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Research Article

Neuronal Approach for Prediction of Electric Charge in Niamey City

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Abstract In this paper, neural networks are used to design a model for predicting the short-term load of Niamey city. Prediction research is extensive, but techniques based on artificial neural networks have recently been developed and used by several researchers. Two (2) approaches such as multilayer Perceptron (MLP) and non-linear autoregressive network with exogenous inputs (NARX) have been implemented in MATLAB software. Several configurations of these two models have been developed and tested on actual electrical load data over five (5) year period from 2012 to 2016. The statistical indicators MAPE (Absolute mean error in percent), R^2 (correlation coefficient) and RMSE (square root of mean square error) were used to evaluate the performance of models. Thus with MAPE of 5.1765%, R^2 of 95.3013% and RMSE of 5.6014% the[ABCD] configuration of NARX model is more suitable compared to MLP model with MAPE of 7.1874%, R^2 of 92.0622% and RMSE of 7.2199%. So NARX model is the most efficient and can be used for future predictions on Niamey city network.

Keywords short-term forecast, artificial neural networks, MLP, NARX, MAPE, R^2, RMSE

1. Introduction

Decisions in area of power generation, transmission, distribution and proper operation must be based on accurate forecast of demand for electrical load [1]. As result, the quality of this forecast, which is essential element of preparation and anticipation, helps to ensure that production-consumption balance is maintained at all times. It therefore has direct impact on operational safety of electrical system [2]. Prediction is made with knowledge of user's consumption over the previous years. Electricity consumption depends on activities of users and therefore on their daily, weekly or annual behavior. Depending on this behavior, the load may increase or decrease from one hour to another, from one day to another or from one season to another [3].

Forecast errors can lead to significant operational costs. The objective is therefore to provide short-term prediction of electrical power demand. Short-term prediction helps to minimize errors, sources of risk and inadequacies in correct generation and distribution of electrical energy to users [4].

In this paper, Artificial Neural Networks are applied for two modelling approaches. For both cases, similar parameters are used. We are talking about network type, activation function and learning rule [5].

2. Materials and methods

The neural network models constructed are of two-layer feed forward type for MLP (Figure 1) and NARX for recurrent network (Figure 2). The neurons of hidden layer have sigmoid activation function and those of output layer a linear function in both cases. This architecture is proposed in the Matlab "ntstool" library that we used.

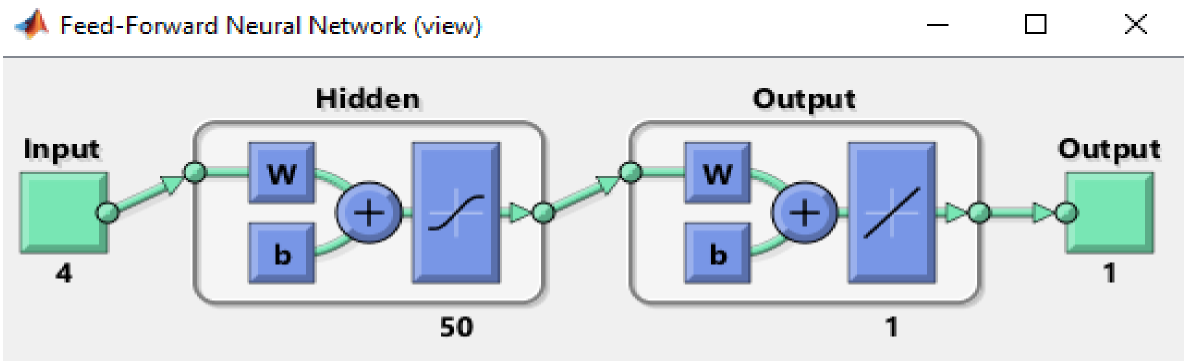

Figure 1: Synoptic diagram of the architecture of MLP neural network models with 50 neurons under the hidden layer

