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Original Article

Hybridization of GREY-PPO and ARIMA-GRNN Algorithms with Rolling Mechanism for the Prediction of Electrical Energy Consumption

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Abstract *- This article deals with the prediction of energy consumption of certain loads whose behavior is difficult to predict using artificial intelligence tools. It examines the prediction of electricity consumption of a Southern Interconnected Grid (SIG) industrial load using the hybrid GM (1,1)-PPO model on the one hand, and that of the electricity consumption of a SIG household load using the hybrid ARIMA-GRNN model on the other hand. The input data taken by our GM (1,1) model is submitted to the Accumulated Generating Operator (AGO) and then to the Inverse Accumulated Generating Operator (IAGO) to determine the forecast values. Finally, a rolling mechanism is applied to enhance the performance of the GM (1,1) configuration. The hybridization of the GM (1,1)-PPO algorithm helps determine and optimize parameters a and b of the PPO. The results of the hybrid GM (1,1)-PPO model show high accuracy according to the LEWIS criteria: MAPE=3.8% against MAPE=11.41% for the GM (1,1) model alone. As for the second tool, the ARIMA model receives the input data, performs a regression and provides the predicted values from the generalized differential equation. Finally, given the random nature of the parameters p, d and q, the ARIMA model is combined with the Generalized Regression Neural Network (GRNN). The prediction results give good accuracy: MAPE = 9.33% versus MAPE = 92.5% for the ARIMA model alone.*

Keywords *- Electric energy consumption, Prediction, GM-PPO model, ARIMA-GRNN model, Rolling mechanism, Hybridization.*

1. Introduction

The electricity sector is constantly evolving due to the ever-increasing demand and social, geographical and technological changes. Given the failure to store electrical energy in large quantities, good management of the primary energy available in power plants is essential to ensure optimal efficiency of the generation-transmission-distribution chain. For the Southern Interconnected Grid (SIG) of Cameroon, the annual demand for electrical energy has a growth rate of 6.7% to 7.5% on average compared to 3% for supply [1]. For the current planning of electrical energy supply, power plant operators need reliable data on energy demand. However, in some cases, the available data is highly variable, which variability does not allow for stability of energy generation. Nowadays, power plant operators are using increasingly precise energy demand prediction tools for better power generation scheduling. These prediction tools that are constantly under investigation are short, medium and long-term or on an hourly basis, allowing the reliable dispatching of energy to consumers. In their work, JUBERIAS et al [2] used the ARIMA (Autoregressive Integrated Moving Average) model to predict the electricity consumption of universities in Japan and to forecast the load in real time. This model is based on the analysis of time series and has the new advantage of using the daily energy forecast as an explanatory variable. B. NEPAL et al [3] proposed a hybrid clustering model and the ARIMA configuration to improve the reliability of the result of the peak electrical load forecast of these same university buildings in Japan. The synthesis of clustering and the ARIMA configuration has been proven to increase the performance of forecasts compared to those using the ARIMA model alone. In the same vein, A. SUMOBAY et al [4] proposed to enhance the forecast of electricity demand in the city of CAGAYAN by combining the ARIMA model with the ANN model. This combined model, used for a non-exponential growth of demand, seems to have limitations when observing the energy supply-demand shortage noted. Regarding the GREY model, ERDAL KAYACAN et al [5], in their article, compare the performances of different modified GREY configurations in the prediction of time series. They showed that the performance of GREY predictors can be improved by considering error residuals. Then, they specified that among these GREY configurations, the modified GM (1,1), which uses the Fourier series over time, is the best in terms of modeling and forecasting. Among the recent comparative works, BILAL SISMAN [6] compared ARIMA and GREY models with error estimates and estimation of future electricity demand in Turkey. His results revealed that ARIMA and GREY configurations produce solutions close to the MAPE (Mean Absolute Percentage Error) errors with 4.9% and 5.6%, respectively. It showed that ARIMA and GREY methods are effective and give better MAE results to forecast long-term prospects. Recently, HAORU DU [9] conducted a systematic review of the theoretical principles, forecasting process and characteristic differences of the ARIMA model, the GREY model and the polynomial regression model. Then, he performed a comprehensive empirical calculation and comparison using China's typical economic indicators: the real GDP (Gross Domestic Product) growth rate and the CPI (Consumer Price Index).

His results show that the sequence predicted by the polynomial regression model has the highest degree of agreement with the actual value, and has the lowest prediction error and better prediction performance, while the other two types of models are not suitable for long-term prediction. Isaac Kofi et al [8] presented an examination of about seventy-seven relevant papers from academic journals over nine years (2010-2020) in the domain of electricity demand. Findings indicated that the nine most commonly used models for electricity forecast were based on Intelligence Artificial (IA), with Artificial Neural Network (ANN) accounting for 28%. Still in IA, Shahzad Ahsan et al [9] found good results in demand prediction with the LTSM (Long Short-Term Memory) model. They concluded that by adding data sources such as smart meter readings and social networks, the accuracy of the forecasts can be further improved. Sasmitoh Rahnad and al [10], Majdi Frikha and al [11] and then C. Ragupathi and al [12] have also used it for predictions in electricity consumption. In this study, the researcher [10] introduces a model and algorithm within the Deep Learning Framework, specifically a Multivariable Time Series Model utilizing the Long Short-Term Memory (LSTMs) Algorithm with the eacher Forcing Technique to predict future electrical energy consumption.

The research compares the performance of Teacher Forcing LTSM versus Non-Teacher Forcing LTSM in a Multivariable Time Series model, employing various activation functions that yield notable differences. For Majdi Frikha and al [11], power consumption forecasting is a challenging time series prediction topic. To address this issue, algorithms combining the Stationary Wavelet Transform (SWT) with deep learning models have been proposed. The findings clearly highlight the success of the SWT denoising technique with the bior2.4 filter in improving the power consumption prediction accuracy. The Deep Energy Predictor Model (DEPM) proposed by C. Ragupathi et al [12] achieved strong results in this study, with a reliability of 98 %, exactness of 0.97, recall of 0.99, and F1-score of 0.98. Despite these achievements, the study has some limitations. The DEPM validation was done on a single dataset, potentially limiting its representation of energy consumption variability in different geographical or climatic conditions. Additionally, the model lacks real-time data integration, limiting its responsiveness to sudden shifts in consumption patterns. However, in some countries, the data available for prediction are related to uncertain and uncontrollable factors such as economic development, hacking of distributed electricity, national policies, and climate change. This makes it difficult to use IA. Our approach is based on recent works [13-15]. Nicolai Bo Vanting et al [13] recommended, thanks to a multivariate deep learning configuration blending convolutional and recurrent neural networks based on findings from the scoping review.

Inputs include historical consumption, patterns, weather conditions and day characteristics as input variables. YAMUR K et AL [14] suggested a multi-objective Genetic Algorithm (GA) based on the ARIMA model. This GA provides further possibilities for calculating the parameters (p,d,q) and improves data forecasting. Its results can help to predict forecasted data with a high level of accuracy. Finally, ZHAO HUIRI et AL [15] proposed a new hybrid electricity consumption forecasting method, namely the GM (1,1) model, optimized by the Moth Flame Optimizer algorithm (MFO) with a rolling mechanism MFO-GM (1,1) to improve the prediction accuracy.

In this paper, a hybrid approach (combination of tools) is proposed that combines the Grey Model and the Predator Prey Optimization (GM (1,1) - PPO) algorithm with a rolling mechanism, to predict the electricity demand of the industrial sector of the city of DOUALA, the largest load of the SIG (Southern Interconnected Grid). Similarly, the ARIMA model hybridized with the Generalized Regression Neural Network (GRNN) is suggested to predict the household load in the city of DOUALA. It addresses the problem of energy prediction in environments where electrical energy demand is volatile and electricity piracy is recurrent. In the remaining section 2, the GM-PPO and the ARIMA-GRNN solutions are implemented, followed by prediction tests using SIG industrial and household loads data. In section 3, the results obtained are analyzed and commented on, and the error levels are assessed. The article closes in section 4 with the work conclusion, which specifies the limits and future prospects.

2. Implementation of Hybrid Solutions Prediction

In this part, the choice of tools used in the prediction of energy demand will be justified first, followed by a reminder of the rules for calculating and assessing the reliability of these tools. Then, the GM-PPO and ARIMA-GRNN solutions will be successively developed. Finally, tests with data from the Southern Interconnected Network (SIG) of energy consumption in the city of Douala will be carried out.

2.1. Growth of the SIG Industrial Load

The industrial consumption data provided in Table 1, the subject of this study, are those of the industrial load of the city of Douala connected to the SIG of Cameroon from the years 2005 to 2020. Figure 1 is representative of the growth of energy consumption of the industrial load. Data appears to have an exponential growth of energy over the years, with an increased profile towards the year 2009. The Grey Model (GM) is best aligned for a more effective prediction

Table 1. Energy of the SIG industrial sector [1]

Years	Energies	Years	Energies	Years	Energies	Years	Energies
2005	411.65 GWh	2009	711.63	2013	922.47	2017	1112.05
2006	499.16	2010	749.63	2014	977.23	2018	1200.19
2007	591.91	2011	864.09	2015	1032.28	2019	1325.18
2008	699.57	2012	907.84	2016	1083.20	2020	1344.96 GWh

