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Electrical Load Forecasting Using Artificial Neural Network: The Case Study of the Grid Inter-Connected Network of Benin Electricity Community (CEB)

[1]Adekunlé Akim Salami, [1]Ayité Sénah Akoda Ajavon, [2]Koffi A. Dotche and [2]Koffi-Sa Bedja

[1]*Department of Electrical Engineering, ENSI, University of Lome, Togo*
[2]*Department of Electrical Technology, College of Technology, University of Education Winneba, Ghana*

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Corresponding Author:
Koffi Agbeblewu
Department of Electrical Technology, College of Technology, University of Education Winneba, Ghana
Email: kdotche2004@gmail.com

Abstract: The low rate of electrification seems challenging in many West African countries and many strategies are underway to improve upon. In this regard, the target of achieving the universal access and services calls for a stable and reliable electrical network. Forecasting of electrical load on a connected grid network is very delicate and requires tremendous task from the utilities (billing Company). It aims at looking at if the offered energy is sufficient or below satisfactory in order to add or inject more compensating energy units into the system. Consequently, the short term forecasting is used in evaluating the risk of electricity shortage and reducing the advent of load shedding in an emerging economy alike the energetic Body of Benin comprising Togo and Benin. This paper evaluates two methods used in Artificial Neural Networks (ANN) for the prediction of electricity consumption. These methods are the Multilayer Perceptron (MLP) and the Radial Basic Function (RBF). Many topologies of the hidden layers' configuration for the learning stages were considered in cross comparison against real data obtained from the grid interconnected Network of Benin. The results have proven that the predicted data are very close to the real data while using these algorithms.

Keywords: Electrical Load, Short Term Forecasting, Artificial Neural Networks, Multilayer Perceptron, Radial Basic Function, Grid Interconnected, Network

Introduction

The electrical load forecast is an important role in the management system. It helps in the load demand planning and the prior performance of the power systems (Chang, 2015). In this circumstance, an efficient prediction of electricity demand remains essential for the performance at utilization of electrical plant. The benefits are measured in the dispatching's time of energy. The overestimation of future charge may lead to unnecessary waste of resources, which in turn may yield an extra cost in the capital of expenditures. However, the under-estimation of the future demand may also translate some dysfunctions or failures that may influence the system stability in long term. Consequently, some discontinuities in the electrical plant may occur due to the challenges accounting for the meteorological conditions such as the time of day, electricity cost, the population and social activity, etc. that (Zjavka and Snášel, 2016).

Traditional methods are used to maintain a stable load curve as indicated in (El-Baz and Tzscheutschler 2015; Frimpong and Okyere, 2012; Barakati *et al*., 2015; Chen *et al*., 2001). The load forecast is based upon a series of collected data in timely basis that are processed into a linear regression filter as suggested in (Chen *et al*., 2001), where the Kalman filter has proven effective in the forecast of chronological series. However, Engle *et al.* (Pan *et al*., 2004) have investigated several methods for the load forecasting. These models included deterministic influences such as holidays and other stochastic events in relying on their mean values to predict the mean load. These methods alike temporal series, are called autoregressive models (Huang, 1997). The Autoreg Ressive Moving Average (ARMA) is presented in (Cho *et al*., 1995), meanwhile the Autoreg

Ressive Integrated Moving Average (ARIMA) are discussed in (Barakat *et al*., 1992; Juberias *et al*., 1999; Mandal *et al*., 2006; He *et al*., 2005; Al-Hamadi and Soliman, 2004) presented some details about Kalman filter to predict the charge load in short term. It will be noted that these prediction models are limited to the environmental cent meteorological conditions. A remedy to this problem, Artificial Neural Networks (ANN) are more convenient in forecasting of electrical load in short term. This work focuses on the prediction of electrical load of Benin Electricity Community Network using two neural approaches, which are Multi Layer Perceptron (MLP) and Radial Basis Function (RBF). These methods were considered in cross comparison against real data obtained from the grid-interconnected network.

The rest of the paper is structured as follows: The next section describes the methods and some statistical indicators for performance evaluation. In section 3, the methodology of data processing and its modelling into ANN toolbox in Matlab software are presented. In section 4, the results and discussion are elaborated. Finally, the conclusion is given in section 5, which leads to further research directions.

The models of the study

The output of a neural network takes into account the learning procedure. The learning stage is based on the retro propagation of error. He output expression is given as:

$$O_k = \sum_{j=1}^{q} w_{kj} b_j(x) - \theta_k \quad (1)$$

Where:

$1<k<m$; m = The number of nodes
O_k = The output of the kth node of the output layer
w_{kj} = The connection between the jth neuron of hidden layer and kth neuron of hidden layer and kth neuron of output layer
$b_j(x)$ = The output of the jth neuron of hidden layer and Θ_k is the bias of the kth neuron of output layer.

For the Multilayer Perceptron (MLP) architectural model as depicted in Fig. 1, showing the hidden and output layer layout, the model's output is given as:

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i h_i \quad (2)$$

Where:

y = The predicted value by the neural network
n = The number of hidden layers
β_0 = Bias, β_i are weighted coefficients
h_i = The result of nonlinear transformation of hidden layer i

The Radial Basis Function model (RBF) differs from the MLP by Gaussian activation function as shown in Fig. 2. During the learning process, each neuron of the hidden layer performs a nonlinear transformation. The output of RBF neuron with Gaussian nonlinearity is expressed as:

$$b_j = exp\left[-\frac{\sum_{i=1}^{n} \left(x_i - \mu_j\right)^2 \beta_i h_i}{2\sigma_j^2} \right] \quad (3)$$

Where:

μ_j = The mean of Gauss's function of jth layer
σ_j = Standard deviation of Gauss's function of jth layer
x_i = Input variables of neurons, such as $1<j<q$; where q is the number of neurons in the hidden layer.