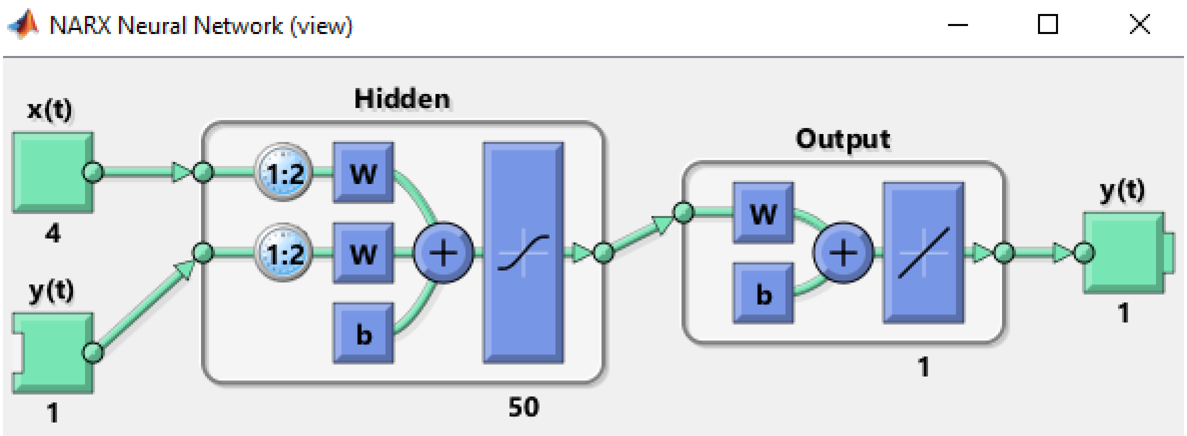

Figure 2: Model architecture in the View of the Network window

To obtain the different models, the choice and methodical analysis of explanatory variables is essential. These variables are used to assess influence of each input parameter on output of forecast model. Indeed, it is very important, for accuracy of the model, to choose appropriate input parameters. This step is very useful because it eliminates some variables that provide very little or no information to describe the output, or eliminates redundant variables [1].

The variables that were chosen to model the electrical load of the city of Niamey are listed in the following:

Table 1: List of explanatory variables

Data types	Mathematical Explanations	Code
Load data from the same time of the previous day	Yh-24	A
Load data from the same time of the previous week	Yh-168	B
Load data from the same time of the previous year	Yh-8760	C
Average of the last 24 hours' charges	$Mean\ (\sum_{i=1}^{24} \text{Yh} - \text{i})$	D
Y= load data		

It is therefore necessary to predict electrical charge with various combinations of these explanatory variables in order to determine the most efficient configuration case on basis of well-defined criterion.

Prediction with the Multi-Layer Perceptron (MLP)

The first model developed in this project is two-layer Perceptron Multi-Layer (MLP) with hidden layer and output layer. This type of network is reliable tool for function approximation problems [6]. The choice of inputs is made using the correlation between the data. The activation function used to activate neurons in hidden layer is sigmoid function. The function provides output values belonging to interval [0.1]. For neurons in the output layer, the activation function is of linear type. The procedure used for the learning phase is error correction procedure (Backward Error Propagation). The principle is easy, error calculated by network is propagated from output layer to input layer [7, 8]. The algorithm used to update weights is Levenberg-Marquardt one. Its principle is based on a minimization of function. It calculates cost function, on which it decides whether or not update will be accepted. It continues calculation until network converges. The calculation is done using Jacobean weights and biases [9, 12].

The output of the network is given by the following equation:

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i \quad (1)$$

- y is the value predicted by the neural network;
- n is the number of hidden units in the network;
- $\beta 0$ the bias;
- βi the weighted coefficients.

