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BiLSTM-CNN network applied to the forecast of electricity consumption in agroindustry of the southwest region of Goiás

BiLSTM-CNN aplicada à previsão de consumo de energia elétrica em agroindústria da região sudoeste de Goiás

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ABSTRACT

This work proposes using the BiLSTM-CNN hybrid network to predict the electricity consumption of an agroindustry. The agroindustry is located in the southwest region of Goiás. The BiLSTM-CNN network is based on integrating the BiLSTM network (Bidirectional Long Short Term Memory) with the CNN network (Convolutional Neural Network). The database presents a daily series of energy consumption between January/2016 and December/2021, totaling 2153 observations. Prediction models based on Artificial Neural Networks were implemented in Python using the Keras framework. Results obtained from the proposed network and the recurrent networks LSTM, GRU, and RNN were compared using the metrics R^2 (Coefficient of Determination), RSME (Root Mean Squared Error), MAPE (Mean Absolute Percent Error), and MAE (Mean Absolute Error). It was found, for a 30-day horizon, that the BiLSTM-CNN model performed better. It was concluded that the proposed forecast model could serve as a support tool for managers of the agroindustry under study.

Palavras-chave Hybrid networks; Time series; Keras; Python.

RESUMO

Este trabalho propõe a utilização da rede híbrida BiLSTM-CNN para prever o consumo de energia elétrica de uma agroindústria. A agroindústria está localizada na região sudoeste do estado de Goiás. A rede BiLSTM-CNN é baseada na integração da rede BiLSTM (*Bidirectional Long Short Term Memory*) com a rede CNN (*Bidirectional Long Short Term Memory*). A base de dados apresenta uma série diária de consumo de energia entre janeiro/2016 e dezembro/2021, totalizando 2153 observações. Modelos de predição baseados em Redes Neurais Artificiais foram implementados em Python usando o *framework* Keras. Os resultados obtidos da rede proposta e das redes recorrentes LSTM, GRU e RNN foram comparados usando as métricas R^2 (*Coefficient of Determination*), RSME (*Root Mean Squared Error*), MAPE (*Mean Absolute Percent Error*) e MAE (*Mean Absolute Error*). Verificou-se, para um horizonte de 30 dias, que o modelo BiLSTM-CNN apresentou melhor desempenho. Concluiu-se que o modelo de previsão proposto pode servir como ferramenta de apoio aos gestores da agroindústria em estudo.

Keywords: Redes híbridas; Séries temporais; Keras; Python.

1. INTRODUÇÃO

Due to the expansion of the commercial, residential, and industrial sectors, the demand for electric energy has grown exponentially. This demand motivates the need for consumption planning and forecasting tools.

Electricity consumption forecasts can provide information for decision-making and bring benefits, such as lining up the actual consumption needs with the contracted demand and avoiding charging fines. The entire construction of the electrical distribution system, the industries spending plans, and their production capacity depend on energy consumption (CASTRO; FERRARI, 2016).

Forecasts for consumers in the free energy market are fundamental because they are bilateral negotiations in which the consumer unit and the energy trader agree on the power to be contracted, the price, and the terms (BARROS et al., 2020; PINTO, 2018).

The over-dimensioning of an electric energy demand contract can cause the waste of resources in unnecessary expenses. On the other hand, an undersized agreement can lead to fines and a stoppage of the manufacturing process due to a lack of energy. Therefore, projections provide information for decision-making that contributes to the continuity of the process, ensuring both financial and operational advantages (KAYTEZ et al., 2015). In this sense, artificial neural network models can be used as support tools in decision-making. Such tools are essential in a planning system because they direct the best way for the company to take advantage of all available resources (PINHEIRO et al., 2020).

Several works used forecasting methods to forecast electric energy consumption. Nichiforov et al. (2017) performed electricity consumption forecasts using ARIMA and Neural Network models. Wang & Meng (2012) used ARIMA and Hybrid Neural Network models to forecast electricity consumption in the Hebei province in China. Santos & Chaukoski (2020) carried out forecasts of electricity consumption in the southeastern region of Brazil, using SARIMA and LSTM. Chou & Tran (2018) performed, using machine learning techniques, predictions of the energy consumption of a residential building. Jeihoonian et al. (2010) presented an approach, based on Artificial Neural Networks, for forecasting the annual energy consumption in basic metals industries in Iran.

