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Application of neuro-fuzzy methods for stock market forecasting: a systematic review

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Abstract

Predicting stock prices is a challenging task owing to the market's chaos and uncertainty. Methods based on traditional approaches are unable to provide a solution to the market predictability issue. Thus, contemporary models using accurate neuro-fuzzy systems are found to be the most effective approach to tackling the problem. However, the existing literature lacks a detailed survey of the application of neuro-fuzzy techniques for stock market prediction. This paper presents a systematic literature review of the use of neuro-fuzzy systems for predicting stock market prices and trends. On this basis, articles issued in various reputed international journals from 2000 to July 2022 were examined, 11 duplicates and 4 non-exclusive articles were removed and, as consequent, 24 eligible studies were retrieved for inclusion. Thus, analysis and discussions were based on two major viewpoints: predictor techniques and accuracy metrics. The review reveals that the researchers, based on their knowledge and research interests, applied a diverse neuro-fuzzy technique and shown stronger preference for certain neuro-fuzzy methods, such as ANFIS. To draw conclusions about the model performance, researchers chose different statistical and non-statistical metrics according to the technique used. It was finally observed that neuro-fuzzy approaches outperform, within its limits, conventional methods. However, each has its own set of constraints regarding the challenges involved in putting it into practice. The complexity of the presented approaches is the most significant potential obstacle that they face. Therefore, stock market prediction is a difficult undertaking, and multiple elements should be considered for accurate prediction. Yet, despite the subject's prominence, there are still promising new frontiers to explore and develop.

Keywords: Fuzzy logic, Artificial neural network, Neuro-fuzzy, stock market forecasting
JEL Classification: F37
Paper type: Theoretical Research

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1. Introduction

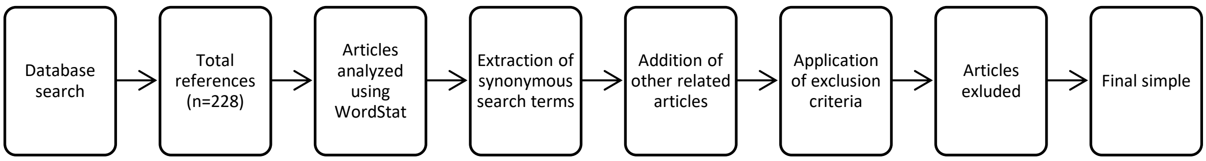
A stock market is a set of marketplaces and exchanges where securities such as stocks, bonds, and other types of securities are issued and traded by stock brokers, individual traders, and investors. Traders constantly buy and sell shares or other assets in order to make quick gains, whereas investors maintain their holdings for a long period to profit from price increases. By choosing to make an investment in the stock market, the investor may find itself confronted with the perceptiveness and consistency of his choices. In order to refine his certainties, investment valuation constitutes a categorical imperative. Moreover, investors and professionals have always sought to predict market movement. In fact, the early stock market researchers were driven by the widespread perception that stock returns were unpredictable, presuming that the stock market followed a random walk and prices reflected all relevant information instantaneously (Bachellier (1900), Osborne (1959)). Likewise, Fama (1970) provided in his survey paper a definite and conclusive declaration of this viewpoint. Cowles (1960), Osborne (1962), and Samuelson (1965) are only a few of the studies that shed light on the random walk character of movements in equity prices. However, researchers began seriously considering predictable market returns until the late 20th century owing to transient deviations from the efficient market hypothesis. Recent research, such as the Dow Theory, has claimed that a financial market typically has a tendency to follow a particular and hard-to-spot pattern and confirmed that stock market returns are given foreseeable historical returns and macroeconomic and financial factors. Predictability of stock market returns spurred researchers to study its sources (Gençay, 1998). Broadly, there are two types of analysis that are used for forecasting – technical and fundamental analysis (Black, 1982). Technical analysis forecasts an asset's price trend using price charts, patterns, and signals. A clear insight on the current market activity is what traders seek in this form of study. Fundamental analysis evaluates all aspects affecting a firm's stock price. The purpose is to assess the asset's intrinsic value and if it is over or undervalued. Usually employed by long-term investors. However, these traditional approaches are unable, at least partially, to provide a solution to the market predictability issues. Stock market price forecasting is a complex and challenging endeavor due to many factors, both micro and macro, that contribute to the creation of stock market prices. These factors reinforce the market's nonlinear and nonstationary traits, hence promoting the complexity of the task. In recent years, the area of artificial intelligence and soft computing methods, including artificial neural networks and fuzzy systems, have made great strides. In point of fact, expert systems, artificial neural networks, and fuzzy logic systems all have characteristics in common with one another. Neural networks perceive patterns and adapt to changing circumstances, while Fuzzy inference system uses human expertise to comprehend trading and forecasting. Using fuzzy logic, neural computing may be linked with symbolic thinking to address complicated real-world issues. Due to its inherent complexity, the stock market prediction issue demands merging many computer approaches synergistically, rather of relying on any one of them entirely, leading to the development of hybrid intelligent system models. They provide valuable forecasting capabilities for noisy environments such as financial markets, capturing their nonlinear nature (Atsalakis & Valavanis, 2009). The combination of these two complimentary methods, along with specific derivative-free optimization techniques, yields neuro-fuzzy system models (Jang et al., 1997). The earliest neuro-fuzzy research dates to the early 1990s with Jang (1992), Lin & Lee (1991) and Berenji & Khedkar (1992) as they proposed using neural network learning computational features as an alternative to automating the generation of fine-tuned fuzzy systems. Since the advent of fuzzy systems, it was well understood that developing a high-performing fuzzy system would be no simple feat. The challenge of finding an accurate membership functions and rules is a time-consuming process

