

Review

# Forecasting Applied to the Electricity, Energy, Gas and Oil Industries: A Systematic Review

Ivan Borisov Todorov<sup>1</sup> and Fernando Sánchez Lasheras<sup>2,3,\*</sup> 

<sup>1</sup> Department of Drilling, Oil and Gas Production & Transport, Faculty of Geology & Exploration, University of Mining and Geology St. Ivan Rilski, 1700 Sofia, Bulgaria

<sup>2</sup> Department of Mathematics, Faculty of Sciences, University of Oviedo, 33007 Oviedo, Spain

<sup>3</sup> Instituto Universitario de Ciencias y Tecnologías Espaciales de Asturias (ICTEA), University of Oviedo, 33004 Oviedo, Spain

\* Correspondence: [sanchezfernando@uniovi.es](mailto:sanchezfernando@uniovi.es); Tel.: +34-985-103-338

**Abstract:** This paper presents a literature review in which methodologies employed for the forecast of the price of stock companies and raw materials in the fields of electricity, oil, gas and energy are studied. This research also makes an analysis of which data variables are employed for training the forecasting models. Three scientific databases were consulted to perform the present research: The Directory of Open Access Journals, the Multidisciplinary Digital Publishing Institute and the Springer Link. After running the same query in the three databases and considering the period from January 2017 to December 2021, a total of 1683 articles were included in the analysis. Of these, only 13 were considered relevant for the topic under study. The results obtained showed that when compared with other areas, few papers focus on the forecasting of the prices of raw materials and stocks of companies in the field under study. Furthermore, most make use of either machine learning methodologies or time series analysis. Finally, it is also remarkable that some not only make use of existing algorithms but also develop and test new methodologies.



**Citation:** Todorov, I.B.; Sánchez Lasheras, F. Forecasting Applied to the Electricity, Energy, Gas and Oil Industries: A Systematic Review. *Mathematics* **2022**, *10*, 3930. <https://doi.org/10.3390/math10213930>

Academic Editors: Stefania Cristina Cureau, Lucian Belascu and Alexandra Horobet

Received: 23 September 2022

Accepted: 21 October 2022

Published: 23 October 2022

**Publisher's Note:** MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



**Copyright:** © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

**Keywords:** stock price forecasting; raw materials price forecasting; electricity companies; energy companies; gas and oil industry; publicly-traded companies; machine learning; time series

**MSC:** 68T20; 62Q32; 68W50; 82C32

## 1. Introduction

The complexity of financial decisions in a changing world has made those who must take such decisions consider multiple variables that require advanced mathematical models for their analysis. Some of the most promising tools employed in this task belong to the fields of multivariate data analysis and machine learning. More specifically, the use of artificial intelligence and machine learning methodologies for stock market forecasting is widespread. According to the World Bank [1], the total market capitalization of all publicly-traded companies in 2020 was 93,686 billion US dollars. Every day, billions of dollars are traded in stock exchanges all over the world. Those investors that play the markets, whether they are long or short-term investors, are in search of profit over their investment horizon. In order to achieve such an aim, they make use of very different methodologies based on scientific foundations of varying solidity. Among these methodologies, machine learning and artificial intelligence techniques are present and gaining in importance year by year.

The weak form of the efficient-market hypothesis (EMH) [2,3] states that asset prices reflect all the available information on past prices and rule out predictions based on price data alone. This means that under such a hypothesis, anybody playing the stock market should be able to obtain the same return and, therefore, nobody would beat the market using technical analysis. In such circumstances, it would not seem worthwhile to develop

machine learning or any other kind of model to predict the evolution of stock prices. Please note that such a hypothesis does not take into account the fact that investors with private information would obtain a higher return.

In spite of the above-mentioned hypothesis, in present times many authors do not consider that markets are totally efficient [3,4], taking into account phenomena like their overreaction in the short term [5,6]. Also, some of the major assumptions made for the EMH have commonly been debunked [7]. The existence of market anomalies [8–10] is what mainly impels market participants to develop and use models that can give forecasts about stock prices.

From a stock market perspective, the methodologies employed can be classified as fundamental analysis [11] and technical analysis [12]. Fundamental analysis focuses on the analysis of basic company data. As an example, fundamental information may include revenues, earnings, return on equity or profit margins [13]. Technical analysis focuses on the time series of stock prices and trading volumes [14,15]. In other words, it can be stated that the basic distinction between technical and fundamental analysis is determined by the type of variables used for the study, and not by the methodologies employed. Both types of analysis can be used for stock market forecasting.

One of the characteristics of this field of research is that due to the background of the researchers in Economy and stock market forecasting, most of the studies performed in this area make use of statistical time-series methodologies based on historical data to predict the evolution of stock prices. It also seems of interest to remark that a lot of research that makes use of machine learning methodologies combines them with time-series methodologies.

In the last few decades, many new methodologies based on artificial intelligence and machine learning have been developed. Due to their performing well in other fields, these techniques have attracted a lot of interest and have also been largely employed in stock market prediction studies [16]. Some of the most promising methodologies developed over the last few decades are different kinds of artificial neural networks, random forest, support vector machines, decision trees, gradient boosted trees and k-nearest neighbors [17]. As a result, these methodologies represent novel and advantageous alternatives, making them appealing to scholars interested in financial market forecasting. However, the performance of machine learning models is also linked to the quality of the input data employed for building the model. The goodness of fit of the different models, when applied to a particular problem, can be measured by making use of different performance indicators, some of which are suitable for classification problems like specificity, sensitivity, precision or the Matthews correlation coefficient [18] or others which are applicable to regression problems. Examples include mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and symmetric mean absolute percentage error (SMAPE) [19]. Studies relating to price forecasting for stock and raw materials are performed by independent researchers under different circumstances and conditions and with different aims. As a consequence, there is a certain heterogeneity in the databases employed for this kind of study. As far as the authors know, there has been relatively little research on the variables used in the model building process for the market prediction of stocks and raw materials. Stock market data frequently includes time series data in a variety of formats, such as stock index prices, returns, volatility, and interest rates [20]. Something similar could be said about raw material price forecasting, also including the historic prices of both the raw materials under study and others.

