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Electrical Charge of Niamey City Modelisation by Neural Network

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Abstract: In order to forecast consumption, electric power generation, transmission and distribution companies need model to predict short-term demand for electric power load so that they can use their electricity infrastructure efficiently, safely and economically. The short-term forecast of electrical energy demand is the forecast of consumption over time interval ranging from one hour to few days. For optimal use of electricity grid, energy production must keep pace with demand. To this end, prediction errors can lead to risks and shortcomings in the generation and distribution of electrical load to users. This paper is part of electrical charge prediction of Niamey city. Several are being carried out in this field, but prediction techniques based on artificial neural networks have recently been developed. This work focused on two (2) neural approaches such as the multilayer Perceptron (MLP) and the non-linear autoregressive network with exogenous inputs (NARX). Several configurations of these two models have been developed and tested on actual electrical load data. We carried out the short-term forecast (hourly basis) of electrical load of Niamey city. All configurations have been implemented in MATLAB software. The statistical indicators MAPE (Mean Absolute Average Error in Percent), R^2 (the correlation coefficient) and RMSE (Square Root of Mean Square Error) were used to evaluate the 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 converges better compared to the MLP model with MAPE of 7.1874%, R^2 of 92.0622% and RMSE of 7.2199%. Where A is the data charge of the same time of the previous day, B is the charge data of the same time of the previous week, C is the charge data of same time of previous year and D is the average of last 24 charge values. So the 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

Electricity is fundamental to modern economic activity. The regularity of its offer poses major challenge, particularly the acquisition of reliable prediction tool. An efficient and high-volume energy storage system has not yet been put in place. The production of energy must follow the demand for optimal use of an electricity grid [1]. Electric power companies are interested in prediction to get an idea of the values of the electric charge, in order to properly manage the supply of electric power [2]. These companies need an effective prediction tool to allow all actors to control their load for good balance of the power system [3].

Predicting the value of the electrical charge is an ideal way to reduce load shedding and ensure good supply of electrical energy [4]. As result, the quality of this forecast, which is essential element of preparation and anticipation, helps to ensure that the production-consumption balance is maintained at all times. It therefore has direct impact on the operational safety of electrical system. The prediction is made with knowledge of users' consumption over previous years. Electricity consumption depends on activities of users and therefore on their daily, weekly or annual behavior [5]. 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 [6].

Short-term forecasting of electricity consumption plays essential role in efficient management of resources allocated to electricity production. Forecast errors can lead to significant operational costs. The objective is therefore to provide short-term prediction (time horizon) of demand for electrical power. Short-term prediction helps to minimize errors, sources of risk and inadequacies in correct generation and distribution of electrical energy to users. There is a lot of research in this area [3].

Artificial Neural Networks are function estimators. They are considered as configurable black boxes, in order to find link between inputs and outputs through sample of data during the learning phase. In this paper, Artificial Neural Networks are applied for two modelling approaches [7, 8]. For both cases, similar parameters are used. We are talking about the type of network, the activation function and the learning rule.

2. 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 [9]. This type of network is reliable tool for problems of approximation of functions. The choice of inputs is made using the correlation between the data. The activation function used to activate the neurons in the hidden layer is sigmoid function. The function provides output values belonging to interval [0.1]. For the neurons in output layer, activation function is of linear type. The procedure used for learning phase is error correction procedure (Backward Error Propagation). The principle is easy, we proceed to propagation of error calculated by network from the output layer to the input layer [10, 11]. The algorithm used to update weights is the Levenberg-Marquardt one. Its principle is based on a minimization of function. It calculates cost function, on which it decides whether or not the update will be accepted. It continues the calculation until the network converges. The calculation is done using the Jacobean weights and biases [12-14].

The output of our network is given by equation (1):

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

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

Table 1. *Summarizes the different parameters of the selected MLP model.*

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

3. Non-linear Autoregressive Network with Exogenous Inputs (NARX)

The recurring network has many applications. It can be used for modeling complex systems. As 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 [15, 16].