of trial and error. As a result, the concept of using learning algorithms with fuzzy systems emerged.
The purpose of this systematic review is to gather and analyze the existing articles in the literature, focusing on neuro-fuzzy techniques for forecasting prices and trends in the stock market, highlighting the accuracy metrics used to validate the model adopted. Thus, this paper is organized as follows. Section 2 presents the research methodology. An analysis of the considered articles is presented in Section 3. Section 4 reports on the research gaps. Finally, Section 5 sets the conclusions.

2. Research Methodology

This literature review intends to give comprehensive insights into the application of neuro-fuzzy methods for stock market forecasting and to outline the potential directions of study. Thence, the study's methodology is based on the systematic literature review, a common method that collects complete and fair evidence from the existing literature (Kitchenham and Charters, 2007) and pinpoint its shortcomings (Xiao & Watson, 2017). Therefore, given the gathered information, the criteria used in this work are justified, and the methodology that was applied in conducting this review will be described in further depth below (figure 1).

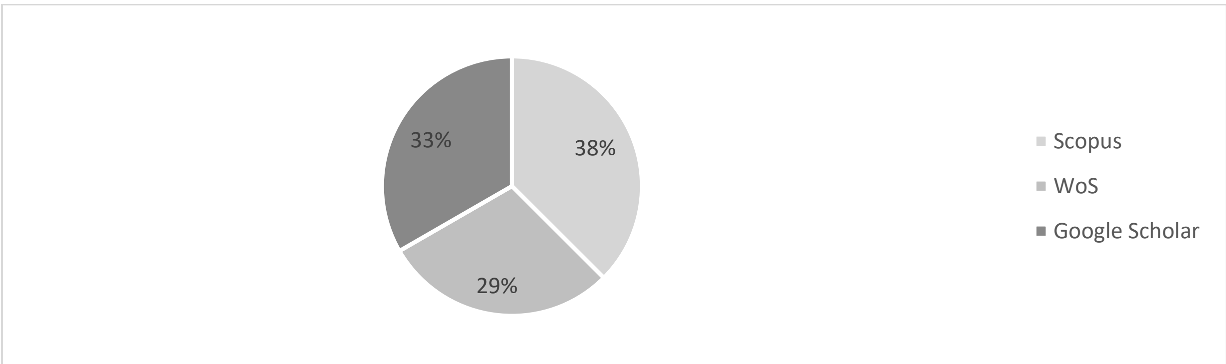
Figure 1: ***Synthesis of the systematic review procedure***



