Prediction of electrical energy consumption through recurrent neural networks

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Abstract

It is almost unthinkable to conceive the modern world without the use of electricity; every day around the world demand for electric energy is increasing, not only for society development but also to reduce the fossil fuel consumption and CO_2 emissions to combat climate change, as recommended in the UN Sustainable Development Goals (SDGs). One approach to improve energy efficiency related to electricity consumption is the use information and communication technologies (ICT) integrated with the electrical systems to model and predict electricity consumption. This article presents a prediction model based on recurrent neural networks (RNN) for the prediction of electricity consumption, verifying its validity with real data taken from a local company. The model is compared to an ARIMA model and to real data to verify its prediction capacity, the results showed a 95% similarity using the Deep learning model while ARIMA yields 40% of similarity.

Keywords

RNN, Forecasting, electrical consumption, ARIMA, Correlation coefficient

1. Introduction

Electricity is one of the fundamental energy resources for the development of society. A large part of current technologies works with electrical energy and is therefore necessary for the development of civilization [1]. This dependence on society has a major impact on economic, social and environmental aspects.

In 2015, the UN approved the Agenda 2030 on Sustainable Development, with the development of the Sustainable Development Goals (SDGs), in which goal 7 (affordable, secure, sustainable and modern energy) and 13 (urgent action to combat climate change and its effects) involve the generation, transmission and distribution systems of electric power [2].

Because of this, research focused on both modeling and optimizing electrical systems is of great importance, in particular one of the most relevant topics are energy consumption prediction studies [3].

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On the other hand, deep learning techniques have enabled interesting developments in different areas of technology, with applications in very diverse sectors: from sound and visual pattern recognition, through facial recognition, mobile communications, genomic analysis, and even data prediction systems [4].

Among the different deep learning techniques, Recurrent Neural Networks (RNN) allow handling the time dependence of the data, which is not fully taken into account with other deep learning techniques.

These networks incorporate feedback loops, which allow them to maintain a certain persistence of information, similar to a long-term memory, in order to model aspects and behaviors that depend on time [5].

Compared to an artificial neural network, the general equation governing a neuron in a recurrent neural network is described by the equation 1.

$$y(t) = f(\mathbf{W}\mathbf{x}(t) + \mathbf{U}\mathbf{y}(t-1) + b) \tag{1}$$

Where two matrices are defined: the weight matrix $\mathbf{W}$ of the previous layer of the network, and the weight matrix $\mathbf{U}$ that introduces the influence of the network at a previous time instant [6].

This paper presents a prediction model based on RNN for electricity consumption prediction, verifying its validity with real data taken from a local company. The model is compared with respect to an ARIMA model and real data to verify its predictive capability.

The background section presents a review of some of the techniques used for electricity consumption prediction, the prediction model section presents the architecture and details of the model, the results section presents the details of the model training and its comparison with an ARIMA reference model and with real data, and finally the last section presents the conclusions and future work.

2. Background

The prediction of electricity consumption in various energy systems has had significant efforts. In [7] it is presented a review of models to evaluate and predict energy efficiency in buildings, taking into account not only the electrical systems but all their associated systems (e.g. HVAC systems), to obtain the overall building efficiency and equivalent CO_2 emissions. It highlights the use of system modeling techniques, statistical methods, "gray" models (where the system information is limited) and models based on artificial intelligence: neural networks and support vector machines.

A review of artificial intelligence-based techniques used to predict energy consumption (both electrical and from other sources such as fossil fuels) is given in [8]. It highlights the use of hybrid techniques that include physical models based on thermodynamics with models based on autonomous learning such as multiple linear regression, artificial neural networks, support vector machines, and ensemble forecasting.

ARIMA (Auto Regressive Integrated Moving Average) models are also used to model time series, which are widely used in statistics and econometrics [9, 10]. Due to its characteristics for modeling time-regular behaviors, this model has also been used for electric power consumption prediction [8].

The use of deep learning techniques have been applied in different research, such as in [11], which describes the application of neural networks in the long-term prediction of electricity consumption in Greece.

In [12] it is proposed the use of artificial neural networks together with other techniques (particle cloud optimization, principal component analysis and genetic algorithms), for the prediction of electricity consumption in buildings in China.

In [13] it is proposed a framework based on LSTM (Long Short-Term Memory) and recurrent neural networks for consumption prediction in residential environments, comparing their results with data obtained from smart meters.

