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Curve Fitting Optimization for French Electricity Exports Using Recurrent Neural Networks

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ABSTRACT

The employment of a model to predict future values based on previously observed values is known as time series forecasting. Time series forecasting has several practical applications, and these types of challenges are a tough sort of predictive modeling problem. The capacity of recurrent neural networks (RNN) to conduct time-series forecasting is investigated in this research. RNNs use the signals traveling across recurrent connections to create an effective memory for the network, which it may then use to better forecast future time series values using the information in memory. We apply a recurrent dynamic network in this article, and the results show that the RNN model achieves good accuracy in time series forecasting. The purpose of this paper is to use the best types of artificial neural networks to determine the best curve fit for the export chain of Electricity of France. These findings provide the following insights for future research: Adoption of RNN as an alternative to time series prediction methods.

Keywords: Artificial neural networks, RNN, Forecasting, Time series

INTRODUCTION

The objective of supervised learning is to predict something from data. A training set of output (target) and some input variables is fed to an algorithm that learns to predict the target values. The output may be categorical. The task of the algorithm is to deliver high-quality predictions, all by itself, extracting the required knowledge solely from the available data. Neural networks are a popular framework for supervised learning a network-like system of weighted summations and differentiable functions that can learn astoundingly complex things. Usually, variants of gradient descent together with backpropagate are used to find the optimal values of the network weights. This is all simple and intuitive, yet the resulting networks are usually difficult for people to understand. There are so many weights and connections that we just wonder how the system produced the results. We don't understand neural networks, but we like them. The reason for their ever-high popularity is simple: they are good. They can learn arbitrarily complex functions, and they often provide excellent predictions for difficult machine learning problems. NNs are widely used in machine learning, time series prediction is just one example application. In 1974 and 1988 made pioneering work in the field of neural networks by developing a general formulation of backpropagation. applied the method to forecasting and compared it to traditional forecasting methods. In 1991 also made a neural network vs. Box Jenkins comparison and found that NNs outperform the Box-Jenkins model for series with a short memory. For series with a long memory, both methods produced similar results. In 1998 compared neural networks with Box-Jenkins and Holt-Winter's methods for forecasting and found that the design of network architecture and the choice of input variables require great care, and so applying neural networks in black-box mode is not a good idea. They also found that increasing the number of hidden nodes may deteriorate out-of-sample performance. in 2005 Zhang and Qi found that neural networks are not able to capture seasonality by default, and depersonalization and detrending can help their forecasting performance. In 2000, differencing is unnecessary for neural network-based forecasting, but a log transformation may be beneficial. in 2017 provides a more recent review of the applications of deep learning to time series. This paper's purpose is to build the best fit curve for our France electricity export chain using recurrent neural networks. The structure of the paper is divided into three main parts: the introduction, the theoretical and practical part, as well as the conclusions.

METHODS

Artificial Neural Network

Artificial neural networks (ANNs) are computing models for information processing and pattern identification. They grow out of research interest in modeling biological neural systems, especially human brains. An ANN is a network of many simple computing units called neurons or cells, which are highly interconnected and organized in layers. Each neuron performs the simple task of information processing by converting received inputs into processed outputs. Through the linking arcs among these neurons, knowledge can be generated and stored regarding the strength of the relationship between different nodes. Although the ANN models used in all applications are much simpler than actual neural systems, they can perform a variety of tasks and achieve remarkable results. Over the last several decades, many types of ANN models have been developed, each aimed at solving different problems. But by far the most widely and successfully used for forecasting has been the feedforward type neural network (Anbalagan et al., 2020; Ashour et al., 2018; Ashour & Abbas, 2018a, 2018b; Jamal et al., 2021; Minu et al., 2010). Figure 1 shows the architecture of a three-layer feedforward neural network that consists of neurons (circles) organized in three layers: input layer, hidden layer, and output layer. The neurons in the input nodes correspond to the independent or predictor variables (x) that are believed to be useful for forecasting the dependent variable (y) which corresponds to the output neuron. Neurons in the hidden layer are connected to both input and output neurons and are key to learning the pattern in the data and mapping the relationship from input variables to the output variable. With nonlinear transfer functions, hidden neurons can process complex information received from input neurons and then send processed information to the output