Source: Authors

The initial phase of the identification procedure was a search of all publications published up until July 2022 for the occurrence of the phrase "Neuro-fuzzy methods for stock market forecasting" in the title, abstract or keywords. As suggested by vom Brocke et al. (2015), our search included many databases and a variety of search techniques. As a result, the searches were conducted, as shown in Figure 2, in three distinct databases: Scopus, Google Scholar and Web of Science.

Figure 2: The references collected by source



Source: Authors

This search yielded a total of 228 articles. Therefore, all the 228 articles were retrieved and evaluated with the software WordStat 9 to obtain search terms that related to the subject matter.

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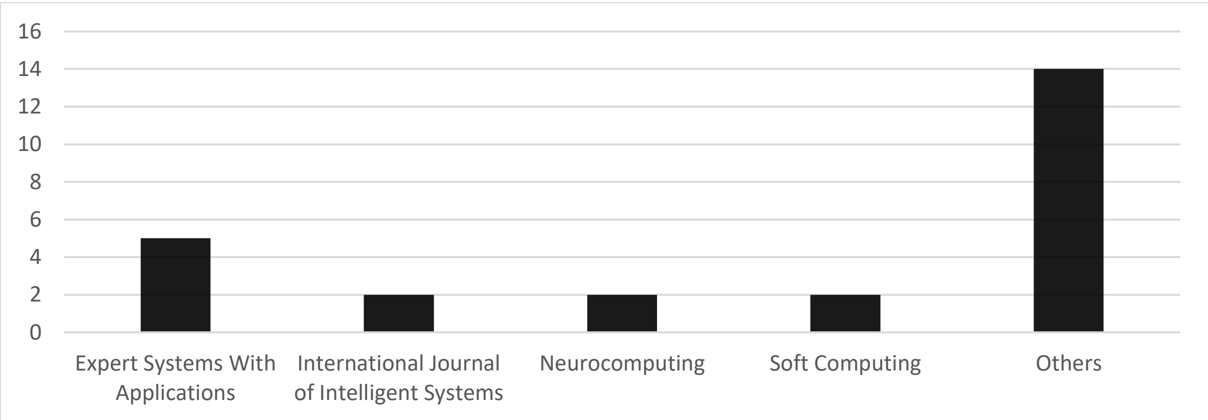
This long array of supplementary search strings was essential in catching possible synonyms and variants. Thus, the search string used was: ((‘‘Artificial Neural Network’’) OR (‘‘Fuzzy Logic’’) OR (‘‘Fuzzy Inference System’’) OR (‘‘Neuro-fuzzy System’’) OR (‘‘Soft Computing’’)) AND ((‘‘Stock Market’’) OR (‘‘Financial Market’’) OR (‘‘Equity Market’’) OR (‘‘Stock Exchange’’) OR (‘‘Foreign Exchange’’) OR (‘‘Stock Index’’)) AND ((‘‘Prediction’’) OR (‘‘Forecasting’’)). To the 228 initial articles, 14 more were added. To balance practicality and comprehensiveness, as suggested by Paré et al. (2015) and Tranfield et al. (2003), 11 duplicates and 4 non-exclusive articles were removed. Furthermore, in order to guarantee decent quality of the academic work, two additional exclusion criteria were implemented:

- Editorial notes, monographs, theses, presentations, working papers and book reviews were omitted and we exclusively used peer-reviewed studies to assure quality (Davison et al., 2005);
- Articles published in a language other than English are eliminated. We considered English journal articles since they play a key role in the research and dissemination process in disciplines with rapidly evolving information. (Bandara et al., 2011).

As a result, this process retrieved a sample of 24 articles. The majority of the evaluated articles come from indexed journals, as can be seen in Figure 3. The remaining articles are disseminated in 9 other journals.

