IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 4, August 2025, pp. 2601~2612
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i4.pp2601-2612

Hybrid forecasting methods across varied domains-a systematic review

Malvina Xhabafti, Valentina Sinaj
Department of Statistics and Applied Informatics, Faculty of Economy, University of Tirana, Tirana, Albania

Article Info

Article history:

Received Sep 13, 2024
Revised Feb 18, 2025
Accepted Mar 15, 2025

Keywords:

Domain
Evaluation metric
Hybrid model
PRISMA checklist
Systematic review

ABSTRACT

Time series forecasting is one of the links that has developed since early times due to risk management, efficient allocation of resources, performance evaluation, strategic planning, and the formulation of effective policies for individuals, organizations, and societies. Forecasting models have evolved steadily by hybridizing statistical and neural network techniques ensuring efficiency and accurate predictions. In this paper, a systematic review of the literature was made through the preferred reporting items for systematic reviews and meta-analyses (PRISMA) methodology, highlighting the domains that mostly use hybrid techniques by defining the ones with the highest frequency of implementation in each domain we predefined. During the selection process from the 4 selected databases, 2251 works were taken into consideration, of which 25 were the ones that were included in the review process through various filtering steps and exclusion criteria. Ongoing, we defined four main categories where we presented each paper individually by briefly explaining the underlying data, the proposed hybrid forecasting approach and the evaluation performance metrics such as root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). In a summary table, we highlight the most used hybrid methods for each domain, concluding which of the statistical and deep learning methods are mostly applied in the specified domains.

Corresponding Author:

Malvina Xhabafti
Department of Statistics and Applied Informatics, Faculty of Economy, University of Tirana
Road Arben Broci, Tirana, Albania
Email: xhabaftimalvina1@gmail.com

1. INTRODUCTION

The forecasting of time series nowadays has become a necessity since important actors of a country's economy support their decision-making in these forecasts. Suppose we want to see the benefits that these forecasts have brought in different domains. In that case, we can focus on for example the financial and stock market field where the forecasts have helped in the decision-making processes and provided valuable knowledge in the forecast of stock prices, the identification of market trends, portfolio optimization, and risk management [1]–[3], the field of energy load where it has helped in better planning of policies related to energy, for analyzing the dynamics of the energy market and price forecasting or even electricity forecasting demand in general [4], [5].

Also, forecasts have helped in other sensitive domains such as healthcare and medicine in the management of chronic diseases, the allocation of healthcare resources, and surveillance of diseases that have a risk of an outbreak [6], [7] and weather and climate domain in the prediction of long and short-term climate trends and changes, prediction of extreme weather events, forecasting future water availability, flooding events, and drought conditions [8]–[11]. So, the importance of time series forecasting not only in the aforementioned domains but in general in different fields, has been demonstrated from time to time by applying techniques or methods, starting with the traditional ones that are statistical and moving on to artificial intelligence methods. Statistical methods have always been recognized as effective in different predictions as a result of the quantitative analysis they perform, interpretable results, and ease of implementation, but they are limited to the typology of data because they work better with linear data [12]–[14]. For the typology of non-linear data, intelligent forecasting methods were seen as the most effective, which demonstrate the ability to capture complex patterns, to adapt to dynamic data while also increasing the performance of large data sets, making them very effective tools for time series forecasting in various fields [15]–[18]. But besides their effectiveness and the application of each technique individually in time series, the hybridization of statistical and intelligent methods has shown an improved forecasting performance, flexibility, adaptability, stability, risk mitigation as well as more accurate interpretability making them more suitable for forecasting time series data in various fields and applications [19]–[21].

Our focus in this paper is not to evidence the effectiveness and high performance of hybrid methods compared to traditional or individual ones because other works have proved this matter. Hybrid forecasting methods have emerged as powerful decision-making tools in various fields, offering computational efficiency, predictive accuracy, and significant improvements in forecasting performance and have become important tools for informed decision-making in finance, energy, healthcare, and weather forecasting [22]–[24]. The aim is to highlight the different methods concerning those domains that apply them the most and that have shown an improvement and positive impact on their respective decision-making.

In this form, we can conclude the hybrid method that is widely used in the respective domains but also in general. Our motivation started with the fact that this type of approach was missing in the current literature and therefore developed it and elaborated it further. To identify the relevant literature we needed in this case, we used the methodology established by preferred reporting items for systematic reviews and meta-analyses (PRISMA) for this systematic literature review [25].

First, we formulated the research question based on the keywords that helped us in the search through different databases, followed by the planning of the research protocol where we defined: the objectives, the specific method that we will use PRISMA, the suitability criterion of the individual studies, the planning of data extraction from individual studies as well as what analysis we will follow. Then we proceeded with the literature search referring to several databases that widely offer works in our field of interest by defining the main key terms, the year they will cover, the number of results held, the language of the works and the possibility of access. In the following, we proceeded with the screening of the literature that was developed in two phases: pre-screening and screening, with the evaluation of the quality of the works, and the extraction of the data, where we then determined the domains in which we would focus by dividing them into four categories and we analyzed the results.

We present each paper individually for each category by briefly explaining the underlying data, the proposed hybrid forecasting approach, and the evaluation results they scored based on different metrics such as root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). We presented each of these steps in a PRISMA flow chart. The works were selected based on the inclusion and exclusion criteria, which are detailed in the methods section. In the end, we interpreted and presented the results of the works in a summary table on which we drew the relevant conclusions. In addition to reemphasizing the importance of hybrid models concerning individual ones, this paper specifically highlights the techniques that have a wider range of use in some of the most well-known and sensitive domains.

2. METHOD

The main purpose of this paper is to identify the hybrid methods that are used the most in different domains, highlighting the statistical method and, on the other hand, the neural networks (deep learning method) most used in hybridization. This was done using the PRISMA technique to identify the most accurate and suitable studies for our work [25]. First, we formulated the main research question through participants, interventions, comparators, outcomes (PICO). In the following, we have planned our research protocol, highlighting the research objectives, the specific methods and processes that we will use, the suitability criteria of individual studies, the method of data extraction from these works, as well as the determination of the path of analysis that we will follow. We have defined the databases that we will search and the year that they will cover, the search strategies including the terms that we have used as well as the number of saved results that we have presented in the PRISMA checklist chart.

To identify the most relevant works, we used some search terms which helped us to synthesize the results of the searches in the different databases. We have used terms such as "Hybrid forecast", and "Hybrid model" to direct the search towards those works that have used hybrid methods. We have also used

the terms "Statistical", autoregressive integrated moving average ("ARIMA"), and seasonal autoregressive integrated moving average ("SARIMA"), because various works have referred directly to the techniques without using the term hybridization, as we have cited among the most used techniques in statistics. Regarding intelligent techniques, we have used the terms "deep learning", artificial neural network ("ANN"), recurrent neural network ("RNN"), "neural network", and long short-term memory ("LSTM"), to capture works that can be addressed with such terms as we have also referred to the terms and techniques that most used deep learning techniques. Our search is performed in four databases as follows:
– IEEE (through the IEEE Xplore platform);
– Elsevier (through the ScienceDirect platform);
– MDPI (through the Multidisciplinary Digital Publishing Institute library);
– Wiley Online Library (through the Wiley Online Library platform).