The accuracy of a model is measured by the difference between the expected true value and the observed value E_{abs}. This is expressed as:

$$E_{abs} = Y_{j,p} - Y_{j,r} \quad (4)$$

The difference between the predicted value to the actual denotes an excess load, E_{Load} and its mean value is given as:

$$E_{Load} = \frac{1}{N}\left| \sum_{j=1}^{N} \left(Y_{j,p} - Y_{j,r}\right) \right| \quad (5)$$

Three indicators are considered in assessing the performances of the different configurations: Mean Absolute Percentage Error (MAPE); Root Mean Square Error (RMSE) and correlation coefficient (R^2). The correlation coefficient, ought to be close to 1, translating strong relationship between the predicted and the observed value:

$$MAPE = \frac{1}{N} \sum_{j=1}^{N} \left| \frac{Y_{j,p} - Y_{j,r}}{Y_{j,r}} \right| \times 100 \quad (6)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{j=1}^{N} \left(Y_{j,p} - Y_{j,r}\right)^2} \quad (7)$$

$$R^2 = \frac{\sum_{j=1}^{N} \left(Y_{j,p} - Y_{p,avg}\right) \times \left(Y_{j,r} - Y_{r,avg}\right)}{\sqrt{\left[\sum_{j=1}^{N} \left(Y_{j,p} - Y_{p,avg}\right)^2\right] \times \left[\sum_{j=1}^{N} \left(Y_{j,r} - Y_{r,avg}\right)^2\right]}} \quad (8)$$

In (4), (5), (6) and (7):

N = The measured data number
$Y_{j,p}$ = The forecast load at index j
$Y_{p,avg}$ = The mean value of predicted load
$Y_{j,r}$ = Real load observed at index j
$Y_{r,avg}$ = Average value of real load

We recall that the excess load could be regarded as the difference between the true load (the produced energy) and the actual load. The knowledge of the mean can help in system compensation for the energy demand by the insertion of other means of power supply generation such as a renewable or clean energy provision. The residual energy ΔE that compensates the demand is a factor of k given as:

$$k = 1 \pm 1/2 \times MAPE \tag{9}$$

Methodology

This section highlights the steps in investigating the performances of the ANN algorithms in study.

The data processing and implementation of the forecast models were made with the help of the ntstool toolbox in Matlab version R2016a.

Input Data

These variables are used to evaluate the influence of each input parameter on the output of prediction model. The accuracy of the model may depend on the adequate input parameters. This involves eliminating some redundant variables or those providing less or no information to describe the output. Table 1 presents the variables used to model the electrical load of CEB. The various combination of the variables and the efficient stages in the configuration are given in Table 2.

Measured Data

The data used are from the hourly observation on the electrical joint consumption of Togo and Benin. The data were stored in log-files every day per hours from 2010 to 2014 (about 43824 data). A preliminary processing was conducted to avoid a false prediction. Therefore, these data were arranged into three groups. The first group intends for the learning includes data from 2010 to 2012. The second and last group uses respectively 2013's data to validate the efficiency of prediction and 2014's data for the test.

Results and Discussion

The hidden neurons configurations and the network outputs are given for both models, the MLP and the RBF. For these models, ten learning tags are considered in the simulation under the assumed hidden neurons as shown in the Tables 3 and 4, respectively MLP and RBF performances. Indeed, the synaptic weight changes with every execution, which introduces a slight difference in the results at each iteration.

In Table 3 and 4, the (*) symbol implies the best performance of a given configuration.

When using other statistical methods such as linear regressive multiple points, we obtain results that are tabulated in Table 5.

Table 6 presents the summary of the considered models with respect to the set number of neurons for the hidden layers, which may indicate the best performances.

The obtained results in Table 7 may show that the number of hidden layer has significant impact on the performance of layered networks. However, it is providing that as the number of hidden layer increases, the performance decreases and the errors becomes very significant.

The second analysis may better describe the behavioral characteristics of neural networks. It may indicate that neural networks are best suitable in the modeling of electrical load profile. Noting that the environment error does not exceed 4%.

The analysis may indicate that the regression methods are fast in forecasting with respect to time constraint. The best configuration is [ABDEF] for a MAPE of 4.29% and correlation coefficient for 90.90%. The worst case is 10 ([BCEG]) with a MAPE of 6.22% and correlation coefficient of 80.51%.

Table 7 shows the most appropriate configuration of electrical load modeling. The case 6 of MLP model provides the smallest MAPE and most important correlation coefficient. It is noted that the number of neurons in the hidden layer is the criterion used to select the model's performance. As a fact, the case 6 of the RBF model could be viewed as the most suitable because its MAPE error is around 3.05% and having the best correlation coefficient (93.73%). It is necessary to find a compromise between these factors in order to obtain an efficient forecast. It seems legitimate to choose the neural model to carry out the prediction.

The Fig. 4 presents the simulation of MLP, RBF and Multiple Linear Regression (MLR) models over one week duration. The values obtained for the different MAPE show that neural models give the least error. For the MLP model, the MAPE error is 0.92% compared to 2.125% for RBF model. In Fig. 5, a training over 24 h was considered with emphasis on the comparative analysis of the different prediction models.

