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Demand-Supply Forecasting based on Deep Learning for Electricity Balance in Cameroon

Wulfran Fendzi Mbasso*, Reagan Jean Jacques Molu, Serge Raoul Dzonde Naoussi, Saatong Kenfack

Laboratory of Technology and Applied Sciences, University Institute of Technology of Douala, University of Douala, Douala, Cameroon. *Email: fendzi.wulfran@yahoo.fr

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ABSTRACT

Electricity is becoming an important commodity in Cameroon. Within the years, its consumption and production have led to many studies. Hence, having an idea on its progression is one of research' concerns. Thus, this paper aims to develop a model for forecasting electricity production and consumption in Cameroon based on long short-term memory (LSTM). Indeed, the LSTM approach, showing a good ability to grab the long-term dependencies between time steps of electricity production and consumption, allows a good prediction in 2030 of 7178GWh for consumption with 0.067 RMSE and 0.2965% MAPE and 8686GWh for production with 0.1631 RMSE and 0.4291% MAPE. Hence, the proposed model is more reliable, what makes possible to monitor the growth in electricity supply and demand, falling to the study of balance in Cameroon.

Keywords: Forecasting, Long Short-term Memory, Electricity Production and Consumption
JEL Classifications: Q4, Q471.

INTRODUCTION

The fast growth of human populace on the earth has brought a huge demand of energy, especially electricity (Yashwant et al., 2018). Both developed and developing countries are concerned (Aydin, 2015).

Furthermore, research in both electricity production and consumption has known of a big interest in Cameroon. Indeed, it is more important for the country as it helps to adopt better strategies in terms of development. Initially, power grids were focused on production, transmission, and distribution of energy. Their capacities were not enough to meet energy requirements. With the current emergence of the country based on the various projects launched, mastering the progression of electricity production and consumption is very crucial. This will help to ensure better management of energy, thus ensuring a good balance supply - demand.

In the literature, several models have been deployed for forecasting electrical energy, especially consumption. These models include: conventional models and artificial intelligence models. (Zhang et al., 2020) explored forecasting of electrical load by recurrent support vector regression model with variational decomposition mode and the cuckoo search algorithm. This model has the advantage of being applicable to real data. Predicting electrical load by data mining techniques has also been studied by (Abubaker, 2021) who proposed a combination of these data mining techniques such as K-Means, K-Nearest Neighbours (KNN) and autoregressive integrated moving average (ARIMA). Other authors have also worked on conventional models for time series (Dritsaki1 et al., 2021; Sutthichaimethee and Wahab, 2021; Billah et al., 2021). Regarding the ARIMA, vector autoregressive (VAR) and Grey Models (GM), various works have been proposed with the aim of energy forecasting (Xu et al., 2015; Chaoqing et al., 2016; Feng et al., 2020; Yuan et al., 2016). Similarly, (Guefano et al., 2020) worked on forecasting electricity consumption in the Cameroonian residential sector using Grey and vector autoregressive models. These authors have also projected on forecasting consumption using the multilinear regression model (Guefano et al., 2020).

Among the artificial intelligence models, Abdulsalam and Babatunde (2019) proposed a model for forecasting demand of electrical energy using a neural network for Lagos State in Nigeria. This model provides better results in terms of accuracy compared to other models. (Wei et al., 2019) reviewed conventional models and artificial intelligence models. The conventional models are time series (TS) models, regression models and grid models. For artificial intelligence (AI) models, it introduced artificial neural network (ANN) models, SVM models, and random forest (RF) models. Aghay-Kaboli et al., 2017, in their paper performed long-term formulation and prediction of electrical energy consumption through genetic-optimized programming. This genetic programming is applied to precisely formulate the relationship between historical data and electricity consumption. The authors compared their method with other methods such as the neural network, support vector machine (SVM), adaptive neuro-fuzzy inference system (ANFIS), and cuckoo search algorithm.