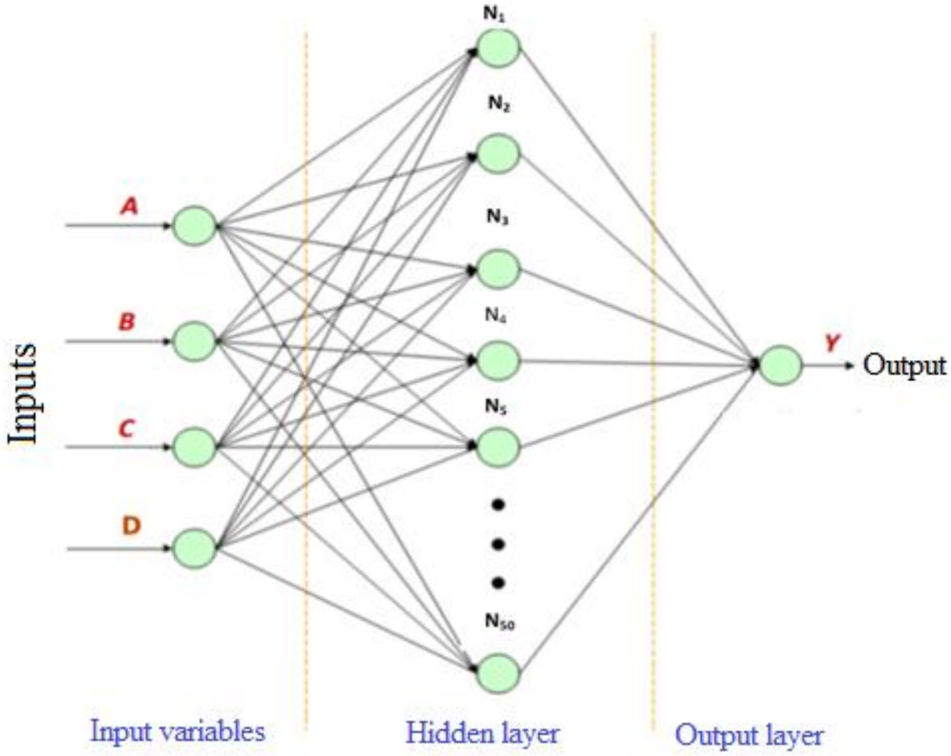

Figure 3: Complete MPL architecture

Table 2: Summarizes the different parameters of the selected MLP model

Model	Perceptron Multi-layer (MLP)
Number of layers	2
Number of hidden layers	1
Function to activate neurons in hidden layer	Sigmoid function
Function to activate neurons of output layer	Simple linear function
Learning algorithm	Retro propagation of error
Algorithm for updating synaptic weights	Levenberg-Marquardt

The non-linear autoregressive network with exogenous inputs (NARX).

The recurring network has many applications. It can be used for modeling complex systems. As a preacher, he can predict the next value of the output signal. In addition to the same parameters as the first model it has a number of delays [10, 11, 12].

$$y(t)=f(y(t-1),y(t-2),\ldots,y(t-n_y),u(t-1),u(t-2),\ldots,u(t-n_u)) \quad (2)$$

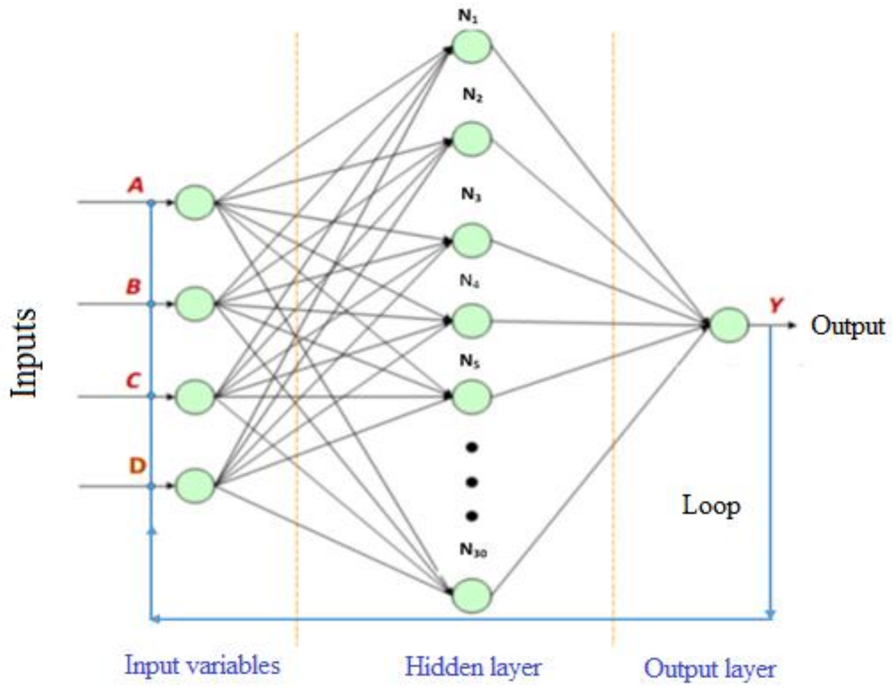

Figure 4: Complete NARX architecture

Table 3: Summarizes the different parameters of the selected NARX model

Model	**Non-linear autoregressive network with exogenous inputs (NARX)**
Number of layers	2
Number of hidden layers	1
Number of delays (nombre de retards)	2
Function to activate neurons in hidden layer	Sigmoid function
Function to activate neurons of output layer	Simple linear function
Learning algorithm	Retro propagation of error
Algorithm for updating synaptic weights	Levenberg-Marquardt

3. Results and Discussions

In this section, the main task is to present results of research and then to choose the most appropriate model for predicting electrical load based on indicators chosen to evaluate the performance of these models.