The MAPE errors for the models are calculated. The MAPE for the MLP's model gives a lower MAPE error around 0.61% than that of the RBF's model (1.9%).

The energy compensating system could be decided in regard to (4) and (5). Assuming the worst case, an extra-energy of (1-2%)*X will be required to sustain the daily energy demand. Where X is the daily produced energy by the hydro-plant.

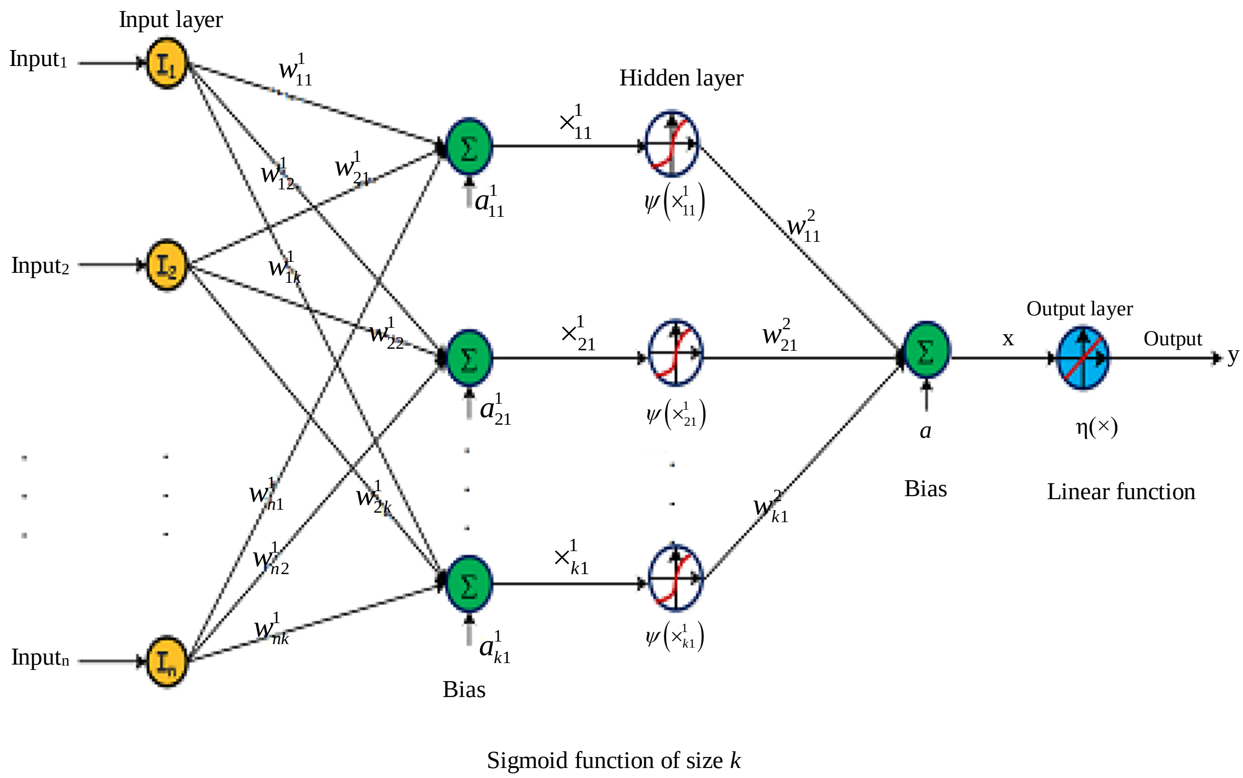

Fig. 1: MLP Neuronal architectural model

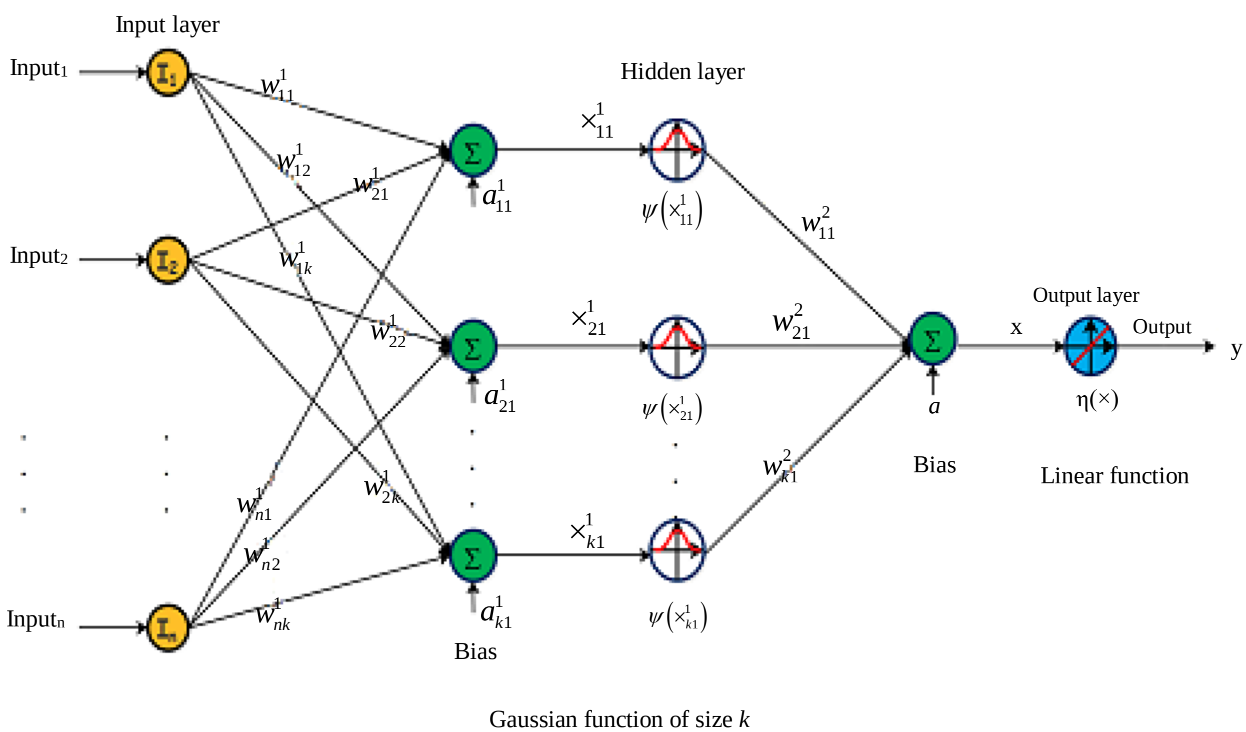

Fig. 2: The RBF architectural model

Table 1: Input variables

Data	Mathematical explanation	Code
Working day or not	$\begin{cases} \text{if} \quad \text{working} \quad \text{then} \quad 1 \\ \text{if} \quad \text{not} \quad \text{then} \quad 0 \end{cases}$	A
Day week	Sunday = 1; Monday = 2;Tuesday =3; Wednesday = 4; Thursday = 4; Friday = 5; Saturday = 7	B
Day hours	H (1 to 24)	C
Previous Day Same Hour Load	$Y_{h\text{-}24}$	D
Previous Week Same Hour Load	$Y_{h\text{-}168}$	E
Previous Year Same Hour Load	$Y_{h\text{-}8760}$	F
Previous 24 h Average Load	$Mean\left(\sum_{i=1}^{24} Y_{h-i}\right)$	G
	Y = load's data	

Table 2: Summary of the possible configurations

Case	Configuration
1	[D E F]
2	[A B D E F]
3	[A B C D E F G]
4	[A C D E G]
5	[A B C D G]
6	[A B C G]
