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Electric load forecasting by using dynamic neural network

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ABSTRACT

Electrical energy is fundamental for the wellbeing and for the economic development of any country. However, all countries must ensure access to essential resources and ensure the continuity of its supply. Due to the non-storable nature of electrical energy, the amount of consumed active power should always be equal the produced active power just to avoid power system frequency deviation problem. In order to keep the relationship production –consumption relation in compliance with different standards and to secure profitable operations of power system, electric load consumption must be predicted and controlled instantaneously. Several statistical and classical techniques are proposed in the literature but unfortunately all these methods are not accurate in a satisfactory manner. In this paper, a dynamic neural network is used for the prediction of daily power consumption. The suitability and the performance of the proposed approach is illustrated and verified with simulations on load data collected from French Transmission System Operator (RTE) website. The obtained results show that the accuracy and the efficiency are improved comparatively to conventional methods widely used in this field of research.

Introduction

Due to the non-storable character of electrical energy, it is necessary to balance at all times to the electrical power network to ensure that the supply is equal to the demand. However, the increase in the gap between the generated power and the consumption generates voltage/frequency deviations, which is harmful for electric networks devices and customers and can even present serious damages as in the case of blackout. To keep the balance of the electrical network, accurate load forecasting models are needed for a variety of time horizons: very short-term for load-frequency control and economic dispatch functions; short-term for the day-to-day operation, scheduling and load-shedding plans of power utilities; medium-term for maintenance programs; and long-term for power system expansion planning. Prediction of electricity demand calls for a thorough analysis and for an implementation of highly advanced forecasting techniques.

The electricity demand reflects the economic and social activity of the country and it is generally predictable with a random notable margin. Despite the scientific research in this subject, the electrical load forecasting is always a difficult

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task. Several methods have been proposed in the literature with different degrees of success. They may be classified in statistical and artificial intelligence techniques like neural networks, fuzzy logic and hybrid systems which are able to model empirically the nonlinearity of the electricity demand variation and the complex relationship that exists between the load and the parameters that influence on it. Applied soft computing and intelligent engineering theory has been largely used in many field of forecasting to overcome the accuracy problem that exists with the classical model [1]. Siraj et al. in their work [2] propose a hydrological model to estimate the future value for monthly river flow. The proposed model was constructed by combining three components: i.e. Discrete Wavelet Transform, Principal Component Analysis and Least Square Support Vector Machine. They conclude that the proposed model is stable, reliable and produced an appreciative level of accuracy.

Lately, hybrid models are largely used in load forecasting. Abdolah Kavouci-Fard et al. [3] have proposed a hybrid prediction algorithm composed of Support Vector Regression (SVR) and Modified Firefly Algorithm (MFA). The last method is employed to overcome the problem of parameter identification used in SVR. The proposed approach has been applied to the electrical load demand in Fars, Iran and compared to ARMA model, ANN, SVR-GA, SVR-HBMO, SVR-PSO and SVR-FA. The obtained results affirm that the proposed algorithm outperforms other techniques. In their papers, A. Selakov et al. [4] propose a practical new hybrid model for Short Term Load Forecasting (STLF) based on particle swarm optimization (PSO) and support vector machines (SVM). Authors have managed to model the demand in the short term during periods of significant change in temperatures. The architecture of the proposed solution is composed of three modules, a preprocessing module, a SVM module and the latter is an optimization module based on the PSO method. The proposed model detects periods of temperature changes, forecast and decides whether the model can be trained or not. The results of the proposed model shows better accuracy compared to generated results generated with classical methods. G. Dudek in his paper [5] proposes a random forest model for short term load forecasting. The advantages of the proposed approach are its capability to generalization and built-in cross-validation and low sensitivity to parameter values. The results are compared to some alternative statistical models and show good accuracy. Laouafi et al. [6] present the development and the implementation of three new electricity demand-forecasting models using the adaptive neuro-fuzzy inference system (ANFIS) approach in parallel load series. The obtained results and the forecasting performance reveal the effectiveness of the third proposed approach and show that 56% of the forecasted loads have an APE (absolute percentage error) under 0.5, and an APE under one was achieved for about 80% of cases. Xiaomin et al. propose an optimized non-homogeneous exponential model as a method of forecasting electricity consumption by using trend extrapolation to improve the accuracy of their model, the authors used particle swarm optimization (PSO) algorithm to optimize the equation parameters [7].

G. Cao and L. Wu [8] propose the use of a hybrid model based on support vector regression, fruit fly optimization algorithm (FAO), and seasonal index adjustment for performing monthly electricity consumption forecasting. The monthly electricity consumption of China and the monthly electricity of the United States were employed as illustrative examples to demonstrate the forecasting performance. The results from this study showed that the hybrid approach is found better than traditional models and it is a viable option for improving the monthly electricity consumption forecasting accuracy.