Table 4: Models best performances summary

Model		**Number of neurons in the hidden layer**	**MAPE (%)**		**RMSE (%)**		**R (%)**	
			MAX	**MIN**	**MAX**	**MIN**	**MAX**	**MIN**
MLP	1	50	8,6701	8,6260	8,5790	8,5528	88,6599	88,5858
	2	50	8,4992	8,4652	8,0124	7,9856	90,1937	90,1243
	3	50	10,1168	10,0951	9,1202	9,0995	87,0538	86,9906
	4	50	7,9651	7,9044	8,0649	8,0190	90,1071	89,9874
	5	50	8,3287	8,2981	8,2900	8,2500	89,4953	89,3872
	6	40	8,0530	8,0036	7,6711	7,6308	91,0880	90,9888
	7	**50***	**7,2850**	**7,1874**	**7,3041**	**7,2199**	**92,0622**	**91,8678**
NARX	**1**	40	5,4248	5,3123	5,7859	5,7313	95,0748	94,9831
	2	30	5,3557	5,2443	5,7202	5,6550	95,2107	95,0943
	3	50	5,4206	5,3438	5,7639	5,7324	95,0753	95,0176
	4	30	5,5895	5,4949	6,0086	5,9083	94,7583	94,5734
	5	30	5,4193	5,2967	5,8090	5,7090	95,1167	94,9372
	6	50	5,3888	5,2862	5,7607	5,6784	95,1684	95,0234
	7	**30***	**5,3327**	**5,1765**	**5,7596**	**5,6014**	**95,3013**	**95,0255**

The final choice of the best performance for each model is made using the MAPE indicator and the correlation coefficient R^2. The results are shown in Table 5 (* refers to the best performance of all models and configurations).

Table 5: Better performance of the different models

Model	**Case**	**Number of neurons in the hidden layer**	**MAPE (%)**		**RMSE (%)**		**R (%)**	
			MAX	**MIN**	**MAX**	**MIN**	**MAX**	**MIN**
MLP	7	50	7,2850	7,1874	7,3041	7,2199	92,0622	91,8678
NARX	7	**30***	**5,3327**	**5,1765**	**5,7596**	**5,6014**	**95,3013**	**95,0255**

Table 5 allows us to choose the most appropriate configuration for electrical charge modeling. Thus case 7 (configuration [ABCD] with 30 neurons) of the NARX model provides MAPE of 5.1765%, R^2 of 95.3013% and RMSE of 5.6014%. This model can therefore be used as model since it offers the best results over the MLP case 7 model (configuration [ABCD] with 50 neurons) with MAPE of 7.1874%, R^2 of 92.0622% and RMSE of 7.2199%. These results confirm once again the approximation and adjustment strength of neural networks.
This choice is amply justified by observing the different comparative curves of following predictions in one day.