In this context, this work proposes using the BiLSTM-CNN hybrid network to forecast the electricity consumption of an agroindustry in the state of Goiás.

It is essential to highlight that the BiLSTM-CNN neural network has already been used in scientific works in other areas, such as: detecting offensive language on Twitter

(WIDEMANN, 2018), short-term wind energy forecasting (HUANG et al., 2022), classification of sound (UTEBAYEVA, 2020), malicious code family detection (WANG et al., 2020) and Facial expression recognition (FEBRIAN et al., 2023). However, so far, no studies are related to the forecast of electricity consumption in agroindustries using the BiLSTM-CNN model.

The paper is organized as follows. In Section 2, the structure of the proposed network is presented. The methodology used and the steps of the work are presented in section 3. Section 4 presents the results of the BiLSTM-CNN, LSTM, GRU, and RNN networks. Final remarks and conclusions in Section 5 close the article.

2. MATERIAIS E MÉTODOS

The methodology used in this study can be considered as follows: Applied since it seeks solutions to specific problems, generating knowledge for practical application; Descriptive as it describes the characteristics of a given population, seeking to detect potential relationships between variables and Quantitative because it emphasizes deductive reasoning, logic, and measurable arguments (GIL, 2010, ANTONIOLLI, 2021).

BiLSTM-CNN Neural Network:

The LSTM network, a type of recurrent neural network, is capable of capturing long-term sequences. It is widely used in tasks involving sequential entries, such as time series (SANTOS, 2022).

The LSTM network uses memory cells in its topology. The memory cell controls, through gates (input (i_t), output (o_t), and forgetfulness (f_t)), how information flows into and out of the cell. The cell state (C_t) represents the information that reached that step of instants of past times. All these values are concatenated, multiplied, or added, as shown in the circuit shown in Figure 1 (GRAVES et al., 2013; SANTOS; CHAUCOSKI, 2020; PASSOS, 2021).

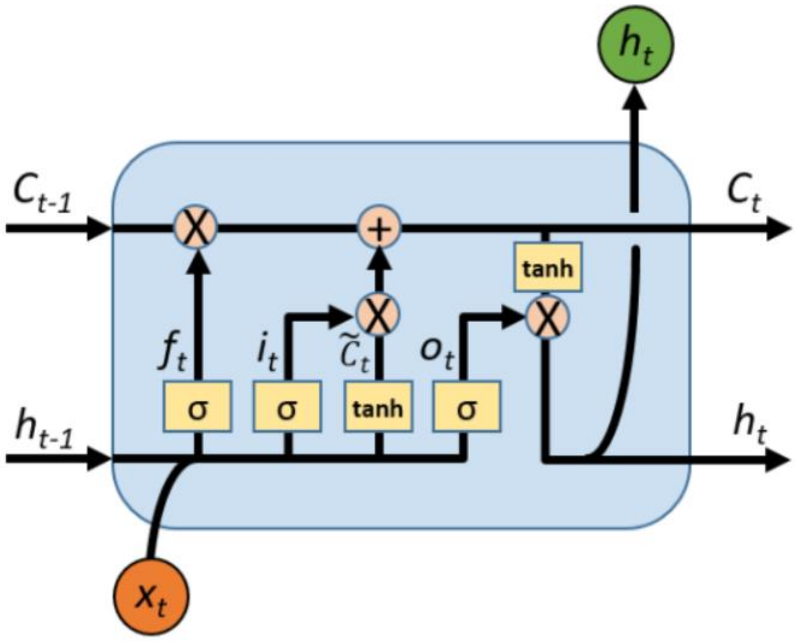

Figure 1. Memory cell
Source: Sun et al. (2018).

