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RESEARCH ARTICLE

Prediction of a City's Power Consumption by Artificial Neural Networks

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ABSTRACT: Electricity is the most important and useful energy form for our modern society. This calls for smart management to have optimal usage. Artificial neural networks (ANNs) have emerged as a powerful tool in forecasting power demand, especially when multiple variables are involved. In this paper, taking a city in Morocco as an illustrating example, a long short-term memory (LSTM) neural network is developed to predict power consumption via five weather factors. Our numerical results corroborate the merits of LSTM in forecasting the load demand with which temperature exhibits the strongest correlation.

KEYWORDS: Robotics and Intelligent Machines; Machine Learning; Artificial Neural Networks; LSTM; Power Consumption Prediction.

Introduction

Electricity is indispensable in our society, giving life to our appliances and electronic gadgets and powering our critical infrastructure. Therefore, developing effective technologies to protect our electrical grid is important. One strategy is to accurately predict spikes and dips in power consumption, preventing property damage and ensuring that every customer has electricity access. Indeed, power consumption forecasting is an important task in the energy industry, enabling energy providers to allocate their resources and optimize their operations efficiently. This can be achieved using statistical methods, such as linear regression, polynomials, and ARIMA (autoregressive integrated moving average). For instance, in a previous study,[1] we demonstrated that ARIMA was a reasonably reliable tool in predicting power consumption by using data from several California counties as the illustrating examples. Nevertheless, ARIMA-based forecasting performs best on data points strongly correlated to each other in the time domain. Thus, expanding the prediction toolset that can be applied to a wide range of data and variables and producing accurate results is important.

Recently, there has been a growing interest in using artificial neural networks (ANN) to forecast power consumption.[2] Neural networks are a class of machine learning algorithms that are particularly well-suited for complex, non-linear data patterns, making them an ideal choice for forecasting power consumption. By analyzing historical data on power consumption, weather patterns, and other relevant variables, neural networks can accurately predict future power demand with a high degree of accuracy. In this way, power providers can adjust their energy generation and distribution strategies to meet the changing needs of their customers while minimizing waste and improving overall efficiency. Notably, ANN can be used for a wide range of systems. For instance, Stošovic *et al.*[3] employed five different network structures, i.e., ordinary recurrent neural network (RNN), long short-term memory (LSTM), gated recurrent units (GRU), bidirectional LSTM, and bidirectional GRU, to predict the electricity consumption of a cold storage facility. The results showed that the modifications of RNN performed much better than ordinary RNN, and more significantly, GRU and LSTM exhibited the best performances. Chen *et al.*[4] constructed an ANN to predict the electricity demands in several office buildings by splitting the time variable for different occupancy rates within the context of multiple weather factors. Adhiswara *et al.*[5] developed an ANN algorithm to predict long-term electricity consumption in Indonesia for 2019-2025. Jamii *et al.*[6] propose an ANN-based paradigm to effectively and accurately predict wind power generation and load demand.

Motivated by these successes, in the present study, an LSTM-based ANN is constructed for power demand forecasting using data from a city in Morocco as the illustrating example. Unlike a feed-forward network that only allows data to move in a single direction, an LSTM has many feedback loops that will enable past data to influence the data being inputted, allowing for more accurate output. The results indeed show that LSTM is a reliable and feasible tool for predicting power consumption within the context of multiple weather factors.

Methods

The dataset selected for this project is from a city in Morocco called Tetuan City.[7] This dataset contains five environmental variables along with power consumption. These are time, temperature in Celsius, humidity in percentage, wind speed in kilometers per hour, and diffuse flow and general diffuse flow, which are related to groundwater flow. It is also important to note that the data spans from the entirety of 2017, and is in 10-minute intervals, therefore amounting to over 52,000 data points.