Other hybrid models have been developed, (Hafeez et al., 2020) proposed a fast and accurate machine learning model for predicting electrical energy consumption in a smart grid. This hybrid electrical power consumption forecasting algorithm proposed is being based on deep learning using linear rectified unit. This hybrid model is then tested and evaluated on data from the United States power grid on three performance factors: the average percentage deviation, the variance, the correlation coefficient, and the convergence rate. Likewise, (Li et al., 2020) presented a hybrid learning neural network for electrical energy consumption forecasting in buildings. This combined algorithm is made up of neural networks and applied for the hourly electrical prediction of two buildings in the United States and China. A hybrid random drill model combined with a multilayer perceptron is also proposed by (Moon et al., 2018) for forecasting daily energy demand in a university campus. Also, (Souhe et al., 2021) proposed a hybrid model to forecast electrical energy consumption of households in a smart grid, based on Grey-ANFIS-PSO. The final results show that the precision of this model is good compared to other models.

With the advances in artificial intelligence, machine learning (ML) models have attracted increasing attention in the research community and have been widely used for prediction. Short-term forecasts, whether in water (Walker et al., 2015; Candelieri et al., 2015), in electricity (Deb et al., 2017; Liu et al., 2020) or even in gas (Szoplik, 2015), have been reported in the literature with a variety of approaches and with different horizons. Most of these studies focus on forecasting consumption depending on the nature of the input data and the sought objectives. Indeed, (Rashidul et al., 2020) proposed a LSTM model for a planned smart grid system in Chattogram city, the commercial capital of Bangladesh. The proposed LSTM method outperforms the SVM method with accurate RMSE and MAE. (Shahzadd et al., 2019) have picked up an electrical load data with exogenous variables including temperature, humidity, and wind speed. The data is used to train the LSTM network. The forecasts generated by the LSTM are compared with the results of traditional methods using RMSE and MAPE for all the forecast horizons. The results of a number of experiments show that the LSTM based forecast is better than other methods and have the potential to further improve the accuracies of forecasts.

To cope with this point of view, we have picked up the data of electricity production and consumption in Cameroon from 1990 to 2019. The data are used to train the LSTM network. The trained LSTM network and the developed model are then used to do our forecasting.

This paper is structured as follows: section 2 presents the materials and methods. We compare the progression of the electricity production and consumption from 1990 to 2019, studying the balance of electricity in the country within this period. Then, the data are trained with the LSTM and the proposed model is developed for forecasting up to 2030. Section 3 presents the simulation results and the forecast obtained from the training data and the validation data in order to show the capacity of the accurate model proposed in this paper. Finally, a conclusion is given in section 4.

2. LSTM APPROACH FOR FORECASTING

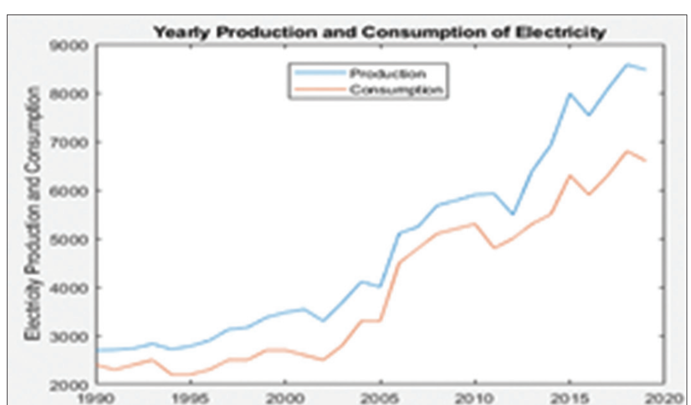
This section consists in the presentation of the context of our work and next the method used for the forecasting.

2.1. Data Description

Cameroon, developing country, had in 2019 a total electricity consumption of 5600GWh and 8505GWh electricity production. This shows an increase of 3399GWh in terms of production, compared to 2006 when electricity sector development plan (ESDP) has been launched.