Forecasting approaches have been largely handled in renewable energy prediction. In the field of wind energy production, the accuracy of the wind forecasting model has been enhanced by using Support Vector Regression (SVR) model considering operation condition relatively to those considering meteorological information [9]. In solar systems, a daily output of the PV system forecasting model has been proposed by Guochang et al. [10] using a partial functional linear regression approach. The model is a generalization of the various linear regression models using some parameters of estimation. The results show that the accuracy of prediction has been improved compared to the classical models [11]. In term of load forecasting, several economic models have recently gained popularity to minimize peak electricity energy consumption in buildings [12].

The adaptation of energy production to demand is not only required for extremely large areas, such as nations and big regions, but is also necessary in micro-grids where many intelligent elements have to adapt their behavior depending on the future generation and consumption conditions. In the work presented by L. Hernandez et al. [13], a solution for short-term load forecasting in micro-grids, based on three-stage architecture has been evaluated. The validation model was performed with data from a micro-grid sized environment provided by the Spanish company Iberdrola, The results obtained from the studied case indicated that the model has provided low forecasting errors compared to other simple models that are not specialized by means of classification and clustering.

The problem of exceeding the maximum levels of power demand resulting in power outages and load shedding has been investigated by several researchers. Laouafi et al. in their work [14] use an adaptive hybrid two-stage structure on load data gathered from the Algerian power system. In the first stage, double seasonal Holt–Winters exponential smoothing method is used which prevents counting seasonal factors. For accuracy improvement, the benefits of Fuzzy c-means clustering; K-nearest neighbor's algorithm; Wavelet packet decomposition; and Adaptive Neuro-Fuzzy Inference System have been used. The attained results show that the proposed hybrid model is efficient in both normal and special days.

The main objective of this work is to develop an accurate short term forecasting model of electric load. As mentioned, such very short-term forecasts are essential for decision and managements of electric network and for insuring the adjustment of supply to demand at any time in the best conditions of cost and safety. When the load forecasting model is not accurate, incorrect programming can occur, causing daily operational costs caused by the use of higher costs.

Neural networks considered as a well-liked means for computing are used in many engineering field. It can be used for character recognition, stock market prediction, for solving traveling saleman's problem, in process control and modeling [15,16], and finally in complex linear and multi-system identification [17].

The nature of electric load is well suited to the technology of artificial neural networks (ANNs) as they can model the complex non-linear relationships through a learning process involving historical data trends. This paper is organized as follows. Section Electricity load profiles emphasis the factors causing variations in electrical power consumption pattern in Algeria with the rise in temperature. Section Review of some short term load forecasting (STLF) neural network models is a review for short term neural network electrical load forecasting model. Sections Dynamic neural network and training algorithm and Electric load prediction model development by dynamic neural networks introduces the structure and the training algorithm of dynamic neural network and the proposed short term load forecasting model and its results. Finally, Section Conclusions presents our conclusions and prospects.

Electricity load profiles

Series of electric load exhibit seasonality at the daily, weekly and annual time scales. Because of its dependence with several exogenous variables such as weather conditions and social events that should be considered. In Algeria, in recent years, over-consumption of electric power up to several hundred MW was recorded mainly due to higher summer temperatures as shown in the Fig. 1 which compares the hourly consumption for working day of summer season (July) to a similar working day of spring season (April) [18]. It should be noted that the Algerian homes have completely changed their way of consumption in just a few years. In the very recent past years, the power demand of subscriber barely exceeded 2 kW. Today this power is multiplied by 3 or by 4 in some areas.

Indeed, while the average power consumption per household was changing, the average specific consumption by low voltage customer has increased. This increase was driven mainly by south customers (Sahara) who only represent barely 10% of the total number of low voltage subscribers [18].

The trend during the day and throughout the week is observed in Fig. 2a and b respectively. From Fig. 2a we can see that the daily consumption begins with low values early in the morning followed by morning peak and decreases significantly towards the end of the day.

We can also observe from Fig. 3 that the electric load consumed during a week is affected by various factors such as weather fluctuations and the power demand on weekend is different from workdays. However, the electric power consumed in cold winter due to the increasing use of electric heater is much higher relatively to power consumed in warm summer which also increases due to the use of air conditioning equipments. The profile and the variation of the electric power consumption during a year from Fig. 4 show that the trend of the load is affected by several factors at a given time.

Review of some short term load forecasting (STLF) neural network models

Recently, a lot of investigations and research have been accomplished on the utilization and implementation of artificial intelligences approaches especially Neural Networks (NNs) to the electrical load forecasting problem. The first papers on the utilization of NNs in load prediction field were issued in the late 1980's and early in 2016's [19,20]. Different variants, homogenous and hybrid models by using artificial neural network combined to stochastic learning approaches have been successfully used in forecasting short term electrical load consumption [21]. From some papers in the