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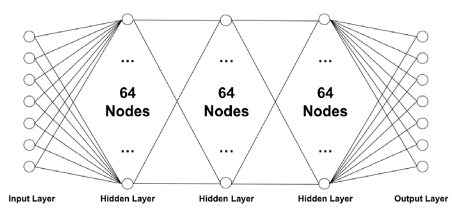
Four tools were used to write the LSTM neural network (Scheme 1). The first tool is the Pycharm IDE, an application to create and run Python programs. The second is NumPy, a Python library that gives access to many useful mathematical functions. The third is matplotlib, another Python library that allows one to plot custom graphs using data points and equations. Finally, the most important tool is Pytorch, another Python library. This library provides neural network functions that one can use to create the program's framework.

Before inputting data into the neural network, they needed to be converted into the appropriate format for the LSTM. This was done by writing code to scale data to a range from 0 to 1 to lower the resources used and make the training much more efficient. The data was then sorted into two matrices directly used in the neural network. The first matrix was the input matrix. This matrix contained a series of consecutive data points that corresponded with the length of the specified input length. The next matrix was the input comparison matrix. This matrix had the same data points as the input matrix and contained additional data that would be used to compare with the neural network's output. By comparing the output with the comparison matrix, the neural network lowered the validation loss and therefore increased the accuracy of the prediction. Overall, 700 iterations of the training loop were run, in conjunction with the use of the Adam activation function and the Smooth L1 Loss function in order to produce high-quality results.



Scheme 1: Schematic representation of an LSTM neural network.

Results and Discussion

Analysis was first carried out to evaluate the correlation of these weather factors to power consumption. Figure 1 shows the comparison graphs where the red curves are the power consumption (in kilowatt, kW) and the blue ones are the respective weather factors for the entire time period. Of course, some variables are more related to power consumption than others. For example, the patterns of temperature variation rather closely resembled those of power consumption, whereas only a weak correlation was observed with wind speed and diffuse flow.

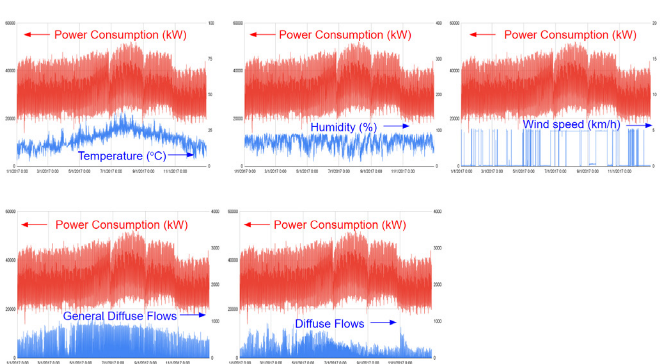


Figure 1: Comparison of power consumption (red curves) with various weather factors (blue curves) within the year 2017, such as temperature, humidity, general diffuse flows, wind speed, and diffuse flows. The results show that temperature exhibits the highest correlation with power consumption, whereas wind speed and diffuse flow are weakly correlated.

This can be further confirmed by calculating the r^2 coefficient of each variable in relation to power consumption. For example, from Figure 2, one can see that the r^2 value decreases in the order of temperature (0.194) > humidity (0.083) > general diffuse flow (0.035) > wind speed (0.028) > diffuse flow (0.006). This suggests that power consumption is correlated to multiple weather factors, and temperature exhibits the highest r^2 value and is hence the most correlated to power consumption.

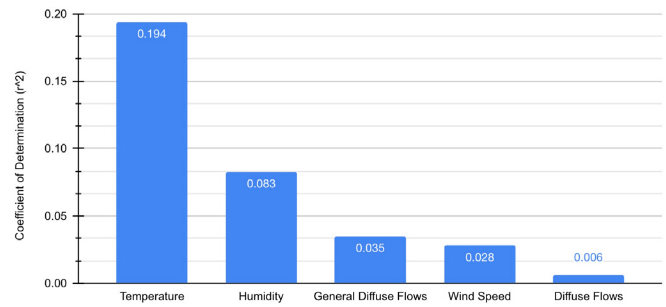


Figure 2: Comparison of the r^2 coefficient of each weather factor in relation to power consumption. Values are obtained from statistical calculations of data in Figure 1. The results show that power consumption is the most correlated with temperature, followed by humidity, general diffuse flow, wind speed, and diffuse flow.