7	[B C D E F G]
8	[B D E F G]
9	[A B C D]
10	[B C E G]

Table 3: MLP model performances

			MAPE (%)		RMSE (%)		R^2 (%)	
Configuration	Case	Number of hidden layer's neurons	Min	Max	Min	Max	Max	Min
[DEF]	1	1	4.4283	4.4883	0.5036	0.5040	88.84	88.56
		5	3.6523	3.8103	0.4641	0.4923	91.37	91.22
		10	3.6759	3.8094	0.4964	0.4977	91.62	91.16
		15	3.6146	3.7838	0.4398	0.4719	91.92	91.10
		20*	3.5961	3.8560	0.4967	0.6067	91.86	90.98
		30	3.6105	4.3757	0.5033	0.8066	92.09	77.36
		40	3.6163	3.9521	0.4558	0.5027	91.84	90.90
		60	3.6334	3.8567	0.4585	0.4984	91.85	91.03
[ABDEF]	2	1	4.3251	4.4127	0.4994	0.5013	89.20	88.85
		5	3.5624	3.8603	0.5024	0.9521	92.05	74.87
		10	3.5304	3.9022	0.4865	0.4920	92.16	91.00
		15	3.5370	3.7109	0.3518	0.4737	91.77	91.65
		20*	3.4602	3.7383	0.4948	0.5028	92.39	91.28
		30	3.5062	3.6840	0.4734	0.4842	92.20	91.57
		40	3.5911	3.7061	0.4978	0.5134	92.06	91.50
		60	3.5653	3.7376	0.4689	0.5006	92.12	91.57
[ABCDEFG]	3	1	4.2156	5.2602	0.4616	0.5070	89.73	82.60
		5	3.2402	3.9699	0.4938	0.5404	93.01	90.65
		10*	3.1702	3.6138	0.5013	0.5072	93.34	91.93
		15	3.2410	3.5869	0.4177	0.5064	92.99	91.97
		20	3.3022	3.6708	0.4754	0.5183	92.86	91.81
		30	3.3253	3.8117	0.4748	0.5056	92.88	91.41
		40	3.3736	3.6791	0.4626	0.5177	92.81	91.78
		60	3.4890	3.8295	0.4591	0.5034	92.29	91.32