The LSTM network equations are defined as (SHEWALKAR et al., 2019):

$$f_t = \sigma\left(w_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (1)$$

$$i_t = \sigma(w_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

$$\tilde{C}_t = tanh(w_C \cdot [h_{t-1}, x_t] + b_C) \quad (3)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (4)$$

$$o_t = \sigma(w_o \cdot [h_{t-1}, x_t] + b_o) \quad (5)$$

$$h_t = o_t * tanh(C_t) \quad (6)$$

Where x_t and h_t are the input and output vectors, w_f, w_i, w_c, and w_o are the weights, b_f, b_i, b_c, and b_o the biases, σ is the sigmoid activation function, and *tanh* is the hyperbolic tangent activation function.

The BiLSTM network, introduced by Schuster and Paliwal in 1997, can be created through two intermediate layers, considering a forward sequence ($\vec{h}_t$) and a backward sequence ($\overleftarrow{h}_t$) that are transmitted to the output layer (Figure 2) (SUN et al., 2018). The bidirectional structure of the BiLSTM network allows the capture of past and future information, enabling greater learning power for the network (GRAVES et al., 2013).

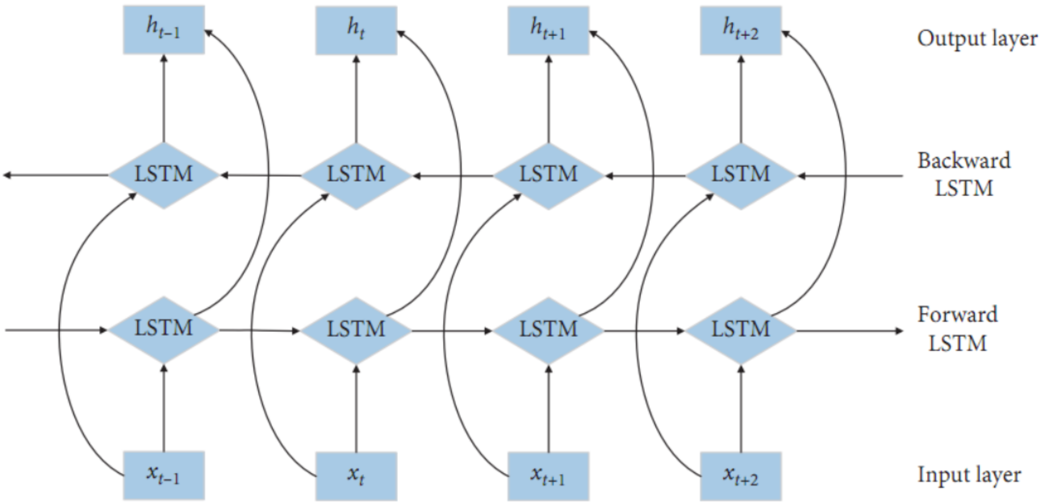

Figure 2. Structure of BiLSTM
Source: Chen et al. (2021).

The $\vec{h}_t$ and $\overleftarrow{h}_t$ sequences are combined to find the BiLSTM output sequence h_t for time *t* (DENG et al., 2021):

$$h_t = [\vec{h}_t, \overleftarrow{h}_t] \quad 7$$

Finally, the BiLSTM output is given by:

$$h = \{h_1, h_2, \cdots, h_n\} \quad 8$$

The CNN network (Convolutional neural network), inspired by the biological process of visual data processing, was initially developed for image classification (LI et al., 2020; VARGAS, 2016, LAWAL, 2021).

In addition to the input layer, CNN networks are composed of three main layers: a convolutional layer, a pooling layer, and a fully connected layer (Figure 3).

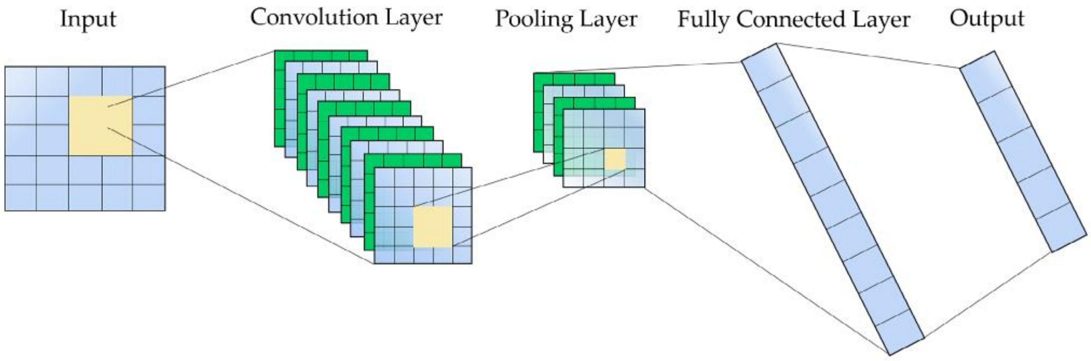

Figure 3. Structure of CNN
Source: Wu et al. (2021).