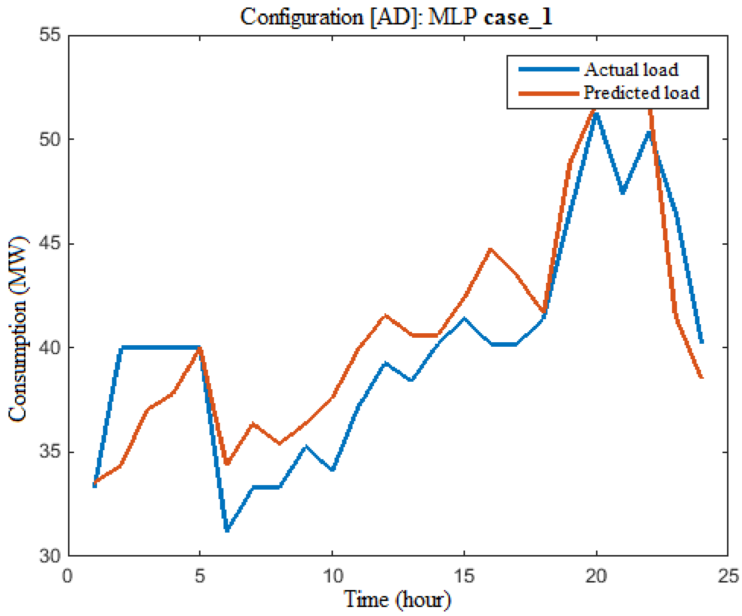

Figure 5: Daily representation (02 January 2013), MLP [AD]: neurons number =50

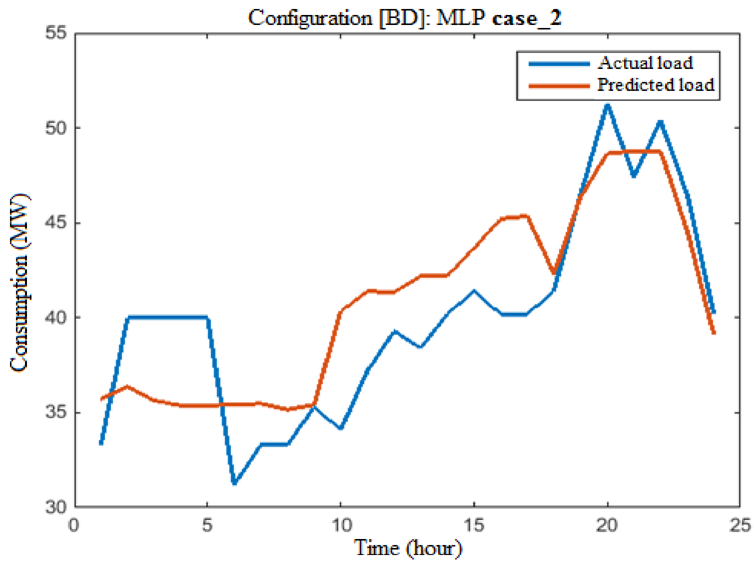

Figure 6: Daily representation (02 January 2013), MLP [BD]: neurons number =50

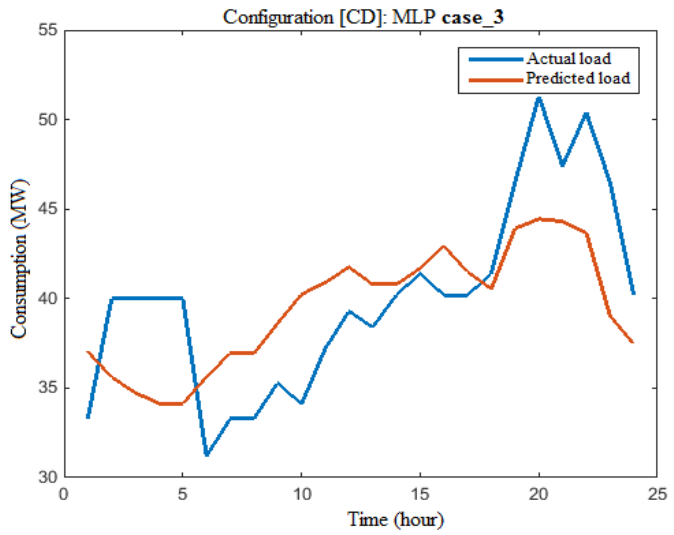

Figure 7: Daily representation (02 January 2013), MLP [CD]: neurons number =50

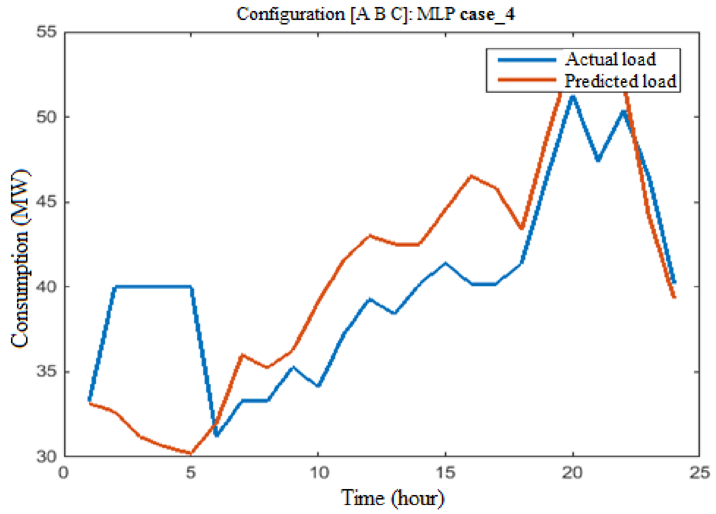

Figure 8: Daily representation (02 January 2013), MLP [ABC]: neurons number =50