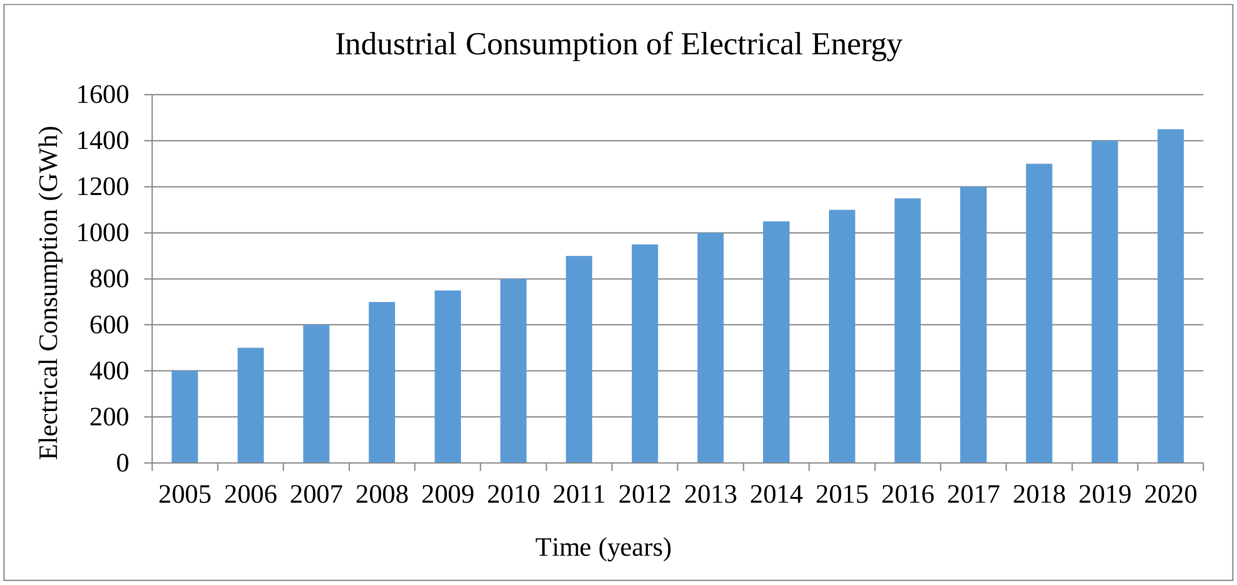

Fig. 1 Industrial consumption profile

2.2. Growth of a SIG Household Load

Table 2 provides the values of energy consumed by the household users of the city of Douala, a major load of the SIG, at each hour of the day, from September 2013 to March 2016. From the data in Table 2, the shape of the variation in electricity demand illustrated in Figure 2 is obtained. Since these values have a non-exponential growth of energy over the years, the ARIMA model is best suited for a more efficient prediction.

Table 2. Household energy consumed in the city of Douala between 2013 and 2016 [1]

Date and Time	Electrical Energy Consumption (GWh)	Date and Time	Electrical Energy Consumption(GWh)	Date and Time	Electrical Energy Consumption(GWh)
01/09/2013 01:00	121 956	01/09/2013 11:00	105 009	01/09/2013 21:00	142 020
01/09/2013 02:00	116 705	01/09/2013 12:00	100 686	01/09/2013 22:00	144 635
01/09/2013 03:00	112 089	01/09/2013 13:00	80 380	01/09/2013 23:00	136 049
01/09/2013 04:00	109 115	01/09/2013 14:00	89 510	02/09/2013 00:00	127 185
01/09/2013 05:00	106 328	01/09/2013 15:00	98 189	02/09/2013 01:00	117 492
01/09/2013 06:00	106 035	01/09/2013 16:00	100 340	02/09/2013 02:00	111 584

01/09/2013 07:00	104 442	01/09/2013 17:00	100 423	…	**…**
01/09/2013 08:00	102 280	01/09/2013 18:00	104 507	18/03/2016 00:00	229 809
01/09/2013 09:00	105 099	01/09/2013 19:00	118 153		
01/09/2013 10:00	105 227	01/09/2013 20:00	136 174		

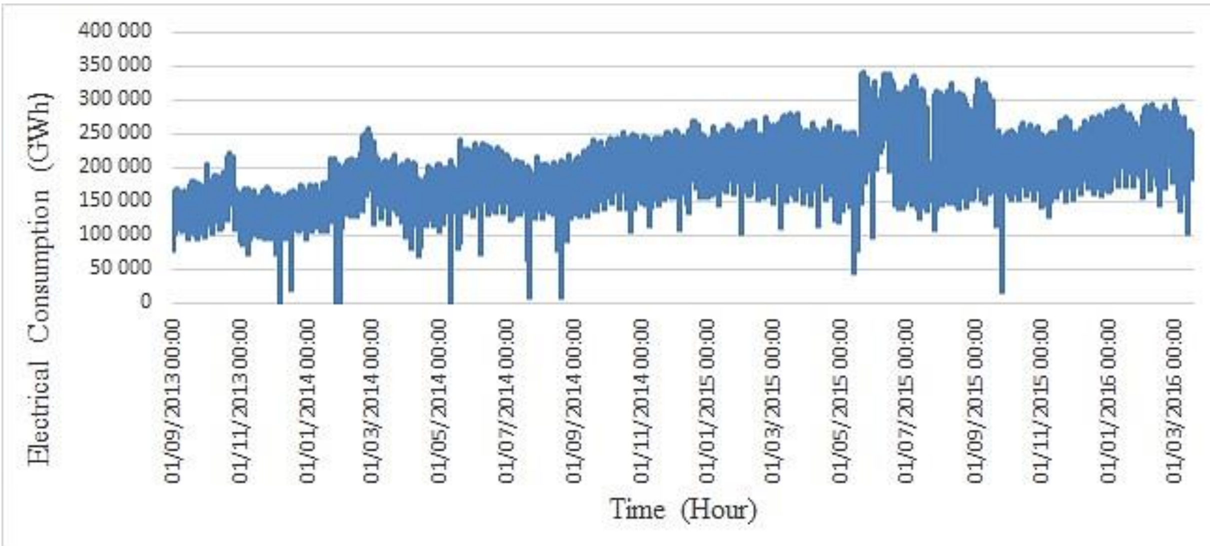

Fig. 2 Household electric energy between 2013 and 2016

2.3. Recall of Methods for Calculating the Reliability of Prediction Tools

Three main criteria were used to estimate the prediction of electricity demand [16].

The Mean Absolute Percentage Error (MAPE) is determined as follows:

$$MAPE = \frac{1}{K}\sum_{i+1}^{K}\left|\frac{|Actual_i - Forecast_i|}{Actual_i}\right| * 100\% \qquad (1)$$

It allows for the comparison of the performance of different prediction models, even if the consumption scales are different.

The Root Mean Square Error (RMSE) is obtained by:

$$RMSE = \frac{1}{K}\sqrt{\sum_{ii=1}^{K}(Actual_i - Forecast_i)^2} \qquad (2)$$

The Mean Absolute Error (MAE) is thus obtained:

$$RMSE = \frac{1}{K}\sum_{i=\&}^{K}|Actual_i - Forecast_i| \qquad (3)$$

Lewis [13] recommends the benchmarks for accuracy assessment based on MAPE index values as shown in Table 3 below.

Table 3. Prediction assessment [16]

MAPE (%)	**<10**	**10-20**	**20-50**	**>50**
Rating level	High precision	Good	Reasonable	Inaccurate

2.4. Study Assumption

Logarithmic transformations, non-seasonal, and seasonal differences are used here to stabilize the time series. Our prediction model considers the following factors:

- The network's behavior is non-linear for household and industrial loads.
- The system is stochastic.
- The prediction is limited to two future values to ensure accurate predictions.
- The forecast is designed for systems with non-linear, chaotic, uncontrollable properties.
- The trend in electrical load data does not take into account disturbances (rain, public holidays, weekends, etc.).

2.5. Constructing the GM-PPO Model

The GM-PPO Model is the association of the Grey first-order one variable model (GM (1.1)) to which the Predator Prey Optimization (PPO) algorithm is associated for a better prediction of the demand in the industrial sector. This is done by determining the values of parameters a and b that significantly reduce the prediction error.

2.5.1. Implementation of the GM (1,1) Model

The Grey Model First Order One Variable, GM ((1,1)), is used here to predict the energy demand in the SIG. This model will take the data of the electrical energy consumption of the industrial sector provided by Table 1 as input, following a process of accumulation and regression in order to obtain a sequence of data from an original sequence. Data in the GREY model is generated by Equation (4).

$$X^{(0)} = x^{(0)}(1), x^{(0)}(2), x^{(0)}(3)\ldots x^{(0)}(n)); n \geq 4 \quad (4)$$

$x^{(0)}$: Initial consumption at each date

$X^{(0)}$: Is the initial sequence of the database of electrical energy actually consumed.

$x^{(0)}(1)$: Energy consumption on the date t_1

n is the number of energy observations, here 16, according to Table 1.

Data in Table 1 is then submitted to an operator named Accumulating Generation Operator (AGO) [17] in order to smooth out their randomness. Then, using this predicted value, the purpose of the inverse generation and accumulation (IAGO) operator is to help determine the forecast values of the original data. Finally, in order to enhance the output of the original Grey configuration, we propose a rolling mechanism.

Accumulation Process (AGO)

The accumulation process of $X^{(0)}$ is defined by Equation (5):

$$X^{(1)} = x^{(1)}(1), x^{(1)}(2), x^{(1)}(3)\ldots x^{(1)}(n)) \quad (5)$$

$x^{(1)}(1)$, the accumulation process of the data $X^{(1)}$, on the date t_1. The accumulation process $X^{(2)}$,$X^{(3)}$,$X^{(4)}$,etc. is subsequently defined as Equation (6).

In Equation (6),

$$(x^{(1)}(K)) = \sum_{j=1}^{n} x^{(0)}(j) K = 1,2,3\ldots n \quad (6)$$

$x^{(1)}(k)$is given by the following first-order differential equation:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \quad (7)$$

It therefore results that :

$$x^{(0)} + aZ^{(1)}(k) = b; k = 1,2,3\ldots\ldots n \quad (8)$$

With the Grey growth factor, $Z^{(1),}$ the background value, b, represents the Grey control factor, and k is the data series number.