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

Table 2. *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 the neurons in the hidden layer	Sigmoid function
Function to activate the neurons of the output layer	Simple linear function
Learning algorithm	Retro propagation of error
Algorithm for updating synaptic weights	Levenberg-Marquardt

4. Experimental Approach to Modelling

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

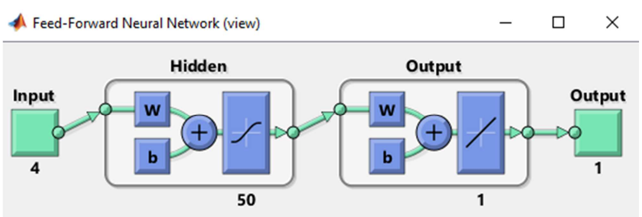

Figure 1. *Synoptic diagram of the architecture MLP.*

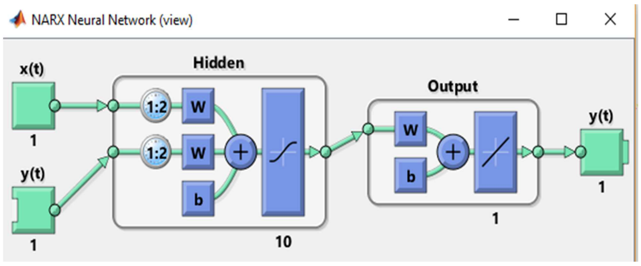

Figure 2. *Synoptic diagram of the architecture of NARX neural network models with 10 neurons under the hidden layer.*

To obtain the different models, the choice and methodical analysis of the explanatory variables is essential. These variables are used to assess the influence of each input parameter on the 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, 4].

The variables that were chosen to model the electrical load of Niamey city are listed in Table 3.

Table 3. *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	$Mean\,(\sum_{i=1}^{24} Yh - i\,)$	D
Y= load data		

Table 4. *Summary of Simulation Cases in MATLAB.*

Case	Configuration
1	[A D]
2	[B D]
3	[C D]
4	[A B C]
5	[A C D]
6	[B C D]
7	[A B C D]

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

We tested different configuration cases that are summarized in Table 4, for total of 7 configuration cases.

5. Results and Interpretations

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

To obtain the different results, programs are designed for each configuration case and for each learning.

For given configuration case and neurons number in the hidden layer, each model was run 10 times for the learning and simulation phases.

Indeed, the synaptic weights change values with each execution, giving slightly different results from previous executions.

Neurons number is varied as follows: 10, 20, 30, 40 and 50. Two models, MLP and NARX, are studied. For each model there are seven (7) configuration cases. For each configuration case neurons number is varied in five steps (10, 20, 30, 40, and 50) and for each neurons number considered, ten (10) learning are performed.

In total there are 2x7x5x10 = 700 learnings, so 700 programs on MATLAB.

The learning time is 12 to 15 minutes for MLP and 3 to 6 minutes for NARX.

For each learning experience it is ensured that the results are automatically recorded by our program. In addition to the end that each learning of the curves is automatically traced also to graphically observe the results.

Finally, for each model and for each number of neurons given, the results of the best performance on the 10 learning outcomes are classified in tables 5 to 14.

5.1. Performances of Perceptron Multilayer Models (MLP)

We have reported the minimum and maximum of considered performance criteria of different cases in tables.

Table 5. *MLP performances – configuration [AD]: case_1.*

Number of neurons in the hidden layer	MAPE (%)		RMSE (%)		R (%)	
	MAX	MIN	MAX	MIN	MAX	MIN
10	8,8422	8,6798	8,6924	8,5937	88,5441	88,2617
20	8,8319	8,6495	8,6745	8,5714	88,6073	88,3133
30	8,7235	8,6333	8,6109	8,5584	88,6441	88,4952
40	8,6725	8,6291	8,5803	8,5549	88,6540	88,5823
50*	8,6701	8,6260	8,5790	8,5528	88,6599	88,5858

Table 6. *MLP performances - configuration [BD]: case_2.*

Number of neurons in the hidden layer	MAPE (%)		RMSE (%)		R (%)	
	MAX	MIN	MAX	MIN	MAX	MIN
10	8,6068	8,5375	8,1037	8,0459	90,0370	89,8853
20	8,5304	8,5081	8,0454	8,0268	90,0866	90,0381
30	8,5249	8,4924	8,0365	8,0114	90,1268	90,0613

Number of neurons in the hidden layer	MAPE (%)		RMSE (%)		R (%)	
	MAX	MIN	MAX	MIN	MAX	MIN
40	8,5063	8,4678	8,0225	7,9891	90,1846	90,0979
50*	8,4992	8,4652	8,0124	7,9856	90,1937	90,1243