3. Prediction model

The model architecture (Figure 1) is based of an RNN with an input of the time series existing at the time, an output with the prediction for time $n + 1$ and a set of 120 neurons for the hidden layer.

The size of the hidden layer was chosen to strike a balance between best fitting and computational resources usage.

This network uses a window of 20 observations per iteration with a total of 200000 iterations per training time. Data input consists of a current consumption secuence of samples evenly spaced in time.

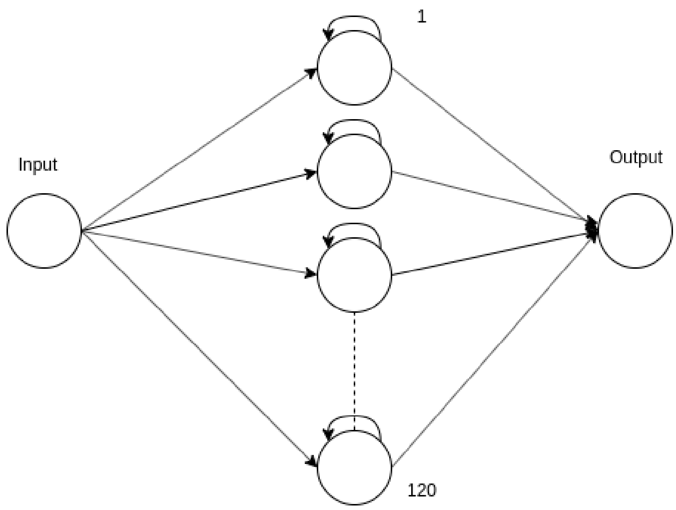

Figure 1: Proposed architecture

To train the RNN a time series was used that relates the daily electricity consumption of an undisclosed company in the city of Tunja in Colombia between June 22, 2019 and July 1 of the same year, the data were provided by the company Wavelet S.A.S.

In this company the measurement data was taken from a single office in a office building, with lighting loads, computers and small office appliances. Average current in this office was around 2.5 $A_{(RMS)}$. Test data is shown in Figure 2.

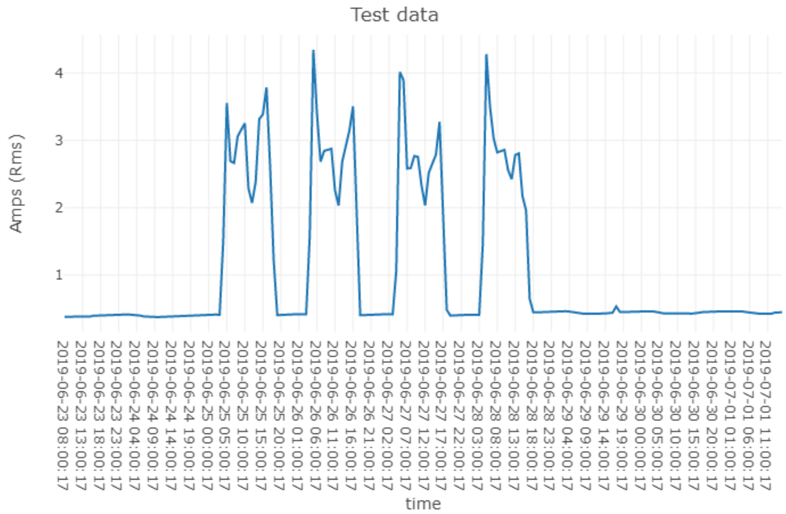

Figure 2: Test data

This time series consists of 2200 data samples where 2000 were used for training (90%) and the remaining (10%) was used to test the generalization capacity of the network. Data separation was done sequentially, that is, the first data samples were used for training, and the last data samples were used for test.

The training time is determined by the learning rate set at each stage. In this study 4 different learning rates (0.005, 0.001, 0.0001 and 0.01) were used, the training result is evidenced in Figure 3.