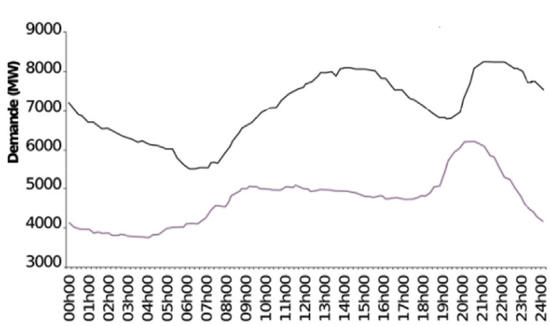
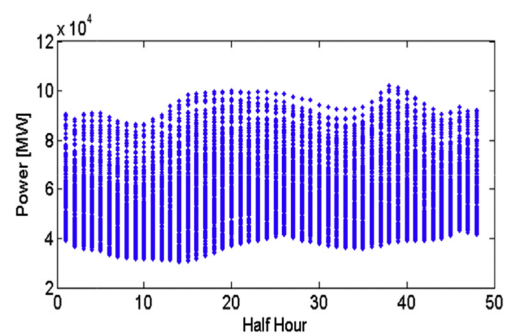
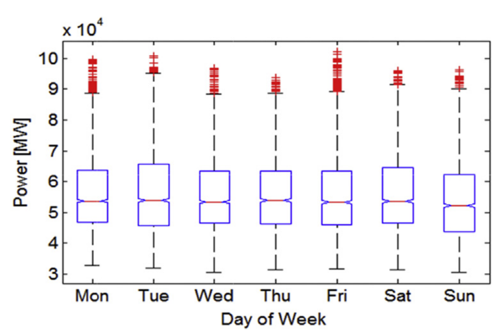


Fig. 1 – Load demand variation with the rise in temperature [18]. In Black: One day of summer 2011 (July). In Magenta: One day of spring 2011 (April). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



a. Power consumption during the day



b. Power consumption vs day of the week

Fig. 2 – Power vs Half hour of the day.

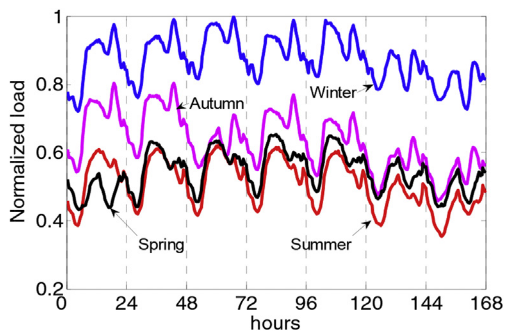


Fig. 3 – Comparison of weekly sketch over the year.

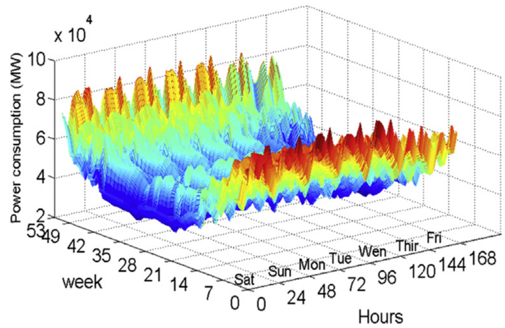


Fig. 4 – Electric power consumption within a year.

literature, the back propagation training algorithm is mostly used to train the neural network models. However, Artificial Immune System (AIS) learning algorithm [22] and back propagation momentum training algorithm [23] have been used to overcome accuracy speed and convergence problem. In some cases, especially with large input data, system structure needs to be simplified to improve forecasting performance. To do this, a clustering approach as an excellent tool to enhance forecasting accuracy must used, generally based on similar day [24] and on fuzzy logic and adaptive neural fuzzy inference system [25].

The number of neurons and the weights of the neural network forecasting model are generally optimized by using heuristic approaches or combined to some other techniques to improve the prediction accuracy and performances [26,27].

In Ref. [28], a Deep Belief Networks (DBN) made up from multiple layers of constrained Boltzmann machines is used for short-term electricity load forecasting based on the Macedonian hourly electricity consumption data. The layer-by-layer unsupervised training scheme succeeds in adjusting the parameters by employing a supervised back-propagation training algorithm. A novel input variable selection is also introduced to improve the quality of the electricity consumption data. The mean absolute percentage error (MAPE) is reduced by up to 8.6% compared to the predicted data supplied by Macedonian system operator (MEPSO) for the 24-h ahead forecasting, and the MAPE for daily peak forecasting is reduced by up to 21%. Indeed, results from this study indicate the suitability and the superior accuracy of DBN for both daily peak and daily load curve prediction compared to traditional methods. In the work presented by L. Xiao et al. [29], several artificial neural network combined models based on multi-objective optimization and data preprocessing techniques have been presented simultaneously to obtain high accuracy and great stability of the forecasting model. The experimental results from an application to the half-hourly electrical load data of three Australian states showed that both the accuracy and stability of the combined model are superior to those of other benchmark models. In Ref. [30] a probability density forecasting method based on quantile regression neural network using triangle kernel function is proposed to quantify uncertainty associated with power load and obtaining more information of future load. The nonlinear structure of neural network is applied to transform the quantile regression model for constructing probabilistic forecasting method. Moreover, the triangle kernel function and direct plug-in bandwidth selection method are employed to perform kernel density estimation. The experimental study from the case of study indicates the favorable performance of the probability density forecasting method in comparison with several existing forecasting methods.