It should be noted that these databases were chosen as those that included the wide range of works in our focus, i.e., the hybridization of statistical techniques and deep learning, as well as those that provided the possibility of open-source works for access. The search was carried out for the last 5 years, 2019-2023, to analyze the most recent studies, as well as select those papers that were in the English language (Table 1).

Table 1. Table of search queries and filters applied to the different databases

Database	Query	Additional features
IEEE Xplore	("All Metadata": "Hybrid model*" OR "Hybrid forecast" OR "Time series Forecast*") AND ("Abstract": "Statistical" OR ("Abstract": ARIMA OR "Abstract": SARIMA OR "Abstract" : moving-average) AND ("Abstract": "deep learning" OR "Abstract": ANN OR "Abstract": RNN OR "Abstract": LSTM OR "Abstract": "Neural Network")	Years: 2019–2023 Language: English
Science Direct	(Hybrid model OR Hybrid forecast) AND "Time series forecasting" AND Title, abstract or author-specified keywords:(statistical OR ARIMA OR SARIMA OR moving average) AND ("deep learning" OR ANN OR RNN OR LSTM OR "neural network")	Years: 2019–2023 Language: English
Multidisciplinary Digital Publishing Institute (MDPI)	((All Fields: "Hybrid model") OR (All fields: Hybrid forecast)) AND ((Abstract: Statistical) OR (Abstract: ARIMA) OR (Abstract: SARIMA) OR (Abstract: Moving-average)) AND ((Abstract: "Deep learning") OR (Abstract: ANN) OR (Abstract: RNN) OR (Abstract: LSTM) OR (Abstract: "Neural network"))	Years: 2019–2023 Language: English
Wiley Online Library	""Hybrid model" OR "Time series forecast" anywhere and "statistical OR ARIMA OR SARIMA OR moving-average " in the Abstract and "deep learning" OR ANN OR RNN OR LSTM OR "neural network"" in the Abstract	Years: 2019–2023 Language: English

In Figure 1, we present the PRISMA 2020 flow diagram for new systematic reviews involving only searches of databases and registries. In total, we have selected 2251 reports from the databases we mentioned above. The program we used to manage the pre-screening process and eliminate duplicates is Citavi. About 225 duplicates were identified which were eliminated and then continued with the screening the literature process which was carried out in two phases: the first phase, title and abstract screening where all the titles and abstracts were read and then the selection of those more appropriate as well as the second phase, full text downloading and screening of selected studies. After the completion of the first phase, 1404 reports were eliminated, and 622 reports were transferred to be processed in the second phase.

The latter were filtered by evaluating the methodological quality of these articles as well as based on different inclusion and exclusion criteria. The step of data extraction and quality assessment oriented us towards the works that have an orientation towards the research question of this paper. The works that were included in the review process are all hybrid models of statistical methods and deep learning because our main goal, as mentioned above, is not to identify the fact that hybrid methods are better than individual methods, but to determine that hybrid methods that outperformed the others in different domains. The domains that we have focused on in this work have been selected referring to the amount of work that we have recorded for each of these areas, that used different hybrid techniques as well as the quality and compatibility of these reports with the objectives of our work. Specifically, the domains in which we have focused are finance and stock market prediction, energy forecasting, healthcare and medical forecasting and weather and climate forecasting, domains in which hybrid prediction has positively impacted. Reports that did not propose hybrid models or were only statistical or ANN, neural network and deep learning hybrid models were excluded from the analysis. A significant part of the reports was not included because we did not have access to their full text even after contacting the respective authors of the papers. Several other reports were not included due to a lack of precision in the methods used. Finally, 25 reports were selected that met the inclusion criteria. Because the data from the selected studies have different results referring to the subfield, they can address but also the database in which the hybrid techniques are applied, only the most important conclusions were considered in this review.

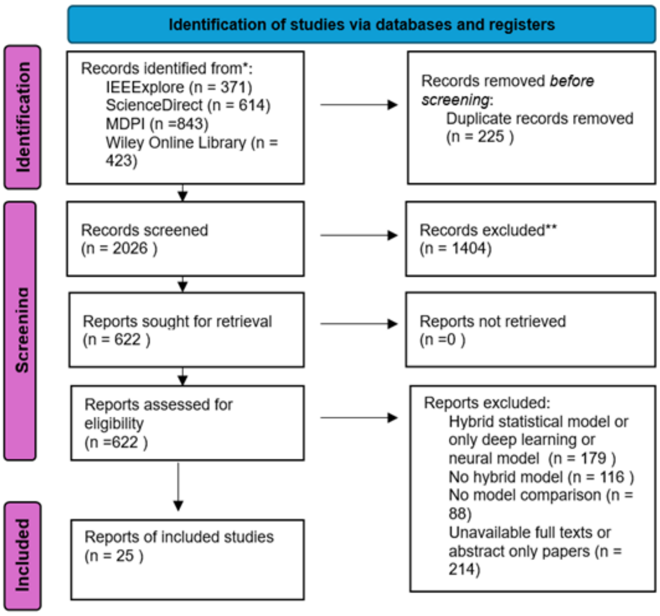

Figure 1. PRISMA flow chart showing the filtered results for each filter step according to [25]

3. RESULTS AND DISCUSSION

3.1. Results

The results that we have included in this paragraph are divided according to the different domains where we have focused. The studies included in this review show the importance of hybrid techniques by highlighting the term "hybridization" for the relevant field that is evidenced and tested. In the following, we have grouped the results into four categories based on the respective domain. The first category is finance and stock market prediction [26]–[32]. The second category is energy forecasting [33]–[38]. The third category is healthcare and medical forecasting [39]–[44]. The fourth category is weather and climate forecasting [45]–[50].

3.1.1. Finance and stock market prediction

Abdulrahman *et al*. [26] predicted stock price using a hybrid ARIMA-LSTM model, based on data decomposition with a low-pass filter of the discrete Fourier transform. Abdulrahman *et al*. [26] used the Ghana stock exchange, which is the stock price of a bank with 1398 instances for the period February 1 to September 21, 2020. They also predicted the individual techniques besides the hybrid technique which was the main goal, noting the best performance of the hybrid technique, ARIMA-LSTM based on the RMSE values [26]. Peng *et al*. [27] predicted the performance of three stock market indices using hybrid ARIMA-multilayer perceptrons (MLP) and ARIMA-RNN methods on historical data obtained from the Pakistan stock exchange, the national stock exchange of India, and the Sri Lanka stock exchange for the period September 6, 2009 to December 26, 2019. The implementation of the methodologies was divided into three parts according to the respective countries that have been studied, that is Pakistan, Sri Lanka, and India [27]. The results showed that ARIMA-MLP outperformed ARIMA-RNN for the case of India and Pakistan, while for the case of Sri Lanka, ARIMA-RNN performed better [27]. Comparisons of each method were made through RMSE, MAPE, and MAE.