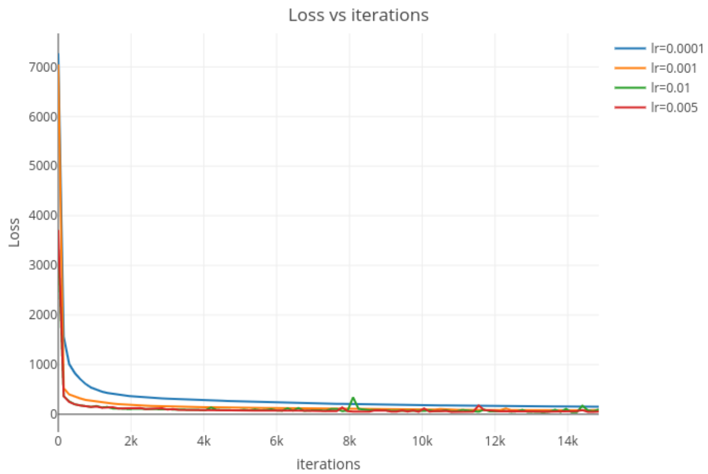

Figure 3: Training error for different learning rates

Network implementation was done using the Nvidia Jetson Nano [14] (Figure 4) and the open source Tensorflow library [15].

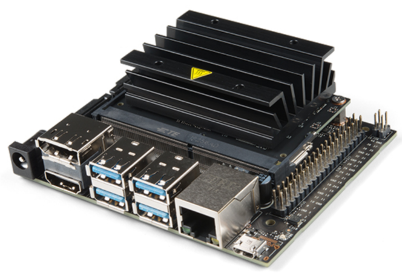

Figure 4: Nvidia Jetson Nano

4. Results

Figure 5 represents the results of the data using different learning rates.

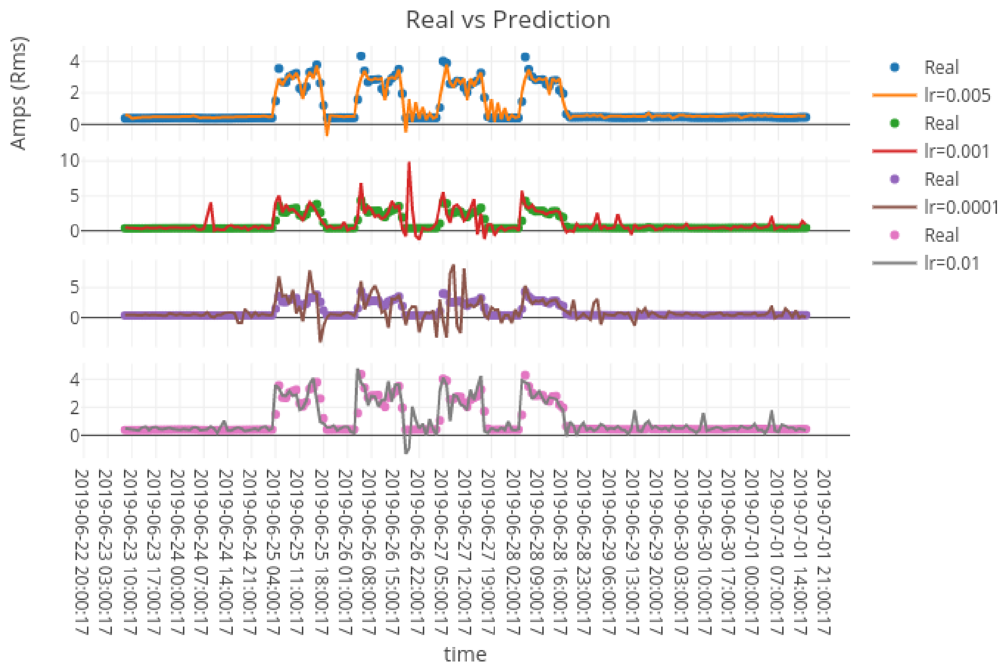

Figure 5: Prediction at different learning rates

To determine the generalization capacity of each model due to each learning rate, a graph was constructed with the correlation coefficient between the real output and the output estimated by the network vs. each learning rate (Figure 6).

The image shows that the learning rate that generates the highest correlation coefficient is 0.005, on the other hand the other rates generate a considerable amount of noise reaching a maximum of 0.85 in the coefficient unlike the rate mentioned that achieves a value close to 0.95 of similarity with the original signal.