The differential Equation (8) is therefore a model with one variable of order 1, recorded as GM (1,1), where a and b are determined in the technique of minimising squared errors by:

$$\begin{bmatrix} a \\ b \end{bmatrix} = [a \quad b]^T + (B^T.B)^{-1}.B^T.Y_n \quad (9)$$

$$B = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ \ldots & 1 \\ -Z^{(n)}(n) & 1 \end{bmatrix} = \begin{bmatrix} \frac{-1}{2}\left[x^{(1)}(1) + x^{(1)}(2)\right] & 1 \\ \ldots & 1 \\ \frac{-1}{2}\left[x^{(1)}(n-1) + x^{(1)}(n)\right] & 1 \end{bmatrix} \quad (10)$$

$$Y_n = \begin{bmatrix} x^{(0)}(2) \\ x^{(n)}(n) \end{bmatrix} \quad (11)$$

Yn and B: matrices used to détermine a and b

$$Z^{(1)} = \left\{z^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(n)\right\}, k = 2,3\ldots\ldots n \quad (12)$$

With

$$z(1)(k) = \lambda x(1)(k-1) + (1-\lambda)x(1)(k), k = 2,3\ldots \quad (13)$$

$Z^{(1)}$: background

The value of the horizontal adjustment coefficient λ is comprised in [0, 1]. Value λ=0.5, which represents the average, has been taken.

$X^{(0)}(k)$: time response sequence of the GM (1,1);

The final solution for calculating energy prediction is then given by the differential Equation (14) :

$$\widehat{x}^{(1)}(k+1) = x^{(1)}(k+1) = \left[x^{(1)}(1) \quad \frac{-b}{a}\right].e^{-ak} + \frac{b}{a}, k = 1,2,.n \quad (14)$$

$x^{(1)}(k+1)$ is the predicted value of electrical energy consumption at time k+1 following the first accumulation sequence.

Application of IAGO

Using IAGO, the predicted values $x_p^{(0)}(k)$ for the primary data are thus calculated as follows:

$$\hat{X}^{(0)} = \begin{Bmatrix} \hat{x}^{(0)}(1) = x_p^{(0)}(1) \\ \hat{x}^{(0)}(k+1) = x_p^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \end{Bmatrix}$$

$$x_p^{(0)}(k+1) = \left[x^{(0)}(1) \quad \frac{-b}{a}\right] e^{-a(k-1)}(1-e^{a}), k = 2,3..n \quad (15)$$

Rolling Mechanism

The rolling mechanism to improve our Grey model is as follows:

Step 1: ($x^{(0)}(k+1)$ is estimated using the GM (1,1) model for

$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), \ldots, x^{(1)}(n))$, $k < 16$

Step 2: The procedure is repeated, and the new energy value x(0)(k+1) is added at the end of the series, and the first energy value ($x(0)(1)$) is removed from the data series. $X(0) = (x(0)(2), (x(0)(3), (x(0)(4), \ldots, (x(0)(k+1))$ is used to estimate ($x(0)(k+2)$).

Finally, for $k + 1 < 16$, the mean absolute percentage error (MAPE), given by Equation (1), is calculated for k = 1, 2, 3, 4.5,... (15) using the following equation:

$$MAPE = \frac{1}{n}\left|\frac{\sum_{k=1}^{n-1} x^{(0)}(k)-\hat{x}^{(0)}(k)}{x^{(0)}(k)}\right| . 100 \qquad (16)$$

The algorithm given in Figure 3 illustrates the various steps shown above.

The prediction results using the GM model (1.1) of one and several future values are shown in sections 3.1.1 and 3.1.2.

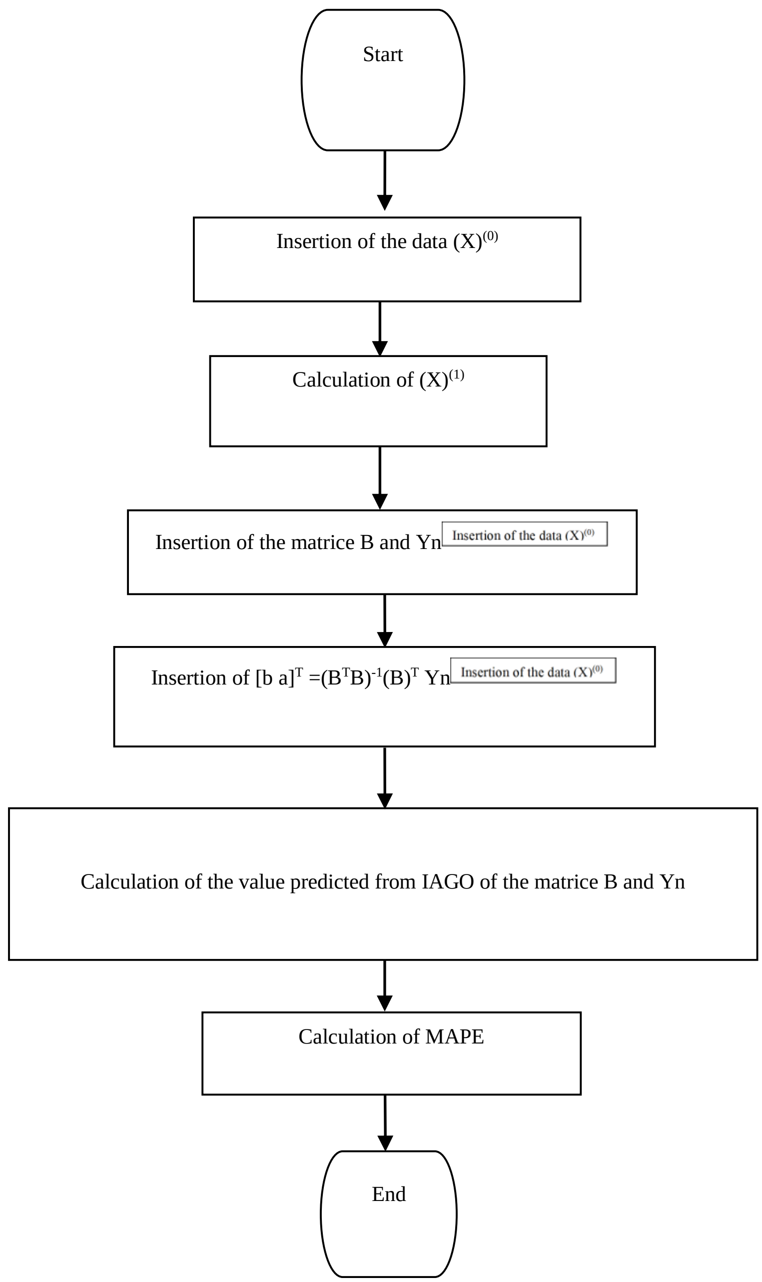

Fig. 3 Flowchart for calculating grey model prediction values

2.5.2. Hybridization of the GM (1,1)-PPO algorithm

This section concerns the determination of the optimal values of parameters a and b using the PPO algorithm for a better prediction of electricity demand. The Grey model and the PPO algorithm are combined, and then a rolling mechanism is applied. This hybridization process is done in 3 steps:

Step 1: Initialization of GM (1,1)-PPO parameters.

The GM(1,1) – PPO method is applied to data sequences $x^{(0)} = [\ x^{(0)}(1), (x^{(0)}(2), (x^{(0)}(3), \ldots, (x^{(0)}(k)]$ with k < 16, in order to predict the sequence $\hat{X}^{(0)} = [\ (\hat{x}^{(0)}(n+1)\ (\hat{x}^{(0)}(n+2), \hat{x}^{(0)}(n+3), \ldots, \hat{x}^{(0)}(n+p)]$.

Step 2: The PPO algorithm optimizes the parameters a and b of the Grey whose objective function f is defined from the MAPE by :

$$f = min\frac{1}{n}\sum_{k=1}^{n}\left|\frac{x^{(0)}(k)-\hat{x}^{(0)}(k)}{x^{(0)}(k)}\right| \quad (17)$$

With :

$$\hat{x}^{(0)}(k) = x_p^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1)\ , k = 2,3 \ldots \ldots \ldots n$$

Generating multiple MAPE values from various values of a and b, finding the optimal values of a and b from the PPO using Equation (17) and calculating the predicted value from these values of a and b by substituting in Equation (15).

Step 3: Apply the rolling mechanism to the previous data. Our current data is $X^{(0)}= [\ x^{(0)}(p+1), (x^{(0)}(P+2), (x^{(0)}(P+3), \ldots, (x^{(0)}(p+n))]$. The parameters a and b are optimized again from the PPO, and the new predicted values are:

$$\hat{x}^{(0)}(p+n+1), \hat{x}^{(0)}(p+n+2), \ldots, \hat{x}^{(0)}(p+n+p)$$

These steps are repeated until all the predicted values are obtained. The algorithm given in Figure 4 shows the development of this procedure.