Dynamic neural network and training algorithm

Dynamic neural network can adaptively learn the patterns from data. It can predict unknown patterns based on the information acquired from the historical data. It is a flexible mathematical structure capable to identify highly non-linear relationship between input and output data. Dynamic neural networks can be trained to learn sequential or time-varying patterns. These are useful and efficient especially in prediction, because the processing units (neurons) have natural ability for storing experimental knowledge and making it available for future use. In the field of time series prediction and forecasting, supervised training algorithm is used in which the ANN is trained to minimize the error between the network output and the target.

In Matlab neural network Toolbox [31], dynamic network are trained using the gradient based algorithms which are used for static networks, but the performance in dynamic neural network is relatively different because the gradient is computed in a more difficult means. The most used training algorithm is the Levenberg–Marquardt algorithm which is given in his general form by the following flow diagram [32]:

1. Evaluate the sum square error (SSE) by using the initial weights generated randomly by Eq. (1):

$$E(x,w)=\frac{1}{2}\sum_{p=1}^{P}\sum_{m=1}^{M}e_{p,m}^2 \tag{1}$$

where
x is the input and w is the weight vector.
$e_{p,m}$ is the training error. It's given by Eq. (2):

$$e_{p,m}=d_{p,m}-o_{p,m} \tag{2}$$

where
d is the desired output and o the actual output vector at the output m for the applied pattern p.

2. Adjust and update rules by using Eq. (3) given by:

$$w_{k+1} = w_k - (H)^{-1} J_k e_k \tag{3}$$

H is the Hessian matrix, it is defined by:

$$H \simeq J^T J + \mu I \tag{4}$$

where

μ is a combination coefficient and I is the identity matrix and J is the Jacobian matrix in Eq. (4).

From Eq. (3), we can say that, the Levenberg–Marquardt training process is a combination of the steepest descent algorithm and the Gauss–Newton algorithm. In the case where μ is very small, the training process used is the Gauss–Newton algorithm but the steepest descend method is used for a large combination coefficient μ.

3. Calculate the SSE for new weights
4. If the SSE is increased, reset the weight vector to the previous value and augment μ and go to step two and try then updating again.
5. If SSE is decreased, then accept the step and decrease μ.
6. Go to step two with the new weights until the SSE is smaller than the required value.

Electric load prediction model development by dynamic neural networks

The nature of electric load makes it difficult to be expressed and predicted accurately by using equations. However, various approximations can be used as exponential smoothing and regression of the dependency of the predicted variable which are extrapolated to the future. Fortunately, the development of artificial intelligence techniques, particularly the neural networks with their advantage of automatic learning from measured data without the need to add more information about the system and the prediction error as a powerful tool to measure its performance can be used in electric load prediction with different levels of success.

Neural network electric load forecasting model development requires an overall knowledge of past consumption and what parameters can affect the load at any time. However, in our work, the short term load model developments were achieved and performed using Matlab Neural Networks Toolbox. The model was trained by the historical loads data to determine the weights of the network. However, the use of obtained weights allows the prediction of the output for a given input. The data used for training the network are composed by six input variables: the day of the week; the month; the type of the day; the time of the day; the load consumption of the previous week of the day ahead to be predicted and finally, the load consumption of the previous day of the day ahead to be predicted for the historical load data gathered for the time interval from 01 February 2012 to 31 January 2013. The proposed neural network was trained by using Levenberg–Marquardt back propagation algorithm by using Trainlm function of Matlab toolbox and tested in order to find the best structure regarding the accuracy of modeling. By means of Trainlm function, the bias and weights are updated according to the Levenberg–Marquardt optimization. The main advantage of this function is that supports training with validation and test. The validation is used to stop the network training. However, the back-propagation algorithm is used to calculate the Jacobian of performance with respect to the weight and bias variables adjusted conforming to Levenberg–Marquardt.

The mean absolute percentage error is used to evaluate the accuracy of neural network and the predicted load defined by:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{\left|Load_{i,actual} - Load_{i,predicted}\right|}{Load_{i,actual}} \times 100 \tag{5}$$

where n is the length of data points.

The flowchart of the proposed forecasting model is summarized by the diagram of Fig. 5. If the network is not sufficiently accurate after training, we can try to initialize it and training it again or we increase the number of hidden layer neurons to above 20 neurons in the learning loop until the SSE is smaller than the desired error.

In this study, a good training result is obtained with 3.266% of Mean Absolute Percent Error (MAPE) by using Eq. (5) for the forecasted load of one day ahead as presented in Table 1 and 4.223% for historical loads. However, the best network architecture shown by Fig. 6 is with 7 neurons in the hidden layer obtained by training and the adaptation of the neural network to satisfy desired error fixed to 4%.

The network performance is validated by the regression plots that exhibit the network outputs regarding the targets for training, the validation and test sets are given in (Fig. 7).