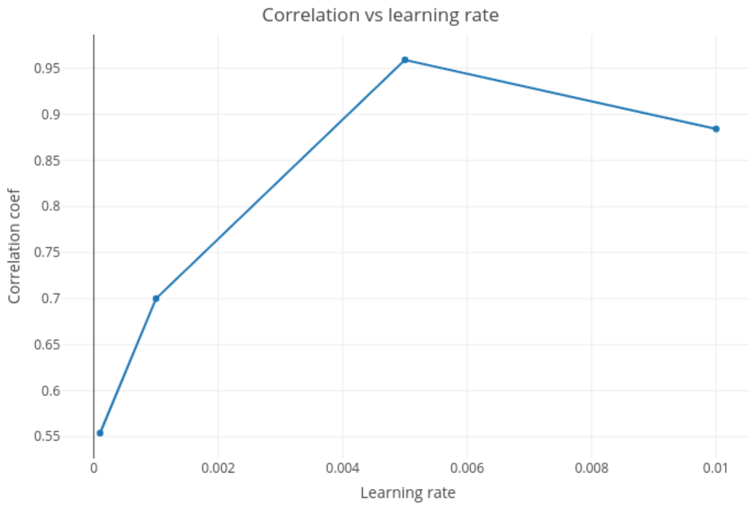

Figure 6: Correlation between actual signal and predictions at different learning rates

On the other hand, an ARIMA model was used to predict the power consumption and to compare it with the result of the RNN as can be seen in Figure 7.

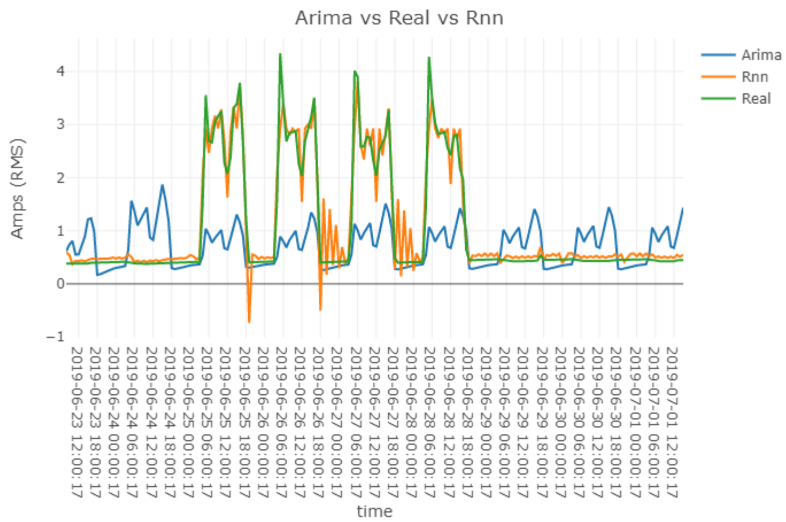

Figure 7: Arima vs RNN vs Real

The comparison of the different trained models with respect to the real output of the power consumption signal can be seen in Figure 8, highlighting the degree of similarity between the different predictions given by each of the models based on recurrent neural networks and ARIMA.

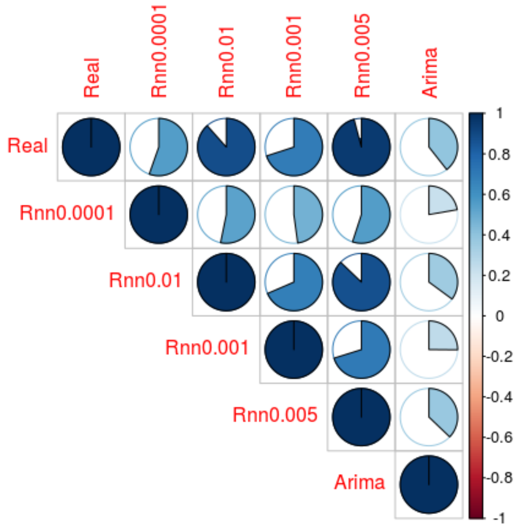

Figure 8: Correlation matrix between models

5. Conclusions

The RNN is a model capable of making predictions with a higher degree of accuracy than the ARIMA model, taking into account a relatively lower amount of training data than those usually used by deep learning models. On the other hand, the correlation value of the ARIMA model with respect to the original consumption signal reached a value of 39% while the lowest correlation value reached by the RNN was 55% ($lr = 0.001$), highlighting in the same way the highest value obtained of 95% ($lr = 0.005$) with the RNN of better performance. On the other hand and according to the Figure 6 it is evident that as the learning rate decreases it does not mean that the generalization capacity of the RNN is increasing, this is largely due to the fact that the network is incurring in overfitting problems with the training data. However, the same graph shows the problem of bias when the learning rate decreases.

This type of predictive models are very useful for issues related to energy efficiency, carbon footprint reduction and cost projection in companies and institutions whose electricity consumption may represent a significant monetary investment.

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