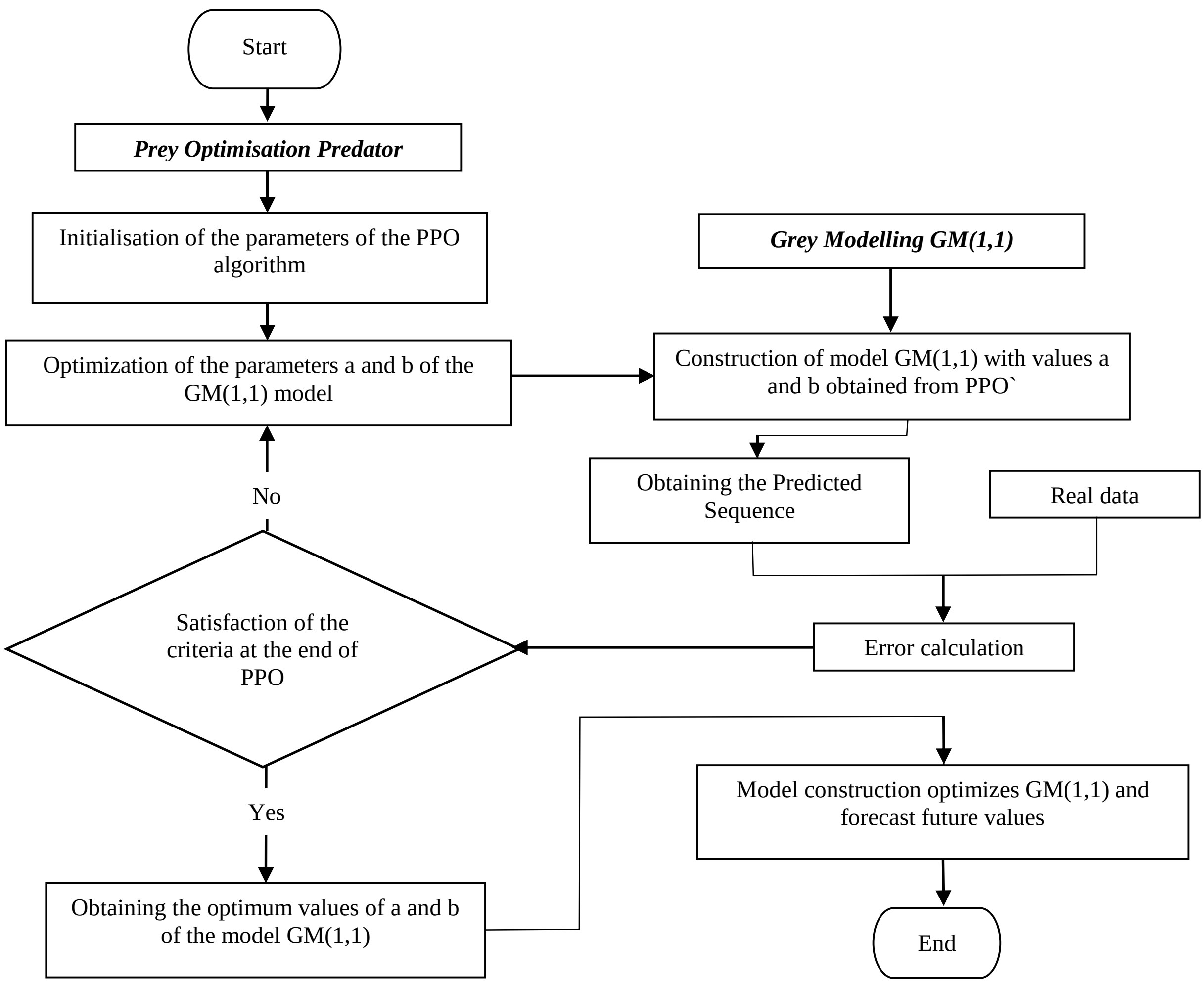

Fig. 4 GM (1,1) prediction model based on PPO

The combined GM(1,1)-PPO prediction results are presented in Section 3.2

2.6. Constructing ARIMA-GRNN Model

2.6.1. Implementation of the ARIMA model

The analysis of the household energy consumption data shows that the data is stationary, allowing us to justify using the ARIMA model. The ARIMA model will take the data on household electrical energy consumption in the city of Douala as input. A regression is then carried out in order to obtain a sequence of data from an original sequence given by Equation (4). Then the differential quantity is given by Equation (18) and the predicted value at time t by Equation (19).

$$\left[1-\sum_{i=1}^{i=p}\phi_i B^i\right][1-B]^d x_t=\left[1+\sum_{j=1}^{j=p}\phi_j B^j\right]\in_t;$$

$$\phi(B).(1-B)^d.y_t=\theta(B)\in_t \tag{18}$$

$$x_t=\sum_{i=1}^{p}\phi_i x_{t-i}+\in_t+\sum_{i=1}^{p}\theta_j.\in_{t-j} \tag{19}$$

By studying the value of the AKAIKE Information Criterion (AIC), it is possible to check the order of the ARIMA (Autoregressive Integrated Moving Average). AIC is defined as follows:

$$AIC(p,q)=ln\,\sigma^2\,(p,q)+\frac{2(p+q)}{N} \tag{20}$$

The reals $\emptyset_i(i=1,2,\dots,p)$ and $\theta_j(j=1,2,\dots,q)$ are respectively the autoregressive and moving average parameters;

$\in_t$	:	Random error at t period is a white noise of variance σ^2;
Ø(B), θ(B)	:	Are relatively prime polynomials in the delay operator B of orders p, q with free coefficient 1.
P	:	Number of autoregressive terms (AR order);
D	:	Non-seasonal difference numbers;
q	:	Number of Moving Average (MA) terms.

Our household energy consumption data is divided into two parts: 46 training data and 9 validation data. The validation data will allow us to assess the prediction in order to have an idea of the reliability of the predicted values. The correlation function used here characterizes the observations at the current time and the observations at all previous times.

This function is used to determine the number of MA where the standard model is ARIMA(p,d,q)×(P, D, Q)s, with s being the number of periods per season and P, D and Q are the seasonal equivalents of p,d and q. The AKAIKE Information Criterion (AIC) and the SCHWARZ Bayesian Information Criterion (SBC) are used to choose the preferred model.

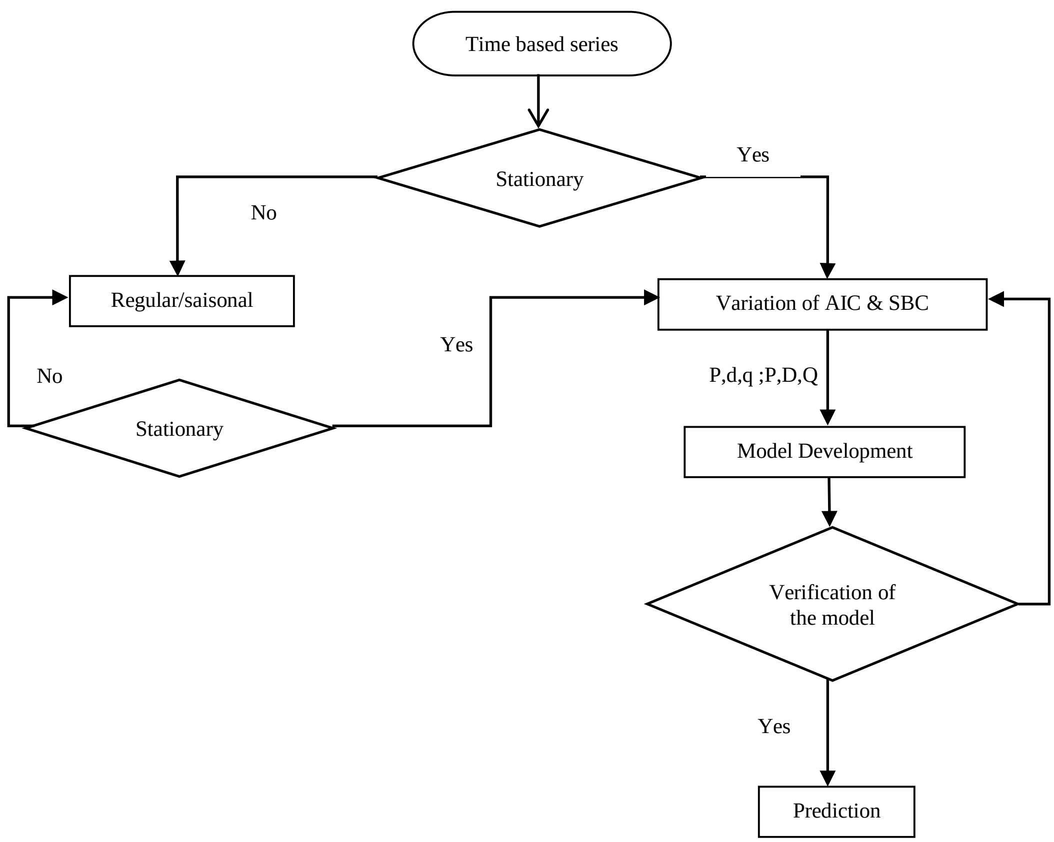

Fig. 5 ARIMA-GRNN flowchart model

The one that has the minimum AIC and SBC values. Since the values of parameters p, d, and q are generated randomly, we will combine this model with a generalized regression neural network to generate optimal values of these parameters for a more accurate prediction. Since the values of parameters p, d, and q are generated randomly, this model will be combined with a generalized regression neural network to generate optimal values of these parameters for more accurate prediction.

Since the values of parameters p, d, and q are generated randomly, this model will be combined with a generalized regression neural network to generate optimal values of these parameters for more accurate prediction. The flowchart given in Figure 5 presents the calculation steps of the ARIMA model.

2.6.2. GRNN Model

Generalized Regression Neural Network (GRNN) is a branch of radial basis function neural network, which is a powerful regression tool with a dynamic network structure [18]. The structure of the GRNN includes four strata: input stratum, pattern stratum, summation stratum and output stratum. The relationship between each pair of the input X and the observed output Y is examined by the network to infer the inherent function. The following Equation (21) summarizes the GRNN.

$$x_t = F(x_1, x_2, \dots, x_{1-k}, w) \tag{21}$$

Let x_t be the predicted value by the F function, produced by the GRNN network, and t is the connection weight.

$x_1, x_2, \dots, x_{t-k}$: set of prior consumption

ω is the vector of all parameters

In our non-linear regression method, Equation (22) below summarizes the GRNN

$$E\left[\frac{Y}{X}\right] = \frac{\int_{-\infty}^{+\infty} Y f(X,Y)dY}{\int_{-\infty}^{+\infty} f(X,Y)dY} \tag{22}$$

Where

X denotes the input vector (X1, X2, Xn) which consists of n predictor variables;

Y denotes the output values predicted by the GRNN;

E[Y/X] is the expected value of output Y given an input vector X;

f(X, Y) is the joint probability density of X and Y.

2.6.3. ARIMA-GRNN Hybrid Model

Predicting the electrical load without considering factors such as holidays, the use of heating and air conditioning, the occurrence of events, the use of experimental facilities, etc., may result in a significant error in the forecast result. Hybridization is therefore necessary. The combined ARIMA-GRNN prediction results are shown in Section 3.3.