Figure 3: Main journals of corresponding papers



Source: Authors

3. Analysis of the considered articles

After exposing the research front's structure, all sample papers were scrutinized and differentiated based on the predictor techniques and the accuracy measures.

3.2. Analysis based on predictor techniques

There are several ways to tackle the challenging task of developing an expert system for the financial markets, which are notoriously difficult to predict. Models incorporating fuzzy logic, neural networks, and hybrid learning procedures have been developed to accurately anticipate stock market movements. The researchers used a variety of neuro-fuzzy methods and learning techniques depending on their expertise, research interest and abilities. The review indicates an interesting diversification in the use of neuro-fuzzy techniques. But among the various neuro-fuzzy techniques, some techniques like ANFIS have been more favored by the researchers.

Cheng et al. (2007) proposed using ANFIS and neuro-fuzzy network to predict investors' actions prior to before an event change or a company’s results announcement. Their research demonstrates the ANFIS's forecasting capabilities in the financial sector, but they also imply that some market behaviors are outside the scope of prediction. Atsalakis & Valavanis (2009) challenged the Efficient Market Hypothesis by exhibiting significantly enhanced and better forecasts of short-term stock market movements, in particular the next day's trend of chosen stocks, using an ANFIS-based neuro-fuzzy system. The proposed method is proven to be better than the "buy and hold" strategy and various other approaches. A different model was proposed Alizadeh et al. (2010), they suggested using ANFIS to predict stock portfolio returns. They found that predicted portfolio profits may be improved by using technical and basic attributes of different stock exchange indices as ANFIS inputs and that the suggested approach outperforms the traditional Markowitz portfolio optimization method and others in terms of predicting future portfolio returns, according to experimental data. Boyacioglu & Avci (2010), used ANFIS to explore the possibility of predicting the monthly return of the stock market considering a total of six macroeconomic factors and three indices. The experimental results confirmed that the model based on the ANFIS algorithm was able to accurately anticipate monthly earnings by predicting the prices of stocks listed on the Istanbul Stock Exchange. Trinkle (2005) utilized ANFIS and a neural network to predict the companies' yearly excess returns. Based on the findings, it is clear that both the methods may give reliable predictions. But neither method outperformed the traditional or naïve models. In turn, Cuong & Chien (2012) presented a stock price prediction experiment based on ANFIS. The suggested model outperforms the traditional model, according to the results. Furthermore, Yeh & Chang (2012) used the neural network and ANFIS for anticipating chaotic traffic volumes. The two models have approximately the same accuracy, but ANFIS is more time-consuming to train. Regarding the works that employed the ANFIS method, which constitutes more than half of the publications that were examined and some of these studies took a similar tack in terms of data pre-processing, results comparisons, and accuracy measures. The results indicate that the capacity of the ANFIS model to learn and make predictions in financial applications, but they also reveal that certain of the behaviors of the market are too complicated to be predicted.

On the other hand, Kumar Chandar (2019) suggested that a model forecast the stock market using a fusion of wavelet-adaptive network-based fuzzy inference system (WANFIS). The suggested fusion model yields greater predicting accuracy than either model independently. Based on the findings, the fusion model WANFIS is seen as a potentially valuable tool for economists and practitioners in the stock market. Moreover, Cheng et al. (2009) proposes a novel fusion ANFIS model for forecasting Taiwanese stock prices. Experimental results reveal that the proposed model outperforms both Yu's and Chen's in terms of RMSE and realized profit. Unlike most published works, Tan et al. (2007) presented an innovative RSPOP Intelligent Stock Trading System, which makes use of the widely established Moving Average and Relative Strength Indicator Trading Rules in conjunction with the powerful forecasting potential of RSPOP FNN. Empirical evidence shows that the method achieves much larger Multiplicative Returns than a standard technical rule trading system. A different model was proposed by Nair et al. (2010), they suggested an automated decision tree-adaptive neuro-fuzzy hybrid automated stock market prediction system. Comparisons with decision tree based and ANFIS without feature selection and dimensionality reduction demonstrated that the developed hybrid system generates substantially greater accuracy. Moreover, Bekiros (2007) studied the predictive capacity of trading techniques utilizing neurofuzzy models, recurrent neural networks, and linear regression. The results show that the neurofuzzy model's trading rule is more profitable than other models and a buy-and-hold strategy in markets downturn. Furthermore, Mahmud & Meesad (2015) used a recurrent error-based neuro-fuzzy system with momentum (RENFSM) that uses time series price momentum and time series prediction error adjusted to ANFIS to forecast stock market prices. Compared to other approaches, including ANFIS and neural networks, the suggested RENFSM was proven to be more effective and