Figure 1 shows the yearly electricity consumption and production in Cameroon from 1990 to 2019 (INTERNATIONAL ENERGY AGENCY data base, 2021). It is interesting to note that the production is the sum of both renewable and conventional energy sources. The various sources are biofuels, natural gas, oil, hydroelectricity, PV which shared part on the total production is less than 1% (Guefano et al., 2020). It presents the predominance of production over consumption within the years. Nevertheless, the country is still suffering from energy deficit. It would therefore be interesting to focus on the evolution of electricity production and consumption until 2030. This will help to evaluate the electricity balance and optimize electricity usage, both in terms of production and consumption.

Figure 1: Annual electricity production and consumption in Cameroon from 1990 to 2019



Let us denote *data* the electricity consumption and *data1* the production. Hence, the series are defined as following relations (1) and (2):

$$data=\{cons(i)\};\ \forall i\in\{1,2,\ldots,30\} \quad (1)$$

$$data1=\{prod(i)\};\ \forall i\in\{1,2,\ldots,30\} \quad (2)$$

2.2. Training the LSTM Network

The LSTM (Kong et al., 2017) is a special type of recurrent neural network (Kong et al., 2017). It is a sequential learning model which can establish temporal correlations between a previous instant t−1 and a current instant t. Consequently, the LSTM seems the most suitable model for forecasting processes, given its ability to deduce the intrinsic consumption and production. The LSTM is based on the Back-Propagation through time (BPTT) learning algorithm (Kong et al., 2017) to calculate the weights. It is made up of units called memory blocks. Each memory block contains an "input gate", an "output gate" and a "forget gate", as shown in Figure 2. LSTM divides the hidden state of RNN into two parts, memory cells and working memory h_t. The memory cell is responsible for the retention of the sequence features. The memory of the previous sequence is controlled by the forgetting gate f_t. The working memory h_t is used as the output, and the output gate o_t controls the portion of the current memory to be written. The input gate i is responsible for controlling the portion of the current state information h_{t-1} and the current input x_t to be written to the memory cells. The above three kinds of gates are not static. The former state information h_{t-1} and the current input x_t are jointly determined by non-linear activation after linear combination.

The model is obtained as shown in Figure 3:

The trained data for production and consumption are then standardized by the following relations:

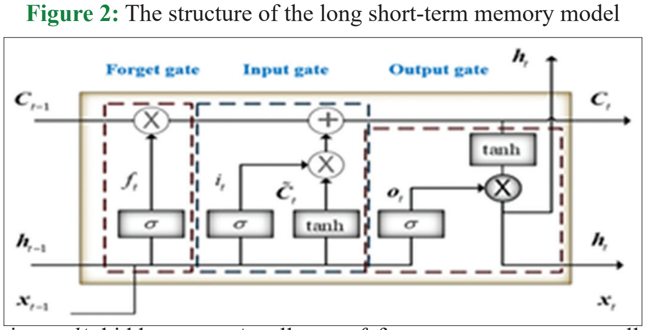
$$dataTrainStandardized=(dataTrain-\mu)/\sigma \quad (3)$$

$$data1TrainStandardized=(data1Train-\mu_1)/\sigma_1 \quad (4)$$

where: $\mu=\sum dataTrain/(numel(data)$ (5)

$$\mu_1=\sum data1Train/numel(data1) \quad (6)$$

Figure 2: The structure of the long short-term memory model



x^t: input; h^t: hidden state; c^t: cell state; f: forget gate; σ: memory cell; i: input gate; o: output gate; ⊗: pointwise multiply; ⊕: pointwise add

$$\sigma=\sqrt{\sum(dataTrain-\mu)^2/numel(data)} \quad (7)$$

$$\sigma 1=\sqrt{\sum(data1Train-\mu 1)^2/numel(data1)} \quad (8)$$

Furthermore, let us introduce y^* as the forecast of the model. Hence, y^* follows a linear regression $y^*=f(x)$; where x denotes the years of study.

Moreover, the accuracy of the models is evaluated with the root mean square error (RMSE), the mean average percentage error (MAPE) and the correlation coefficient (R) using the following equations:

$$RMSE=\sqrt{\sum(y-y^*)^2/N} \quad (9)$$

$$MAPE=\sum\left|(y-y^*)/y\right|/N \quad (10)$$

$$R=(\sum x*y-\bar{x}*\bar{y})/(\sqrt{\sum(x-\bar{x})^2*\sum(y-\bar{y})^2}) \quad (11)$$

With:

- N: size of data
- y: actual test value
- $\bar{x}$: mean value of x
- $\bar{y}$: Mean value of y.