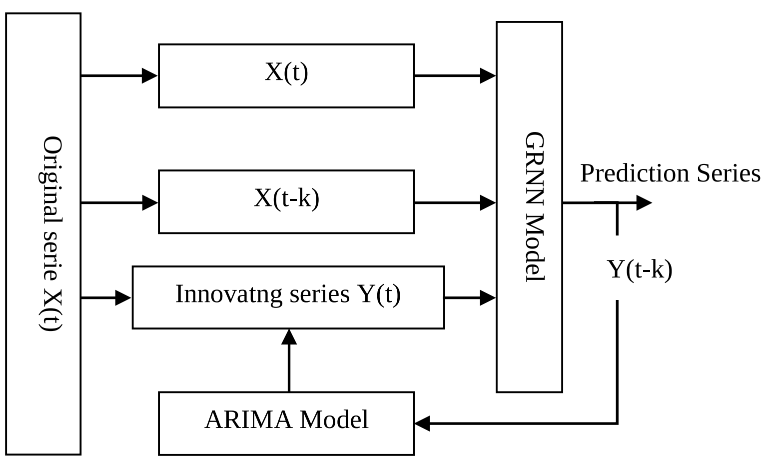

Fig. 6 ARIMA-GRNN flowchart hybrid model

3. Results and Discussions

In this section, the results are presented from the implementation of various algorithms developed, namely the Grey models, the GM (1,1) - PPO models to predict electricity consumption for a time series, and the ARIMA-GRNN model. All the required stages were coded into the MATLAB software environment. The simulation results of the algorithms are presented, discussed and compared to other algorithms based on the prediction approach in order to demonstrate the effectiveness of our prediction approach.

Several parameters, including the MAE, the RMSE, the MAPE and the MSE, were used to compare the performances of the different models.

3.1. GM (1,1) Forecast Result

3.1.1. Forecasting a Future Value

Figure 7 depicts the result of the prediction of a future value, from Equation (14) and data in Table 1. Three behaviors are observed: From 2005 to 2007 and then from 2016 to 2020, the prediction of energy demand was higher than the actual consumption of electrical energy. From 2010 to 2013, the prediction of energy demand was lower than the actual consumption of electrical energy. From 2007 to 2010 and then from 2013 to 2016, the prediction of energy demand was equal to the actual consumption of electrical energy. Thus, the prediction made only from the GM (1,1) model gave the error MAPE = 11.6%. The predicted value is 1392.5173 GWh (While the actual value is 1344.96 GWh).

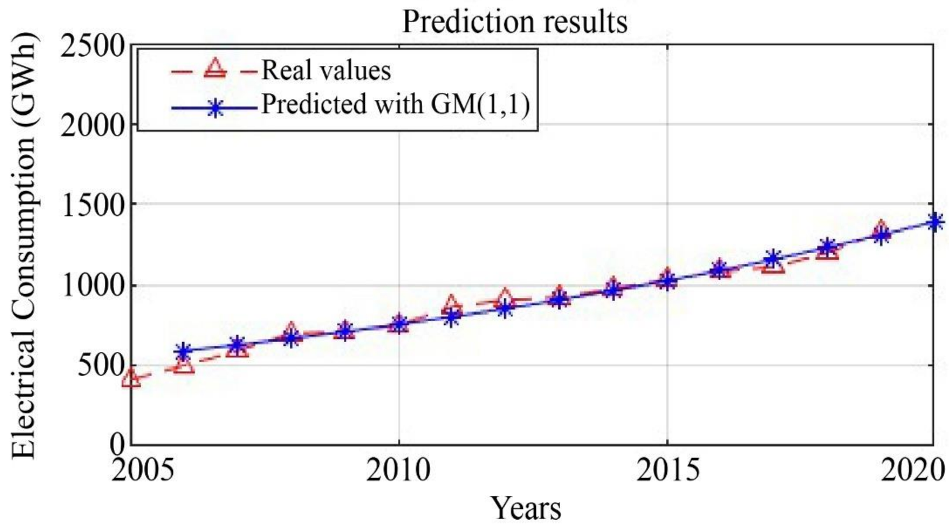

Fig. 7 Prediction of a value by the GM (1,1)

3.1.2. Forecasting Several Future Value

Figure 8 presents the result of the prediction of 6 future values, always from Equation (14) and the data from Table 1 of the industrial load. Figure 8 depicts three behaviors that are different from those observed in Figure 7: From 2005 to 2007 and then from 2013 to 2020, a prediction of energy demand higher than the actual consumption of electrical energy is observed. From 2007 to 2009 and then from 2010 to 2012, a prediction of energy demand lower than the actual consumption of electrical energy is observed. From 2009 to 2010 and then from 2012 to 2013, a prediction of energy demand equal to the actual consumption of electrical energy is observed. Thus, the prediction made solely from the GM (1,1) configuration still gave unacceptable results. Hence, the high error MAPE = 68%. The predicted values are: 1091.31, 1174.29, 1263.58, 1359.66, 1463.05, 1574.29 GWh against respectively 1032.28, 1083.20, 1112.05, 1200.19, 1325.18, 1344.96 GWh for actual values.

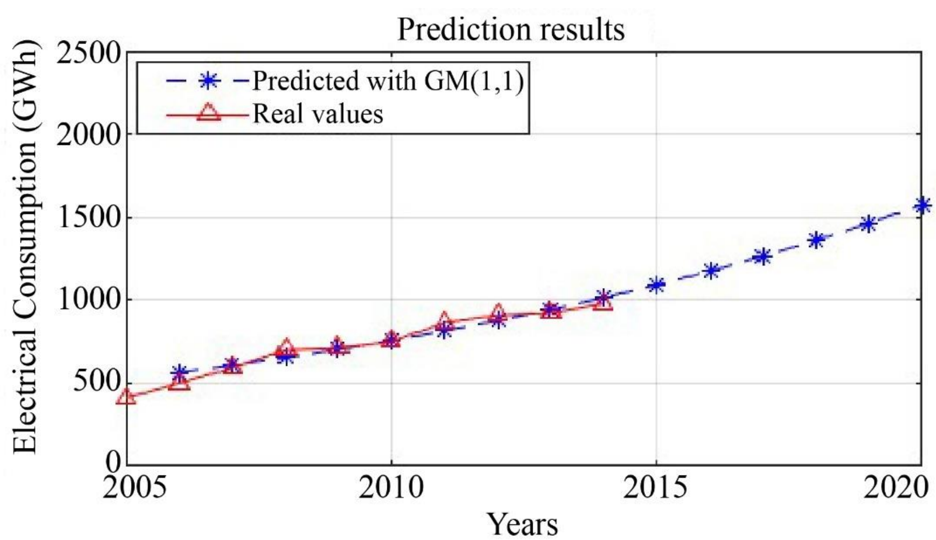

Fig. 8 Prediction of 6 values by the GM (1,1) model

Figure 8 depicts three behaviors that are different from those observed in Figure 7: From 2005 to 2007 and then from 2013 to 2020, a prediction of energy demand higher than the actual consumption of electrical energy was noticed. From 2007 to 2009 and then from 2010 to 2012, a prediction of energy demand lower than the actual consumption of electrical energy was noticed. From 2009 to 2010 and then from 2012 to 2013, a prediction of energy demand equal to the actual consumption of electrical energy was noticed. Thus, the prediction made solely from the GM (1,1) configuration still gave unacceptable results. Hence, the high error MAPE = 68%. The predicted values are: 1091.31, 1174.29, 1263.58, 1359.66, 1463.05, 1574.29 GWh against respectively 1032.28, 1083.20, 1112.05, 1200.19, 1325.18, 1344.96 GWh for actual values.

3.2. GM (1,1)-PPO Hybrid Model Forecasting Results

Since the Grey model prediction results shown in 3.1 were insufficient, the parameters a and b of this model using the PPO algorithm are optimized in order to improve the prediction results.

Table 4. PPO algorithm parameters [19]

Number of iterations	100
Population size	100 predators, 90 prey
a_k=0.5 et b_k= 0.05	Gaussian mutation standard deviations (step sizes)
Probability of predator movement	1/ degree of predator position
a_{k+1} =0,99 a_k; b_{k+1} =0,99 b_k	Decrease in predator step size

3.2.1. GM (1,1) PPO Forecasting Results

The optimization parameters of the objective function given in Equation (17) are defined in Table 4. The simulation results of the PPO and GM(1,1)–PPO models are shown in Figures 9 and 10, respectively. The industrial load data from 2005 to 2014 was used as training data and from 2015 to 2021 as validation data. (Table 1). It is observed that a convergence towards the local minimum occurs by the twelfth iteration. The application of the GM (1,1)-PPO model, set up after obtaining the parameters a and u, allowed us to obtain the prediction data presented in Figure 10.

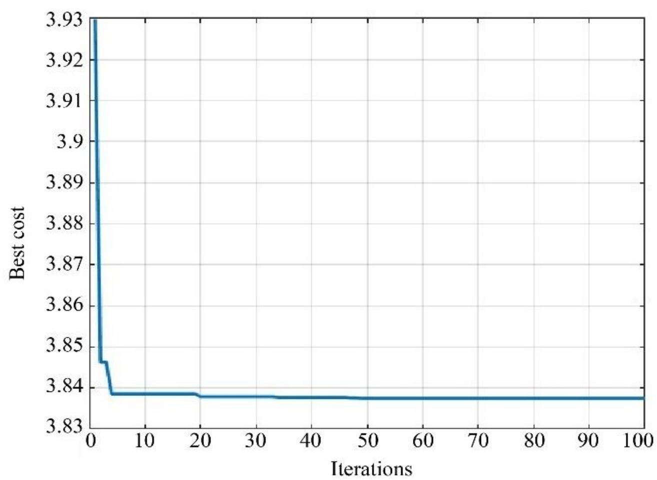

Fig. 9 Process of convergence to the minimum

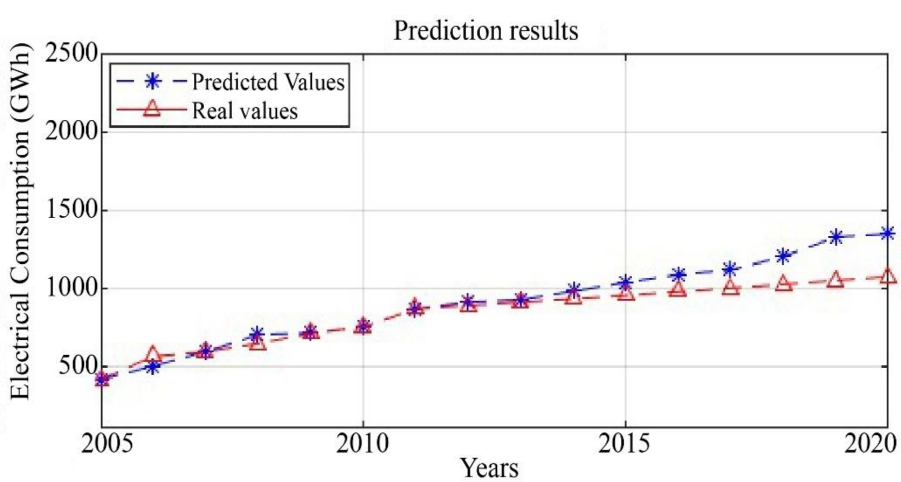

Fig. 10 Prediction of industrial load by the GM (1,1)-PPO model

Figure 10 again depicts three different behaviors. Data from 2005 to 2014 was used for training the developed GM-PPO model with RMSE = 0.3356 and MAE = 0.2791.