Kulshreshtha and Vijayalakshmi [28] have forecasted stock market data directly from the source of the S&P 500 using a preexisting application programming interface (API), using two approaches: a hybrid ARIMA-LSTM technique and a forecasting library called prophet. Through these forecasts, it aims to analyze the rise and fall in stock values in previous years. According to the authors, the ARIMA-LSTM hybrid technique, based on the RMSE, MSE, and MAPE, evaluation metrics, performs much better than the prophet technique [28], [29]. Montaño and Viado [29] forecasted the Peso-Dollar exchange rate using the hybrid ARIMA-ANN technique based on Bangko Sentral ng Pilipinas (BSP) FX rate data for the period 2000-2020. In addition to this technique, the individual results of the Holt-Winters model, ARIMA, and ANN were also tested, making comparisons based on the statistical evaluation metrics MAE, MSE, and RMSE [29]. According to the authors, the hybrid model has the lowest measurement of errors, emphasizing the possibility of introducing a more accurate method for predicting the FX rate with hybrid modeling [29]. In the following paper, García *et al*. [30] made the forecast of closing prices taking into account the following currencies: EUR/USD, GBP/USD, JPY/USD, AUD/USD, and NZD/USD for the period from December 18, 2017 to January 27, 2023. The authors have also chosen the daily closing price of the Bitcoin cryptocurrency futures contract to determine the behavior of the patterns [30]. The forecasting methods that were tested for their effectiveness for these time series were ARIMA, LSTM, and their hybridization. From the evaluation of each respective model using the error measures (MAE, MAPE, and RMSE), it was concluded that the hybrid method, ARIMA-LSTM, regardless of performance for some of the types of currencies, such as for GBP/USD and NZD/USD where LSTM method performed better, in overall suggests a slight improvement compared to individual techniques [30].

Peirano *et al*. [31] predicted the inflation rate in five Latin American countries based on the SARIMA-LSTM hybrid technique with monthly data, for the period from January 1958 to June 2019. After the training of the data, the respective individual and hybrid techniques were applied to see the performance of each one [31]. The authors have applied rolling windows in the models they have studied, not including LSTM, where they have predicted the inflation rate for the next month, moving the windows one month ahead and calculating all again [31]. Besides the SARIMA-LSTM technique, the individual ANN, fuzzy inference system (FIS), adaptive network-based fuzzy inference system (ANFIS), LSTM, and SARIMA techniques, as well as the SARIMA-ANN hybrid, were tested for each country. Overall, based on the MSE error metric, it was concluded that the SARIMA-LSTM technique performed better compared to the other models that were taken in the study [31]. Bukhari *et al*. [32] took into study the daily open price time series of Fauji Fertilizer Company (FFC) with data from January 1, 2009 to May 30, 2018, to forecast the sudden stochastic variety of the financial market. The models included in the study are the ARFIMA-LSTM hybrid model as well as the traditional ARIMA, ARFIMA, LSTM, and generalized regression neural network (GRNN) models [32]. For each of these models, training and testing of the series have been done, demonstrating in detail each step until the final result. The final evaluation was done based on the statistical metrics MAE, RMSE and MAPE. The performance of the proposed hybrid model significantly proved the best model to improve the forecasting of the financial series by increasing the accuracy rate of 80% [32].

3.1.2. Energy forecasting

Dudek *et al*. [33] made the monthly electricity demand forecast for 35 European countries based on the winning entry in the M4 2018 forecast competition for monthly data and point forecasts. The time series used have different lengths ranging from 24 years to 5 years. The model that was used by the authors in this work is the exponential smoothing-residual dilated (ETS-RD)-LSTM hybrid model which demonstrated a good performance based on the evaluation metrics (RMSE and MAPE) as well as its modern competition with the classic and based on machine learning (ML) [33]. The purpose of the study was not only to highlight the benefits of the hybridization of these techniques but also to demonstrate step-by-step the traditional techniques used with the corresponding results [33]. Grandón *et al*. [34] predicted the national demand for electricity in Ukraine, using the hourly demand variable, macroeconomic variables and temperature for the period 2013-2020. The approach used by the authors in this work was hybrid using statistical methods such as ARIMA and deep learning methods such as LSTM. The methodology on which the technique was applied was divided into three categories the time scale: long-term (annual), medium-term (daily) and short-term (hourly resolution) [34]. They managed to get good results noting that the combination of ARIMA as a classical statistical model and LSTM as a deep learning model based on ML algorithms, corrects the residuals and increases the forecast accuracy [34].

Rashid and Vig [35] aimed to ensure a stable electricity supply by developing a hybrid forecasting model using historical load data provided by the New York Independent System Operator (NYISO) for the period from January 2019 to December 2021. The models analyzed in their study included ARIMA, ANN, and a hybrid ARIMA–ANN approach [35]. These were applied to perform one-step-ahead and multi-step-ahead electricity load forecasting across different temporal conditions, including weekdays, weekends, and high-demand periods. Forecast accuracy was evaluated using RMSE and MAPE metrics. The authors concluded that the hybrid ARIMA–ANN model achieved superior performance over the standalone methods, with up to 96% improvement in prediction accuracy, making it highly effective for stable and reliable electricity load forecasting [35]. Izudin *et al*. [36] made the electricity consumption forecast for Malaysia for the time period 1978-2017. Individual techniques such as ARIMA and ANN as well as hybrid ARIMA-ANN techniques were implemented. The authors oriented their work towards the hybrid model, relying on the literature studied by them based on the strength of the classical models for the linear nature that characterizes them as ARIMA as well as the ANN model in the non-linear dimension [36]. MAE, RMSE, and MAPE were used as performance measures of each model for the years 2014–2017. It was concluded that the ARIMA-ANN hybrid model gave better results in accurate electricity usage prediction models to increase power system reliability [36]. Sinha *et al*. [37] predicted the power load in the period 2006-2010 in sampling per minute for the state of Canada. The prediction was made using statistical models as well as deep learning models [37]. The focus of the paper was the proposal of the vector auto regressive (VAR)-CNN-LSTM (VACL) hybrid model to combine the capabilities of both typologies of statistical and deep learning models [37]. Seven-time series were included in the model, where the experiments were performed both on the proposed hybrid model and on models such as MLP, LSTM, CNN-LSTM, and VAR. The authors concluded based on the results of the paper that the proposed hybrid model, VACL, makes a more efficient prediction of the short-term power load [37].

Also, in this paper, the evaluation metrics were MSE and RMSE. Jagait *et al*. [38] proposed an approach to predict the electrical load based on the combination of ARIMA with RNN under concept. The data was based on each customer's hourly energy consumption data for three years. Other variables such as temperature, humidity, and pressure were also studied. In addition to the hybrid method, the accuracy of rolling ARIMA and adaptive online RNN was checked, where following the comparison of these load forecasting models, as well as the examination of statistical significance [38]. The authors came to the conclusion that the proposed approach exceeds the rolling ARIMA and online adaptive RNN methods, emphasizing the need to examine the errors that occur under the concept of drift.