3. RESULTS AND DISCUSSION

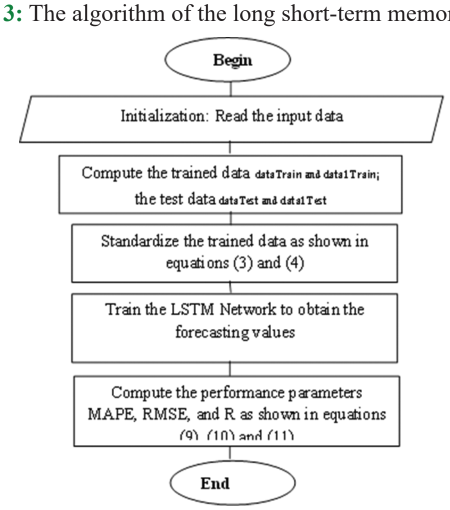
This section consists in presenting the various results obtained with the LSTM.

3.1. Forecasting Based on LSTM Approach

The LSTM is trained with the following layer specifications and the LSTM toolbox in Matlab2018 is used to train the network.

- Input *(data+data1)* = 1
- Output *(data+data1)* = 1
- No. of Hidden LSTM Units = 200
- Solver = adam
- No. of Training Iterations (MaxEpochs) = 150

Figure 3: The algorithm of the long short-term memory model



- Initial Learn Rate: 0.005
- Learn Rate Schedule: none

Figure 4: Training progress of the LSTM for electricity consumption

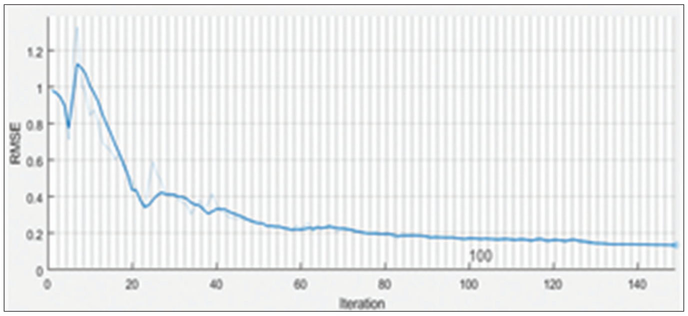


Figure 5: Training progress of the LSTM for electricity production

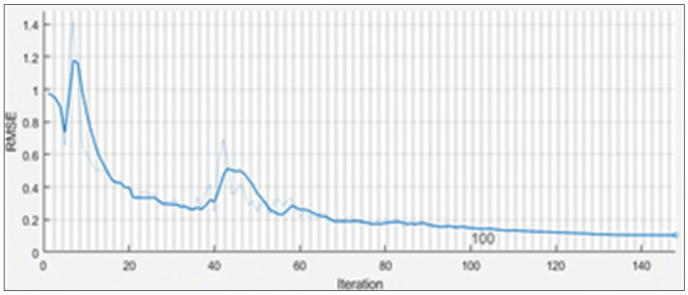


Figure 6: Forecasting of electricity production and consumption up to 2030

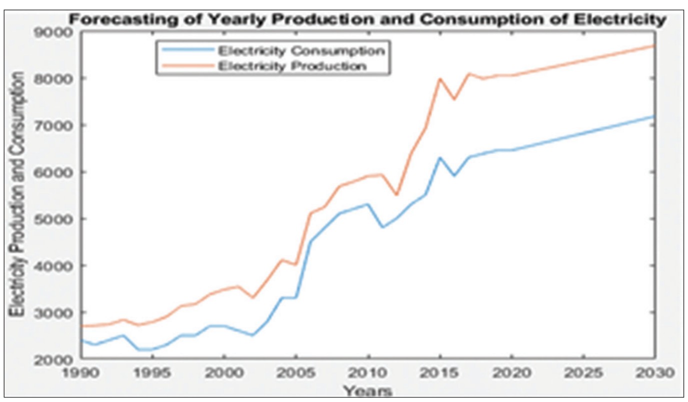


Table 1: LSTM Forecast for electricity production and consumption

LSTM forecast	RMSE	MAPE	Correlation coefficient (R)
Electricity production	0.1000	0.4291	0.9978
Electricity consumption	0.067	0.2965	0.9978