The BiLSTM-CNN model initially extracts the long-term dependencies of the time series through BiLSTM. Next, it uses the CNN network to extract the significant local relationships through the convolution and pooling layers (SOARES, 2022). The structure of the proposed model is shown in Figure 4.

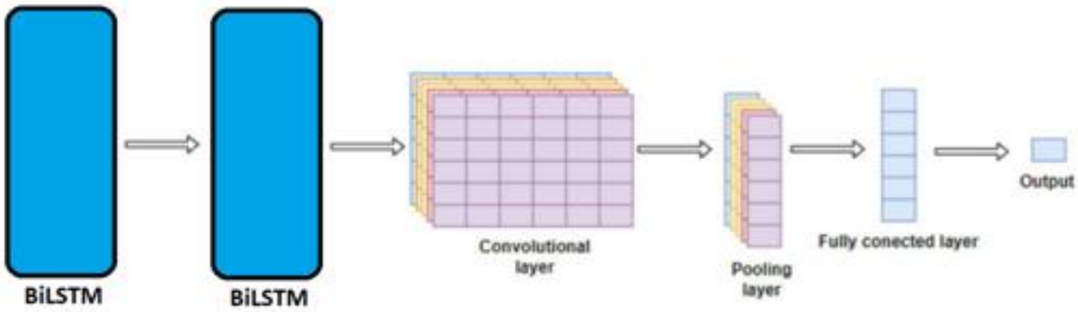

Figure 4. Proposed model flowchart
Source: Wu et al. (2021).

Consumption database:

A database with 2153 observations (Jan/20016 - Dec/2021) was used to forecast electricity consumption. The historical series of energy consumption is shown in Figure 5.

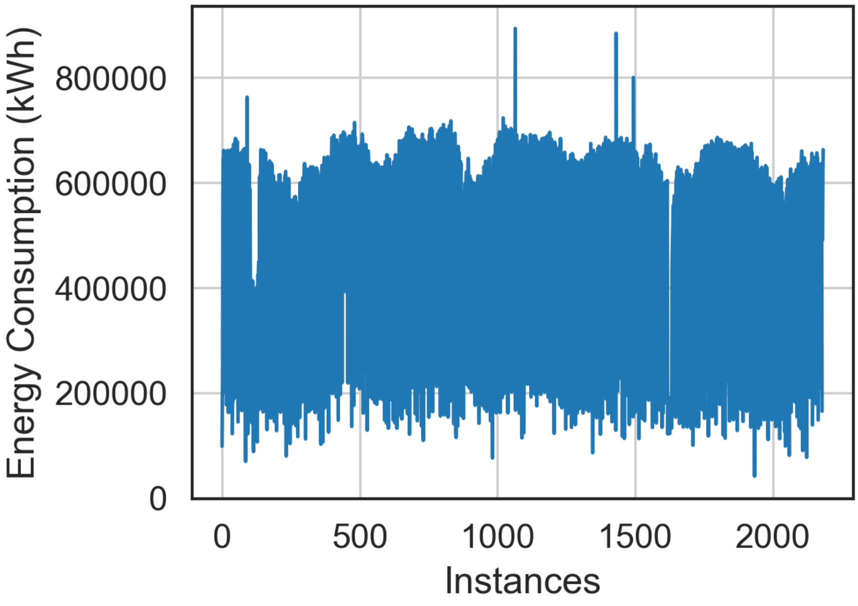

Figure 5. Historical series of energy consumption

Work steps:

To evaluate the Neural Network models implemented in this work, three steps were performed (Table 1):

Table 1. Work steps.