From 2012 onwards, the predicted values are higher than the actual values. In order to assess the accuracy of this model, the predicted values were compared with the actual value to validate the prediction model.

The various error values reported in Table 5 show an improvement in the accuracy of the GM-PPO prediction compared to the single GREY model and the GM-PSO (Particle Swarm Optimization) model. The different error values (MAPE, RMSE, MAE) are recorded in Table 5.

3.2.2. Comparison of GREY-PPO and GREY PSO Results Estimates

Table 5 shows a summary of the various predictions of the demand for electrical energy in the industrial sector by the Grey model and its hybridizations. Data from 2004 to 2014 were used for training, and data from 2015 to 2020 were used as validation data for the developed GM-PPO model with RMSE = 0.3356 and MAE = 0.2791. In order to assess the accuracy of this model, the predicted values were compared with the actual value to validate the prediction model. The various error values reported in Table 5 and Figure 11 show an improvement in the accuracy of the GM-PPO prediction compared to the single GREY model and the GM-PSO (Particle Swarm Optimization) model.

Table 5. Summary of the results of the different GREY-PPO prediction methods

	Real Data (GWh)	**Predicted data (GWh)**				
Years		**GM (1,1)**	**GM (1,1) – PSO**		**GM (1,1) – PPO**	
2015	1032.28	1091.31	1056.25		1065.22	
2016	1083.20	1174.29	1128.27		1133.07	
2017	1112.05	1260.59	1205.20		1205.22	
2018	1200.19	1359.67	1287.37		1282.01	
2019	1325.18	1463.06	1375.14		1363.67	
2020	1344.96	1574.3	1468.90		1450.53	
	Data type		Learning data	Predicted values	Learning data	Predicted values
Error	MAPE (%)	11.41	3.41	6.19	3.39	3.8
	RMSE (%)	148.2	32.93	82.31	33.44	77.56
	MAE (%)	138.06	23.30	74.66	23.27	69.91

In each of the two cases, we obtained an MAPE lower than 10%, which corresponds to a good forecast according to the Lewis classification [16] and is recalled in Table 3, which means that the predicted value of electrical energy consumption is good and close to the real value consumed. This represents a clear improvement compared to the GM (1.1), whose MAPE, RMSE, and MAE values are recorded in Table 5.

Finally, an improvement in the accuracy of the results of the GM (1,1) - PPO model, better than those of the GM (1,1) + PSO model.

Thus, the Grey model hybridized with the PPO allowed us, after training and validation, to re-predict the electrical energy consumption of the industrial sector between 2022 and 2025. Table 6 gives these energy values.

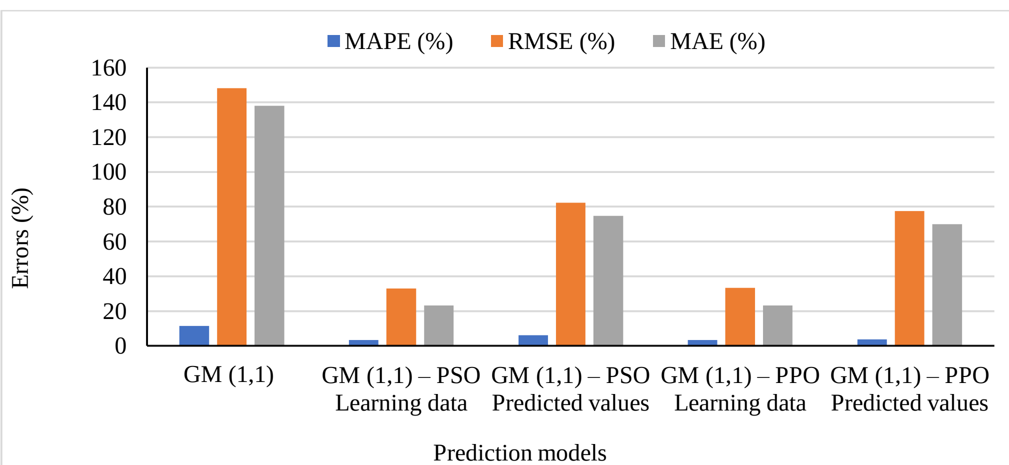

Fig. 11 Illustration of errors in different prediction methods

Table 6. Prediction of industrial sector consumption of Douala between 2022 and 2025 by the GM (1,1) - PPO

YEARS	ENERGIES (GWh)	YEARS	ENERGIES (GWh)
2022	1501.96	2024	1766.59
2023	1628.91	2025	1915.91

3.3. Forecasting Results by the ARIMA-GRNN Model

3.3.1. ARIMA Forecast Results

The data set is the household consumption of electrical energy at 12 noon by household users in the city of Douala, every day, from October 1, 2014, to November 25, 2014, i.e. 55 data points (from Table 2). Figure 12 depicts the variations of this energy every day for 55 days. These data were divided into two blocks (46 training data and nine validation data).

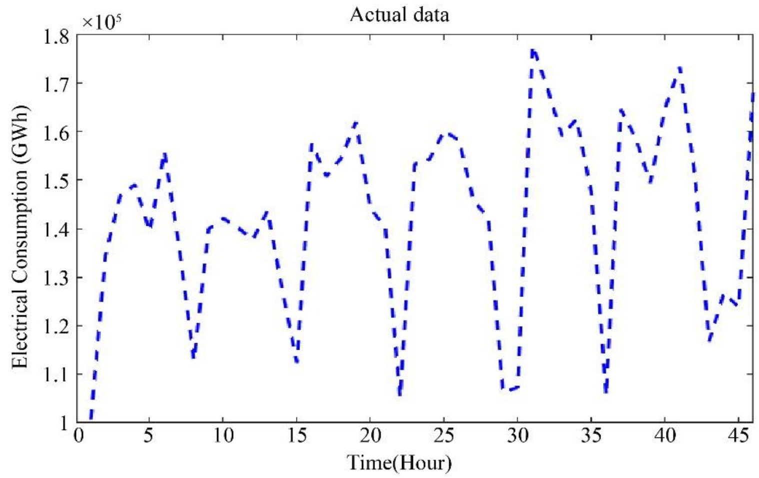

Fig. 12 Household consumption profile every day at 12 o'clock

Table 7. ARIMA model parameters

Model	AIC	SBC
ARIMA (0,1,2)(1,1,1)$_{12}$	-1.0542	-0.9268
ARIMA (0,1,1)(1,1,1)$_{12}$	-1.0492	-0.9536
ARIMA (1,1,1)(1,1,1)$_{12}$	-1.0539	-0.9255

This figure shows a dynamic and fluctuating variation of the demand for electric energy at midnight (11:00 pm - 11:59 pm). Table 7 presents the parameters of the ARIMA models according to the AIC and SBC [20]. The ARIMA (0,1,2) (1,1,1) model being the most appropriate with the residual test showing a white noise sequence, the possible values of q and Q are 1, 2, 3 and 1 base on the Auto Correlation Function (ACF) plot, and the possible values of p and P are 1, 2, 3 and 1 base on the Partial Auto Correlation Function (PACF) plot. Out of the 55 data points, 46 data points (from October 1, 2014, to November 16, 2014) were used to train our ARIMA model. Figure 12 depicts the profile of the training model of the household electrical energy consumption data. The predicted training data values of the household load by the ARIMA model, as shown in Figure 13, are higher than the demand.

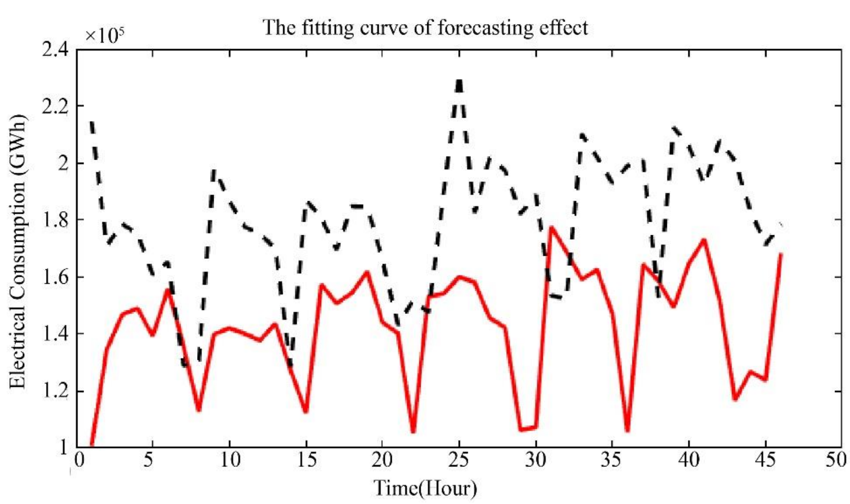

Fig. 13 ARIMA (0,1,2)(1,1,1) training model profile

The 46 input data vary between [100686,..., 168378] GWh. The negative values of AIC (-1.2084) and BIC (-0.92366) and the fact that the AIC is lower than the BIC, indicate that the model fits the data well. Subsequently, 09 electrical energy consumption data (from November 17, 2014, to November 25, 2014) were used to validate our model. Figure 14 depicts the profiles of the validation model for household electrical energy consumption data.