3.1.3. Healthcare and medical forecasting

Ketu and Mishra [39] predicted the outbreak of COVID-19 through the ARIMA-LSTM hybrid method, in the period was characterized as the most delicate period where it occurred and the greatest spread in almost all countries of the world, i.e., December 31, 2019 to October 6, 2020. Data, such as the number of active cases, number of confirmed cases, and total number of deaths, were obtained for 50 states [39]. The authors aimed to evaluate how the hybrid model performs by comparing it with the two individual models, i.e., ARIMA and LSTM. From the prediction results, where RMSE, MAPE, and R-squared (R^2) were used as evaluative parameters, it was proven that the proposed hybrid model had values with significant differences, outperforming other known traditional models [39].

Zhang *et al*. [40] followed in their work with a hybrid approach, autoregressive (AR)-LSTM, for the prediction of COVID-19 cases. The database used consisted of two datasets: a specific database for California counties as well as seven countries around the world for comparative analysis. The purpose of the authors is to build a model that will effectively influence the control of public health policies and above all COVID-19, also helping in possible predictions for pandemics that may occur in the future [40]. The results of the paper showed through the quantitative evaluation metric MAPE, that the hybrid AR-LSTM model offers a more accurate prediction compared to individual traditional methods, making more evident the transition path of the stages of virus transmission as well as improving decision-making [40]. Jin *et al*. [41] also made a study for the prediction of the spread of COVID-19, for the case of China in the period January 1, 2021 to October 10, 2022, applying the weighting method of the regression coefficient in the ARIMA-LSTM hybrid parallel model. Besides this method, he also studied other models such as ARIMA, ARIMA-LSTM in series and support vector regression (SVR). Based on some evaluation metrics such as RMSE, MAPE, and MSE, each of the models included in the work was evaluated and it was concluded that the proposed model performed better than the other models, thus creating a predictive model that guides the prevention of the spread of COVID-19 and its control [41]. The contribution of this paper also focuses on providing a reference for the future decisions of the government.

Jin *et al*. [42] improved the model used in the work mentioned above, combining different statistical and deep learning models such as particle swarm optimization (PSO)-LSTM-ARIMA, multiple linear regression (MLR)-LSTM-ARIMA, and back-propagation neural network (BPNN)-LSTM-ARIMA. The data obtained in the study were for Germany and Japan regarding the outbreak of COVID-19 for the period April 1, 2020 to March 9, 2023. Based on the values of MSE, RMSE, and MAE, the BPNN-LSTM-ARIMA model proved a higher prediction accuracy, emphasizing once again the contribution that this work can give to the government and public health authorities [42]. Li *et al*. [43] analyzed the ARIMA and ARIMA-GRNN models to predict the incidence of tuberculosis in China, with monthly data for the period January 2007 to June 2016. The prediction accuracy of the models was evaluated through RMSE, and MAPE concluding that the hybrid ARIMA-GRNN model shows higher performance in fitting and predicting the short-term incidence of tuberculosis without peak and border incidence [43]. Deng *et al*. [44] made a forecast of outpatient visits in hospitals with the argument that they can be complex and change according to the seasons of the year, using the hybrid ARIMA-LSTM method optimized by BP, for the period June 1, 2014 to February 17, 2019. Three departments were taken in the study for a period of 24 weeks (September 9, 2018 to February 17, 2019): the respiratory department, which compared ARIMA, LSTM, and ARIMA-LSTM optimized by BP; and the cardiology departments and digestive departments, which compared ARIMA-LSTM based on traditional methods and ARIMA-LSTM optimized by BP [44]. In the respective comparison that was made for each case through the performance indicators, in the respiratory department the hybrid model performed better, while in the other two departments, the proposed ARIMA-LSTM optimized by the BP model offered a better prediction accuracy [44]. The authors concluded that this model helps the respective policymakers to know in advance the changes in the volume of outpatients in the coming weeks or months.

3.1.4. Weather and climate forecasting

Xu *et al*. [45] predicted drought for 7 sub-regions of China, using a total of six models (individual and hybrid), ARIMA, SVR, LSTM, ARIMA-SVR, LS-SVR, and ARIMA-LSTM, for the period January 1980 to December 2019. These models are analyzed for their prediction accuracy for the standardized precipitation evaporation index (SPEI). The results obtained in the study, based on the monthly rainfall and temperature data, which carried out LSTM and SVR modeling with SPEI values at 6, 12, and 24-month scales, initially concluded that the hybrid models (ARIMA-SVR, LS-SVR, and ARIMA-LSTM) had higher prediction accuracy than the single model and in conclusion that the ARIMA-LSTM model from the three hybrid models taken in the study has the highest prediction accuracy on a multi-time scale [45]. In conclusion, the authors concluded that this model contributes to the improvement of the short-term and long-term prediction of drought in China.

Khan *et al*. [46] proposed a combination of Wavelet transform, statistical models and artificial intelligence i.e., Wavelet-ARIMA-ANN for the prediction of droughts in the Langat River basin of Malaysia for 30 years with data from January to December 1986. The inputs received in the study were the meteorological drought index, the standardized precipitation index and the standard daily precipitation index [46]. Based on the results of the work, the authors conclude that the proposed hybrid model performed better than the other models, providing a greater prediction accuracy concerning the R2 metric. Zhao *et al*. [47] proposed a combined ensemble empirical mode decomposition (EEMD)-LSTM-ARIMA model for forecasting monthly rainfall in Luoyang City, Henan Province, China, for the period January 1973 to December 2021 [47]. Besides this hybrid combination, individual models and hybridizations of others which did not perform better than the model proposed by the authors. Initially, a comparison was made between the hybrid and individual models where the hybrids performed better and then the hybrid models with each other [47]. The comparison between the models was made through indicators that are commonly used for model evaluation such as: RMSE and MAE. The authors rely on the fact that a traditional individual model, because of the fluctuating variation of the model data, cannot summarize the characteristics of this series, bringing an inaccurate forecast. In the end, it was concluded that the EEMD-LSTM-ARIMA hybrid model, for which the forecast for the monthly rainfall from 2022 to 2024 was made, performs correctly in forecasting the monthly rainfall for this region [47].

Parasyris *et al*. [48] predicted several metrological variables such as temperature, humidity, wind speed and direction, firstly variables that present seasonality as well as those that are more stochastic and without seasonality, using the SARIMA-LSTM hybrid method. The work was divided into two parts where first the temperature and humidity were predicted and then in the other part the wind was predicted. The data were taken from a specific area of Greece, a hotel in Crete where a data acquisition device was installed and the time resolution of the measurements used was 3 hours covering the years 1975–2004 and the total forecast horizon considered it was up to 2 days [48]. Based on the localized time series, the SARIMA-LSTM hybrid model outperformed the individual SARIMA and LSTM methods for forecast horizons of 1-2 days, contributing to a better forecast of temperature and wind speed for the specific area studied [48].