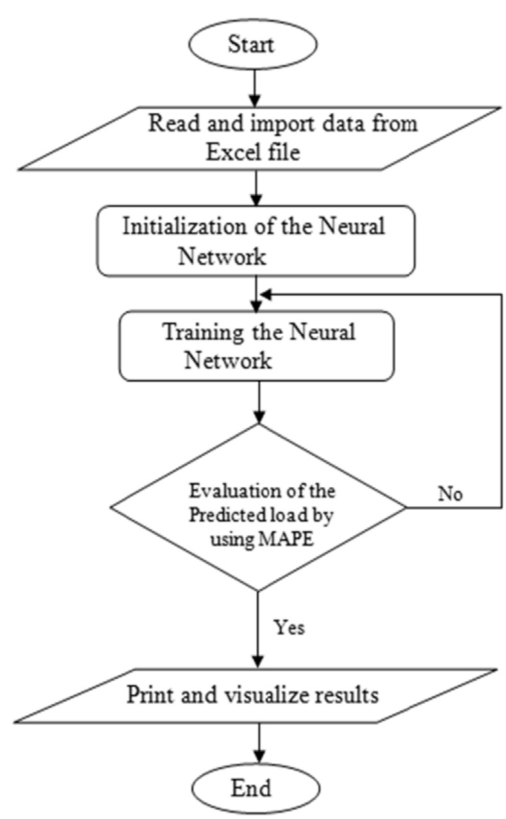


Fig. 5 – Flowchart of the neural network model.

Table 1 – MAPE and absolute percent error for actual and forecasted load.

No	Forecasted load	Actual load	Absolute percent error (%)	No	Forecasted load	Actual load	Absolute percent error (%)	MAPE
01	63,021	64,706	2.673	25	71,811	70,544	1.765	3.266%
02	60,122	63,082	4.923	26	72,074	70,629	2.005	
03	60,034	63,337	5.501	27	70,822	69,938	1.248	
04	59,513	63,149	6.110	28	69,984	69,518	0.666	
05	59,059	63,089	6.824	29	69,724	69,317	0.583	
06	57,265	62,060	8.372	30	68,452	68,279	0.253	
07	56,038	61,549	9.834	31	67,459	67,753	0.436	
08	55,085	61,030	10.793	32	66,866	67,504	0.955	
09	54,839	61,047	11.320	33	66,336	67,390	1.589	
10	55,323	61,271	10.751	34	66,285	67,536	1.887	
11	56,945	62,239	9.296	35	67,153	68,080	1.381	
12	58,688	63,273	7.813	36	69,466	69,751	0.410	
13	62,678	65,665	4.766	37	71,858	71,784	0.102	
14	65,863	68,128	3.439	38	73,379	73,161	0.297	
15	69,549	70,994	2.,077	39	72,101	72,471	0.513	
16	71,176	72,163	1.386	40	70,502	71,078	0.817	
17	71,239	72,048	1.135	41	68,284	69,692	2.062	
18	71,310	71,878	0.797	42	66,410	68,500	3.147	
19	71,545	71,846	0.421	43	64,448	67,476	4.698	
20	71,458	71,663	0.287	44	63,099	66,790	5.849	
21	71,546	71,320	0.315	45	63,734	66,972	5.080	
22	71,528	71,167	0.505	46	66,417	68,062	2.477	
23	71,803	71,284	0.723	47	65,289	67,639	3.600	
24	72,417	71,389	1.419	48	65,346	67,623	3.484	

The excellent fit is obtained when the data fall beside a 45° line. For the proposed model, the fit is fairly acceptable with R = 0.96875 for training, R = 0.9679 for validation and R = 0.97333 for test and R-value is over 0.97 for the total response. We note that, the dotted line in all figures shows the ideal result that corresponds to the equality between outputs and targets but the solid lines confirm the best fit linear regression line between targets and outputs.

The training errors, validation errors, and test errors plots are shown in Fig. 8. The results are feasible because of the similarity between the test curve and the validation curve and for nihility of the over fitting. The training state plot of the neural network which represents the variation in gradient coefficient and validation fails with respect to number of epochs is shown in Fig. 9. We note that Matlab stops training after 6 fails in a row.

Fig. 10 shows the actual and validation data for the considered day-ahead (01 February 2013) and Fig. 11 shows actual and forecasted historical load data. Fig. 12 shows the actual and forecasted data for one week zoomed from historical load data.

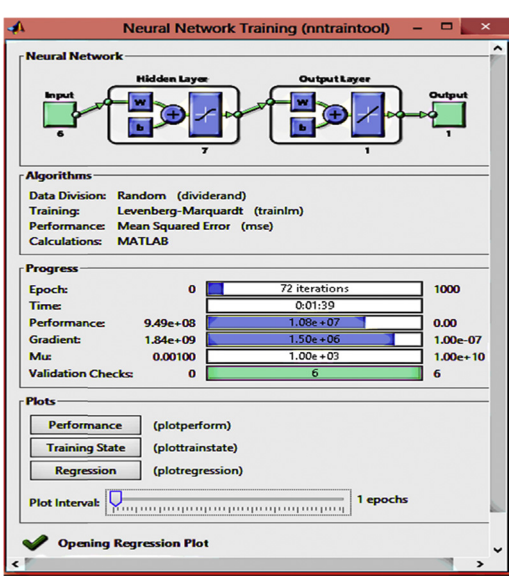


Fig. 6 – Training of the neural network load model.