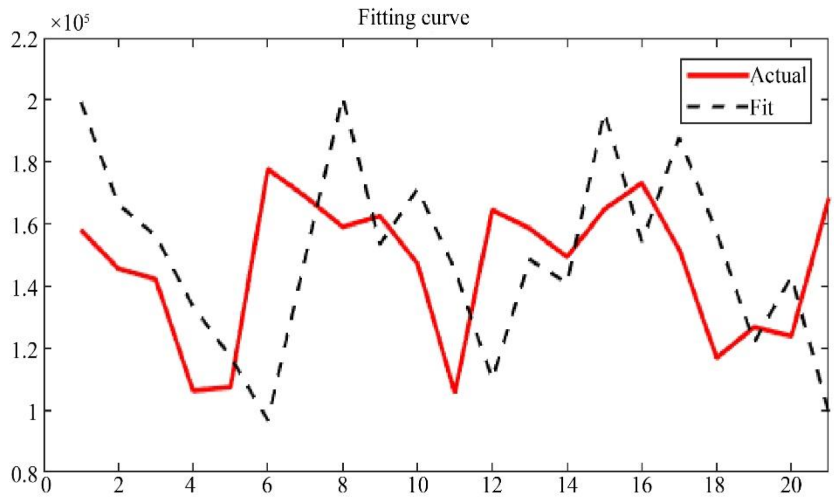

Fig. 14 ARIMA (0, 1, 2)(1, 1, 1) profile of the validation model

Data from [172711...,185081] GWh were used for the validation of the ARIMA model developed with an RMSE = 0.9391 and a MAE = 0.0878, which characterizes an unacceptable prediction. The prediction values were subsequently used to predict the hybrid ARIMA-GRNN model.

It appears that our ARIMA model, which takes our time series data as input, generates the various values of AIC (-1.2084) and BIC (-0.923) after verifying the stationarity of these data by calculating the MAPE, and provides prediction values that the hybrid model uses to improve the accuracy of the ARIMA model.

3.3.2. Assessing the GRNN model

The 12h electric load data (1st October 2014 to 25th November 2014) were again used as samples. The GRNN model has the lowest RMSE; therefore, 1.7 was selected as the most appropriate smoothing factor to develop our GRNN model. Subsequently, the prediction findings of the ARIMA model were picked as the input values of the GRNN model, and the output values were the predictive values of the combined ARIMA-GRNN model. Figure 15 depicts the profile of the generalized neural network training data. It appears that the GRNN model shows a good prediction of demand from our training data; however, some error values are recorded in Table 8. Here, the curves are merged.

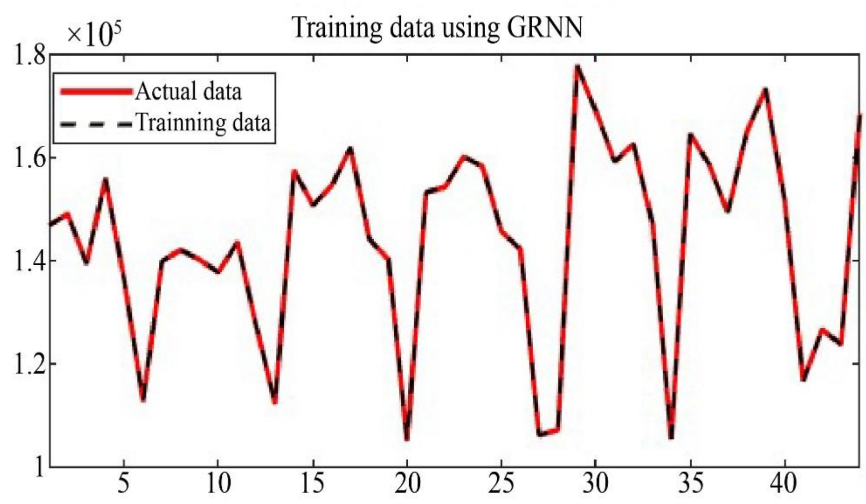

Fig. 15 Profile of the training data using GRNN

The model shows a perfect fit to the input data. However, it raises concerns regarding overlearning as the model may have captured the noise of the learning data.

Which is a problem in our case, where data variation is inevitable? The prediction values were subsequently used to predict the hybrid ARIMA-GRNN model.

3.3.3. Test of the ARIMA-GRNN model

The smoothing factor, taken from 0.01 to 0.40 with a 0.01 gap, was picked to find the least RMSE for the GRNN model. The GRNN configuration has the lowest RMSE when the smoothing factor reaches 0.07 [21]. Figure 16 presents the MATLAB GUI interface of the input and output data of the ARIMA-GRNN configuration.

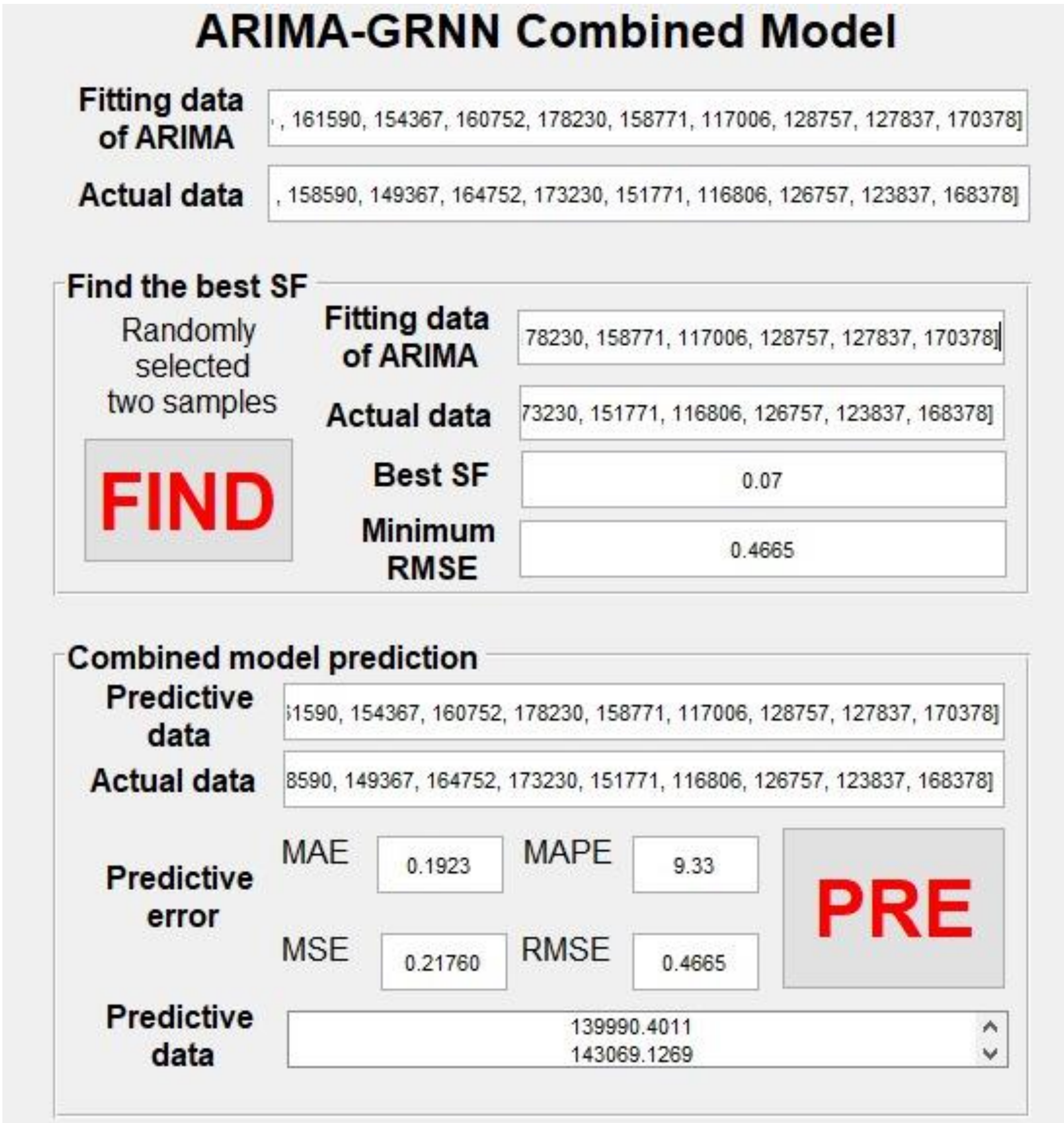

Fig. 16 MATLAB GUI interface for prediction and accuracy of ARIMA-GRNN

These details were put into two blocks, of which 46 training data varied between [100686, 168378] GWh and 9 validation data varied between [172711...,185081] GWh. The prediction result of the ARIMA configuration is used to predict the ARIMA-GRNN model with an acceptable MAE =01933 and RMSE = 0.4665. The different error values used to assess the accuracy of the prediction are presented in Table 8. Figures 17 and 18 depict the prediction profiles of the ARIMA-GRNN training and validation model for the 55 days of household load consumption. These two figures show a dynamic and fluctuating variation of the demand for electrical energy at 12 hours (11:00-11:59) precisely. Whether it is the training or validation model, the predicted values are slightly higher than the actual values. The various error values analysed to rate the exactness of the prediction are also shown in Table 8.