Belmahdi *et al*. [49] forecasted the daily global solar radiation in two cities in Morocco with data from January 1, 2015 to December 31, 2015, from a meteorological station installed in a specific location, relying on the feedforward backpropagation neural network (FFBP), ARIMA, and auto-regressive moving average (ARMA) models as well as their hybridization. In the realized forecast, the model that had the highest correlation coefficient, i.e., performed better with reference to the evaluation metrics, was the ARIMA-FFBP hybrid model [49]. The authors concluded that this model could contribute to the prediction of global solar radiation in other locations, taking into consideration whether we will have similar weather conditions in the future. Luo and Gong [50] proposed the ARIMA-WOA-LSTM model to forecast air pollutants in two large cities in China, Shijiazhuang and Baoding for the period January 1, 2015 to March 1, 2022. In the comparison of the proposed model with five other individual and hybrid models (ARIMA, LSTM, ARIMA-LSTM, whale optimization algorithm (WOA)-SLTM, complete ensemble empirical mode decomposition (CEEMDAN)-WOA-SLTM) through RMSE and MAE. Metrics it was concluded that this model performs better in pollutant prediction accuracy, model, and prediction stability [50]. The authors managed to identify a model that can help manage air pollution better and improve the way air pollution is treated.

3.2. Discussion

In this paper, to develop a systematic review of literature, we used the PRISMA checklist methodology, which from the entire list of possible articles for review extracted from the various databases that were taken into consideration, through the screening process as well as data extraction and quality assessment, we reached 25 papers. These works were classified according to different domains such as: finance and stock market prediction, energy forecasting, healthcare and medical forecasting, and weather and climate forecasting, seeing the importance that hybrid methods had for each of them. In addition to the classification through domains, we mainly focused on scientific papers that have hybridization of statistical methods and neural networks, comparison of hybrid models with traditional individual models or hybrid with hybrid, through performance metrics such as RMSE, MAE, and MAPE. So, the main purpose of this paper, as it is mentioned above in the introduction section, is not to point out the effectiveness that hybrid methods have in different domains because this has already been proven by other works [22], but familiarity with different hybrid typologies in the domains we have specified, considering the frequency of use of different methods in the group of statistical methods as well as that of the neural network (deep learning), in these domains. Thus, we highlight which would be the most widely used hybridization model in each domain, in the range of methods presented in each paper.

In the analysis made for each paper, we started by identifying the field of prediction, the hybrid methodology used, the size of the data obtained in the study as well as the metrics or performance evaluation indicators of each model. In various works, we noticed that there were comparisons of hybrid combinations with traditional individual methods where it was always concluded that the hybrid method performed better than the individual one or by comparing different hybridizations, through metrics such as RMSE, MAE, MAPE, and MSE. From the hybrid methods used that performed better in the various papers we analyzed, we evidenced that in the domain of finance and stock market prediction, the methods that outperformed the others were: ARIMA-LSTM [26], [28], ARIMA-RNN [27], and autoregressive fractionally integrated moving-average (ARFIMA)-LSTM [32] for stock price prediction, ARIMA-ANN [29], and ARIMA-LSTM [30], for exchange rate prediction as well as SARIMA-LSTM for inflation rate prediction [31]. In the domain of energy forecasting, hybrid models such as: ETS-LSTM [33], ARIMA-LSTM [34], ARIMA-ANN [35], [36], VAR-CNN-LSTM [37], and ARIMA-RNN [38] performed better through different studies for forecasting electricity demand or load. In the domain of healthcare and medical forecasting, the methods that outperformed the others were: ARIMA-LSTM [39], [41], AR-LSTM [40] and ARIMA-BPNN-LSTM [42], for the prediction of the outbreak of COVID-19, ARIMA-GRNN [43], for the prediction of tuberculosis and ARIMA-LSTM [44], for the prediction of outpatient visits in a hospital. Lastly, in the field of weather and climate forecasting, we have: ARIMA-LSTM [45] and ARIMA-ANN [46], for the prediction of drought analysis, ARIMA-EEMD-LSTM [47], for the prediction of monthly rainfalls, SARIMA-LSTM [48] for the prediction of some metrological variables such as temperature, humidity, wind speed and direction, ARIMA-FFBP [49], for the prediction of global solar radiation and ARIMA-WOA-LSTM [50] for air pollutants prediction. We also have works that separate the linear and non-linear components using wavelet transformers.

Our work was divided into four groups which were based on specific domains: i) group 1: finance and stock market forecasting; ii) group 2: energy forecasting; iii) group 3: healthcare and medical forecasting; and iv) group 4: weather and climate forecasting. For each domain, different hybrid methods were identified that were used and that outperformed the other methods with which they were compared in the respective works. In Table 2, we have presented a summary of the studies defining the domain, size of data, the models that were used and those that outperformed as well as the performance indicators. This table helps us to identify and highlight which combinations of hybrid methods are the most used in each domain as well as in general. In general, regardless of the different combinations that have been applied, it is noted that most of the papers present a hybrid approach using the ARIMA method in combination mostly with the LSTM method.

ARIMA is the statistical method that prevails in 80% of the works, while LSTM in 60% of them. If we were to identify the methods that were used the most for each specific domain, we would have: for finance and stock market prediction, ARIMA-LSTM, for energy forecasting, ARIMA-LSTM and ARIMA-ANN, for healthcare and medical forecasting, ARIMA-LSTM and for weather and climate forecasting we have ARIMA-LSTM. We cannot say that this hybridization outperforms all the other methods used because the results of the predictions rely on the data we are using in a specific model, but we are basing it on the frequency of use of these methods in different domains for various predictions. So overall, if we compare these results that we managed to obtain with each of the works that we have included in the study, we can say that the hybrid methods are the ones that perform best in predicting the domains as well as the most popular methods used for hybridization are ARIMA with ANN or LSTM.

Table 2. Summary of studies applying hybrid techniques and models for forecasting various domains