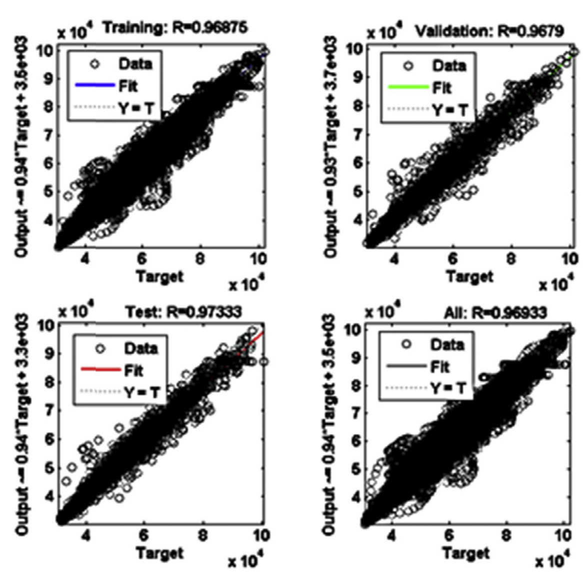


Fig. 7 – Regression plot of the network.

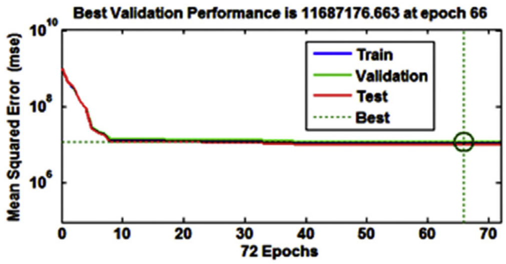


Fig. 8 – Mean squared error for training, validation and test vs number of epoch.

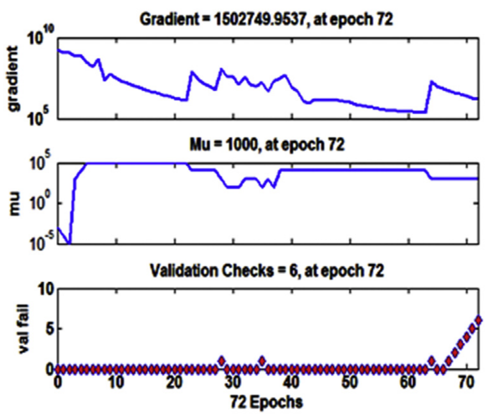


Fig. 9 – Training state plot vs number of epoch.

To assess the effectiveness of the proposed short-term load forecasting model, we also compare the results of the dynamic neural network model against two other forecasting methods. These comparison methods include the Holt–Winters (HW) exponential smoothing and the seasonal autoregressive integrated moving average (SARIMA) approaches [33]. Both two methods have been widely used in the literature of load forecasting for modeling the different components of the electric load time series. As represented by Eqs. (6)–(9), the modeling process of the Holt–Winters exponential smoothing method is based on the representation of the load as a function of three main components:

$$S_t = \alpha\left(\frac{y_t}{D_{t-s}}\right) + (1-\alpha)(S_{t-1} + T_{t-1}) \tag{6}$$

$$T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)T_{t-1} \tag{7}$$

$$D_t = \delta\left(\frac{y_t}{S_t}\right) + (1-\delta)D_{t-s} \tag{8}$$

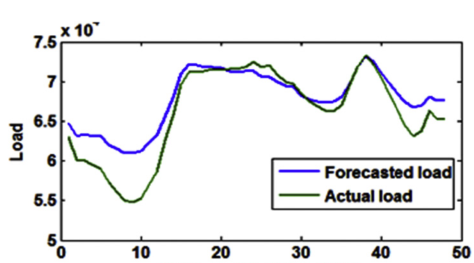


Fig. 10 – Forecasted and actual load for one day ahead.

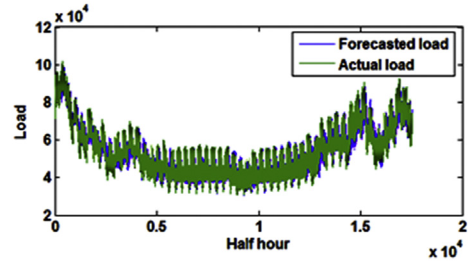


Fig. 11 – Forecasted and actual load for historical data.

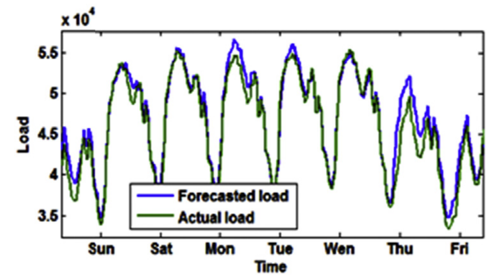


Fig. 12 – Zoom in the forecasted and actual load for historical data.

$$\hat{y}_t(k) = (S_t + kT_t)D_{t-s+k} \tag{9}$$

S_t and T_t, are the smoothed level and trend; D_t is the seasonal indices for the intraday seasonal cycle s of duration 48 periods; α, γ, δ are the smoothing parameters; y_t is the actual value of the time series in period t; and $\hat{y}_t(k)$ is the k step-ahead forecast made from forecast origin t. The smoothing parameters of the proposed Holt–Winters method are as follows: $\alpha = 0.826$; $\gamma = 0.1$; and $\delta = 0.498$.