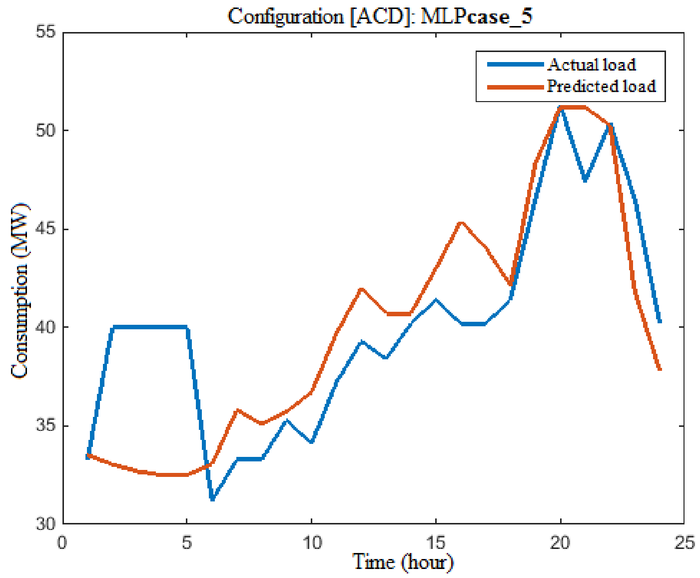

Figure 9: Daily representation (02 January 2013), MLP [ACD]: neurons number =50

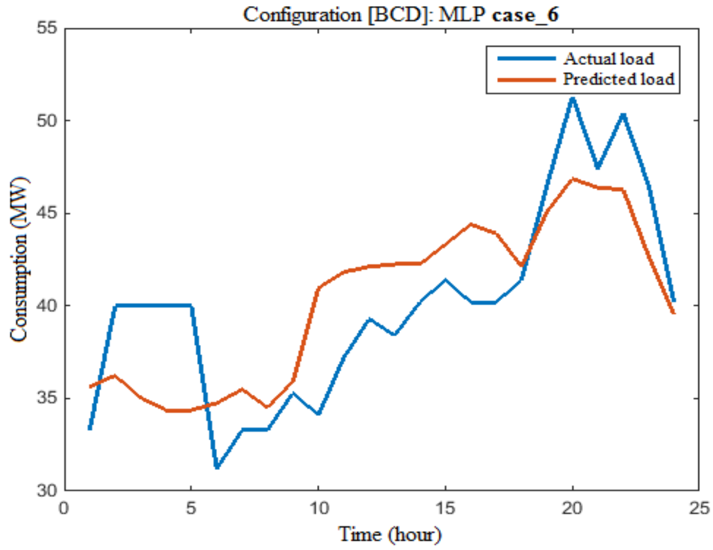

Figure 10: Daily representation (02 January 2013), MLP [BCD]: neurons number =50

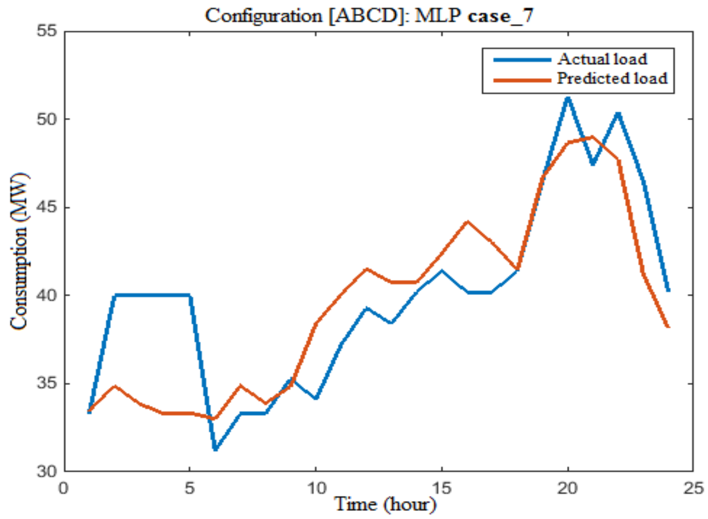

Figure 11: Daily representation (02 January 2013), MLP [ABCD]: neurons number =50

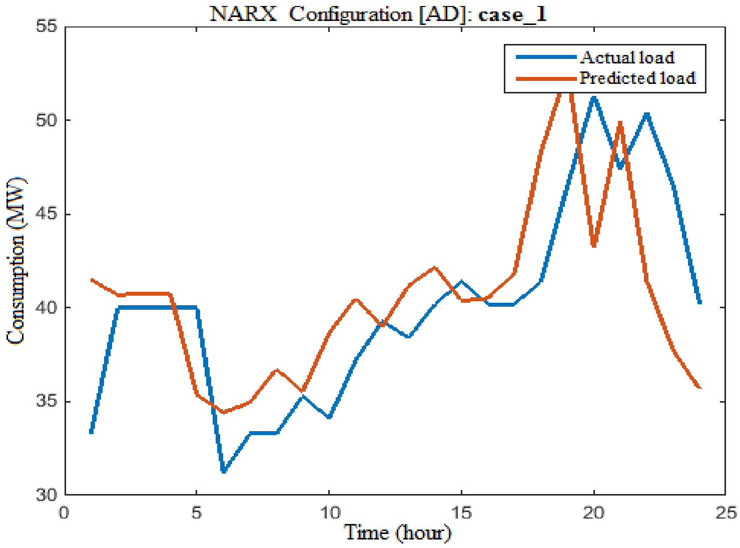

Figure 12: Daily representation (January 02, 2013), NARX [AD]: neurons number =30