Authors	Domain	Size of data	Model used	Best model	Performance indicators
Abdulrahman *et al.* [26]	Finance and stock market forecasting	1st February-21st September 2020	ARIMA, LSTM, ARIMA-LSTM	ARIMA-LSTM	RMSE
Peng, *et al*. [27]	Finance and stock market forecasting	September 6, 2009-December 26, 2019	ARIMA, MLP, RNN, ARIMA-MLP, ARIMA-RNN	ARIMA-RNN and ARIMA-MLP	RMSE, MAPE, MAE
Kulshreshtha and Vijayalakshmi [28]	Finance and stock market forecasting	500 data	ARIMA, ARIMA-LSTM, Prophet	ARIMA-LSTM	RMSE, MSE, MAPE, R^2
Montaño and Viado [29]	Finance and stock market forecasting	2000-2020	HoltWinters, ARIMA, ANN, ARIMA-ANN	ARIMA-ANN	RMSE, MAE, MSE
García *et al.* [30]	Finance and stock market forecasting	December 18, 2017-January 27, 2023	ARIMA, LSTM, ARIMA-LSTM	ARIMA-LSTM	RMSE, MAPE, MAE
Peirano *et al*. [31]	Finance and stock market forecasting	January 1958-June 2019	ANN, FIS, ANFIS, LSTM, SARIMA SARIMA-ANN, SARIMA-LSTM	SARIMA-LSTM	MSE
Bukhari *et al*. [32]	Finance and stock market forecasting	January 1, 2009-May 30, 2018	ARIMA, ARFIMA, LSTM, GRNN, ARFIMA-LSTM	ARFIMA-LSTM	RMSE, MAE, MAPE
Dudek *et al*. [33]	Energy forecasting	24 years	GRNN, ANFIS, LSTM, ARIMA, ETS, ETS-GRNN, ANFIS-ETS, ETS-RD-LSTM.	ETS-RD-LSTM	RMSE, MAE, Median APE
Grandón *et al*. [34]	Energy forecasting	2013 - 2020	ARIMA, LSTM, ARIMA-LSTM	ARIMA-LSTM	RMSE, MAE, MASE
Rashid and Vig [35]	Energy forecasting	January 2019-December 2021	ARIMA, ANN, ARIMA-ANN	ARIMA-ANN	RMSE and MAPE
Izudin *et al*. [36]	Energy forecasting	1978-2017	ARIMA, ANN, ARIMA-ANN	ARIMA-ANN	MAE, RMSE, MAPE
Sinha *et al*. [37]	Energy forecasting	2006-2010	VAR, MLP, LSTM, CNN-LSTM, VAR-CNN-LSTM	VAR-CNN-LSTM	MAE, RMSE, MSE
Jagait *et al*. [38]	Energy forecasting	hourly energy consumption data for three years	ARIMA, RNN, ARIMA-RNN	ARIMA-RNN	MAE and MSE
Ketu and Mishra [39]	Healthcare and medical forecasting	December 31, 2019-October 6, 2020	ARIMA, LSTM, ARIMA-LSTM	ARIMA-LSTM	RMSE, MAPE, R^2
Zhang *et al*. [40]	Healthcare and medical forecasting	Februrary 01, 2020-September 05, 2022	ARIMA, LSTM, LSTM double, ARIMA-LSTM	ARIMA-LSTM	MAPE
Jin *et al*. [41]	Healthcare and medical forecasting	January 1, 2021-October 10, 2022	ARIMA, LSTM, ARIMA-LSTM, SVR, paralel ARIMA-LSTM	paralel ARIMA-LSTM	RMSE, MAPE, MSE, MAE, R2
Jin *et al*. [42]	Healthcare and medical forecasting	April 1, 2020 to March 9, 2023	ARIMA, LSTM, PSO-LSTM-ARIMA, MLR-LSTM-ARIMA and BPNN-LSTM-ARIMA	BPNN-LSTM-ARIMA	MSE, RMSE, MAE
Li *et al*. [43]	Healthcare and medical forecasting	January 2007-June 2016	ARIMA, ARIMA-GRNN	ARIMA-GRNN	RMSE, MAE, MAPE, MER
Deng *et al*. [44]	Healthcare and medical forecasting	June 1, 2014 to February 17, 2019	ARIMA, LSTM, ARIMA-LSTM	ARIMA-LSTM	RMSE, MAE, MAPE
Xu *et al*. [45]	Weather and climate forecasting	January 1980-December 2019	ARIMA, SVR, LSTM, ARIMA-SVR, LS-SVR, ARIMA-LSTM	ARIMA-LSTM	MSE, NSE, RMSE, MAE
Khan *et al*. [46]	Weather and climate forecasting	January 1986-December 2016	ARIMA, ANN, Walvelet ARIMA-ANN	Walvelet ARIMA-ANN	RMSE, R^2
Zhao *et al*. [47]	Weather and climate forecasting	January 1973-December 2021	ARIMA, LSTM, EMD-LSTM, EEMD-LSTM, EEMD-ARIMA, EEMD-LSTM-ARIMA	EEMD-LSTM-ARIMA	MAE, MSE, RMSE, R^2
Parasyris *et al*. [48]	Weather and climate forecasting	2 days	LSTM, SARIMA, SARIMA-LSTM	SARIMA-LSTM	MAE
Belmahdi *et al*. [49]	Weather and climate forecasting	January 1, 2015-December 31, 2015	ARIMA, ARMA, FFBP, ARIMA-FFBP, ARMA-FFBP	ARIMA-FFBP	RMSE
Luo and Gong [50]	Weather and climate forecasting	January 1, 2015-March 1, 2022	ARIMA, LSTM, ARIMA-LSTM, WOA-LSTM, CEEMDAN-WOA-SLTM, ARIMA-WOA-LSTM	ARIMA-WOA-LSTM	RMSE and R^2

4. CONCLUSION

The systematic review carried out for this paper used the PRISMA methodology where we followed its main steps from the formulation of the research questions to the interpretation and presentation of the results. Four databases were selected and the main key terms on which the search will be carried out were defined. The terms were chosen in such a way as to avoid works that did not use hybrid applications or that the hybridization was not between statistical techniques and deep learning. The entire work process from downloading the references of the selected works to the screening process was carried out in the Citavi program. Following the screening process of full-text articles, the domains we would focus on were identified based on the dynamics of the studies we had available. Four were the categories of domains in which we focused and presented each paper individually for each category by briefly explaining the field of prediction, the hybrid methodology used, the size of the data obtained in the study as well as the metrics or performance evaluation indicators of each model such as RMSE, MAPE, and MSE. In this paper, the main focus was on hybrid methods where, in addition to demonstrating the improvement and positive impact on decision-making in areas such as finance, energy, health care, weather and climate forecasting, we identified those methods that have a more frequent range of use compared to traditional methods or other hybrid (statistical and deep learning) methods. The characteristics of the studies were summarized in a table which helped us in concluding the conclusions. During the analysis, it was observed that most of the papers present a hybrid approach using the ARIMA method in combination mainly with the LSTM method. ARIMA is the statistical method that prevails in 80% of the works, while LSTM in 60% of them. We also identified the methods that are used most often for each domain: financial, healthcare, energy, and weather forecast. Obviously, we cannot confidently say that this hybridization outperforms all other methods used because the prediction results rely on the data we use in a specific model, but we are basing it on the frequency of use of these methods in different fields by highlighting a hybrid model that can be generalized and used in all mentioned domains above. In the near future, we aim to do a deeper analysis in each of the specific domains by analyzing a wider range of works and highlighting for each domain the relevant subcategories and the hybrid methods they apply, and how effective they are overall.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Malvina Xhabafti	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			
Valentina Sinaj	✓			✓	✓			✓	✓		✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] R. Mucaj and V. Sinaj, "Exchange rate forecasting using ARIMA, NAR and ARIMA-ANN hybrid model," *Journal of Multidisciplinary Engineering Science and Technology (JMEST)*, vol. 4, pp. 2458–9403, 2017.
[2] F. Iqbal, D. Koutmos, E. A. Ahmed, and L. M. Al-Essa, "A novel hybrid deep learning method for accurate exchange rate prediction," *Risks*, vol. 12, no. 9, Aug. 2024, doi: 10.3390/risks12090139.