Global concern about climate change and the legislative limitations imposed on pollution in developed countries have been major limitations for the development of the business of oil and gas companies in recent years. Currently, the oil and gas industries are in a process of transition to clean energy [21,22]. Such a process will inevitably be long and slow, given its high complexity. The efforts made all around the world to limit the rise in global temperatures that impacts the climate affects the profitability and future of most of the industrial fields. In other words, the whole economy will be affected by the transition to clean energy, and all sectors of the industry need to consider how to respond.

The shift of oil and gas companies to green energies is key to reaching a good level of development of some renewable energy options such as offshore wind, and for the research in others such as carbon capture. Meanwhile, the use of hydrogen still requires time to reach maturity [23]. Remarkable proof of the shift of these companies to green energies is that in recent years some oil and gas companies have diversified their energy operations to include renewables and other low-carbon technologies.

Given the need to survive in a changing and highly-competitive energy market, it can be stated that the risk assumed by private companies for this green transition is larger than the one assumed by the state-owned ones [24]. Most money is put into solar and wind technology, but some oil and gas firms have also diversified by buying up already-existing non-core businesses such as energy distribution, electric car charging, and batteries. It must additionally be taken into account that changes in global energy trends have led many major resource holders to reaffirm their commitment to reform and economic diversification [25,26]. In addition, fundamental changes to development models are seemingly inevitable in many other major resource holders. According to this concept, if large national oil firms perform successfully and remain vigilant to both risks and possibilities, they can contribute significantly to economic stability during this process.

Trends in the mining industry were affected by the commodity boom in the years between 2004 and 2012 [27], which also sparked some significant long-term changes in the sector. These adjustments included a sizeable shift in the industry's clientele towards emerging economies, particularly those in Asia. There was also a move away from contract pricing toward spot pricing, which increased the volatility of mineral prices. A growing role appeared for emerging economy mining companies in the global mining sector, while operating and capital cost pressures increased due to the depletion and tightening of environmental standards and ongoing pressures on the resource sector. These challenges, taken together, create a difficult backdrop for developing sector regulatory frameworks that meet the interests of investors while also providing fair and long-term benefits to mineral-hosting governments. According to estimates, more than 3.7 million people will be employed globally in the mining industry in 2022, with 1.5 million of them working in industrialized nations and 2.2 million in underdeveloped nations [28].

Finally, the electric power sector is one of the core fields in the economy, as almost all industrial activities require electricity. The importance of this sector to the economy is expected to grow in the long term as wind, solar, geothermal, and hydropower sources substitute other forms of electrical production while increasing the generation costs involved [29,30].

In this context, the objective of this study was to perform a systematic review of existing literature on the methodologies applied to the forecasting of stock prices of companies in the energy, mining, electricity, oil and gas sectors, and also to the forecasting of the prices of those raw materials. The period considered was from 2017 to 2021.

## 2. Materials and Methods

A systematic review of the machine learning methodologies employed for the forecasting of the stock prices of energy and mining companies and the price of raw materials like oil, gas, electricity and minerals was conducted. The following databases were employed for the search for papers: The Directory of Open Access Journals (DOAJ), the Multidisciplinary Digital Publishing Institute (MDPI) and the Springer Link.

The research period was from January 2017 to December 2021, which means that articles published for a total of 5 years were screened. Due to the great advances in some forecasting methodologies such as machine learning in recent years, the analysis of a framework comprising only the last 5 years was considered to be enough. The search strategy was based on making use of the same keywords for the search in all of the databases.

### 3. Inclusion and Exclusion Criteria and the Revision Process

All of the documents analysed were in the English language. A revision of the title, abstract and full text was performed independently by the two authors of the present research. Discrepancies in the classification of papers were discussed by both until agreement was reached. After selecting and reading the papers, a summary of their contents was made by both authors and reports were read by both. Some summarization tables were created at that stage of the process to help in the classification task of finding relevant papers.

### 4. Filters Employed for Searches

The same queries were run for all of the databases.

For each search, synonyms, related terms and spelling variations were taken into account, and Boolean operators were used to relate the terms. Boolean operators were utilized to connect the phrases for each search, taking into account synonyms, similar terms, and spelling variants. Before using these terms, searches were conducted in the three databases mentioned using:

‘stock price forecasting’ AND ‘energy company OR mining company OR electric company OR oil company OR gas company’

To avoid possible problems due to the different syntax employed in each database and the behaviour of the AND and OR commands, the queries were applied individually without using the logic operators. In other words, the following individual queries were run in each database: ‘stock price forecasting energy company’, ‘stock price forecasting mining company’, ‘stock price forecasting electric company’, ‘stock price forecasting oil company’ and ‘stock price forecasting gas company’.

### 5. Results

The search strategy was fixed in order to maximize the number of documents identified. The number of documents found making use of the queries referred to in the previous section are listed in Table 1. The results obtained were carefully examined in search of results that would be of interest. A total of 1683 documents were found with the help of those queries.

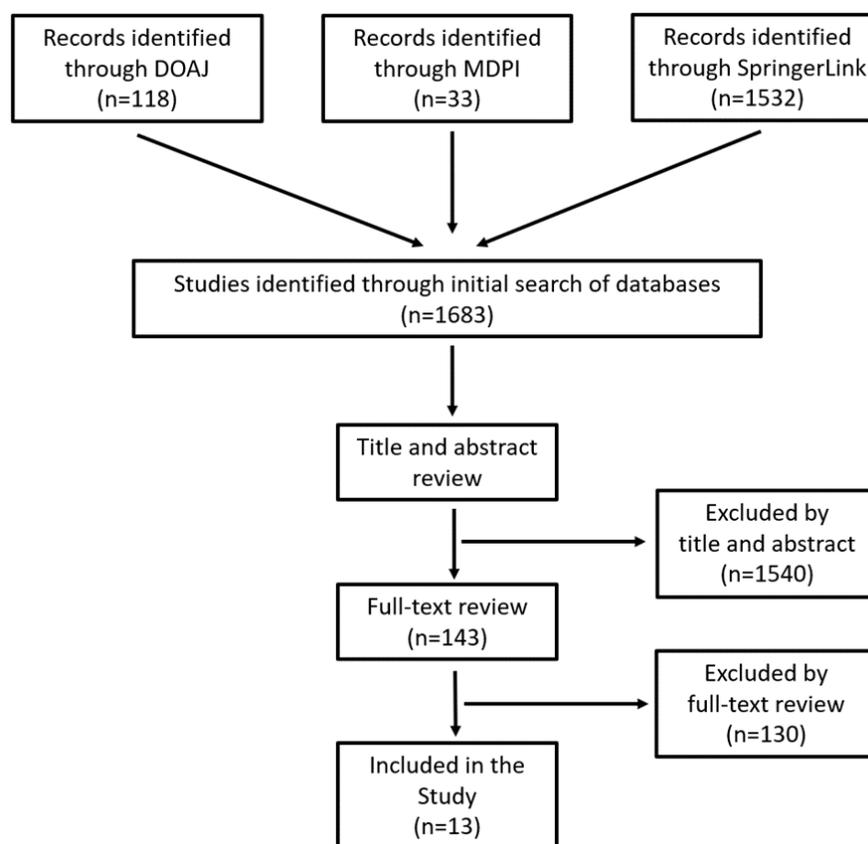
**Table 1.** Articles found in the databases under study.