Table 7. *MLP performances - configuration [CD]: case_3.*

Number of neurons in the hidden layer	MAPE (%)		RMSE (%)		R (%)	
	MAX	MIN	MAX	MIN	MAX	MIN
10	10,2247	10,1670	9,1950	9,1481	86,9048	86,7601
20	10,1613	10,1466	9,1424	9,1351	86,9448	86,9222
30	10,1493	10,1136	9,1341	9,1172	86,9997	86,9480
40	10,1332	10,0956	9,1220	9,1050	87,0371	86,9851
50*	10,1168	10,0951	9,1202	9,0995	87,0538	86,9906

Table 8. *MLP performances - configuration [A B C]: case_4.*

Number of neurons in the hidden layer	MAPE (%)		RMSE (%)		R (%)	
	MAX	MIN	MAX	MIN	MAX	MIN
10	8,1102	8,0042	8,1884	8,1344	89,8040	89,6605
20	8,0493	7,9522	8,1384	8,0767	89,9564	89,7938
30	7,9890	7,9361	8,0855	8,0519	90,0214	89,9330
40	7,9585	7,9149	8,0757	8,0283	90,0829	89,9589
50*	7,9651	7,9044	8,0649	8,0190	90,1071	89,9874

Table 9. *MLP performances - configuration [ACD]: case_5.*

Number of neurons in the hidden layer	MAPE (%)		RMSE (%)		R (%)	
	MAX	MIN	MAX	MIN	MAX	MIN
10	8,4387	8,4020	8,3798	8,3257	89,2900	89,1419
20	8,3858	8,3666	8,3411	8,3236	89,2959	89,2481
30	8,3522	8,3232	8,3148	8,2822	89,4083	89,3197
40	8,3714	8,3054	8,3147	8,2632	89,4598	89,3200
50*	8,3287	8,2981	8,2900	8,2500	89,4953	89,3872

Table 10. *MLP performances - configuration [BCD]: case_6.*

Number of neurons in the hidden layer	MAPE (%)		RMSE (%)		R (%)	
	MAX	MIN	MAX	MIN	MAX	MIN
10	8,2383	8,1431	7,8250	7,7597	90,7689	90,6046
20	8,1280	8,0758	7,7484	7,6959	90,9275	90,7971
30	8,0957	8,0518	7,7125	7,6821	90,9616	90,8863
40*	8,0530	8,0036	7,6711	7,6308	91,0880	90,9888
50	8,0630	8,0081	7,6694	7,6297	91,0905	90,9930

Table 11. *MLP performances - configuration [ABCD]: case_7.*

Number of neurons in the hidden layer	MAPE (%)		RMSE (%)		R (%)	
	MAX	MIN	MAX	MIN	MAX	MIN
10	7,5077	7,3877	7,4916	7,4022	91,6378	91,4253
20	7,3600	7,3121	7,3865	7,3266	91,8154	91,6749
30	7,2905	7,2628	7,3091	7,2942	91,8908	91,8563
40	7,2856	7,2152	7,2946	7,2430	92,0092	91,8899
50*	7,2850	7,1874	7,3041	7,2199	92,0622	91,8678

5.2. Performance of Non-linear Autoregressive Network Models with Exogenous Inputs (NARX)

The results of different configurations of this model are also presented in tables.

Table 12. *NARX performances - configuration [AD]: case_1.*

Number of neurons in the hidden layer	MAPE (%)		RMSE (%)		R (%)	
	MAX	MIN	MAX	MIN	MAX	MIN
10	5,5741	5,3569	5,9149	5,7758	94,9960	94,7454
20	5,4585	5,2688	5,8471	5,7246	95,0888	94,8685
30	5,4409	5,2939	5,8027	5,7161	95,1017	94,9502
40*	5,4248	5,3123	5,7859	5,7313	95,0748	94,9831
50	5,4725	5,2951	5,8559	5,6998	95,1304	94,8525

Table 13. *NARX performances - configuration [BD]: case_2.*

Number of neurons in the hidden layer	MAPE (%)		RMSE (%)		R (%)	
	MAX	MIN	MAX	MIN	MAX	MIN
10	5,5646	5,2267	5,9384	5,6575	94,9786	94,7036
20	5,4748	5,3173	5,8953	5,7028	95,1275	94,7810
30*	5,3557	5,2443	5,7202	5,6550	95,2107	95,0943
40	5,4181	5,2444	5,7912	5,6428	95,2294	94,9686
50	5,4791	5,2923	5,8346	5,6911	95,1453	94,8909