The SARIMA model is similar to Holt–Winters method in modeling time series with trends, seasonal pattern and other components. However, the seasonal autoregressive integrated moving average process is more beneficial for non-stationary time series, since an initial differencing step can be used for translating the time series into smooth and a stationary process.

A SARIMA, denoted by $SARIMA(p,d,q)\times(P,D,Q)_s$, can be stated in the following form:

$$\Phi_P(B^s)\varphi_p(B)(1-B)^d(1-B^s)^D y_t = \Theta_Q(B^s)\theta_q(B)\varepsilon_t \tag{10}$$

where y_t and ε_t are the actual value and random error at time t, respectively. B is the lag operator that satisfies: $B^t y_t = y_{t-1}$. $\Phi_p(B^s)$, $\Theta_Q(B^s)$ and $(1-B^s)^D$ are corresponding autoregressive, moving average and differencing parts for seasonal components. While $\varphi_p(B)$, $\theta_q(B)$ and $(1-B)^d$ are corresponding autoregressive, moving average and differencing parts for the non-seasonal component. S is the length of the season.

Results of the conventional methods compared to the proposed neural network model are shown by Fig. 13. The Mean Absolute Percent Error (MAPE) was 3.7276% and 3.6223% for Holt–Winter and ARIMA models respectively (Table 2). However, the forecasting results indicated that our approach showed better performance and the MAPE improvement by using dynamic neural network compared to both conventional models is equal to 12.38% relatively to HW model and 9.84% compared to ARIMA model.

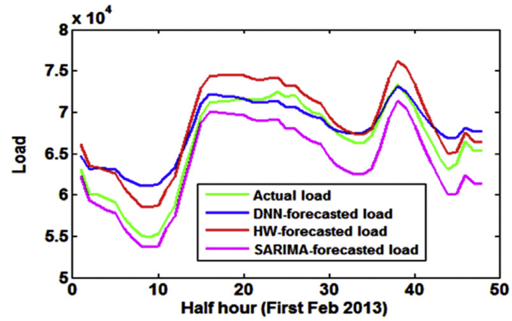


Fig. 13 – Forecasted and actual load for day ahead.

Table 2 – Day ahead forecasting accuracy.

Accuracy	DNN	HW	SARIMA
MAPE [%]	3.266	3.7276	3.6223
RMSE [MW]	2684.5	2604.4	2680.3

From the reported results in this work, it can be fulfilled that the dynamic neural network based forecasting algorithms are proved to be efficient approach for electric load prediction.

Conclusions

This paper deals with dynamic neural network forecasting for one day electrical load demand. The key idea of the proposed methodology is based on a back-propagation neural network largely used in times series prediction. The neural network structure proposed even outperforms the classical and hybrid forecasting methods. It is justified by the MAPE indices between the actual and the forecasted data. The obtained results of forecasting performance reveal the effectiveness of the model, since the mean absolute percent error for the forecasted load of one day ahead is 3.266% and 4.223% for historical loads.

In addition, the proposed model provides high enough margin to be useful in real time, it shows the capability and the robustness of the dynamic neural network to predict complex time series. Dynamic networks provide better and accurate results comparatively to ordinary neural networks. This may be due to the adaptation of the network structure to time series variation. The prospects of this work is the inclusion of random search approaches to the dynamic neural network which are capable of global learning capabilities for developing a hybrid forecasting models and enjoy the benefits of the resulting approach.

REFERENCES

[1] Montgomery Douglas C, Jennings Cheryl L, Kulahci Murat. Introduction to time series analysis and forecasting. John Wiley & Sons; 2015.

[2] Pandhiani Siraj M, Shabri Ani Bin. A hybrid model for monthly time series forecasting. Int J Appl Math Inf Sci Nov 2015;9(6):2943–53.

[3] Kavousi-Fard A, Samel A, Marzbani F. A new hybrid modified firefly algorithm and support vector regression model for accurate short term load forecasting. Expert Syst Appl Oct 2014;41(13):6047–56.

[4] Selakov A, Cvijetinović D, Milović L, Mellon S, Bekut D. Hybrid PSO–SVM method for short-term load forecasting during periods with significant temperature variations in city of Burbank. Appl Soft Comput March 2014;16:80–8.

[5] Dudek Grzegorz. Short-term load forecasting using random forests. Intelligent Systems' 2014 advances in intelligent systems and computing, vol. 323; 2015. p. 821–8.

[6] Laouafi A, Mordjaoui M, Dib D. One-hour ahead electric load forecasting using neuro-fuzzy system in a parallel approach. Computational intelligence applications in modeling and control. Studies in Computational Intelligence, vol. 575; 2015. p. 95–121.

[7] Xu Xiaomin, Niu Dongxiao, Meng Ming, Shi Huifeng. Yearly electricity consumption forecasting using a non-homogeneous exponential model optimized by PSO algorithm. Int J Appl Math Inf Sci 2014;8(3):1063–9.