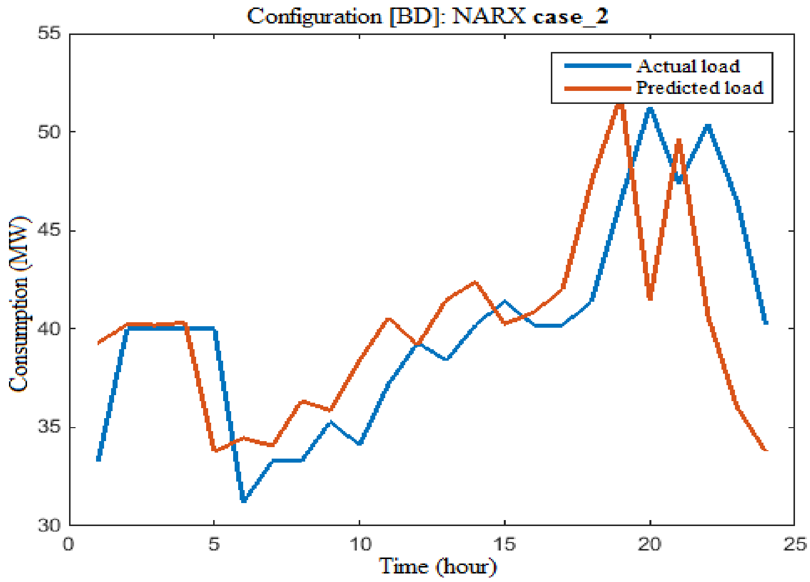

Figure 13: Daily representation (January 02, 2013), NARX [BD]: neurons number =30

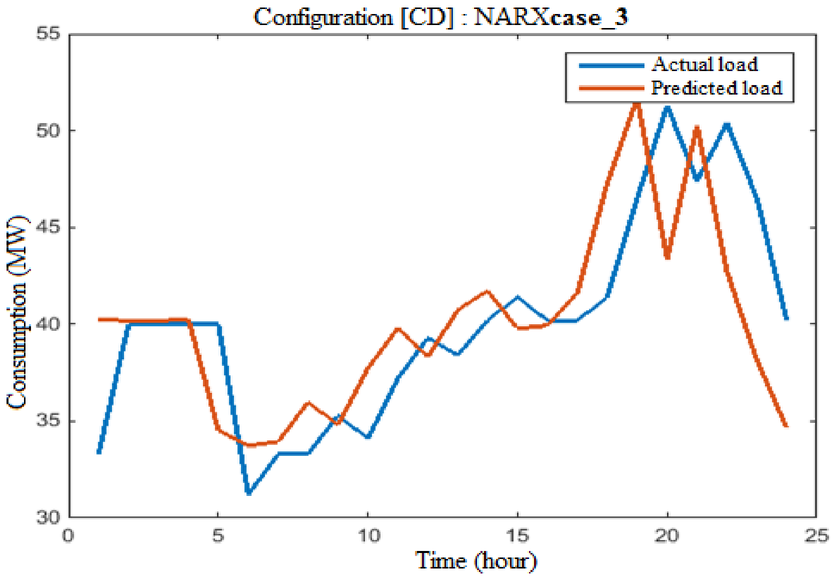

Figure 14: Daily representation (January 02, 2013), NARX [CD]: neurons number =30

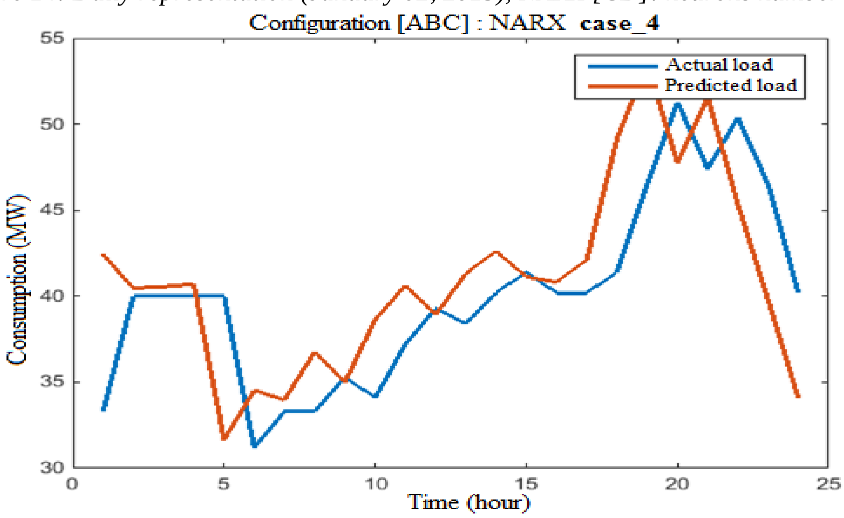

Figure 15: Daily representation (January 02, 2013), NARX [ABC]: neurons number =30