Table 3: Continue

[ACDEG]	4	1	4.2003	4.3892	0.5014	0.5027	89.69	88.79
		5	3.2716	3.9021	0.3021	0.5426	93.00	90.78
		10*	3.0947	3.9071	0.4844	0.5308	93.50	90.87
		15	3.2504	3.6040	0.4732	0.5201	92.84	91.87
		20	3.2063	3.7798	0.4874	0.5126	93.24	91.34
		30	3.2083	3.6491	0.4054	0.5056	93.24	91.87
		40	3.2673	3.5755	0.5076	0.5223	93.08	92.15
		60	3.3245	3.6400	0.5158	0.5167	92.99	92.05
[ABCDG]	5	1	4.1819	5.1654	0.4827	0.5193	89.74	85.13
		5	3.1992	4.0551	0.4821	0.5231	93.36	90.50
		10	3.2063	3.9109	0.4867	0.5243	93.36	90.91
		15*	3.1669	3.6838	0.5430	0.5490	93.23	91.48
		20	3.1917	3.6052	0.5146	0.5250	93.26	92.13
		30	3.2450	3.6594	0.4849	0.5386	93.11	91.81
		40	3.2283	3.6646	0.2004	0.4937	93.20	91.61
		60	3.4028	3.6920	0.4999	0.5019	92.76	91.78
[ABCG]	6	1	3.4723	3.4780	0.5547	0.5555	91.82	91.78
		5	3.0409	3.1254	0.5301	0.5379	93.71	93.47
		10	3.0237	3.0531	0.5391	0.5417	93.85	93.76
		15	3.0115	3.1039	0.5228	0.5528	93.76	93.70
		20*	2.9861	3.0999	0.5388	0.5711	93.81	93.37
		30	3.0812	3.1703	0.5219	0.5243	93.76	93.38
		40	3.0923	3.1623	0.5212	0.5367	93.59	93.36
		60	3.1529	3.1890	0.5116	0.5339	93.52	93.39
[BCDEFG]	7	1	4.3415	4.5356	0.4976	0.5015	89.30	88.39
		5*	3.2886	3.3218	0.5078	0.5126	92.94	92.73
		10	3.5365	3.7545	0.5045	0.5213	92.30	91.59
		15	3.4406	3.9684	0.4682	0.6596	92.33	90.70
		20	3.3828	3.4795	0.4957	0.5143	92.70	92.42
		30	3.4252	3.6020	0.4653	0.5273	92.62	92.02
		40	3.3319	3.6941	0.4788	0.5238	92.93	92.02
		60	3.3951	3.9595	0.5280	0.6916	92.66	89.72
[BDEFG]	8	1	4.3493	4.4068	0.5071	0.5088	89.28	89.01
		5	3.5532	3.6728	0.4928	0.5086	92.14	91.88
		10	3.4896	3.8195	0.4723	0.4914	92.27	91.18
		15	3.5062	3.8058	0.4988	0.5012	92.26	91.19
		20*	3.4443	4.0113	0.4577	0.4932	92.41	90.43
		30	3.4124	3.6954	0.5050	0.5243	92.57	91.92
		40	3.4870	3.7229	0.4712	0.5006	92.33	91.54
		60	3.4549	3.6317	0.4959	0.5268	92.31	91.77
[ABCD]	9	1	4.2755	4.3170	0.5125	0.5127	89.27	89.11
		5	3.2834	3.4800	0.4547	0.5193	92.97	92.40
		10	3.1949	3.5667	0.4889	0.5006	93.45	91.67
		15	3.2892	3.5470	0.5147	0.5243	92.99	92.21
		20*	3.1565	3.5268	0.4813	0.5121	93.45	92.47
		30	3.3056	3.4968	0.4817	0.5037	93.08	92.50
		40	3.3064	3.4455	0.5049	0.5234	93.04	92.49
		60	3.3339	3.4968	0.4896	0.5023	92.93	92.46
[BCEG]	10	1	3.4744	3.4939	0.5536	0.5541	9187	91.84
		5	3.0817	3.1200	0.5399	0.5622	93.45	93.27
		10	3.0524	3.2093	0.5221	0.5793	93.71	93.02
		15*	3.0523	3.1607	0.4960	0.5006	93.62	93.29
		20	3.0654	3.1898	0.5113	0.5135	93.61	93.16
		30	3.0894	3.2186	0.4824	0.5203	93.61	93.19
		40	3.0804	3.2311	0.5306	0.5394	93.55	9307
		60	3.1837	3.2302	0.5305	0.5314	93.35	93.13