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accurate. It is worth highlighting the work of Zarandi et al. (2012) who introduced a four-layer fuzzy multiagent system (FMAS) architecture to build a hybrid model for predicting next-day stock prices. Based on the findings, FMAS outperforms competing approaches, hence it can be regarded as a viable tool for stock price prediction. In addition, Su & Cheng (2016) presented a new ANFIS time series model based on the integrated nonlinear feature selection (INFS) technique. The findings reveal that the suggested technique performs in precision, profit evaluation, and statistical testing compared to the other models. Sedighi et al. (2019) introduced a novel integrated technique based on ABC, ANFIS, and SVM to accurately predict future stock prices. The study shows that the proposed method is superior to the alternatives in terms of accuracy and quality and proves that is a useful tool in stock price forecasting and helping traders and investors recognize stock price trends. Rajab & Sharma (2017) offers a neuro-fuzzy system for stock price prediction utilizing many technical indicators. The findings demonstrate that compared to two artificial intelligence and two statistical methods typically employed in stock price prediction, the suggested system finds a superior trade-off between accuracy and interpretability. Finally, Sharma et al., (2021) developed forecasting models utilizing ANFIS and WT for the DOW30 and NASDAQ100. The empirical findings showed that the model with the trapezoidal membership function is more accurate than the bell-shaped model.

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Table 1: Examined articles

Researchers	Market	Period	Time-frame	Predictor	Comparisons	Performance metrics	Results
Abraham et al., 2004	American	January 1995 - January 2002	Monthly	Takagi-Sugeno fuzzy inference system learned using a NN algorithm	ANN trained using the Levenberg-Marquardt algorithm, support vector machine, difference boosting neural network	RMSE, MAPE	All the methods considered could represent the stock indices behavior very accurately.
Alizadeh et al., 2010	Iranian	December 2005 - July 2008	Daily	ANFIS	Neural network, Markowitz approach, Multiple regression, Sugeno-Yasukawa model	RMSE	ANFIS performs better in predicting the portfolio return than the other methods.
Atsalakis & Valavanis, 2009	Greek - American	January 1986 - March 2005	Daily	ANFIS	-	HIT, RMSE, MAE, MSE	The proposed system is superior compared to the "buy and hold" strategy and several other reported methods.
Atsalakis et al., 2011	Greek	April 2007 - November 2008	Daily	WASP - ANFIS	-	-	The WASP System has been found to be extremely useful and accurate, it outperformed the Buy & Hold strategy.

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Bekiros, 2007	Japanese	August 1971 - May 2002	Daily	Neuro-fuzzy model	RNN and linear Autoregression model (AR)	Sign Rate, Sharpe Ratio, Ideal Profit (IP), Henriksson–Merton (HM)	The profitability of the trading rule based on the neuro-fuzzy model is higher to that of the other models as well as of a buy and hold strategy during bear market periods.
Boyacioglu & Avci, 2010	Turkish	January 1990 - December 2008	Monthly	ANFIS	-	RMSE, R2, coefficient of variance	The model successfully forecasts the monthly return of ISE National 100 Index with an accuracy rate of 98.3%.
Cheng et al., 2007	American	July 1999 – June 2002	Daily	ANFIS	-	SE, ME and Fed	The model is more successful in predicting when the investors take actions than what actions they take and the extent of their activities. ANFIS has a good learning and predicting potential in financial applications.
Cheng et al., 2009	Taiwanese	1997 - 2003	Daily	Fusion ANFIS	Two fuzzy models reported in the literature (Chen's model and Yu's model)	RMSE	The proposed model is superior to the listing methods in terms of root mean squared error. The profits comparison results for the proposed model produce higher profits than the listing models.