[3] M.-L. Shen, C.-F. Lee, H.-H. Liu, P.-Y. Chang, and C.-H. Yang, "An effective hybrid approach for forecasting currency exchange rates," *Sustainability*, vol. 13, no. 5, Mar. 2021, doi: 10.3390/su13052761.

[4] G.-F. Fan, X. Wei, Y.-T. Li, and W.-C. Hong, "Forecasting electricity consumption using a novel hybrid model," *Sustainable Cities and Society*, vol. 61, Oct. 2020, doi: 10.1016/j.scs.2020.102320.

[5] A. P. Sumobay, "Forecasting electricity demand using a hybrid statistical model," in *1st International Conference On Information Technology And Education (ICITE 2020)*, 2020, pp. 395–402, doi: 10.2991/assehr.k.201214.267.

[6] E. A. Fridgeirsson, D. Sontag, and P. Rijnbeek, "Attention-based neural networks for clinical prediction modelling on electronic health records," *BMC Medical Research Methodology*, vol. 23, 2023, doi: 10.1186/s12874-023-02112-2.

[7] E. Kar, M. Fakhimi, C. Turner, and T. Eldabi, "Hybrid simulation in healthcare: a systematic exploration of models, applications, and emerging trends," *Journal of Simulation*, vol. 19, no. 2, pp. 231–249, Mar. 2025, doi: 10.1080/17477778.2024.2354250.

[8] M. Xhabafti, B. Vika, and V. Sinaj, "A comparative study of statistical and deep learning model-base weather prediction in Albania," *WSEAS Transactions on Computer Research*, vol. 12, pp. 151–160, Dec. 2023, doi: 10.37394/232018.2024.12.15.

[9] M. Xhabafti and V. Sinaj, "Exploring hybrid approaches for weather forecasting domain: a review," in *The 19th Edition of the Conference European Integration Realities and Perspective (EIRP)*, 2024, pp. 502–510.

[10] M. Xhabafti and V. Sinaj, "Implementation and comparative analysis of a hybrid forecasting model for drought prediction: case of specific region in Albania," in *The 5th International Congress of Applied Statistics (UYIK-2024)*, 2024, pp. 1–10.

[11] N. B. Jarah, A. H. H. Alasadi, and K. M. Hashim, "Earthquake prediction technique: a comparative study," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 12, no. 3, pp. 1026–1032, Sep. 2023, doi: 10.11591/ijai.v12.i3.pp1026-1032.

[12] L. Gowri, K. R. Manjula, K. Sasireka, and D. Deepa, "Assessment of statistical models for rainfall forecasting using machine learning technique," *Journal of Soft Computing in Civil Engineering*, vol. 6, no. 2, pp. 51–67, 2022, doi: 10.22115/SCCE.2022.304260.1363.

[13] A. Nafil, M. Bouzi, K. Anoune, and N. Ettalabi, "Comparative study of forecasting methods for energy demand in Morocco," *Energy Reports*, vol. 6, pp. 523–536, Nov. 2020, doi: 10.1016/j.egyr.2020.09.030.

[14] M. Yousaf, S. Zahir, M. Riaz, S. M. Hussain, and K. Shah, "Statistical analysis of forecasting COVID-19 for upcoming month in Pakistan," *Chaos, Solitons & Fractals*, vol. 138, Sep. 2020, doi: 10.1016/j.chaos.2020.109926.

[15] A. Zeroual, F. Harrou, A. Dairi, and Y. Sun, "Deep learning methods for forecasting covid-19 time-series data: a comparative study," *Chaos, Solitons & Fractals*, vol. 140, Nov. 2020, doi: 10.1016/j.chaos.2020.110121.

[16] K. Amarasinghe, D. L. Marino, and M. Manic, "Deep neural networks for energy load forecasting," in *2017 IEEE 26th International Symposium on Industrial Electronics (ISIE)*, Jun. 2017, pp. 1483–1488, doi: 10.1109/ISIE.2017.8001465.

[17] R. Kumar, P. Kumar, and Y. Kumar, "Analysis of financial time series forecasting using deep learning model," in *2021 11th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*, Jan. 2021, pp. 877–881, doi: 10.1109/Confluence51648.2021.9377158.

[18] E. Hernández, V. Sanchez-Anguix, V. Julian, J. Palanca, and N. Duque, "Rainfall prediction: a deep learning approach," in *Hybrid Artificial Intelligent Systems*, 2016, pp. 151–162, doi: 10.1007/978-3-319-32034-2_13.

[19] W. Xu, H. Peng, X. Zeng, F. Zhou, X. Tian, and X. Peng, "A hybrid modelling method for time series forecasting based on a linear regression model and deep learning," *Applied Intelligence*, vol. 49, no. 8, pp. 3002–3015, Aug. 2019, doi: 10.1007/s10489-019-01426-3.

[20] T. Mathonsi and T. L. van Zyl, "A statistics and deep learning hybrid method for multivariate time series forecasting and mortality modeling," *Forecasting*, vol. 4, no. 1, pp. 1–25, Dec. 2021, doi: 10.3390/forecast4010001.

[21] K. Albeladi, B. Zafar, and A. Mueen, "Time series forecasting using LSTM and ARIMA," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 1, 2023, doi: 10.14569/IJACSA.2023.0140133.

[22] L. B. Sina, C. A. Secco, M. Blazevic, and K. Nazemi, "Hybrid forecasting methods—a systematic review," *Electronics*, vol. 12, no. 9, Apr. 2023, doi: 10.3390/electronics12092019.

[23] A. M. Schweidtmann, D. Zhang, and M. von Stosch, "A review and perspective on hybrid modeling methodologies," *Digital Chemical Engineering*, vol. 10, Mar. 2024, doi: 10.1016/j.dche.2023.100136.

[24] L. Slater *et al.*, "Hybrid forecasting: using statistics and machine learning to integrate predictions from dynamical models," *Hydrology and Earth System Sciences*, pp. 1–35, Sep. 2022, doi: 10.5194/hess-2022-334.

[25] M. J. Page *et al.*, "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews," *BMJ*, vol. 372, pp. 1–9, Mar. 2021, doi: 10.1136/bmj.n71.

[26] U. F. I. Abdulrahman, N. Ussiph, and B. Hayfron-Acquah, "A hybrid ARIMA-LSTM model for stock price prediction," *International Journal of Computer Engineering and Information Technology*, vol. 12, no. 8, pp. 48–51, 2020.

[27] Z. Peng *et al.*, "An application of hybrid models for weekly stock market index prediction: empirical evidence from SAARC countries," *Complexity*, vol. 2021, no. 1, Jan. 2021, doi: 10.1155/2021/5663302.

[28] S. Kulshreshtha and A. Vijayalakshmi, "An ARIMA- LSTM hybrid model for stock market prediction using live data," *Journal of Engineering Science and Technology Review*, vol. 13, no. 4, pp. 117–123, Aug. 2020, doi: 10.25103/jestr.134.11.