Step	Description
Data collection and analysis	In the first stage, exploratory data analysis of electricity consumption was carried out.
Training and validation	In the second stage, training and validation, the hyperparameters of the BiLSTM-CNN network were selected.
Test	In the last stage, the test stage, the results of the BiLSTM-CNN, LSTM, GRU, and RNN networks were compared for data that did not participate in the training and validation stage.

The company:

The company, located in the State of Goiás, operates in the food sector. Its processes include receiving poultry and swine, slaughtering, freezing, and storing. The unit produces broiler cuts, swine cuts, and sausages.

The company's second highest expense is related to hiring electricity, second only to costs with staff.

The unit's electricity supply is provided at 138kV due to the size of the industrial park and its various processes. The company's biggest electricity consumer is the cold generation, comprising compressors, cooling towers, and freezing tunnels.

Metrics:

In this work, the results of the models were evaluated by the parameters: Coefficient of Determination, Root Mean Squared Error, Mean Absolute Error, and Mean Absolute Percentage Error (PINHEIRO et al., 2020; BASTIANI et al., 2018; CANKURT; SUBASI, 2015).

Coefficient of Determination (R^2): Indicates a model's goodness of fit to the variable intended to be explained. This coefficient indicates how much the model could explain the collected data (Equation 9).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2/n}{\sum_{i=1}^{n}(\bar{y}_i - \hat{y}_i)^2/n} \tag{9}$$

Root Mean Squared Error (RMSE): Root Mean Square Error of the difference between the prediction and the actual value (Equation 10).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}((y_i - \hat{y}_i)^2)} \tag{10}$$

Mean Absolute Error (MAE): It evaluates the difference between an estimator and the actual value of the estimated quantity (Equation 11).

$$MAE = \frac{1}{n}\sum_{1}^{n}|(y_i - \hat{y}_i)| \tag{11}$$

Mean Absolute Percentage Error (MAPE): The MAPE measures the size of the error in percentage terms (Equation 12).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|(y_i - \hat{y}_i)/y_i| \times 100 \tag{12}$$

Where: y_i is the actual value for the period *i*, $\hat{y}_i$ is the forecast for period *i*, $\bar{y}_i$ is the average value, and *n* is the number of observations.

3. RESULTADOS E DISCUSSÃO

Initially, in this work, descriptive data analysis was carried out (Table 2).

Table 2. Descriptive analysis.

Analyzed parameter	Consumption
Average (kWh)	515900,46
Median (kWh)	604897,00
Minimum (kWh)	40933,00
Maximum (kWh)	893024,00
Standard Deviation (kWh)	84054,07
Coefficient of variation (%)	16,3%

From the data presented in Table 2, it can be observed that the consumption was, for the period under study, an average of 515900.46 kWh. This period shows minimum and maximum consumption of 40933.00 kWh and 893024.000 kWh, respectively. A mean coefficient of variation of the data (16.3%) is also observed (PIMENTEL, 2009).

Figure 6 shows the data boxplot. It can be observed, in this figure, that there are no discrepant values (outliers). It is also possible to follow the median, represented by the line inside the energy consumption rectangle, in the range of 604897 kWh.

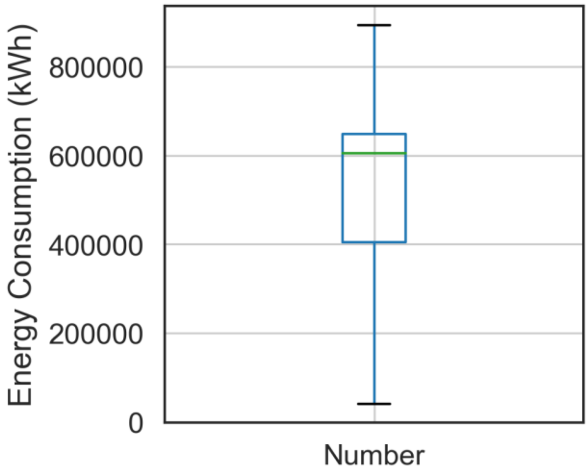

Figure 6. Boxplot of consumption data

The monthly average of energy consumption during the studied period is shown in Figure 7. This figure shows that the months with the lowest consumption occur between April and September. There was also an average minimum consumption of 488771.5 kWh in June and a maximum of 553676 kWh in March.