Cuong & Chien, 2012	Vietnamese	January 2009 to September 2010	Daily	ANFIS	Back propagation, hybrid learning algorithm	RMSE	The proposed model makes higher performance compared to the traditional model.
Esfahanipour & Aghamiri, 2010	Taiwanese and Iranian	July 2003 – December 2005 & April 2006 - January 2009	Daily	ANFIS	BPN, multiple regression, the TSK fuzzy rule model proposed by Chang and Liu (2008)	MAPE	The proposed model had high accuracy near by 97.8% when tested on the Tehran Stock Exchange Indexes.
Guan et al., 2018	Taiwanese and Chinese	January 1999 - October	Daily	HTBP Neural Network model	Single BP neural network	RMSE, MSE, MAE, MPE	The experimental results show that the proposed method can predict the stock market in a very simple way.
Janková & Dostál, 2020	European	2014 - 2018	Daily	ANFIS	-	RMSE	The developed ANFIS model is a suitable tool for predicting stock indexes and it shows a strong predictive capacity of both efficient and less efficient stock markets.
Kumar Chandar, 2019	Indian	January 2010 - June 2015	Daily	WANFIS	ANN, hybrid model of Wavelet with ANN	RMSE, AAE, CoV, MAPE and R^2.	The proposed fusion model achieves better forecasting accuracy than either of the models used separately.

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Mahmud & Meesad, 2015	Bangladesh	January 2009 - August 2013	Daily	RENFSM	ANFIS, FTDNN, and NARX	RMSE, MdAPE, MAPE and MASE	The proposed RENFSM performed superiorly and was more reliable compared to the existing methods such as ANFIS and neural networks.
Nair et al., 2010	Indian	February 2006 – March 2010	Daily	Decision tree-KPCA-ANFIS hybrid system	Decision tree-based system and ANFIS	MSE, RMSE, MAE, Md.AE, MAPE, Md. APE, SMAPE and SMdAPE	The proposed hybrid system produces much higher accuracy when compared to stand-alone decision tree-based system and ANFIS based system without feature selection and dimensionality reduction.
Rajab & Sharma, 2017	Indian	January 2005 - December 2015	Daily	Neuro-fuzzy system for stock market trend prediction using multiple technical indicators	ANFIS, Back-propagation-based ANN, MRA, GARCH	RMSE, MAPE and DA	The proposed system obtains a better balance between accuracy and interpretability than the two AI and statistical techniques.
Sedighi et al., 2019	American	2008 - 2018	Daily	ABC-ANFIS-SVM	-	RMSE, MAE, MAPE, and Theil's U	The proposed model is successful in stock price forecasting and assist traders and investors to

							identify stock price trends, as well as it is an innovation in algorithmic trading.
Sharma et al., 2021	American	January 2015 – January 2020	Daily	WT-ANFIS	ANFIS models	MAE, MAPE, RMSE	The trapezoidal membership function (MF) outperforms the model with the bell-shaped MF with the maximum accuracy. The numbers and types of fuzzy MF have clearly been found to play a substantial effect in the forecasting process.
Su & Cheng, 2016	Taiwanese	1998 - 2006	Daily	Hybrid Fuzzy Time Series Model Based on ANFIS and INFS	Two fuzzy models reported in the literature (Chen's model and Yu's model), INFS + ANFIS model and INFS + SVR model	RMSE and Theil's U Statistic	The proposed method outperforms the listing models in accuracy, profit evaluation and statistical test.
Svalina et al., 2013	Croatian	January 2012 – October 2012	Daily	ANFIS	-	AvCV(RSME), AvRE	The approach is useful for predicting within its limits.
Tan et al., 2007	Singaporean	January 1991 -	Daily	RSPOP	RBFN, ANFIS	Mean Error	The proposed model is able to outperform the buy-and-hold strategy and generate several