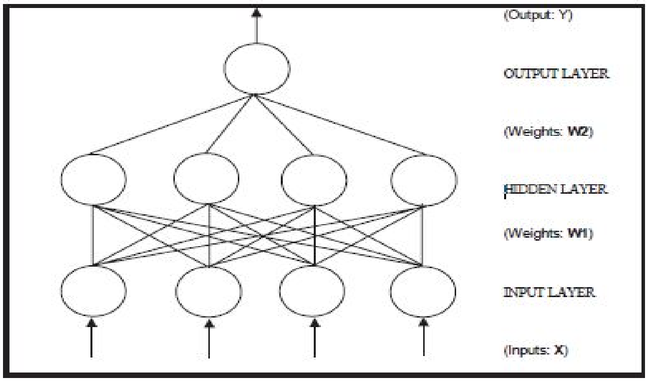

Figure 1: ANN structure.

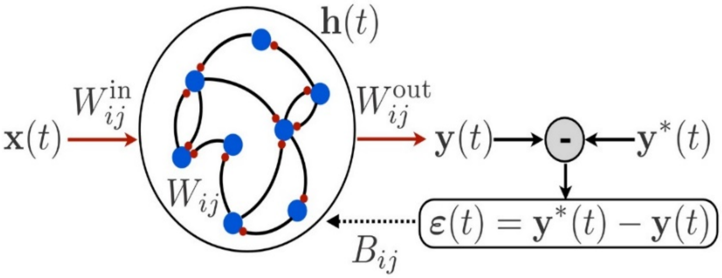

Figure 2: RNN methodology.

layer for further processing to generate forecasts. In feedforward ANNs, the information flow is directional from the input layer to the hidden layer and then to the output layer without any feedback from the output layer (Ahmed et al., 2020; Ashour, 2022; Ashour & Alashari, 2022; Jamal et al., 2021; Minu et al., 2010).

Recurrent Neural Networks

For sequence prediction problems, RNNs are the most commonly used NN architecture. They have grown in popularity, particularly in the field of natural language processing. Unlike ANNs, however, the feedback loops of recurrent cells address the temporal order as well as the temporal dependencies of the sequences. Every RNN is made up of several RNN units. The Elman RNN (ERNN) cell, the long short-term memory (LSTM) cell, and the gated recurrent unit (GRU) cell are the most commonly used RNN units for sequence modeling tasks. Figure 2 illustrates the structure of the recurrent neural network (Abbas et al., 2020; Abdul et al., 2020; Ashour et al., 2018; Ashour & Al-Dahhan, 2021; Derbentsev et al., 2019).

Evaluation

The following criterion is used to evaluate the efficiency of the time series (Ahmed et al., 2020; Ashour, 2022; Ashour et al., 2022; Ashour & Alashari, 2022; Ashour & Al-Dahhan, 2020; Helmi et al., 2018).

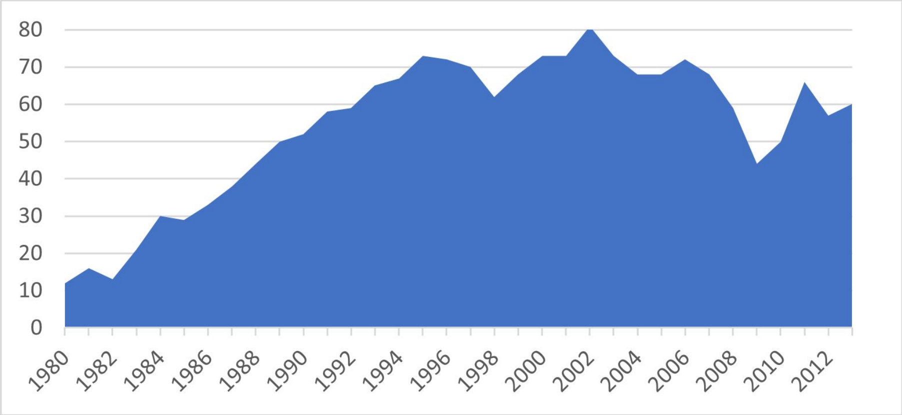

Figure 3: France's electricity exports by year.

Root mean squared error (RMSE)

$$\text{RMSE} = \sqrt[2]{\frac{\sum (y_t - \widehat{y}_t)^2}{n}} \tag{1}$$

Mean absolute percentage error

$$MAPE = \frac{1}{n} \sum \frac{|y_t - \widehat{y}_t|}{y_t} \tag{2}$$

RESULTS AND DISCUSSION

This paper collected 34 years of data consisting of France's electricity export from 1980to 2012 (source: united states energy information). These data are displayed in Figure 3.

Based on the findings of researchers, we assume that short-term trends exist in our foreign exchange series and that we may use various approaches, not necessarily statistical techniques, to model the short-term trend movement of the foreign exchange rates and make predictions. A promising option is the neural network forecasting model.

The ANN structure for this time series is as follows: The variable represents the number of nodes in the input layer, which is one (y_{t-1}). Because the number of time series observed is minimal, the ideal number of nodes in this layer for the first time series is ten. The second time series would have 25 nodes since the amount of time series observed is suitable. The output layer has one node, which is represented by the vector (y_t). For the implementation, the MATLAB high-level programming language was employed. Table 1 shows the quality performers ENN for the time series under consideration.

The results of this study indicate that the Significance and efficiency of error accuracy results, Figure 4 illustrates the curve fitting of the time series.

Table 1. Time series evaluation.

RMSE	MAPE
6.29	9.65

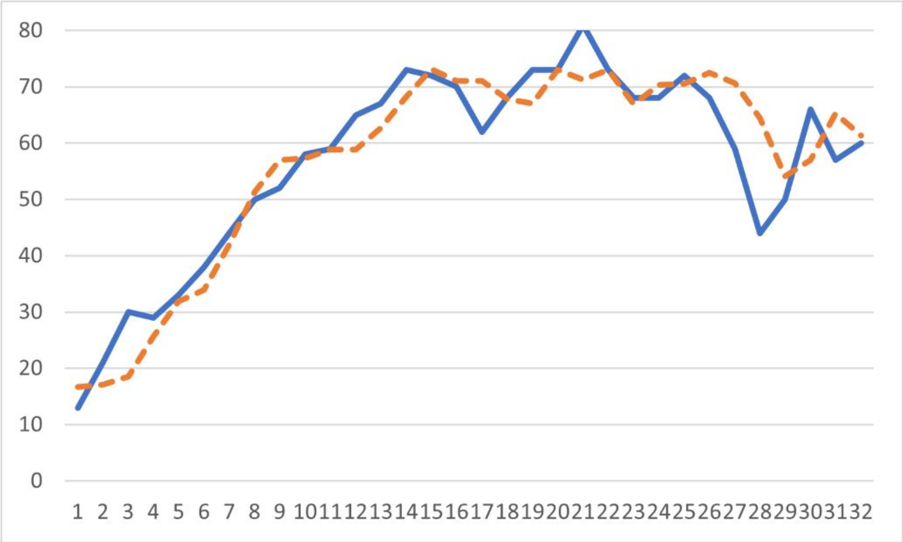

Figure 4: Curve fitting of France's electricity export.

CONCLUSION

In this research, we introduced a method for forecasting time series using recurrent neural networks. RNN has the benefit of requiring minimum preprocessing of the series data and no assumptions about the model underlying the data. In the lack of a strong general nonlinear theory to indicate which strategy is superior in which case, this study relies on experiments and heuristics to guide the methodology, construction, and size of the neural networks. The performance of RNN prediction increased dramatically when each model was utilized independently. Furthermore, the model is likely to be effective in practical applications since it is simple to implement, and the work required to test a large number of prediction models to select the "best" may be decreased.

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