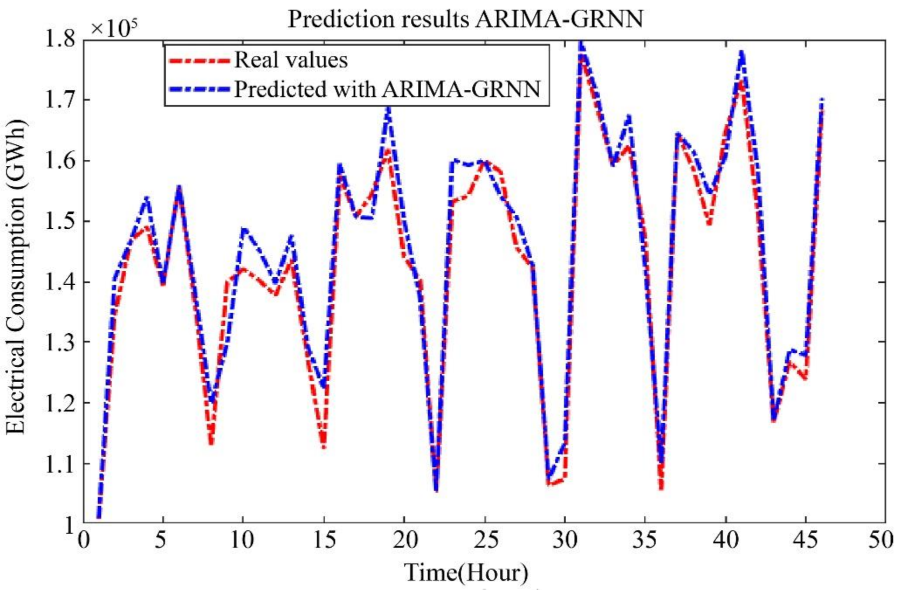

Fig. 17 Prediction profile of the ARIMA-GRNN training model

Figure 17 presents the variations in household energy consumption by users in the city of Douala every day for 46 days as training data by the ARIMA-GRNN model, with an MAE of 8.78, which is a low value indicating that the model is precise and a relatively high RMSE of 93.31, which indicates a reduction in data variance for less precise areas.

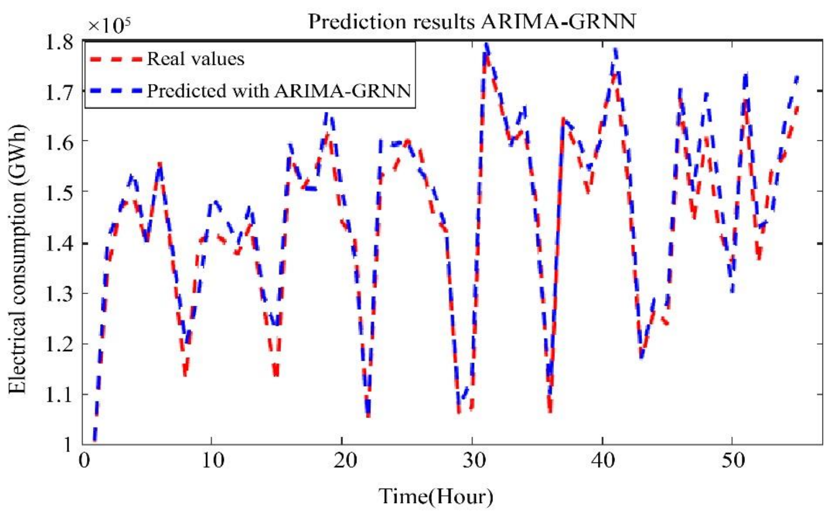

Fig. 18 Prediction profile of the ARIMA-GRNN validation model

Figure 18 presents the variations in household energy consumption by users in the city of Douala every day for 46 days, plus 9 days of validation data by the ARIMA-GRNN model, with a MAE= 0.1933 which is of low value indicating that the model makes accurate predictions and an RMSE=0.4665 relatively higher than the first MAE but of reasonable value indicating that some predictions deviate from the actual value with small errors that do not compromise the prediction.

Table 8. Calculation of the rolling ARIMA-GRNN forecast

	Training data (%)				Validation data (%)			
PREDICTION ERROR	MAPE	MAE	MSE	RMSE	MAPE	MAE	MSE	RMSE
ARIMA	11.5	120.45	242.1	155.6	92.5	99.1	123.2	111.0
GRNN	1.50	15.95	22.33	47.26	82.66	82.66	170.90	130.73
ARIMA-GRNN	8.78	88.20	88.20	93.31	**9.33**	**19.33**	**21.76**	**46.65**

The hybrid ARIMA-GRNN model showed a better prediction of the household load compared to the single ARIMA model and the basic GRNN model. The smoothing factor of the basic GRNN model and the combined GRNN model with ARIMA were 1.7 and 0.07, respectively. It appears from Table 8 that the hybrid ARIMA-GRNN model presents a clear improvement in RMSE compared to the ARIMA model taken alone. Therefore, the ARIMA model hybridized with GRNN allowed for predicting household electricity consumption of household subscribers in Douala for four future days (Table 9), after the training and validation of the model. This training of the model can be done regularly by inserting the new prediction values into the time series.

Table 9. Prediction of energy consumption in the area of Douala by ARIMA-GRNN

Date	Time	ENERGIES (GWh)
26/11/2014	12H00	155414.0995
27/11/2014	12H00	155703.1534
28/11/2014	12H00	155992.745
29/11/2014	12H00	156282.8751

4. Conclusion

This work addresses the problem of forecasting electricity demand in certain countries where uncertain and uncontrollable factors, such as the state of the economy, hacking of distributed electricity and certain policies, disturb the prediction. The article suggests two hybrid models for predicting demand: GM(1,1)-PPO, for predicting the consumption of the industrial sector of the city of Douala and ARIMA-GRNN for predicting the consumption of household users in the city of Douala, a load of the SIG.

These models use data from 2005 to 2020 and from 2013 to 2016, respectively.On the GM (1,1) model assessed on one and on six future values, the data of the electrical energy consumption of the industrial load from 2005 to 2020 were submitted to the Accumulated Generating Operator (AGO), then to the Inverse Accumulated Generating Operator (IAGO) to find the predicted values. Then, a rolling mechanism was applied to enhance the efficiency of the GM (1,1) model.

It turns out that the prediction values found are sometimes lower, sometimes higher than the current values, hence the MAPE error of 68%. Given the unsatisfactory results of this model, the hybridization of the GM (1,1)-PPO algorithm allowed for determining the parameters optimizing a and b of the PPO. It appears that MAPE =3.8%; RMSE = 77.56%; MAE = 69.91% for the hybrid GM (1,1)-PPO model against MAPE = 11.41%; RMSE = 148.2%; MAE = 138.06% for the GM (1,1) model taken alone, then MAPE = 6.19%; RMSE = 82.31%; MAE = 74.66% for its hybridization with the PSO (GM (1,1) - PSO). Therefore, the hybrid GM (1,1)-PPO model provided high precision according to the LEWIS classification.

The second hybrid model was tested for the prediction of the 12:00 period, i.e. 55 data (46 training and 9 validation). It appears that our ARIMA model, which takes our time series data as input, generates different values of AIC (-1.2084) and BIC (-0.923) after checking the stationarity of these data by calculating the MAPE. With this model alone for household loads, it is found that the predicted consumption is generally much higher than the actual consumption, which is not interesting. On the other hand, the GRNN model presents a good prediction of demand, hence the MAPE error value is lower than that of the ARIMA model.

Then, the ARIMA model provides prediction values, which are used by the hybrid ARIMA-GRNN model in order to improve the accuracy of the ARIMA model. The prediction results give a good accuracy: MAPE = 9.33%, RMSE = 46.6%, MAE = 19.33 against MAPE = 92.5%, RMSE = 111%, MAE = 99.1%.

The simulation results showed an improvement in the quality of our solutions regarding prediction error after comparing them with other stationary time series prediction methods, such as the ARMA, ARIMA, AR, GM (1,1)-PSO and MA models taken alone. Electric load forecasting is the initial stage of developing future generation, transmission and distribution facilities.

However, the reliability of the power load prediction often cannot reach the desired result because it is influenced by various uncertain and uncontrollable factors such as economic development, human social activities, national policies and climate change.

The data used in this paper was applied to the prediction methods for household and industrial electric loads. However, there is still work to improve the prediction results. This improvement can be achieved by considering the following aspects:

- The data used in this paper applies only to the electric load. Adding other factors, such as climatic characteristics with temperature as the main variable, can be interesting. A study on the factors that have an impact on the electric load and look for ways to use them in modeling.
- A classification of data can be done so that the modeling is subsequently carried out according to the seasons.
- Making a prediction, taking into account the type of days, can be interesting.

- Using other techniques to predict the electrical load, namely Kalman filters or fuzzy logic, can be helpful.
- Energy fraud by subscribers prevents an accurate estimate of future industrial and domestic consumption data.
- Currently, various options for integrating renewable energy sources and data accumulation are being studied in order to extend this work and improve accuracy. Other possible machine learning packages in the areas mentioned above can be explored.

Acknowledgements

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Nomenclature

Abbreviation	Meaning	Abbreviation	Meaning
SIG	Southern Interconnected Grid	AIC	AKAIKE Information Criteria
GM	Grey Model	PSO	Particle Swarm Optimisation
GM (1,1)	Grey Model first-order one variable	BIC	Bayesian Information Criterion
PPO	Predator Prey Optimization	ACF	Autocorrelation Function
ARIMA	Autoregressive Integrated Moving Average	PACF	Partial Autocorrelation Function
GRNN	Generalized Regression Neural Network	AR	Autoregressive terms
AGO	Accumulated Generating Operator	SBC	Schwarz Bayesian Information Criterion
IAGO	Inverse Accumulated Generating Operation	LSTM	Long Short-Term Memory
MAPE	Mean Absolute Percentage Error	ANN	Artificial Neural Network
RMSE	Root Mean Square Error	CPI	Consumer Price Index
MAE	Mean Absolute Error	MFO	Moth Flame Optimizer Algorithm
MA	Moving Average	SWT	Stationary Wavelet Transform
IA	Intelligence Artificial	DEPM	The Deep Energy Predictor Model
GA	Genetic Algorithm	DWT	Discrete Wavelet Transform

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