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		December 2004					returns over an investment horizon of four years.
Trinkle, 2005	American	1954 - 2002	Annually	ANFIS	ARMA	RMSE and MAPE	The ANFIS and the neural network generated profits in all of the trading scenarios. However, neither technique dominated the other, nor did they consistently outperform the traditional and naive models.
Yeh & Chang, 2012	Taiwanese	November 2008	5-min, 10-min and 15-min	ANFIS	Feedforward Backpropagation Neural Network	-	The two models have almost the same accuracy, while ANFIS takes more time to train. Although the effective number of neurons in the hidden layer is less than half the number of the input elements, the NN can have satisfactory performance.
Zarandi et al., 2012	British and American	Feb 2003 - Mar 2005	Daily	FMAS	HMM, Hybrid of HMM, ANN, and GA, Hybrid of HMM and fuzzy logic, ARIMA, ANN	MAPE	FMAS outperforms all the comparative methods, so it can be considered as a suitable tool for stock price prediction problems.

Source: Authors

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3.3. Analysis based on accuracy metrics

As stock market research, measuring model accuracy is crucial to draw conclusions about the correlations and patterns among the variables in a dataset given the input and the data used to train it. Evaluation metrics change according to the researchers and technique used. Table 1 lists the metrics used to evaluate each author's method. The Mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and R-Squared are the most popularly used accuracy metrics for the evaluation of neuro-fuzzy prediction models. Additionaly, Sedighi et al., (2019) used the Theil's U measure, while Svalina et al. (2013) used AvCV(RSME), AvRE. Yet, there are a variety of measures for accuracy, each based on a unique type of measurement. For instance, squared errors and absolute errors are used as the basis for several error metrics, MSE, RMSE and MAE, while percentage errors are used in both the MAPE and SMAPE calculations. Different accuracy measures reveal differing levels of effectiveness. And due to the fact that all accuracy measurements have their own set of strengths and weaknesses, some accuracy metrics may not be suitable for a given prediction model. As a result, choosing the right accuracy metric for evaluating prediction models is crucial. In addition to these statistical measures, there are some non-statistical performance measures include measures associated with the forecast's financial aspects. Bekiros (2007) used the Sign Rate (SR) which measures the proportion of correctly predicted signs, the Sharpe Ratio (SR) which is defined as the ratio of the mean return of the strategy over its standard deviation, and the Ideal Profit (IP) to evaluate of the forecast accuracy of the models.

To verify the proposed models, an evaluation of the model's accuracy and comparison to other models was implemented. Atsalakis & Valavanis (2009), Boyacioglu & Avci (2010), Cheng et al. (2007), Janková & Dostál (2020) and Svalina et al. (2013) took multiple metrics for model accuracy measurement. They found that ANFIS model is viable and useful for investors and provides higher accuracy. Besides, the related work carried out by Alizadeh et al. (2010), Cheng et al. (2009), Cuong & Chien (2012) and Esfahanipour & Aghamiri (2010) used different models in various markets to compare with the ANFIS model. The results of accuracy metrics revealed that the ANFIS model has higher predictive power than the other model due to its higher predictive accuracy. Whereas Trinkle (2005) and Yeh & Chang (2012) have found that neither the neuro-fuzzy or the comparative model dominated the other, nor did they consistently outperform the traditional and naive models.

4. Research Gaps and Issues

Regardless of the variety of techniques to predict the stock market, each has its own set of constraints that must be overcome before accurate predictions can be made. In this section, we will discuss the study limitations and gaps that exist within the various methods of predicting the stock market.

Forecasting financial market values is exceedingly challenging since there are many economic and political elements that impact them. The review demonstrates large differences in the usage of neuro-fuzzy approaches as the researchers applied their learning strategies based on their areas of competence and research interests. The use of soft computing techniques is effective in financial forecasting, but there are usually a considerable number of challenges involved in putting them into practice. The complexity of the presented approaches is the most significant potential obstacle that they face.