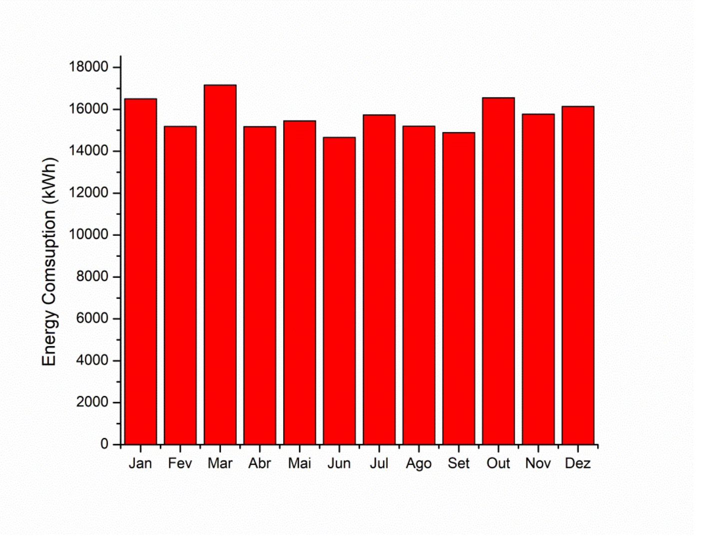

Figure 7. Average monthly energy consumption

Hyperparameters:

The construction of the models explored different layers of architectures and adjustments of the hyperparameters to obtain the best possible modeling of the energy consumption of the agroindustry. The best combination used the RMSprop optimization algorithm with the following parameters: time step = 120, learning rate = 0.0001, epochs = 500, and batch = 40. The neural networks were trained with 1442 samples (67%) and validated with 711 (33 %).

The BiLSTM-CNN network parameters are shown in Table 3.

Table 3. BiLSTM-CNN network parameters.

Parâmetros	Valor
Convolution layer filters	32
Convolution layer kernel size	7
Convolution layer activation function	Relu
Convolution layer padding	Same
Pooling layer pool size	1
Pooling layer padding	Same
Pooling layer activation function	Relu
Number of BiLSTM layer	2
Numbers of hidden units in BiLSTM layer	16-8

Dropout	0.1
BiLSTM activation function	tanh
Dense units	1

Figure 8 presents the learning curves for electricity consumption of the agroindustry.

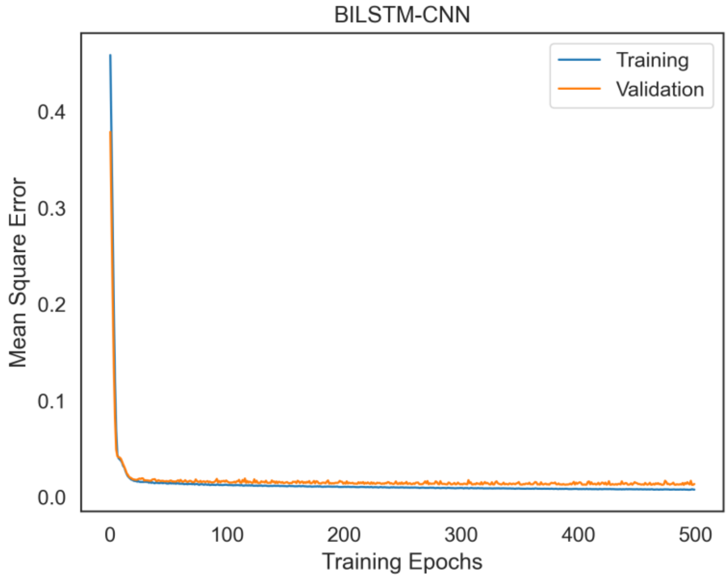

Figure 8. Training and validation learning curves

Figure 9 presents, as an example, the training and validation results for the BiLSTM-CNN model.