Table 14. *NARX performances - configuration [CD]: case_3.*

Number of neurons in the hidden layer	MAPE (%)		RMSE (%)		R (%)	
	MAX	MIN	MAX	MIN	MAX	MIN
10	5,4958	5,3378	5,8494	5,7549	95,0345	94,8647
20	5,4316	5,2654	5,8159	5,6961	95,1370	94,9264
30	5,6953	5,3018	5,9454	5,7043	95,1230	94,6921
40	5,4395	5,2938	5,8081	5,7269	95,0827	94,9388
50*	5,4206	5,3438	5,7639	5,7324	95,0753	95,0176

Table 15. *NARX performances - configuration [ABC]: case_4.*

Number of neurons in the hidden layer	MAPE (%)		RMSE (%)		R (%)	
	MAX	MIN	MAX	MIN	MAX	MIN
10	5,6630	5,6036	6,0510	6,0218	94,5495	94,4959
20	5,7976	5,4336	6,0384	5,9215	94,7356	94,5328
30*	5,5895	5,4949	6,0086	5,9083	94,7583	94,5734
40	5,6012	5,4868	6,0045	5,9452	94,6903	94,5805
50	5,6969	5,5375	6,1065	5,9559	94,6718	94,3895

Table 16. *NARX performances - configuration [ACD]: case_5.*

Number of neurons in the hidden layer	MAPE (%)		RMSE (%)		R (%)	
	MAX	MIN	MAX	MIN	MAX	MIN
10	5,3849	5,3087	5,8100	5,7691	95,0085	94,9352
20	5,4612	5,3056	5,8231	5,7229	95,0899	94,9130
30*	5,4193	5,2967	5,8090	5,7090	95,1167	94,9372
40	5,5729	5,3076	5,8784	5,7470	95,0478	94,8167
50	5,3849	5,3087	5,8100	5,7691	95,0085	94,9352

Table 17. *NARX performances - configuration [BCD]: case_6.*

Number of neurons in the hidden layer	MAPE (%)		RMSE (%)		R (%)	
	MAX	MIN	MAX	MIN	MAX	MIN
10	5,4221	5,2541	5,8240	5,7016	95,1270	94,9104
20	5,4227	5,3532	5,7818	5,7477	95,0469	94,9862
30	5,4607	5,1884	5,8188	5,6707	95,1813	94,9195
40	5,4216	5,3029	5,8056	5,7182	95,0979	94,9431
50*	5,3888	5,2862	5,7607	5,6784	95,1684	95,0234

Table 18. *NARX performances - configuration [ABCD]: case_7.*

Number of neurons in the hidden layer	MAPE (%)		RMSE (%)		R (%)	
	MAX	MIN	MAX	MIN	MAX	MIN
10	5,3803	5,3233	5,8215	5,7609	95,0232	94,9212
20	5,4484	5,1943	5,8254	5,6472	95,2221	94,9076
30*	5,3227	5,1765	5,7596	5,6014	95,3013	95,0255
40	5,4562	5,2638	5,7734	5,7058	95,1199	95,0015
50	5,4953	5,2874	5,8101	5,7544	95,0393	94,9359

5.3. Interpretations of Model Performance

The interpretation of the performances of different configurations of priori models has allowed us to identify for each case the neurons number in the hidden layer that gives better results as shown in Table 19 (* indicates the best performances).

Table 19. *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 best performance for each model is made using the MAPE indicator and the correlation coefficient R^2. The results are shown in Table 20 (* refers to best performance of all models and configurations).

Table 20. *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

In addition, the MAPE, RMSE and R^2 values (tables 21, 22, 23) obtained yield the curves in Figure 3, Figure 4 and Figure 5 as function of neurons number under the hidden layer.