Another limitation is associated with the experimental data employed that it comes solely from developed markets with well-founded financial systems. Broadening the scope of the study to include fast expanding emerging economies with underdeveloped financial markets is a viable option. In addition to this, most researchers have opted for daily data samples with minimal

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missing values. Longer data periods used as inputs don't ensure better outcomes. Another limitation about the forces that move stock prices. Alongside with technical and fundamental factors, there is a major element that may influence stock prices: market sentiment which includes market psychology in a trading strategy. These models can be improved considerably by emulating the behavior of real traders in financial markets.

Furthermore, regarding the testing and validation of the model. Proposing a forecasting model that is both straightforward and easy to understand is critical tasks in this field. Despite the fact that no model can be definitively demonstrated to be correct, validation is concerned with assessing the robustness and consistency of model performance. Many research, published in recent years, on the use of neuro-fuzzy systems in financial markets focused on improving accuracy with regard to error measurements like MAE, MSE, RMSE, but interpretability of these models was disregarded. As a result, the creation of interpretable neuro-fuzzy systems that place an emphasis on attaining an accuracy-interpretability balance maybe something to explore. Also, due to the quickly and continuously changing information, model validation needs to be an ongoing process, especially when new information becomes accessible.

Finally, a drawback shared by many previous literature reviews is that our analysis derives findings from a wide, but not complete, collection of studies. A few articles may have been inadvertently excluded.

5. Conclusion

Predicting stock market prices and trends is essential and it may lead to significant returns. It often impacts a trader's decision whether to buy or sell an instrument. Predicting implies knowing which variables predict others. Due to the large number of variables that may affect stock values, these tasks are exceedingly complex and challenging. This article aimed to conduct a systematic literature review on stock market prediction using neuro-fuzzy methods through an in-depth analysis of a sample of 24 articles coming from indexed journals. In order to guarantee decent quality of the academic work, our search included many databases, a variety of search techniques and exclusion criteria. Thus, analysis and discussions were based on two major viewpoints: predictor techniques and accuracy metrics.

It was noted that the conventional approach can't examine big financial data. Hence, the review suggests using modern approaches. Expert systems are yet a better option. However, they are not capable of experiential learning and could not process non-linear information. To tackle these issues, neuro-fuzzy systems that can process both linear and non-linear inputs could be applied. The researchers used a variety of neuro-fuzzy methods and learning techniques depending on their expertise, research interest and abilities. The review indicates an interesting diversification in the use of neuro-fuzzy techniques. But among the various neuro-fuzzy techniques, some techniques like ANFIS have been more favored by the researchers. The results show that the capacity of the ANFIS model to learn and make predictions in financial applications, but they also reveal that certain of the behaviors of the market are too complicated to be predicted. To verify the proposed models, an evaluation of the model's accuracy and comparison to other models was implemented. Evaluation metrics change according to the researchers and technique used. They found that neuro-fuzzy models are successful in predicting stock markets and useful for investors, some of them outperform all the comparative methods, and others have almost the same accuracy, while it sometimes takes more time to train.

Furthermore, the use of neuro-fuzzy techniques has a considerable number of challenges involved in training them, measuring their accuracy and putting them into practice. The complexity of the presented approaches is the most notable obstacle they face. Therefore, broadening the scope of the study to include fast expanding emerging economies with underdeveloped financial markets, the creation of interpretable neuro-fuzzy systems that place

an emphasis on attaining an accuracy-interpretability balance and making model validation an ongoing process since information are continuously changing maybe something to explore.
This study's significant contribution was to show that a large portion of articles demonstrate the potential of neuro-fuzzy-based modeling for financial market prediction and a small portion of models did not consistently outperform the traditional and naive models or have obtained losses even with the model performance above the half. Therefore, the literature review lays out a number of potential directions for future work and research limitations that might spark academic discussion on the topic.

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