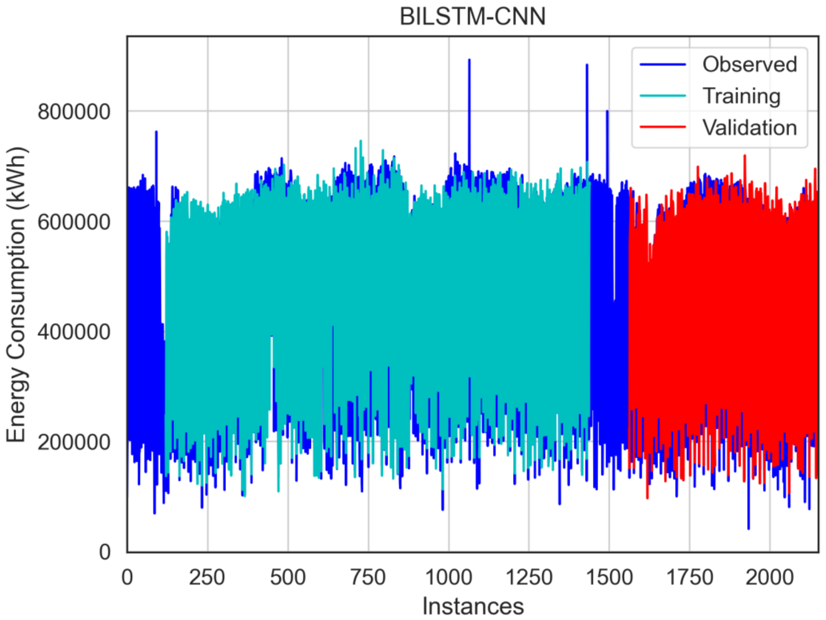

Figure 9. BiLSTM-CNN Network – training and validation

Test:

Table 4 presents the data observed and predicted, by the BiLSTM-CNN, LSTM, GRU, and RNN forecast models, for the 30 days that did not participate in the training and validation stage.

Table 4. Average monthly energy consumption.

Day	Observed	BiLSTM-CNN	LSTM	GRU	RNN
24/11/2021	490630	492724,7	405006,6	452140,3	405646,6
25/11/2021	606354	594472,4	542379,5	556364,3	483115,2
26/11/2021	605398	608063,5	591383,6	528775,2	548002,3
27/11/2021	600573	602165,6	586131,4	560860	568576,2
28/11/2021	656234	539525,5	528489,8	510524,6	524720,6
29/11/2021	535438	201836	220947,5	173892	229387,2
30/11/2021	177954	562020,3	518618,6	447369,9	509767,5
01/12/2021	656234	649056,2	601260,9	566654	519618,4
02/12/2021	651477	646929,6	663061,6	664080,5	642641,9
03/12/2021	641817	643687,3	681025,9	698550,4	628992,1
04/12/2021	646092	620972,5	675598,2	677708,6	594902,2
05/12/2021	304179	517700,3	546215,7	487895,5	505189,8
06/12/2021	147949	184444,4	191291,4	163161,4	178700,6
07/12/2021	625357	555919,5	521465,3	472112,2	444761,5
08/12/2021	619228	623513,5	647315,3	571175,1	534760,9
09/12/2021	617606	604325,9	657922,1	620791,5	579449,3
10/12/2021	600287	610713,4	639480,5	591876,4	640151,6
11/12/2021	593896	627787	699726,2	645808,2	702524,3
2/12/2021	574571	550046,3	554791,1	539217,3	507191,7
13/12/2021	209120	201667,2	223768,9	216387,6	206678,6
14/12/2021	583322	571130,8	618490,2	658733	555152,9
15/12/2021	622162	647810,3	651632,4	683875,5	595906,1
16/12/2021	603667	641698	689200,5	685984,4	615685,3
17/12/2021	635835	634792,5	733756,9	674036,9	657259,4
18/12/2021	631793	620840,5	706981,2	609560,4	634523,8
19/12/2021	439905	451084,6	523584,6	462599,2	485657,1
20/12/2021	164569	154172,3	167935,6	154269,6	164846,5
21/12/2021	490852	495599,1	484999,3	507819,1	446389,8
22/12/2021	617590	631385,5	683673,7	610018,9	473856,9
23/12/2021	662437	667603,2	771450,3	717911,5	667531,7

Figure 10 presents, in graphical form, the results of the predictions of the BiLSTM-CNN network for the test set.