Table 4: RBF model performances

Configuration	Case	Number of hidden layer's neurons	MAPE (%) Min	MAPE (%) Max	RMSE (%) Min	RMSE (%) Max	R^2 (%) Max	R^2 (%) Min
[DEF]	1	1	4.4466	4.4915	0.5041	0.5053	88.76	88.53
		5	3.6966	3.9067	0.4537	0.5031	91.57	90.80
		10*	3.6238	3.8705	0.4709	0.5031	91.78	91.19
		15	3.6269	3.8218	0.4828	0.5042	91.86	91.37
		20	3.7294	3.8580	0.4848	0.4906	91.67	91.07
		30	3.6735	3.8284	0.4691	0.4851	91.66	91.31
		40	3.6311	3.9624	0.4928	0.5058	91.82	90.48
		60	3.7290	3.9346	0.4571	0.4636	91.40	90.99
[ABDEF]	2	1	4.3315	7.1743	0.4003	0.5014	89.18	64.82
		5	3.7570	3.8408	0.4959	0.5016	91.40	91.26
		10	3.6052	3.7405	0.4965	0.5093	92.03	91.37
		15	3.5578	3.7932	0.4821	0.5037	92.06	91.46
		20	3.6511	3.7074	0.4853	0.5009	91.70	91.67
		30	3.5586	3.6529	0.4641	0.5112	92.14	91.94
		40*	3.5314	3.6480	0.4467	0.4709	92.23	91.82
		60	3.6642	3.7368	0.4478	0.4937	91.75	91.41
[ABCDEFG]	3	1	4.4042	5.2482	0.5038	0.5040	88.88	81.69
		5*	3.2111	3.5021	0.4984	0.5017	93.18	92.52
		10	3.3462	3.7863	0.5027	0.5041	92.87	91.49
		15	3.2617	3.6739	0.4945	0.5033	92.83	91.57
		20	3.3959	3.4082	0.5170	0.5306	92.74	92.67
		30	3.4713	3.8071	0.4434	0.4758	92.28	91.23
		40	3.3422	3.5736	0.4625	0.5156	92.84	92.14
		60	3.3792	3.6917	0.4935	0.5287	92.68	91.33
[ACDEG]	4	1	4.1866	4.2142	0.5099	0.5124	89.73	89.62
		5	3.2876	3.5680	0.4984	0.5076	93.04	92.14
		10	3.3041	3.4591	0.4966	0.5223	92.95	92.43
		15	3.3657	3.4485	0.5216	0.5299	92.87	92.53
		20*	3.2390	3.5109	0.4848	0.4929	93.12	92.32
		30	3,3198	3,8010	0,5100	0,5592	92,92	91,08
		40	3,3330	3,5437	0,4999	0,5029	92,86	92,24
		60	3,3126	3,3464	0,5094	0,5206	92,98	92,86
[ABCDG]	5	1	4.1290	5.2150	0.4393	0.4937	89.94	85.53
		5	3.3801	3.9726	0.4676	0.4856	92.67	90.52
		10	3.3321	3.6963	0.4981	0.5073	92.86	91.72
		15	3.3646	3.5324	0.5197	0.5238	92.84	92.37
		20*	3.3317	3.6834	0.4866	0.4979	92.91	91.71
		30	3.3960	3.4606	0.5275	0.5361	92.63	92.53
		40	3.3878	3.4818	0.5198	0.5355	92.68	92.37
		60	3.4813	3.5110	0.4988	0.5026	92.94	92.26
[ABCG]	6	1	3.4732	3.5010	0.5524	0.5538	91.80	91.72
		5	3.1189	3.2255	0.5397	0.5483	93.51	93.04
		10*	3.0534	3.1388	0.5244	0.5298	93.73	93.36
		15	3.0593	3.1019	0.5176	0.5431	93.50	93.50
		20	3.0551	3.1602	0.4958	0.5285	93.76	93.36
		30	3.0743	3.1418	0.4982	0.5583	93.59	93.36
		40	3.1755	3.2229	0.5036	0.5495	93.28	93.08
		60	3.1667	3.2442	0.4833	0.4954	93.38	93.12
[BCDEFG]	7	1	4.3515	4.4340	0.4516	0.5059	89.31	88.90
		5	3.5969	3.9206	0.5021	0.5045	92.00	90.84
		10*	3.3232	3.6711	0.3869	0.4919	92.84	91.87
		15	3.3770	3.7094	0.4700	0.5170	92.75	91.74
		20	3.4748	3.6130	0.3714	0.5077	92.50	92.08
		30	3.4897	3.6205	0.4977	0.5064	92.29	91.99
		40	3.4553	3.5544	0.5187	0.4693	92.55	92.26
		60	3.4738	3.6207	0.4720	0.5050	92.48	91.70
[BDEFG]	8	1	4.3430	5.2756	0.4939	0.5083	89.35	83.30

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Table 4: Continue

		5	3.8322	3.9373	0.4876	0.5308	91.02	90.57
		10*	3.4665	3.5132	0.5082	0.5106	92.26	92.17
		15	3.4831	3.8644	0.4061	0.4867	92.07	90.76
		20	3.6009	3.7588	0.4842	0.5094	92.03	91.38
		30	3.7317	3.7423	0.4624	0.4779	91.38	91.48
		40	3.5842	3.6959	0.4811	0.5169	91.78	91.64
		60	3.6276	3.8165	0.4548	0.5110	91.97	90.88
[ABCD]	9	1	4.3304	4.3473	0.5103	0.5110	89.07	88.96
		5	3.3780	3.6304	0.5267	0.5401	92.55	91.78
		10*	3.1815	3.6116	0.5100	0.5140	93.37	91.88
		15	3.3120	3.5268	0.4877	0.5122	92.84	92.35
		20	3.2298	3.6261	0.4198	0.5078	93.05	92.07
		30	3.2706	3.4945	0.4658	0.5034	92.95	92.44
		40	3.4967	3.7503	0.4715	0.4794	92.25	91.55
		60	3.3243	3.4335	0.5200	0.5380	92.86	92.45
[BCEG]	10	1	3.4661	3.4966	0.5538	0.5551	91.89	91.75
		5	3.1440	3.7883	0.5263	0.5417	93.26	89.86
		10	3.1701	3.1858	0.5199	0.5678	93.32	93.23
		15	3.1059	3.1960	0.5252	0.5258	93.46	93.22
		20*	3.0608	3.1664	0.5092	0.5263	93.63	93.41
		30	3.1526	3.1623	0.4330	0.5074	93.38	93.31
		40	3.0948	3.1910	0.5096	0.5102	93.52	93.41
		60	3.1985	3.2512	0.4598	0.5118	93.26	93.22

Table 5: MLR model performances

Case	1	2*	3	4	5	6	7	8	9	10
MAPE	4.51	4.29	4.68	5.07	4.64	7.52	4.72	4.54	4.57	6.22
RMSE	0.44	0.41	0.47	0.51	0.62	0.63	0.46	0.40	0.50	0.52
R^2	89.7	90.9	89.3	88.4	90	70.2	88.8	89.8	96.4	80.5