- Gradient Threshold: 1

The LSTM network is supposed to learn both the long-term and short-term features of the training data. Toward this end, the type of input data has relevance to the effectiveness of learning. If the data is provided which is leading toward wrong direction or is not enough to make the features clear, the LSTM or RNN will learn accordingly and will not predict or forecast accurately. Hence, we increase the number of hidden units after simulations and set to the minimum value 200 which gives us a better accuracy.

In addition, for both models of production and consumption, the data is divided into two parts. The 28 years data is used for training/modelling purpose, and the 29th year data is used for forecast validation.

In order to make a better representation of the accuracy of the model, the error indications and the correlations of the models are given in Figures 4 and 5.

The trained LSTM networks is used to forecast the electricity production and consumption in Cameroon up to 2030, and the uncertainty of forecasts is measured. Regarding equations (9) and (10), RMSE, MAPE and R of forecasts are computed, and we can conclude that the LSTM network forecasts accurate models. The forecast plots are shown in Figure 6 where we notice a linear regression as mentioned above. Furthermore, the uncertainty results are given in Table 1, where we notice good values of RMSE and MAPE, and a good correlation as we tend to $R \approx 1$.

3.2. Comparisons

It can be seen in Table 2 that our model presents better results in terms of precision. This model, which has never been made before, therefore shows an incredible precision never equaled. We conclude that our model therefore offers better precision and more reliable forecasting capabilities. Therefore, these interesting results that we obtain are due to the fact that our model includes determining components which makes it perfectly operational and allowing to characterize the evolution of the electricity consumption and production. Therefore, the gap between both can be used for further applications. It can be used to supply electrolysers, producing storage tanks of O_2, that can be helpful nowadays with the COVID 19 pandemic ongoing.

4. CONCLUSION

This paper proposed a new optimized model based on deep learning technique namely LSTM applied to electrical energy

Table 2: Comparison of the proposed model with literature

Model	RMSE	MAPE	Correlation coefficient (R)	Authors
GM (1,1)-ARMA (2,1)	-	4.39%	-	Xu et al., 2015
GM (1,1)_ ARIMA (2,1,1)	-	2.30%	-	Chaoqing et al., 2016
VMD_ SVM_PSO	3648.830	-	-	Feng et al., 2020
VMD_SR_ SVRCBCS	85.5	0.9%	-	Zhang et al., 2020
GM (1,1)_ VAR (1)	15.42	1.629%	-	Guefano et al., 2020
GM (1,1)_ ANFIS_ PSO	0.20158	0.62917%	0.9969	Souhe et al., 2021
LSTM-Cons	0.067	0.2965%	0.9978	Writers
LSTM-Prod	0.1631	0.4291%	0.9978	Writers

production and consumption prediction in Cameroon. Indeed, the input data considered in this paper consist of data of electricity production and consumption of Cameroon. The evolution of these parameters is considered between 1994 and 2017. The proposed models can be used for estimating future electrical demand and supply. The LSTM model applied makes it possible to classify, train and validate data. The accuracy of these models is evaluated by errors such as RMSE, MAPE, and R. Thus, we obtain with R=0.9978 a value of 7178GWh for consumption with 0.067 RMSE, 0.2965% MAPE and 8686GWh for production with 0.1631 RMSE, 0.4291%MAPE. These convincing and satisfactory results show the effectiveness of this new model for forecasting the consumption and production of electrical energy. In addition, the precision values in this article are better than those in the literature. Furthermore, this will help to adopt better strategies when evaluating the gap between production and consumption.

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