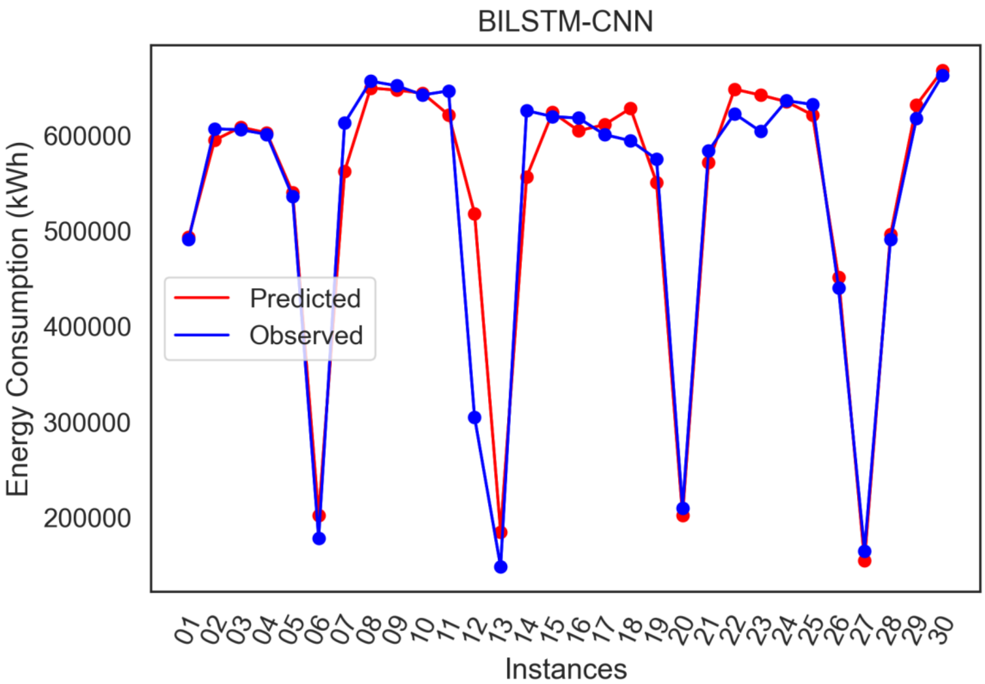

Figure 10. BiLSTM-CNN forecasts – test set

Table 5 presents the results of the metrics, R^2, MAE, RSME, and MAPE, for the test set.

Table 5. Metrics - Test set.

Model	**R^2**	**MAE (kWh)**	**RMSE (kWh)**	**MAPE (%)**
BILSTM-CNN	**0,92**	**22730,62**	**44982,6**	**6**
GRU	0,81	49624,93	67793,12	9,74
LSTM	0,78	56186,98	73730,63	12
RNN	0,74	58507,72	79355,95	12,2

The results in Table 5 show that the BiLSTM-CNN and RNN models obtained the best and worst outcomes, respectively. The BiLSTM-CNN model, compared to the LSTM, GRU, and RNN models, presented minor errors (MAE, RSME, and MAPE) and an R^2 closer to 1.

4. CONSIDERAÇÕES FINAIS

This work used the BiLSTM-CNN, LSTM, GRU, and RNN networks to predict future short-term electricity consumption. The models implemented in this work underwent the training/validation and testing stages.

Initially, data were collected and then treated. The training and validation stage of the BiLSTM-CNN, LSTM, GRU, and RNN models was performed in the sequence. Then, in the test stage, it was observed that the BiLSTM-CNN network proved to be more efficient for the results of the metrics R^2, MAE, RMSE, and MAPE than the recurrent networks LSTM, GRU, and RNN. The proximity between predicted and actual values demonstrates the excellent generalization ability, for a 30-day horizon, of the model proposed in this work.

Finally, it can be observed that the model is valid and can help managers of the agroindustry in the decision-making process.

However, it is observed that more studies must be carried out to prove the superiority of the BiLSTM-CNN network over other models for forecasting the consumption of electricity in agroindustries in general.

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