Table 6: Summary of Performances of different models

		MAPE		RMSE		R^2	
Model	Number of hidden layer's neurons	Min	Max	Min	Max	Max	Min
MLP1	20	3.5961	3.8560	0.4967	0.6067	91.86	90.98
2	20	3.4602	3.7383	0.4948	0.5028	92.399	1.28
3	10	3.1702	3.6138	0.5013	0.5072	93.349	1.93
4	10	3.0947	3.9071	0.4844	0.5308	93.509	0.87
5	15	3.1669	3.6838	0.5430	0.5490	93.23	91.48
6*	20	2.9861	3.0999	0.5388	0.5711	93.81	93.37
7	5	3.2886	3.3218	0.5078	0.5126	92.94	92.73
8	20	3.4443	4.0113	0.4577	0.4932	92.41	90.43
9	20	3.1565	3.5268	0.4813	0.5121	93.45	92.47
10	15	3.0523	3.1607	0.4960	0.5006	93.62	93.29
RBF1	10	3.6238	3.8705	0.4709	0.5031	91.78	91.19
2	40	3.5314	3.6480	0.4467	0.4709	92.23	91.82
3	5	3.2111	3.5021	0.4984	0.5017	93.18	92.52
4	20	3.2390	3.5109	0.4848	0.4929	93.12	92.32
5	20	3.3317	3.6834	0.4866	0.4979	92.91	91.71
6*	10	3.0534	3.1388	0.5244	0.5298	93.73	93.36
7	10	3.3232	3.6711	0.3869	0.4919	92.84	91.87
8	10	3.4665	3.5132	0.5082	0.5106	92.26	92.17
9	10	3.1815	3.6116	0.5100	0.5140	93.37	91.88
10	20	3.0608	3.1664	0.5092	0.5263	93.63	93.41
RML	-	4.2960	0.4134	90.90			

Table 7: Best performances of different models

Model	Case	Number of hidden layer's neurons	MAPE Min	MAPE Max	RMSE Min	RMSE Max	R^2 Max	R^2 Min
MLP*	6	20	2.9861	3.0999	0.5388	0.5711	93.81	93.37
RBF	6	10	3.0534	3.1388	0.5244	0.5298	93.73	93.36
MLR	2	-	4.2960	0.4134	90.90			

