better accuracy than ANN. However, both approaches have been unsuccessful to acquire the demand of 4th February which is a public holiday. Also, the day after the Independence Day is also poorly forecasted, as the inputs to that day forecasts consist of unusual day data.

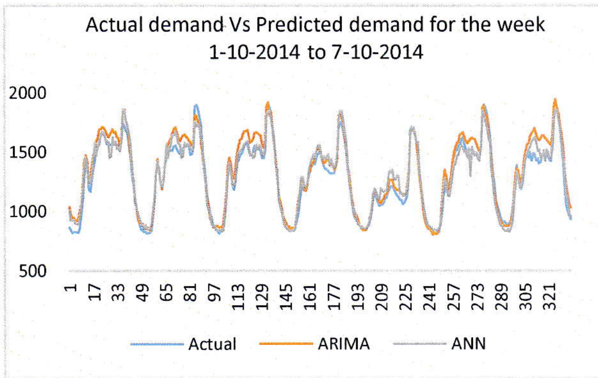

Figure 6: Actual Demand Vs Predicted Demand obtained by ANN during 1-10-2014 to 7-10-2014

For the prediction done for the first week of October, 2014 ANN methodology shows a higher accuracy than ARIMA.

According to Figure 7, some deviations can be observed in the predictions obtained by ARIMA but ANN predictions demonstrate more stability.

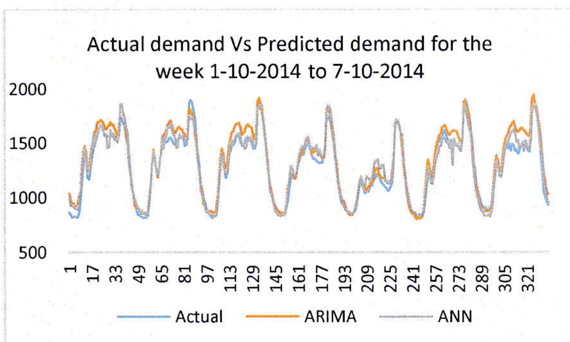

Figure 7: Actual Demand Vs Predicted Demand obtained by ANN during 1-10-2014 to 7-10-2014

4. CONCLUSIONS

Predictions with less accuracy were observed by the implementations of existing techniques for half hourly series and Seasonal ARIMA modelling provides predictions with better accuracy according to Somarathne et al. (2020). Existing techniques were unable to capture the weekday-weekend pattern as well as predictions were highly deviated according to the involvement of holidays (Somarathne et al. 2020). Accordingly, this study proposed ANN technique in addition to ARIMA in order to predict the next day electricity load demand based on the historical data. According to the accuracy measures given in Table 3, 4 and 5, ANN methodology provides better accuracy than ARIMA for the considered week of October, 2014. For the considered weeks of January and February 2014, ARIMA methodology provided better predictions than ANN but the differences of accuracy measures were very low. Thus, it is unable to ignore either ANN or ARIMA as prediction methodologies with less accuracy.
According to the results of Table 6, 7 and 8, predictions made by using artificial neural networks consisted of better accuracy in some of the considered days. However, ARIMA predictions also consisted of better accuracy in some of the days during the considered three weeks. When the prediction time period goes to the end of the year, ANN methodology provides more accurate and stable predictions.

According to the findings of this study, ARIMA and ANN modellings need some improvements so as to reduce the error associated with their predictions to come up with better accuracy. Understanding the effect of special days (e.g. holidays, festive days, etc.,) on load demand is useful as such information may be accommodated to ARIMA, ANN models to improve their prediction accuracy.

In addition to that, weather components like rainfall can be associated with ANN model to obtain predictions with better accuracy because rainfall is highly correlated with the load demand.

5. REFERENCES

Abraham, A; and Nath, B (2001): A neuro-fuzzy approach for modeling electricity demand in Victoria, Applied Soft Computing Journal 1: pp. 127-138.

Al-Hamadi, H and Soliman, S (2004): Short-term electric load forecasting based on Kalman filtering algorithm with moving window weather and load model, Electric Power Systems Research 68: pp. 47-59.

Amjady, N (2001): Short-term hourly load forecasting using time-series modeling with peak load estimation capability, IEEE Transactions on Power Systems 16: pp 498-505.

Hippert, H; Pedreira, C and Souza, R (2001): Neural networks for short-term load forecasting: A review and evaluation, IEEE Transactions on Power Systems 16: pp 44-55

Khan, M R and Abraham, A (2004): Short term load forecasting models in Czech Republic using soft computing paradigms, International Journal of Knowledge-Based Intelligent Engineering Systems IOS Press Netherlands 7(4): pp. 172-179.

Lee, K Y; Cha, Y T and Park, J H (1992): Short-Term Load Forecasting Using An Artificial Neural Network, IEEE Trans. on Power Systems 7: pp. 124-132.

Liu, K; Subbarayan, S; Shoults, R R; Manry, M T; Kwan, C; Lewis, F L and Naccarino, J (1996): Comparison of Very Short Term Load Forecasting Techniques, IEEE Transactions on Power Systems 11: pp. 877-882.

Singh, A K; Ibraheem, S K; Muazzam, M and Chaturvedi, D K (2013): An overview of electricity demand forecasting techniques, Network and Complex Systems *3*(3): 38-48.

Somarathne, E D T; Karunasinghe, D S K and Wijayakulasooriya, J V (2020): Short Term Electricity Demand Forecasting for Generation Scheduling: A Case Study in Sri Lanka, International Conference on Environmental and Medical Statistics (ICEMS 2020) p.32.

Taylor J W, Buizza R (2002) Neural network load forecasting with weather ensemble predictions. IEEE Transactions on Power Systems

Taylor, J W (2003): Short-term electricity demand forecasting using double seasonal exponential smoothing, Journal of the Operational Research Society (01/2003; 54:pp. 799-805. doi: 10.1057/palgrave.jors.2601589

Taylor, J W (2010): Triple Seasonal Methods for Short-Term Electricity Demand Forecasting, European Journal of Operational Research 204: pp. 139-152.

Taylor, J W; de Menezes, L M and McSharry, P E (2006): Short-Term Load Forecasting Methods: An Evaluation Based on European Data, International Journal of Forecasting 2006 22: pp. 1-16.

Yang, J (1974): Power System Short-term Load Forecasting, PhD Dissertation.

Zor, K; Timur, O and Teke, A (2017): A state-of-the-art review of artificial intelligence techniques for short-term electric load forecasting, In 2017 6th international youth conference on energy (IYCE) pp. 1-7.