[29] V. Montaño and M. Viado, "Forecasting exchange rate using ARIMA-ANN hybrid model," *Journal of Global Business*, vol. 10, no. 1, 2021.

[30] F. García, F. Guijarro, J. Oliver, and R. Tamošiūnienė, "Foreign exchange forecasting models: ARIMA and LSTM comparison," *Engineering Proceedings*, vol. 39, no. 1, 2023, doi: 10.3390/engproc2023039081.

[31] R. Peirano, W. Kristjanpoller, and M. C. Minutolo, "Forecasting inflation in Latin American countries using a SARIMA–LSTM combination," *Soft Computing*, vol. 25, no. 16, pp. 10851–10862, Aug. 2021, doi: 10.1007/s00500-021-06016-5.

[32] A. H. Bukhari, M. A. Z. Raja, M. Sulaiman, S. Islam, M. Shoaib, and P. Kumam, "Fractional neuro-sequential ARFIMA-LSTM for financial market forecasting," *IEEE Access*, vol. 8, pp. 71326–71338, 2020, doi: 10.1109/ACCESS.2020.2985763.

[33] G. Dudek, P. Pelka, and S. Smyl, "A hybrid residual dilated LSTM and exponential smoothing model for midterm electric load forecasting," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 33, no. 7, pp. 2879–2891, Jul. 2022, doi: 10.1109/TNNLS.2020.3046629.

[34] T. G. Grandón, J. Schwenzer, T. Steens, and J. Breuing, "Electricity demand forecasting with hybrid classical statistical and machine learning algorithms: case study of Ukraine," *Applied Energy*, vol. 355, Feb. 2024, doi: 10.1016/j.apenergy.2023.122249.

[35] A. B. Rashid and S. Vig, "Improving electric load forecasting using a hybrid ARIMA and artificial neural network model," *Proceedings of the KILBY 100 7th International Conference on Computing Sciences 2023 (ICCS 2023)*, 2023, pp. 1-6.

[36] N. E. M. Izudin, R. Sokkalingam, H. Daud, H. Mardesci, and A. Husin, "Forecasting electricity consumption in Malaysia by hybrid ARIMA-ANN," in *Proceedings of the 6th International Conference on Fundamental and Applied Sciences*, 2021, pp. 749–760, doi: 10.1007/978-981-16-4513-6_66.

[37] A. Sinha, R. Tayal, A. Vyas, P. Pandey, and O. P. Vyas, "Forecasting electricity load with hybrid scalable model based on stacked non linear residual approach," *Frontiers in Energy Research*, vol. 9, Nov. 2021, doi: 10.3389/fenrg.2021.720406.

[38] R. K. Jagait, M. N. Fekri, K. Grolinger, and S. Mir, "Load forecasting under concept drift: online ensemble learning with recurrent neural network and ARIMA," *IEEE Access*, vol. 9, pp. 98992–99008, 2021, doi: 10.1109/ACCESS.2021.3095420.

[39] S. Ketu and P. K. Mishra, "A hybrid deep learning model for covid-19 prediction and current status of clinical trials worldwide," *Computers, Materials & Continua*, vol. 66, no. 2, pp. 1896–1919, 2021, doi: 10.32604/cmc.2020.012423.

[40] Y. Zhang, S. Tang, and G. Yu, "An interpretable hybrid predictive model of covid-19 cases using autoregressive model and LSTM," *Scientific Reports*, vol. 13, no. 1, Apr. 2023, doi: 10.1038/s41598-023-33685-z.

[41] Y. Jin *et al.*, "Prediction of covid-19 data using an ARIMA-LSTM hybrid forecast model," *Mathematics*, vol. 10, no. 21, Oct. 2022, doi: 10.3390/math10214001.

[42] Y.-C. Jin, Q. Cao, K.-N. Wang, Y. Zhou, Y.-P. Cao, and X.-Y. Wang, "Prediction of covid-19 data using improved ARIMA-LSTM hybrid forecast models," *IEEE Access*, vol. 11, pp. 67956–67967, 2023, doi: 10.1109/ACCESS.2023.3291999.

[43] Z. Li *et al.*, "Application of a hybrid model in predicting the incidence of tuberculosis in a Chinese population," *Infection and Drug Resistance*, vol. Volume 12, pp. 1011–1020, Apr. 2019, doi: 10.2147/IDR.S190418.

[44] Y. Deng, H. Fan, and S. Wu, "A hybrid ARIMA-LSTM model optimized by BP in the forecast of outpatient visits," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, no. 5, pp. 5517–5527, May 2023, doi: 10.1007/s12652-020-02602-x.

[45] D. Xu, Q. Zhang, Y. Ding, and D. Zhang, "Application of a hybrid ARIMA-LSTM model based on the SPEI for drought forecasting," *Environmental Science and Pollution Research*, vol. 29, no. 3, pp. 4128–4144, Jan. 2022, doi: 10.1007/s11356-021-15325-z.

[46] M. M. H. Khan, N. S. Muhammad, and A. El-Shafie, "Wavelet based hybrid ANN-ARIMA models for meteorological drought forecasting," *Journal of Hydrology*, vol. 590, 2020, doi: 10.1016/j.jhydrol.2020.125380.

[47] J. Zhao, G. Nie, and Y. Wen, "Monthly precipitation prediction in Luoyang city based on EEMD-LSTM-ARIMA model," *Water Science and Technology*, vol. 87, no. 1, pp. 318–335, Jan. 2023, doi: 10.2166/wst.2022.425.

[48] A. Parasyris, G. Alexandrakis, G. V. Kozyrakis, K. Spanoudaki, and N. A. Kampanis, "Predicting meteorological variables on local level with SARIMA, LSTM and hybrid techniques," *Atmosphere*, vol. 13, no. 6, p. 878, May 2022, doi: 10.3390/atmos13060878.

[49] B. Belmahdi, M. Louzazni, M. Marzband, and A. El Bouardi, "Global solar radiation forecasting based on hybrid model with combinations of meteorological parameters: morocco case study," *Forecasting*, vol. 5, no. 1, pp. 172–195, Jan. 2023, doi: 10.3390/forecast5010009.

[50] J. Luo and Y. Gong, "Air pollutant prediction based on ARIMA-WOA-LSTM model," *Atmospheric Pollution Research*, vol. 14, no. 6, Jun. 2023, doi: 10.1016/j.apr.2023.101761.

BIOGRAPHIES OF AUTHORS

Malvina Xhabafti is a Ph.D. student in the field of artificial intelligence. She is currently an assistant lecturer in the Department of Statistics and Applied Informatics, Faculty of Economy, University of Tirana, Albania. Her areas of interest are artificial intelligence, econometrics, databases and java programming. She can be contacted at email: malvina.xhabafti@unitir.edu.al.

Valentina Sinaj holds the Prof. Dr. title in the Department of Statistics and Applied Informatics, Faculty of Economy, University of Tirana, Albania. She is a lecturer in this department and also a member of the board of the University of Tirana. Her field of research is econometric analysis and mathematical modeling. She can be contacted at email: valentinasinaj@feut.edu.al.