Table 21. *MAPE values according to neurons number and case model7.*

Number of neurons in the hidden layer	MAPE(%): MLP, CASE 7	MAPE(%): NARX, CASE 7
10	7,5077	5,3803
20	7,36	5,4484
30	7,2905	*5,3227*
40	7,2856	5,4562
50	*7,285*	5,4953

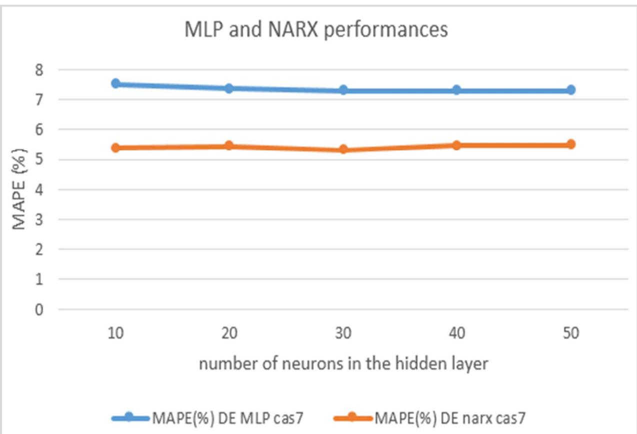

Figure 3. *Evolution of MAPE as function of neurons number in the case model7.*

Table 22. *RMSE values according to neurons number and the case model7.*

Number of neurons in the hidden layer	RMSE(%): MLP CAS 7	RMSE(%): NARX CAS 7
10	7,4916	5,8215
20	7,3865	5,8254
30	7,3091	*5,7596*
40	7,2946	5,7734
50	*7,3041*	5,8101

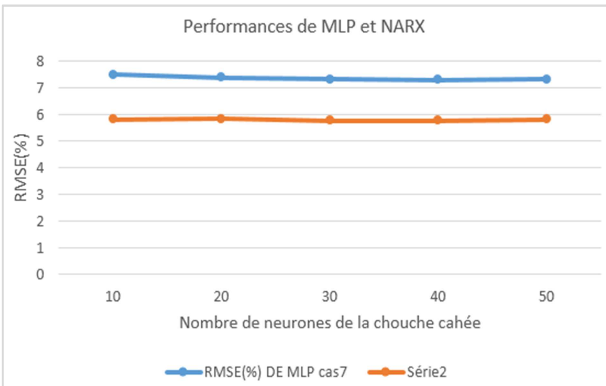

Figure 4. *Evolution of RMSE as a function of neurons number and the case model7.*

Table 23. *R^2 values according to neurons number and the case model7.*

Number of neurons in the hidden layer	R^2 (%): MLP CAS 7	R^2 (%): NARX CAS 7
10	91,6378	95,0232
20	91,8154	95,2221
30	91,8908	*95,3013*
40	92,0092	95,1199
50	*92,0622*	95,0393

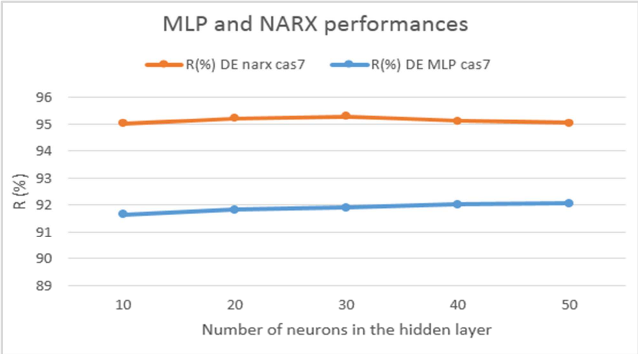

Figure 5. *Evolution of R^2 as function of neurons number and the case model7.*

It has been shown that layer networks offer poor results for neurons number in the hidden layer that are insufficient or too large. Thus, figures 3, 4 and 5 analysis shows that neurons number in hidden layer of each model influences results. Indeed, for each case, the best results are obtained for models with 30, 40 or 50 neurons. Beyond 50 neurons, MAPE errors increase and the simulation time is very long, which forces us to limit the number of neurons for our tests.

6. Conclusion

Objective of this work is to develop a model for predicting electrical charge of Niamey city using artificial neural networks. To achieve this goal, two prediction models were tested: MLP and NARX. Several configurations of the two major models mentioned above have been developed and tested by varying the different explanatory variables. All configurations have been implemented on MATLAB. 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 models. Thus with MAPE of 5.1765%, R^2 of 95.3013% and RMSE of 5.6014%, the [ABCD] configuration of the NARX model is chosen ahead of MLP with MAPE of 7.1874%, R^2 of 92.0622% and RMSE of 7.2199%. So the NARX model is the most efficient and can be used for future predictions on the Niamey city network.

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