Since these weather factors are correlated with power consumption, they must all be included for prediction when the dataset is input into the LSTM. However, to ensure that the neural network can adequately follow the trends of the dataset, it was programmed to have one data point as an input and then output the next predicted point. This was done for every data point in the dataset, and the result is shown in Figure 3, with the blue being the original data and the red being the predicted LSTM points. One can see that the neural network followed the data patterns very closely and matched many of the spikes and dips in power consumption. This suggests that the obtained LSTM algorithm may be an effective tool in reproducing the power consumption data, a critical step in implementing LSTM for power consumption forecasting.

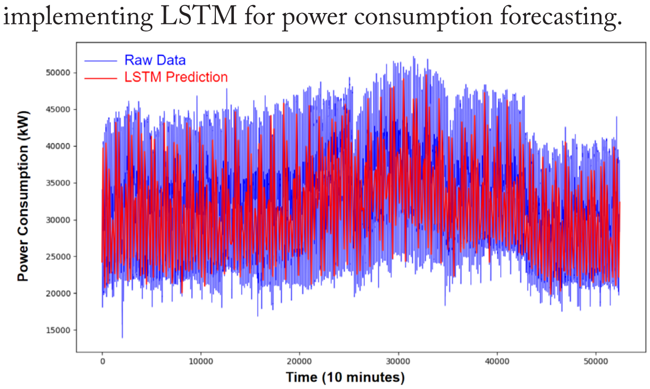


Figure 3: Comparison of raw data versus LSTM prediction using a single previous data point as input, which outputs one prediction data point. Blue curves are raw data, and red curves are LSTM predictions. The similarities between the raw data and LSTM predictions indicate that this algorithm is an effective tool for reproducing power consumption.

Since the LSTM neural network could learn the trends of the dataset, it was then used to predict power demand. This was done by using a train-test split, where 1200 consecutive data points were allocated for training, and the subsequent 252 data points were selected for testing. The training portion of the dataset was input into the LSTM for training, and the testing portion was purely for comparing the output results and was not used for machine learning. The results are shown in Figure 4, where the blue represents the training data, the green represents the testing data, and the red represents the output of the LSTM. One can see that the LSTM output closely follows the patterns of the testing data and suggests that this LSTM is adequate for predicting power consumption.

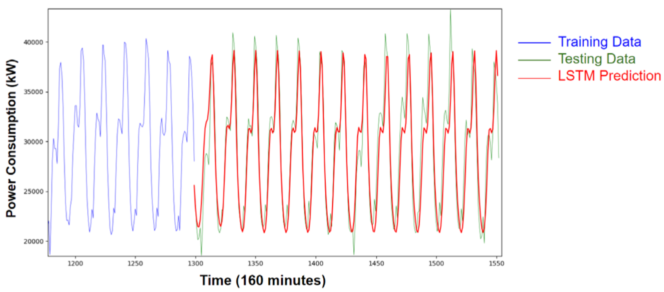


Figure 4: With part of the actual data as training data (blue curve), the remaining data is used as testing data (green curve) to compare the accuracy of LSTM prediction (blue curve). Only a portion of the training data is shown to highlight the details of the comparison. The close agreement of the LSTM prediction to the testing data indicates that this ANN can be used for accurate power consumption prediction.

Conclusion

In summary, an LSTM neural network was developed to analyze the correlation between the power consumption of a Moroccan city with various weather factors within the span of a whole year. The results showed that power consumption depended on these weather variables, with temperature showing the strongest correlation. ANNs were also shown as a powerful tool for forecasting power demand by leveraging these correlated variables, allowing it to be applicable to a wider spectrum of communities, ranging from an apartment complex to an entire nation. The predicted patterns and trends will be important in optimizing power management and developing a smart power grid.

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