[8] Cao G, Wu L. Support vector regression with fruit fly optimization algorithm for seasonal electricity consumption forecasting. Energy 2016;115:734–45.

[9] Fang R, Wang Y, Shang R, Liang Y, Wang L, Peng C. The ultra-short term power prediction of wind farm considering operational condition of wind turbines. Int J Hydrogen Energy 2016;41(35):15733–9.

[10] Wang Guochang, Su Yan, Shu Lianjie. One-day-ahead daily power forecasting of photovoltaic systems based on partial functional linear regression models. Renew Energy 2016;96:469–78.

[11] Cole Wesley J, Morton David P, Edgar Thomas F. Optimal electricity rate structures for peak demand reduction using economic model predictive control. J Process Control 2014;24(8):1311–7.

[12] Sehar Fakeha, Pipattanasomporn Manisa, Rahman Saifur. A peak-load reduction computing tool sensitive to commercial building environmental preferences. Appl Energy 2016;161:279–89.

[13] Hernández L, Baladrón C, Aguiar JM, Carro B, Sánchez-Esguevillas A, Lloret J. Artificial neural networks for short-term load forecasting in microgrids environment. Energy 2014;75:252–64.

[14] Laouafi A, Mordjaoui M, Laouafi F, Boukelia TE. Daily peak electricity demand forecasting based on an adaptive hybrid two-stage methodology. Int J Electr Power Energy Syst 2016;77:136–44.

[15] Ak Ayça Gökhan, Cansever Galip, Delibaşı Akın. Trajectory tracking control of an industrial robot manipulator using fuzzy SMC with RBFNN. Gazi Univ J Sci 2015;28(1):141–8.

[16] Maleki Erfan, Maleki Nasim. Artificial neural network modeling of Pt/C cathode degradation in PEM fuel cells. J Electron Mater 2016;45(8):3822–34.

[17] SAĞIROĞLU Şeref. Identifying three linear systems using only single neural model. Politeknik Derg 2012;15(4).

[18] CREG Information letter. Algerian renewable energy portal. Lettre d'information de la CREG. 14 September 2011.

[19] Hu R, Wen S, Zeng Z, Huang T. A short-term power load forecasting model based on the generalized regression neural network with decreasing step fruit fly optimization algorithm. Neurocomputing 2017;221:24–31.

[20] Ding N, Benoit C, Foggia G, Bésanger Y, Wurtz F. Neural network-based model design for short-term load forecast in distribution systems. IEEE Trans Power Syst 2016;31(1):72–81.

[21] Baliyan Arjun, Gaurav Kumar, Mishra Sudhansu Kumar. A review of short term load forecasting using artificial neural network models. Procedia Comput Sci 2015;48:121–5.

[22] Abdul Hamid MB, Abdul Rahman TK. Short term load forecasting using an artificial neural network trained by artificial Immune system learning algorithm. In: 12th International conference on computer modeling and simulation (UKSim); 2010. p. 408–13.
[23] He Yu-Jun, Zhu You-Chan, Jian-Cheng GU, Yin Cheng-Qun. Similar day selecting based neural network model and its application in short term load forecasting. In: Proceedings of International Conference on Machine Learning and Cybernetics8; Aug. 2005. p. 4760–3.
[24] Panapakidis Ioannis P. Clustering based day-ahead and hour-ahead bus load forecasting models. Int J Electr Power Energy Syst 2016;80:171–8.
[25] Çevik Hasan Hüseyin, Çunkaş Mehmet. Short-term load forecasting using fuzzy logic and ANFIS. Neural Comput Appl 2015;26(6):1355–67.
[26] Filatova ES, Filatov DM, Stotckaia AD. Genetic algorithm to the formation of the optimal structure of fuzzy neural network. In: 2015 XVIII international conference on Soft computing and measurements (SCM). IEEE; 2015.
[27] Liao Gwo-Ching, Tsao Ta-Peng. Application of a fuzzy neural network combined with a chaos genetic algorithm and simulated annealing to short-term load forecasting. IEEE Trans Evol Comput 2006;10(3):330–40.
[28] Dedinec A, Filiposka S, Dedinec A, Kocarev L. Deep belief network based electricity load forecasting: an analysis of Macedonian case. Energy 2016;115:1688–700.
[29] Xiao L, Shao W, Yu M, Ma J, Jin C. Research and application of a combined model based on multi-objective optimization for electrical load forecasting. Energy 2017;119:1057–74.
[30] He Y, Xu Q, Wan J, Yang S. Short-term power load probability density forecasting based on quantile regression neural network and triangle kernel function. Energy 2016;114:498–512.
[31] Beale MH, Hagan MT, Demuth HB. Neural network toolbox™ user's guide. R2012a. 3 Apple Hill Drive Natick, MA: The MathWorks, Inc; 2012. 01760–2098, www.mathworks.com.
[32] Yu Hao, Wilamowski Bogdan M. Levenberg-Marquardt training. Ind Electron Handb 2011;5:12–21.
[33] Taylor James W. An evaluation of methods for very short-term load forecasting using minute-by-minute British data. Int J Forecast 2008;24(4):645–58.