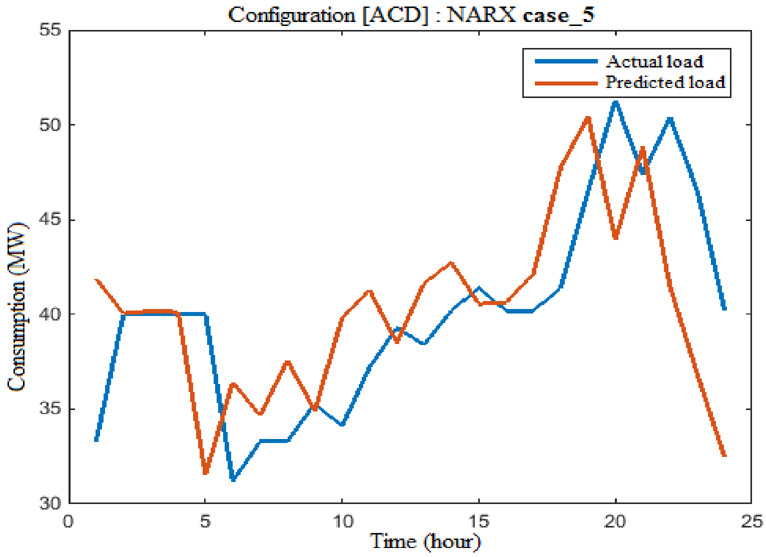

Figure 16: Daily representation (January 02, 2013), NARX [ACD]: neurons number =30

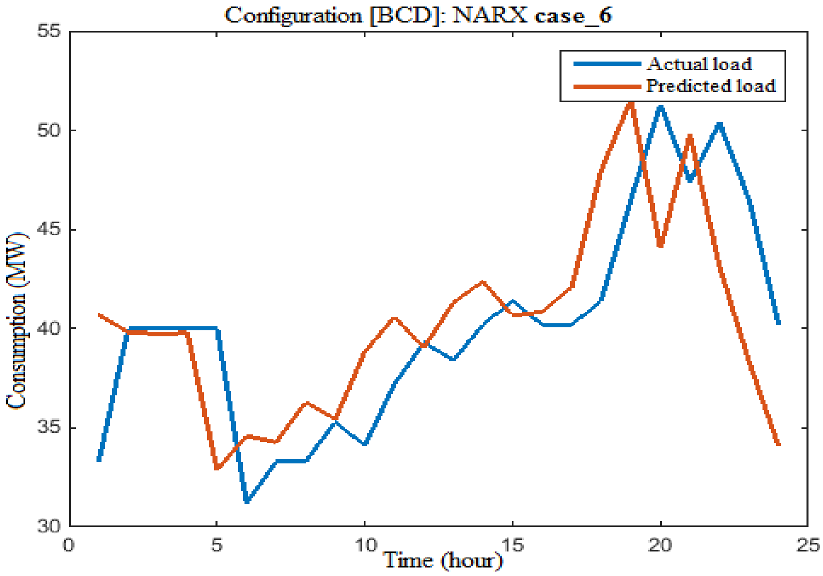

Figure 17: Daily representation (January 02, 2013), NARX [BCD]: neurons number =30

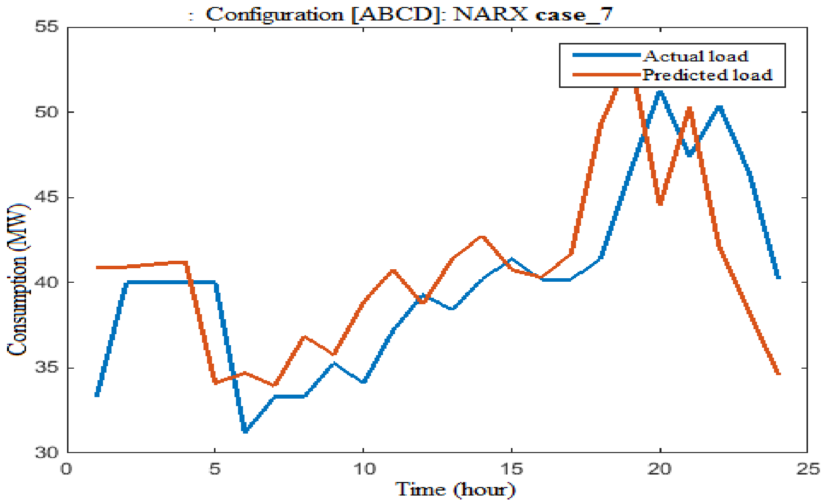

Figure 18: Daily representation (January 02, 2013), NARX [ABCD]: neurons number =30

4. Conclusion

In this paper, two models for predicting electrical charge of Niamey city are developed using artificial neural networks. Several configurations of the two main models were developed and tested by varying different explanatory variables. All configurations have been implemented in MATLAB software. The statistical indicators MAPE (Absolute mean error in percent), R^2 (correlation coefficient) and RMSE (square root of mean square error) were used to evaluate performance of the models. Thus with MAPE of 5.1765%, R^2 of 95.3013% and RMSE of 5.6014% the[ABCD] configuration of NARX model is chosen ahead of MLP with MAPE of 7.1874%, R^2 of 92.0622% and RMSE of 7.2199. Thus, the NARX model is the most efficient and can be used for future predictions on Niamey city network.

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