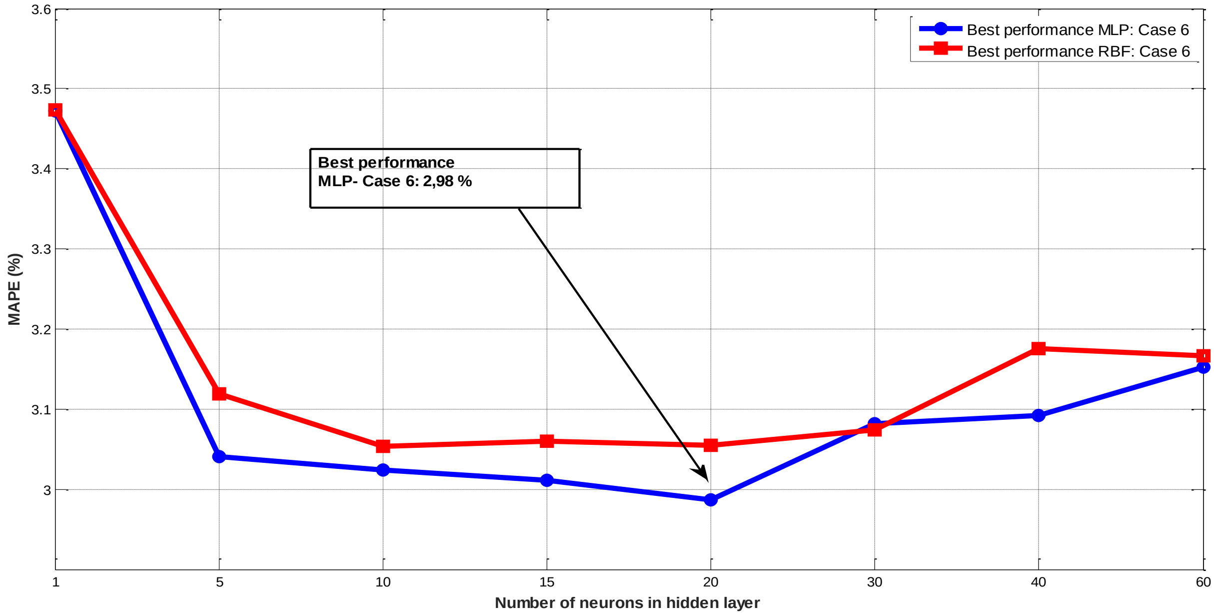

Fig. 3: Error curve for MLP and RBF model

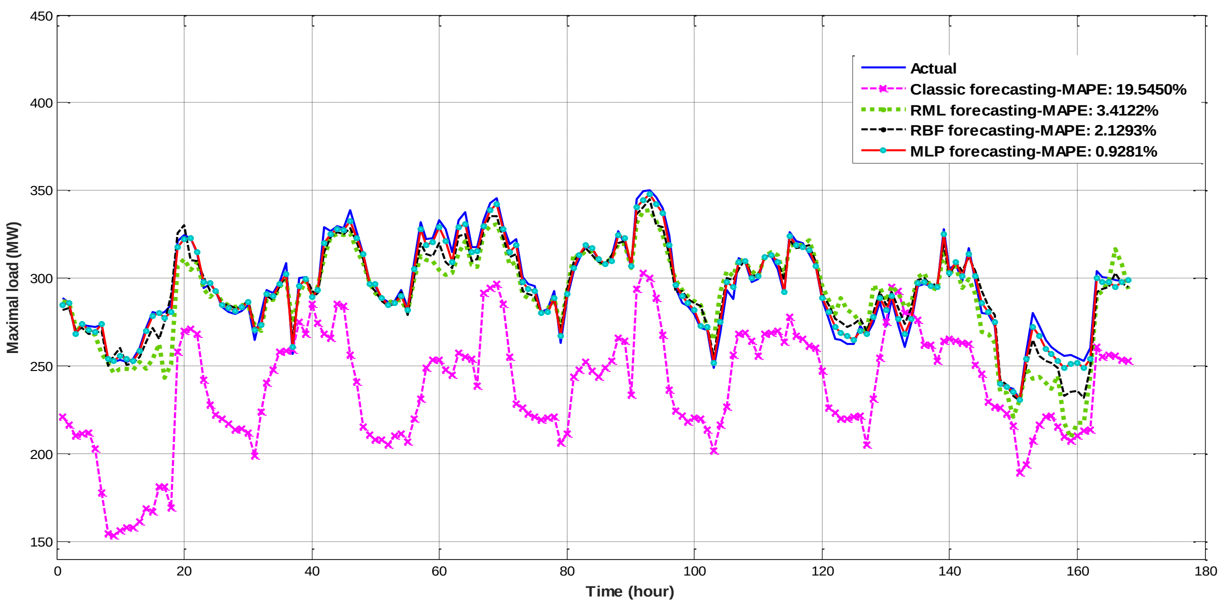

Fig. 4: Simulation of actual and predicted load

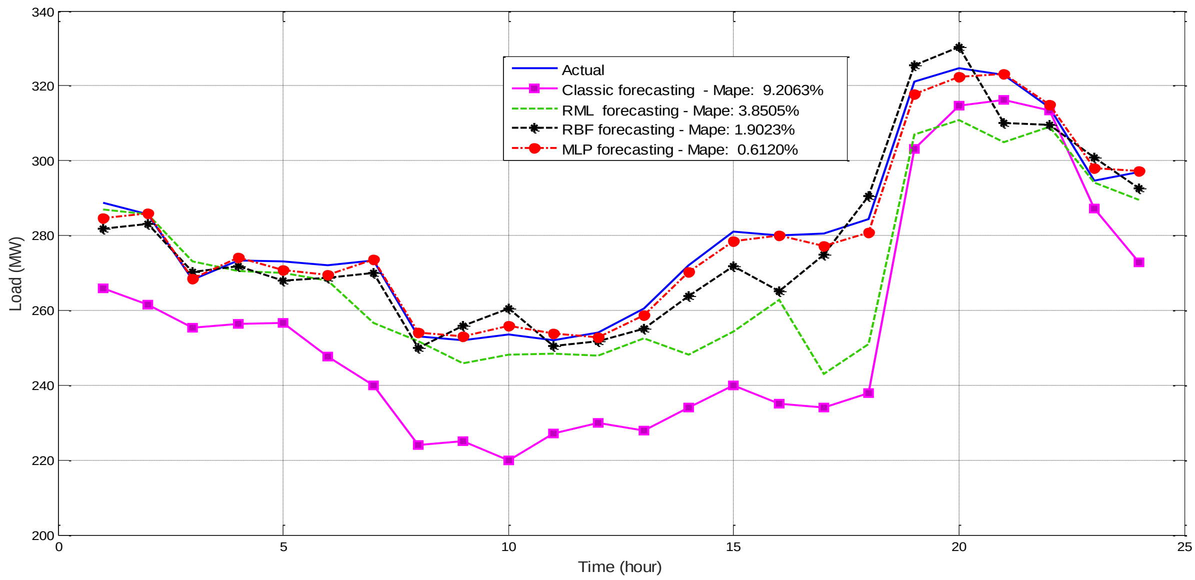

Fig. 5: Simulation of actual and predicted load for different neural model during 24 h

Conclusion

The work presents the short-term prediction about energy demand of the Benin Electricity Community using two neural approaches (MLP and RBF). The Matlab environment, particularly, the ntstool toolbox was used to implement these models and for the learning stages. The obtained results are compared to that of the linear multiple regression method. The calculation of MAPE error may help in deciding the best combination that map the layers and the hidden [ABCG], which could yield the best configuration of the network. For the indicated configuration, the MAPE is 2.98% for 20 neurons in hidden layer compared to 3.05% for 10 neurons in hidden layer. It further extracts a factor from the MAPE, which is proportional to the required energy to meet the daily demand. It could be used to compute for the energy injection from other renewable resources. This would help in the implementation of the universal access and services facilities and full availability and stability in order to help these countries becoming an emerging economy.

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Author’s Contributions

Salami Adekunlé Akim: He proposed the idea of the short term forecasting, participated in the data collection and the modelling. He underlined the use of the MAPE as a dissemination parameter of performance.

Ajavon Ayité Sénah Akoda: He suggested the use of the two algorithms. He contributed in writing the methodological modelling and the data analysis.

Dotche Koffi Agbeblewu: He reviewed the work and placed it into the research context, including the abstract and conclusion. He contributed to the critical analysis of the obtained results. He further introduced the scaling factor of system compensation as function of the MAPE.

Bedja Koffi-Sa: He evaluated the pertinence of the topic and approved the status.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and there are no ethical issues involved.

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