Database	Number of Articles
Directory of Open Access Journals (DOAJ)	118
MDPI (Multidisciplinary Digital Publishing Institute)	33
Springer Link	1532
Total	1683

In the case of the DOAJ database, 118 manuscripts were screened by title and abstract. After this screening, 84 documents were excluded, as it was considered that their content was not related to the topic under analysis and, therefore, the other 34 were included for a full-text review. Of these manuscripts, after the full-text review, 32 were discarded and the other two were included in the final analysis and review performed in the present manuscript. For the MDPI database, 33 different manuscripts were screened by title and abstract. After this screening, 29 documents were excluded and, therefore, only four were included for the full-text review. Of these manuscripts, three were discarded and one was included in the final analysis presented in this paper. Finally, for the case of the SpringerLink database, 1532 manuscripts were screened by title and abstract. After this screening, 1427 documents were excluded due to the lack of a relationship with the topic under study and, therefore, 105 were included for the full-text review. Of these manuscripts, 95 were discarded and 10 were included in the final analysis. The content of the 13 manuscripts that were considered relevant in the three databases under study is described in this section. Please note that due to the small number of results with a

significant content on machine learning and artificial intelligence methodologies applied to the fields under study, other kinds of forecasting were included in the analysis performed in this paper, and these will be detailed later. The articles found cover the fields of energy, electricity, oil, and gas. Unfortunately, no articles were found about stock price forecasting in mining companies or mineral price forecasting.

Figure 1 summarizes the results obtained with the article search detailed previously. As can be observed in this figure, a total of 1683 were identified in the three databases under analysis. A total of 279 of these articles were published in 2017, 286 in 2018, 314 in 2019, 351 in 2020 and 453 in 2021. Please also note that 1540 of those articles were discarded after reading the title and abstract. A full-text review of the other 143 articles was then performed, which led to the exclusion of 130 papers and the inclusion of only 13 in the present research.



**Figure 1.** Summary of article selection process.

Table 2 shows the distribution of articles by field. The field with the largest amount of research dedicated to it was electricity, with a total of seven papers, followed by oil with five papers. In the case of gas and energy, only one paper was found for each. Please note that the research found relating to gas [31] also deals with oil. It is also worth noting that eight of the 13 papers under analysis were published in 2021, the last year in the period considered, which shows that there is a growing interest in this topic.

**Table 2.** Articles found by fields and year.

Field	Reference	Year
ELECTRICITY	[32]	2021
	[33]	2017
	[34]	2017
	[35]	2019
	[36]	2020
	[37]	2019
	[38]	2021
OIL	[31]	2021
	[39]	2021
	[40]	2021
	[41]	2021
	[42]	2021
GAS	[31]	2021
ENERGY	[43]	2021

In the case of research focused on the field of electricity, most of it deals with electricity prices. More specifically, one [32] forecast the hourly electricity prices from the Irish Integrated Single Electricity Market, while another [37] did the same with the prices of the electricity market in Germany for year 2018 one day ahead, making use of hourly values. Two research papers [34,35] make use of hourly prices of energy in the Nord Pool Scandinavian power market. Another research work [36] made use of electricity price data in the United States, whereas yet another [38] does not detail where its data comes from. Finally, another research paper [33] forecast the stock prices of several companies, including Eve Energy Co. Ltd. (Huizhou, China), a firm specialized in battery manufacture.

In this research, four [39–42] of the five papers included that deal with a topic linked to the field of oil are devoted to the forecast of the evolution of crude oil prices. The fifth paper [31] forecasted the daily closing stock prices of the 13 largest oil and gas sector companies of the Nigerian Stock Exchange (NSE). For this reason, this research has been included in both fields. Finally, regarding the field of energy, only one paper has been found [43]. This research is focused on the forecasting of the price evolution of the most important clean energy exchange traded funds.

Table 3 shows the families of methodologies employed in the articles under analysis. As can be observed, most of them make use of machine learning methodologies. The number of methodologies employed is considerable and includes different kinds of artificial neural networks like the adaptive neuro fuzzy inference system (ANFIS) [44], back propagation neural networks [45], extreme learning machines [46], feed forward neural networks [47], generalized regression neural networks [48], the long short-term memory network [49], radial basis function neural networks [50], random vector functional link (RVFL) networks [51], recurrent neural networks [52] and wavelet neural networks [53]. Other kinds of machine learning methodologies employed in the research under study are tree-based algorithms [54]. More specifically, the research considered made use of decision tree bagging [55], extreme gradient boosting [56], gradient boosting [57] and random forest [58]. In addition, other machine learning methodologies like support vector machines [59] and clustering [54] were employed by researchers. Please also note that in this paper, methodologies like generalized linear models, least absolute shrinkage and selection operator (LASSO) [60] and logistic regression [61] have been included in the section related to machine learning methodologies.

**Table 3.** Families of methodologies employed in the papers under analysis.

References	Methodologies			
	Machine Learning	Others	Time Series	Econometrics
[31]	yes	yes	no	no
[32]	yes	no	no	no
[33]	no	yes	no	no
[34]	yes	no	yes	no
[35]	yes	yes	yes	no
[36]	yes	no	yes	no
[37]	yes	no	yes	no
[38]	no	no	no	no
[39]	yes	yes	yes	no
[40]	no	no	no	yes
[41]	yes	no	no	no
[42]	no	no	no	no
[43]	yes	no	no	no

Other non-machine learning methodologies of interest employed in the papers under analysis and that are classified in the category were Bayesian models [62], stochastic differential equations [63], geometric Brownian motion [64], and wavelet transform [65]. In the case of the geometric Brownian motion, this is due to its relationship with the Black-Scholes equation [66]. Also, an econometric methodology called the target capacity utilization rule [67] was found to be of interest by researchers.

Some of the papers under study also made use of time series methodologies. The methodologies employed were as follows: the autoregressive moving average model (ARMA) [68], the autoregressive integrated moving average models (ARIMA) [69], seasonal nonlinear autoregressive models [70], and the seasonal autoregressive integrated moving average (SARIMA) [71].

It is also worth stating that in five of the 13 manuscripts under analysis, different kinds of artificial neural networks were employed, this being the most common methodology of all those considered by the authors. The next most popular methodologies were different kinds of time series forecasting, applied either with any machine learning methodologies or alone. Also, in four papers Brownian movement is applied, in some cases through the Black Scholes equation. With three papers the next most common model was regression in its different forms and, finally, only support vector machines were applied in more than one paper, more specifically in two.

Table 4 presents a list of all those research papers that made use of any kind neural networks topology among all those machine learning methodologies that employ them. Table 5 lists those papers that make use of any machine learning methodology that is not neural networks. The papers listed in Table 5 are classified into three main groups according to the methodologies applied: Tree-based algorithms, regression, and others. In the following paragraphs there is a brief description of all the research listed in Tables 4 and 5. Please note that some of the papers feature in both tables.

**Table 4.** List of papers that make use of any neural network methodology. ANFIS: Adaptive neurofuzzy inference system, BPNN: Back propagation neural networks, ELM: Extreme learning machines, FFNN: Feed forward neural networks, GRNN: Generalized regression neural networks, LSTM: Long short-term memory network, RBF: Radial basis function neural networks, RVFL: Random vector functional link network, RNN: Elman’s recurrent neural networks and WNN: Wavelet neural networks.

References	ANFIS	BPNN	ELM	FFNN	GRNN	LSTM	RBF	RVFL	RNN	WNN
[31]	no	no	no	yes	no	no	no	no	yes	no
[35]	no	no	no	yes	no	no	no	no	no	no

**Table 4.** *Cont.*

References	ANFIS	BPNN	ELM	FFNN	GRNN	LSTM	RBF	RVFL	RNN	WNN
[34]	no	no	no	yes	no	no	no	no	no	no
[36]	yes	yes	yes	no	yes	yes	yes	no	yes	yes
[39]	no	no	no	no	yes	yes	no	no	yes	yes
[41]	no	no	no	no	no	no	no	yes	no	no

**Table 5.** List of papers that make use of any machine learning methodology that is not of the neural networks category. DTB: Decision tree bagging, GB: Gradient boosting, EGB: Extreme gradient boosting, RF: Random forest, GLM: Generalized linear model, LASSO: Least absolute shrinkage and selection operator regression, LR: Logistic regression, SVM: Support vector machines.

References	DTB	Tree-Based Algorithms			Regression			Others	
		GB	EGB	RF	GLM	LASSO	LR	Clustering	SVM
[31]	no	no	no	no	no	no	yes	no	yes
[32]	no	yes	yes	yes	no	no	no	no	no
[36]	no	no	no	no	no	no	no	no	yes
[37]	no	no	no	no	no	no	no	yes	no
[39]	no	no	no	no	yes	yes	no	no	no
[43]	yes	no	no	yes	no	no	yes	no	no

In the study by Fu et al. [36], the authors suggest a hybrid system for forecasting power prices. This consists of modules for data analysis, sub-model selection strategy, optimized forecasting processing, and model evaluation. The aforementioned hybrid system takes advantage of the strengths of a single model, enhancing the combined model’s forecasting capabilities. The experimental findings demonstrated that the suggested method selects appropriate sub-models successfully and predicts future trend changes in the price of electricity. As a result, the system may be a useful tool in the design and construction of smart grids. The proposed hybrid forecasting model made use of the following neural networks methodologies: ANFIS, back propagation neural networks (BPNN), extreme learning machines (ELM), generalized regression neural networks (GRNN), long short-term memory network (LSTM), radial basis function neural networks (RBF) and Elman’s recurrent neural networks (RNN). A wavelet neural networks (WNN) article is also listed in Table 5, as it also made use of support vector machines (SVM) as a benchmark methodology.

The research of Lu et al. [39] proposed the study and forecasting of the evolution of crude oil prices by making use of an innovative model based on LSTM able to select those variables of importance for said price forecasting. The research made also use of the elastic-net regularized generalized linear Model (GLMNET), spike-slab lasso method, and Bayesian model average (BMA) to select the core influence factors. Secondly, the LSTM was employed, and afterwards, six different forecasting techniques, such as random walk (RW), ARMA, RNN, WNN, GRNN and LASSO were used to forecast the price. According to the results shown by the authors, the variable selection-LSTM method outperforms the benchmark methods in both level and directional forecasting accuracy.

The work of Oyewola et al. [31] made use of different machine learning methodologies and proposed a nature-inspired algorithm based on differential equations known as auditory algorithms (AA) by the authors. This program mimics the auditory system of the human ear. Some machine learning methods and continuous-time stochastic processes are used to compare the performance of AA. In addition to continuous-time models like stochastic differential equations (SDE) and geometric Brownian motion (GBM), machine learning methods including logistic regression (LR), SVM, feed forward neural networks (FFN) and RNN were also used. The results obtained by the AA outperformed the benchmark methodologies when applied to the prediction of the daily closing stock prices of the 13 largest companies in the oil and gas sectors of the Nigerian Stock Exchange (NSE).

In order to forecast electricity spot prices, Saâdaoui and Rabbouch's research [35] introduced a novel approach that made use of wavelet-based hybridization that utilized nonlinear smooth functions, the autoregressive fractionally integrated moving average (ARFIMA) model, and feedforward artificial neural networks. These patterns of power time series, including the nonlinear trend and various seasonal influences, may be precisely extrapolated over the time scale thanks to the application of the wavelet decomposition in this model. The authors were also able to precisely infer key patterns of power time series. Examples of this are the nonlinear trend and numerous seasonal effects in this study thanks to the use of wavelet decomposition. In order to test the model performance, hourly power prices from the Nord Pool Exchange were employed. Please note that in this research, hourly information from the years 2012 to 2017 was employed, which means a total of more than 50,000 records were accessed. As expressed by the authors in this manuscript, the model outcome confirmed that the proposed method was capable of outperforming the benchmark methodologies employed in this paper, namely the regression SARIMA model and the seasonal nonlinear autoregressive model.

The work presented by Saâdaoui [34] defined a new machine learning model based on an artificial neural network called seasonal autoregressive neural network (SAR-NN). This artificial neural network is a dynamic feedforward and was primarily designed to predict electricity costs. SAR-NN is an autoregressive model based on artificial neural networks that only take into account autoregressors that are lagged by a multiple of the period  $p$  of the dominant seasonality. This neural network advances step by step, enabling the generation of accurate projections for numerous steps in the future. This model was tested making use of hourly prices of energy in the Nord Pool Scandinavian power market, which is one of the most mature energy markets worldwide. The results were then compared with those achieved by other methodologies like feed-forward neural networks, SARIMA, and seasonal nonlinear autoregressive. It is worth noting that the neural network architecture proposed by the authors was conceived by considering the model to be a system of hour-by-hour daily-indexed time series. Technically, this might be done by creating an autoregressive artificial neural network model that only takes into account variables that are lagged by multiples of 24, which is the dominant period. The result is a multi-steps-ahead forecast when hourly forecasts are moved in the artificial neural network. With the use of an empirical study that used the Nord Pool spot prices data as its foundation, the model's performance was evaluated, and the new approach was contrasted with three benchmark models. The authors were able to claim that the new artificial neural network model they had presented could provide very accurate extrapolations and required minimal effort to execute because the results of the new methodology were encouraging.

The research presented by Yu et al. [41] insisted on the drawback of those models that made use of a single machine methodology for price forecasting. The main reason given by those authors is that they cannot capture the complex hidden factors of price variations, which in the case of this research refers to crude oil prices. In order to achieve a satisfactory performance, the authors recommended using RVFL networks as the foundational models for the ensemble learning framework and studied diversity tactics in the proposed RVFL network ensemble forecasting model. According to the experimental findings, choosing diversity techniques properly would boost the accuracy of ensemble learning models.

Table 5 cites, among others, the work of Krome et al. [37]. This research employed a method for determining clusters of time series. In the case of this research, what the authors propose helps to simplify time series analysis. The methodology was applied by making use of one-day-ahead hourly prices of the electricity market in Germany for 2018. Please note that although this research would not be considered as a work of price forecasting, it was included in this study as the results obtained can be useful for building a forecasting model.

Eight technical indicators acceptable for the forecasting of hourly electricity prices from the Irish Integrated Single Electricity Market were reported in the work by McHugh et al. [32]. The three primary categories of price indicators—trend, oscillator, and

momentum—are taken into account by the suggested indicators. Building technical indicators from the raw price data for energy helps in the understanding of market behaviour and in uncovering data to forecast future lucrative pricing. Data on electricity prices was gathered for the suggested indicators between February 2019 and March 2020. On the basis of the suggested technical indicators, three machine learning regression algorithms were trained. Those models were Extreme Gradient Boosting, Gradient Boosting, and Random Forest. The results obtained by the authors affirm that forecasting is more accurate when models are trained making use of certain technical indicators described in the paper than when models make use of raw prices.

Finally, the last paper that made use of a machine learning methodology was the one written by Sadorsky [43]. In this research the author employed tree bagging and random forest in the framework of traded funds. More specifically, the author forecasted five traded funds included in the clean energy exchange. Those funds are: Invesco Wilder Hill Clean Energy ETF, the iShares Global Clean Energy ETF, the First Trust NASDAQ Clean Edge Green Energy Index Fund, the Invesco Solar ETF and the First Trust Global Wind Energy ETF. The results obtained with this methodology were compared with those achieved by a classic model: the logistic regression model. The fact that some well-known technical indicators from this research were used as input variables for the models employed in this study was also intriguing. Examples of these models were the relative strength indicator (RSI), stochastic oscillator (slow, fast), advance-decline line (ADX), moving average cross-over divergence (MACD), price rate of change (ROC) on balance volume, and the 200-day moving average. These indicators were calculated from daily data rather than directly from daily fund prices. The outcomes demonstrated that predictions of stock price direction made using decision tree bagging and random forests more precise than those made using logistic regression models. Tree bagging and random forests approaches in this study generate accuracy rates of between 85% and 90% over a 20-day forecast horizon, while the logistic regression models employed as a benchmark produce accuracy rates of between 55% and 60%.

As was presented in Table 6, some of the papers considered in this research did not make use of machine learning methodologies, which goes to show that they are not the only kind of forecasting methodologies employed in this field. Those articles are now described in order to give a complete overview of those methodologies that have been employed in the last years.

**Table 6.** List of papers that propose a new algorithm and a short description of their proposals.

Reference	New Algorithm	Description of the Proposal
[31]	yes	Based on differential equations
[32]	no	
[34]	yes	Based on artificial neural networks
[35]	yes	Based on wavelets
[36]	yes	Combines several kinds of neural networks
[37]	yes	Based on ARIMA and clustering
[38]	no	
[39]	yes	Combines well-known methodologies in a workflow
[40]	no	
[42]	no	
[43]	no	
[70]	no	
[41]	no	

In the study of Bollapragada et al. [40], the researchers used an econometric approach to create a forecasting model that could forecast oil prices. This aided management in lowering operational costs, boosting profits, and strengthening competitive advantage. The model was tested using historical data from 1987 to 2017 and using the Target Capacity Utilization Rule recursive simulation model [67] to forecast crude oil prices for the years 1991

to 2017. The study modified a few model parameters to find the best monthly adjustment, and the results obtained were found to be of interest.

A Brownian motion-based optimal stopping model was put forward by Boubaker et al. [42] in their study to determine the best moment to sell oil crude futures contracts. This model relies on the border and drop in crude oil futures prices to determine when a downturn will start. The authors' findings, which were supported by numerical simulation and empirical investigations, demonstrated the efficiency of the suggested model for the ideal stopping time.

The work of Pałowski and Nowak [38] dealt with a model of electricity spot prices that made use of the Black and Scholes model based on Brownian motion [66] with fuzzy parameters. In order to show the model performance, the research presented several numerical examples.

The research of Yang et al. [70] made use of wavelet transform to forecast the evolution of several companies' stock prices. One of the companies analysed in this research was Eve Energy Co. Ltd. (Huizhou, China), a battery manufacturer. Although strictly speaking this company does not belong to the core business of the fields under analysis, this is one example of the type of company employed by gas and oil firms with the aim of making them diversify and become greener. By comparing the trend of the stock prices and the data of the individual stocks, the usage of the plate in the leading stock data and individual stock data was compared and analysed. Comprehensive data analysis is used to evaluate the stability of the individual stocks, allowing investors to understand the volatility of the stock market in a clear and simple way. However, more research on individual stock data and the trend of leading stocks is still required for a correct analysis of volatility.

It is also worth pointing out that six of the thirteen articles analysed in this research proposed new algorithms. They are all listed in Table 6, which provides a short description of the proposed algorithms. All of them employed machine-learning-based methodologies, except for the work of Saâdaoui and Rabbouch [35], which made use of wavelets, and the work of Oyewola et al. [31], which was based on differential equations. The works of Fu et al. [36], Lu et al. [39] and Saâdaoui [34] made use of different kinds of neural networks, while the proposal in the research of Krome et al. [37] was clustering methodologies.

## 6. Discussion

The articles selected and presented in this paper show that research on forecast methodologies applied to the fields of energy, electricity, oil and gas can be classified into four broad groups. These are machine learning, time series, econometrics, and a fourth category of others in which other interesting methodologies like wavelets are included. It is also remarkable that most research papers written in the last 5 years made use of machine learning methodologies and that some of those papers combined them with other non-machine learning techniques.

Although we searched in three of the most relevant databases and retrieved more than 1600 documents, the present research presents some limitations. The first of these is that only articles in the English language were selected, which could result in a selection bias. In addition, the results obtained are also conditioned by the keywords employed for the queries. Finally, it is also noteworthy that no work has been found in which predictions are made regarding either mining companies or raw materials obtained in mining. In spite of this, the authors are aware that these kinds of studies [72] can be found in other databases.

A surprising fact is that despite the great interest that deep learning has aroused in many branches of science and technology in recent years, no article has been found that made use of any of the methodologies included in this family. Finally, it should also be noted that through the searches that have been proposed, a large number of results were obtained that were not relevant at all or related in any way to the search carried out.

As the reader will be aware, this is not the first paper about literature reviews that includes articles about forecasting methodologies in the fields of the energy, gas and oil industries. Although it is relatively easy to find papers that review the state of the art

of forecasting methodologies applied to the demand of oil, electricity or gas or to the forecasting of stock markets, it is, however, not so common to find research focused on the fields under study in the present paper. From the authors' point of view, the most relevant works published in the last decade are those that are briefly summarized and compared with the present work in the following paragraphs.

Among the most outstanding research is that published in 2018 by Tamba et al. [73], which presents a state-of-the-art survey of those papers that forecast natural gas production, consumption, demand, etc. This paper made an exhaustive revision of all of the works published from 1949 to 2015 that include machine learning methodologies. Despite this, none of the papers included in this work forecasted the stock prices of gas companies.

Another article that may be considered to be of interest is the one published by Lago et al. in 2021 [74], in which they review the state of the art of algorithms devoted to forecasting of one-day-ahead electricity prices. Please note that this paper is only focused on this particular topic and suffers from not considering the forecasting of stock prices of electrical companies in any case. In a similar vein is the research published in 2014 by Weron [75] and the one of Singh and Mohanty of 2015 [76], while as far as the authors know, none of the revisions of the state of the art of electrical companies focus on their company's stock price. Finally, and in a similar way to that of the previous research into the state of the art of forecasting of electricity prices, the research published by Acaroglu and García Márquez in 2021 [77] is also worth mentioning here.

Another work of literature review is the one by Kumbure et al. (2022) [78]. This deals with stock market forecasting without considering any specific field and does not even mention those under analysis in our work. Another paper of interest is the one published by Thakkar and Chaudhari in 2021 [79], which analyses the different kinds of deep neural networks that have been employed for stock market forecasting, but none of these considered the forecasting of companies in the fields under analysis in this research. Therefore, and as a summary of the articles that make a review of the state of the art, it can be said that none of them performs an analysis that includes all the markets contained in our work.

We would like to say that, in our opinion, the main interest of the present research is that it provides the reader with a complete list of updated papers that employ different forecasting methodologies in the industries of electricity, energy, gas and oil. The reader has access to a classification of articles by industries and methodologies (machine learning, time series, econometrics, etc.). The articles listed in this paper would be a good starting point for anybody interested in this topic and would help to accelerate their learning process in this field of research. Please also note that the flowchart presented in Figure 1 would be of interest for all those involved in a literature review.

The main limitations of this research are two-fold. On the one hand, only papers from the last five years have been considered. On the other, there are other interesting databases whose articles have not been included in this work. The reason for this is the large number of articles that would have had to be managed by authors.

## 7. Conclusions and Future Research Lines

From the authors' point of view, the present research provides some contributions that would be of interest to future researchers. Firstly, this paper provides a systematic review of recent literature on methodologies for stock market forecasting for the fields of energy, mining, electricity, oil and gas. It also provides an analysis of the stocks, derivatives, financial markets and raw materials. The present paper also explores the types and specific variables used for predictions in literature from the last five years. In addition, it includes a detailed presentation of existing forecasting approaches and how they have been used in the existing literature.

After the revision of a total of 1683 articles only 13 have been included as relevant for the topic under study in this manuscript. This fact can give the reader an idea of how uncommon this topic still is in the field under study. In other words, there is still a vast

field to explore in the application of machine learning and statistical methodologies to forecasting in the electricity, energy, gas and oil industries. Please also note that this revision task included the full-text review of 143 articles. As future research lines that would be of interest for readers, the authors consider that in any future work, the literature review should be extended to a period of ten years and also include other databases like Scopus, Web of Science, and Emerald.

**Author Contributions:** Conceptualization, I.B.T. and F.S.L.; data curation, I.B.T. and F.S.L.; formal analysis, I.B.T. and F.S.L.; methodology, F.S.L. and I.B.T.; project administration, F.S.L.; resources, F.S.L.; software, I.B.T. and F.S.L.; validation, F.S.L.; visualization, F.S.L.; writing—original draft, I.B.T.; writing—review and editing, I.B.T. and F.S.L. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Data Availability Statement:** Not applicable.

**Acknowledgments:** The authors would like to thank Anthony Ashworth for his revision of the English grammar and spelling in the manuscript.

**Conflicts of Interest:** The authors declare that they have no conflict of interest.

## References

- World Bank Market Capitalization of Listed Domestic Companies (% of GDP). World Federation of Exchanges Database. Available online: <https://data.worldbank.org/> (accessed on 11 April 2022).
- Fama, E. Efficient capital markets: A review of the theory. *J. Financ.* **1970**, *25*, 383–417. [CrossRef]
- Shmilovici, A.; Alon-Brimer, Y.; Hauser, S. Using a Stochastic Complexity Measure to Check the Efficient Market Hypothesis. *Comput. Econ.* **2003**, *22*, 273–284. [CrossRef]
- Borovkova, S.; Tsiamas, I. An ensemble of LSTM neural networks for high-frequency stock market classification. *J. Forecast.* **2019**, *38*, 600–619. [CrossRef]
- de Bondt, W.F.M.; Thaler, R. Does the Stock Market Overreact? *J. Financ.* **1985**, *40*, 793–805. [CrossRef]
- Caporale, G.M.; Gil-Alana, L.; Plastun, A. Short-Term Price Overreactions: Identification, Testing, Exploitation. *Comput. Econ.* **2018**, *51*, 913–940. [CrossRef]
- Muthusamy, S.K.; Kannan, R. Market Efficiency or Lack Thereof: A Critique and Rethinking on Corporate Governance. 2019. Available online: <https://ssrn.com/abstract=2592843> (accessed on 10 November 2019).
- Caporale, G.M.; Gil-Alana, L.; Plastun, A. Intraday Anomalies and Market Efficiency: A Trading Robot Analysis. *Comput. Econ.* **2016**, *47*, 275–295. [CrossRef]
- Khan, M.S.R.; Rabbani, N. Market Conditions and Calendar Anomalies in Japanese Stock Returns. *Asia Pac. Financ. Mark.* **2019**, *26*, 187–209. [CrossRef]
- Anjum, S. Impact of market anomalies on stock exchange: A comparative study of KSE and PSX. *Future Bus. J.* **2020**, *6*, 1. [CrossRef]
- Ahmed, S.W.; Hassan, H.; Mabrouk, A. Fundamental Analysis Models in Financial Markets—Review Study. *Procedia Econ. Financ.* **2015**, *30*, 939–947.
- Ayala, J.; García-Torres, M.; Noguera, J.L.V. Technical analysis strategy optimization using a machine learning approach in stock market indices. *Knowl. Based Syst.* **2021**, *225*, 107119. [CrossRef]
- Bodie, Z.; Kane, A.; Marcus, A.J. *Investments*; McGraw-Hill: New York, NY, USA, 2009.
- Wei, L.Y.; Chen, T.L.; Ho, T.H. A hybrid model based on adaptive-networkbased fuzzy inference system to forecast Taiwan stock market. *Expert Syst. Appl.* **2011**, *38*, 13625–13631.
- Lohrmann, C.; Luukka, P.; Jablonska-Sabuka, M.; Kauranne, T. A combination of fuzzy similarity measures and fuzzy entropy measures for supervised feature selection. *Expert Syst. Appl.* **2018**, *110*, 216–236. [CrossRef]
- Chen, Y.; Hao, Y. A feature weighted support vector machine and K-nearest neighbor algorithm for stock market indices prediction. *Expert Syst. Appl.* **2017**, *80*, 340–355. [CrossRef]
- Thakur, N.; Han, C.Y. A Study of Fall Detection in Assisted Living: Identifying and Improving the Optimal Machine Learning Method. *J. Sens. Actuator Netw.* **2021**, *10*, 39. [CrossRef]
- Ioannou, C.; Vassiliou, V. Network Attack Classification in IoT Using Support Vector Machines. *J. Sens. Actuator Netw.* **2021**, *10*, 58. [CrossRef]
- Jierula, A.; Wang, S.; OH, T.-M.; Wang, P. Study on Accuracy Metrics for Evaluating the Predictions of Damage Locations in Deep Piles Using Artificial Neural Networks with Acoustic Emission Data. *Appl. Sci.* **2021**, *11*, 2314. [CrossRef]
- Enke, D.; Thawornwong, S. The use of data mining and neural networks for forecasting stock market returns. *Expert Syst. Appl.* **2005**, *29*, 927–940. [CrossRef]

21. Zhao, X. Do the stock returns of clean energy corporations respond to oil price shocks and policy uncertainty? *J. Econ. Struct.* **2020**, *9*, 53. [CrossRef]
22. Hartmann, J.; Inkpen, A.C.; Ramaswamy, K. Different shades of green: Global oil and gas companies and renewable energy. *J. Int. Bus. Stud.* **2021**, *52*, 879–903. [CrossRef]
23. Fattouh, B.; Poudineh, R.; West, R. The rise of renewables and energy transition: What adaptation strategy exists for oil companies and oil-exporting countries? *Energy Transit.* **2019**, *3*, 45–58. [CrossRef]
24. Patala, S.; Juntunen, J.K.; Lundan, S. Multinational energy utilities in the energy transition: A configurational study of the drivers of FDI in renewables. *J. Int. Bus. Stud.* **2021**, *52*, 930–950. [CrossRef]
25. Shaffer, B. Global energy trends: Demands for scientific innovation. *MRS Energy Sustain.* **2019**, *6*, 2. [CrossRef]
26. Heidari, H.; Akbari, M.; Souhankar, A. Review of global energy trends towards 2040 and recommendations for Iran oil and gas sector. *Int. J. Environ. Sci. Technol.* **2022**, *19*, 8007–8018. [CrossRef]
27. Humphreys, D. The mining industry after the boom. *Min. Econ.* **2019**, *32*, 145–151. [CrossRef]
28. Industrial Global Union. Mining and DGOJP (Diamond, Gem, Ornament and Jewellery Processing). Available online: <https://www.industrial-union.org/mining-and-dgojp> (accessed on 15 April 2022).
29. Binder, K.E.; Mjelde, J.W. Projecting impacts of carbon dioxide emission reductions in the US electric power sector: Evidence from a data-rich approach. *Clim. Chang.* **2018**, *151*, 143–155. [CrossRef]
30. Brown, M.A.; Li, Y. Carbon pricing and energy efficiency: Pathways to deep decarbonization of the US electric sector. *Energ. Effic.* **2019**, *12*, 463–481. [CrossRef]
31. Oyewola, D.O.; Ibrahim, A.; Joshua, A.K.; Dada, E.G. A new auditory algorithm in stock market prediction on oil and gas sector in Nigerian stock exchange. *Soft Comput. Lett.* **2021**, *3*, 100013. [CrossRef]
32. McHugh, C.; Coleman, S.; Kerr, D. Technical indicators for energy market trading. *Mach. Learn. Appl.* **2021**, *6*, 100182. [CrossRef]
33. Yang, J.; Li, J.; Liu, S. A new algorithm of stock data mining in Internet of Multimedia Things. *J. Supercomput.* **2017**, *26*, 2374–2389. [CrossRef]
34. Saâdaoui, F. A seasonal feedforward neural network to forecast electricity prices. *Neural Comput. Appl.* **2017**, *28*, 835–847. [CrossRef]
35. Saâdaoui, F.; Rabbouch, H. A wavelet-based hybrid neural network for short-term electricity prices forecasting. *Artif. Intell. Rev.* **2019**, *52*, 649–669. [CrossRef]
36. Fu, T.; Zhang, S.; Wang, C. Application and research for electricity price forecasting system based on multi-objective optimization and sub-models selection strategy. *Soft Comput.* **2020**, *24*, 15611–15637. [CrossRef]
37. Krome, C.; Höft, J.; Sander, V. Clustering time series applied to energy markets. *Energ. Inf.* **2019**, *2*, 17. [CrossRef]
38. Pawlowski, M.; Nowak, P. Stochastic approach model spot price and value forward contracts on energy markets under uncertainty. *J. Ambient Intell. Hum. Comput.* **2021**. [CrossRef]
39. Lu, Q.; Sun, S.; Duan, H. Analysis and forecasting of crude oil price based on the variable selection-LSTM integrated model. *Energ. Inf.* **2021**, *4*, 47. [CrossRef]
40. Bollapragada, R.; Mankude, A.; Udayabhanu, V. Forecasting the price of crude oil. *DECISION* **2021**, *48*, 207–231. [CrossRef]
41. Yu, L.; Wu, Y.; Tang, L.; Yin, H.; Lai, K.K. Investigation of diversity strategies in RVFL network ensemble learning for crude oil price forecasting. *Soft Comput.* **2021**, *25*, 3609–3622. [CrossRef]
42. Boubaker, S.; Liu, Z.; Zhang, Y. Risk management for crude oil futures: An optimal stopping-timing approach. *Ann. Oper. Res.* **2021**, *313*, 9–27. [CrossRef]
43. Sadorsky, P. A Random Forests Approach to Predicting Clean Energy Stock Prices. *J. Risk Financ. Manag.* **2021**, *14*, 48. [CrossRef]
44. Jang, J.S. ANFIS: Adaptive-network-based fuzzy inference system. *IEEE Trans Syst Man Cybern* **1993**, *23*, 665–685. [CrossRef]
45. Rojas, R. *Neural Networks: A Systematic Introduction*; Springer: Berlin/Heidelberg, Germany, 1996.
46. Huang, G.B.; Zhu, Q.-Y.; Siew, C.-K. Extreme learning machine: Theory and applications. *Neurocomputing* **2006**, *70*, 489–501. [CrossRef]
47. Hemeida, A.M.; Hassan, S.A.; Mohamed, A.-A.A.; Alkhalaf, S.; Mahmoud, M.M.; Senjyu, T.; El-Din, A.B. Nature-inspired algorithms for feed-forward neural network classifiers: A survey of one decade of research. *Ain Shams Eng. J.* **2020**, *11*, 659–675. [CrossRef]
48. Specht, D.F. A general regression neural network. *IEEE Trans. Neural Netw.* **1991**, *2*, 568576. [CrossRef] [PubMed]
49. Hochreiter, S.; Schmidhuber, J.A. Long short-term memory. *Neural Comput.* **1997**, *9*, 1735–1780. [CrossRef] [PubMed]
50. Broomhead, D.S.; Lowe, D. Multivariable functional interpolation and adaptive networks. *Complex Syst.* **1988**, *2*, 321–355.
51. Husmeier, D. Random Vector Functional Link (RVFL) Networks. In *Neural Networks for Conditional Probability Estimation. Perspectives in Neural Computing*; Springer: London, UK, 1999; pp. 87–97.
52. Sánchez, A.B.; Galán, C.O.; Lasheras, F.S. Forecasting SO<sub>2</sub> Pollution Incidents by means of Elman Artificial Neural Networks and ARIMA Models. *Abstr. Appl. Anal.* **2013**, *2013*, 1–6. [CrossRef]
53. Alexandridis, A.K.; Zapranis, A.D. Wavelet neural networks: A practical guide. *Neural Netw.* **2013**, *42*, 1–27. [CrossRef]
54. Hastie, T.; Tibshirani, R.; Friedman, J.H. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*; Springer: New York, NY, USA, 2001.
55. Dietterich, T.G. An Experimental Comparison of Three Methods for Constructing Ensembles of Decision Trees: Bagging, Boosting, and Randomization. *Mach. Learn.* **2000**, *40*, 139–157. [CrossRef]

56. Chen, T.; Guestrin, C. XGBoost: A Scalable Tree Boosting System. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, 13–17 August 2016.
57. Friedman, J.H. Greedy function approximation: A gradient boosting machine. *Ann. Stat.* **2001**, *29*, 1189–1232. [[CrossRef](#)]
58. Ho, T.K. Random decision forests. In Proceedings of the 3rd International Conference on Document Analysis and Recognition, Montreal, QC, Canada, 14–16 August 1995.
59. Rosado, P.; Lequerica-Fernández, P.; Villallain, L. