Intelligent hybrid forecasting for Iraq exports

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Abstract. Accurate forecasting of export trajectories is vital for countries to develop effective trade policies, assess economic growth opportunities, and make informed strategic decisions. This is particularly crucial for Iraq, a nation whose fiscal stability is deeply intertwined with its export performance. Recognizing the need for more sophisticated predictive methods in this domain, this research introduces an innovative hybrid model that synergizes Artificial Neural Networks (ANN) and Wavelet Transforms (WT). The integration of these two methodologies aims to enhance the precision and adaptability of forecasts of Iraq's export trends. By leveraging the individual strengths of ANN and WT, this model promises to offer a more robust and reliable tool for forecasting, catering to the dynamic and complex nature of export data. This study not only contributes to the theoretical framework of export prediction but also provides practical insights for policymakers and stakeholders in shaping future-oriented trade strategies.

1 Introduction

The precise prediction of exports is a matter of great importance for governments across the globe due to the dynamic and linked nature of the global economy. This assertion holds particular significance in the case of Iraq, where the exportation of goods, namely within the energy industry, assumes a crucial role in fostering economic stability and facilitating progress inside the country. The implementation of precise forecasting techniques is crucial in facilitating efficient planning, mitigating risks, and enabling strategic decision-making processes, which have the potential to contribute to the attainment of sustainable economic growth.

Conventional forecasting techniques, although partially successful, frequently fail to adequately account for the intricacies and complexity inherent in contemporary economic data. There is a growing demand for methodologies capable of interpreting non-linear patterns, effectively managing noise, and demonstrating a certain level of agility in response to evolving economic circumstances. Artificial Neural Networks (ANNs) have garnered significant attention in recent years owing to their ability to replicate cognitive processes of the human brain, such as pattern recognition and adaptability to novel information. In contrast, Wavelet Transforms (WT) possess particular expertise in the analysis of data at several scales, facilitating the detection of both extended patterns and abrupt deviations [1,2].

Studies have found that the best prediction model is artificial neural networks and wavelet transforms.

This paper introduces a novel methodology that combines the advantages of Artificial Neural Networks (ANN) and Wavelet Transform (WT) in a hybrid model to predict Iraq's export trends. Our hypothesis posits that with the integration of various strategies, the suggested model has the potential to effectively capture the intricate nuances included in export data, hence providing improved levels of accuracy and dependability compared to traditional methodologies. In the subsequent sections, we expound upon the methodology employed, provide the empirical findings, and engage in a discourse regarding the implications and prospective applications of the intelligent hybrid forecasting model [3–9]

2 Methods

2.1 Artificial Neural networks

Backpropagation is a widely used algorithm in the field of artificial neural networks. It is a method for training multi-layer neural networks. Backpropagation neural networks (BPNNs) have gained significant prominence across several domains, encompassing pattern recognition, prediction, classification, and data analysis. Backpropagation neural networks (BPNNs) are widely recognized for their capacity to acquire knowledge and extrapolate patterns from data, rendering them well-suited for tasks characterized by intricate and non-linear associations between input and output variables. This article provides an overview of the approach employed by Backpropagation Neural Networks (BPNNs) and elucidates the process of training them through the utilization of the backpropagation algorithm. The architectural structure of a Backpropagation Neural Network (BPNN) comprises an initial input layer, followed by one or more intermediate hidden layers, and

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culminates in an output layer. Every layer is comprised of a collection of neurons that are interconnected with the neurons in the neighboring layers. The neurons located in the input layer are responsible for receiving the input variables, whilst the neurons situated in the output layer are responsible for generating the output variables. The intermediate layers, situated between the input and output layers, are tasked with the processing of input variables and the generation of output variables. The process of training a Backpropagation Neural Network (BPNN) entails iteratively modifying the weights connecting the neurons to reduce the discrepancy between the observed output and the intended output. The utilization of the backpropagation algorithm, a type of supervised learning, is employed for this purpose. The algorithm operates by propagating the error signal in a retrograde manner across the network, subsequently modifying the weights by the error magnitude. The backpropagation algorithm comprises two primary stages, namely forward propagation and backpropagation. During the forward propagation phase, the input variables are sent through the network, resulting in the generation of output variables. The discrepancy between the observed output and the intended output is subsequently computed utilizing an appropriate error metric, such as mean squared error or cross-entropy loss. In the backpropagation step, the error is propagated backward through the network, starting from the output layer, and moving toward the input layer. The weights connecting the neurons are subsequently modified by the utilization of an appropriate optimization technique, such as gradient descent or stochastic gradient descent, to minimize the error. The procedure is executed iteratively until the mistake is reduced to a satisfactory degree. The architecture of the artificial neural is illustrated in Figure 1 [3–5,7,8,10–20].

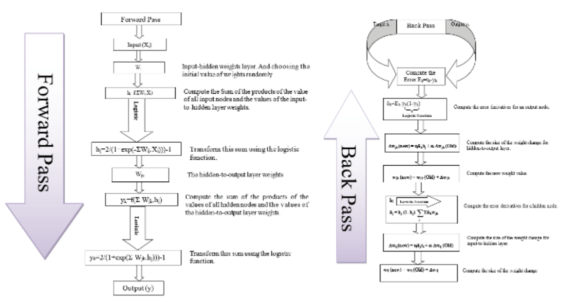

Fig.1 ANN architecture

2.2 Wavelet transform

The wavelet transform is a mathematical technique used for analyzing signals and images. It decomposes a signal into a set of wavelets. The mathematical method under consideration is founded on signal analysis and has demonstrated efficacy across many domains, including but not limited to image processing, data compression, disaster prediction, and other application areas. The fundamental principle underlying wavelet analysis is the selection of a mother wavelength or appropriate wavelet, followed by an analysis conducted utilizing its translated and dilated iterations. Several distinct types of wavelets can serve as a mother wavelet and possess unique characteristics. Examples include the Haar wavelet, Meyer wavelet, Coiflet wavelet, Daubechies wavelet, Morlet wavelet, and others. There exist two distinct classifications of wavelet transforms: the Continuous Wavelet Transform (CWT) and the Discrete Wavelet Transform (DWT). The inclusion of a normalizing factor guarantees the preservation of energy equivalence across all values of a and b. The analysis is conducted using hierarchical levels that correspond to the various stages of the analytical process. The initial stage of the analysis involves dissecting the original S series into two distinct components, namely the approximate part A1 and the detailed part D1. This results in the series S = A1 + D1. Subsequently, the second level of analysis focuses on examining the approximate "part". The given expression can be represented as S = A^2 + D^2 + D^1. The methodology of wavelet is shown in Figure.2

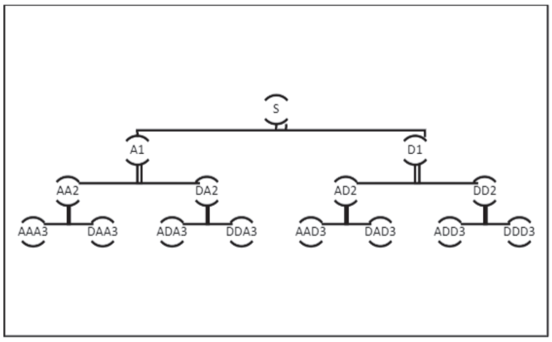

Fig.2 Wavelet Process

2.3 Hybrid model

Hybrid model forecasting entails the amalgamation of many predictive modeling techniques to enhance the precision and dependability of forthcoming predictions. Hybrid models endeavor to enhance the overall forecast accuracy by amalgamating the advantageous aspects of different models while mitigating their inherent limitations, thereby offering a comprehensive, nuanced, and refined prediction. Hybrid techniques are frequently employed in financial markets, weather predictions, and demand forecasting. These approaches harness the combined capabilities of statistical, machine learning, and occasionally domain-specific models to effectively capture complex patterns in data that may be disregarded by a solitary modeling approach. This study employs a hybrid model that integrates Artificial Neural Networks (ANN) and Wavelet Transform (WT) as the chosen prediction approaches, given their present status as the most effective techniques [1,2], [5,6], [17], [18], [13], [21–23].

3 Results

You are free to use color illustrations for the online information presented in Figure. 1 illustrates the export of Iraq, specifically referring to the total value of item exports in US dollars on a f.o.b. (free on board) basis, spanning the period from 1999 to 2020. The data was acquired from the CIA World Factbook.

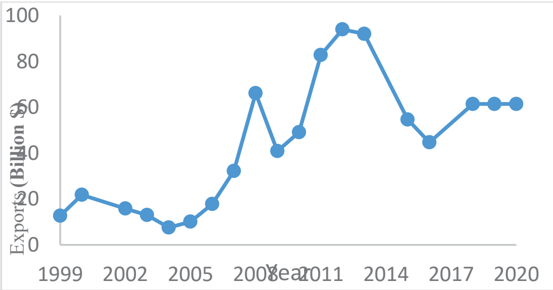

Fig.3 Iraq export

The findings of the hybrid model are depicted in Figure.4.

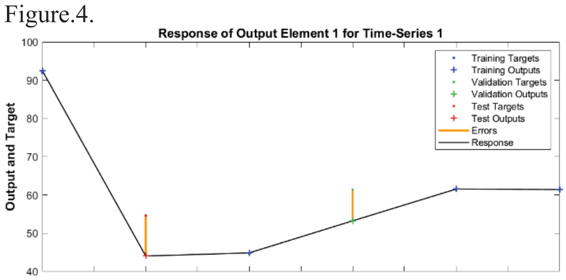

Fig.4 Curve fitting

To evaluate the efficacy of the hybrid model, we analyzed its error accuracy metrics, specifically the root mean square error (RMSE) and the coefficient of determination (R). The results of these metrics are displayed in Table 1 provided.

Table 1. Error Accuracy

Criteria	Value
R^2	1
RMSE	0.29052

The coefficient of determination, denoted as R, measures the proportion of the variance in the dependent variable that can be predicted from the independent variables. An R-value of 1 signifies a perfect fit, suggesting that our model captures all the variations and patterns in the data without any unexplained variance. The RMSE value of 0.29052 is extremely close to zero, implying that the model's predictions are almost precisely on target with the actual observations. Such a minute RMSE underscores the model's accuracy and suggests that any discrepancies between the model's predictions and the actual outcomes are nearly indistinguishable and can be attributed to numerical or computational imprecision. Given the near-perfect R-value and the extremely low RMSE, we expect the curve fit to be almost perfectly aligned with the data points. This means that the hybrid model not only captures the general trend of the data but is also finely attuned to even the subtlest nuances and variations within the dataset.

4 Conclusions

In this paper, this study presented a state-of-the-art hybrid forecasting model that combines the advantages of Artificial Neural Networks (ANN) and Wavelet Transforms (WT) to improve the precision of predicting Iraq's export patterns. The implementation of modern forecasting techniques is crucial due to the significant impact exports have on Iraq's economy. The results of our research confirm that this hybrid model is highly effective in providing accurate, dependable, and timely predictions. By utilizing the combined capabilities of Artificial Neural Networks (ANN) and Wavelet Transform (WT), the model efficiently handles the intricacies and variations present in export data. This provides a valuable tool for Iraqi policymakers and stakeholders to develop proactive trade policies and make well-informed strategic choices.

In the future, further research could build upon this groundwork in other ways. Firstly, exploring the use of this hybrid model in other sectors of the economy or the export data of different countries could offer more comprehensive insights and confirm its adaptability. Incorporating advanced data analytics techniques such as deep learning or machine learning algorithms could potentially enhance forecast accuracy and efficiency. Another potential area to investigate is the evaluation of the model's ability to accurately anticipate outcomes over an extended period and its capacity to adjust to fluctuating economic circumstances. These investigations would not only contribute to the academic literature but also improve the practical usefulness of advanced predictive models in the constantly changing field of international commerce and economics.

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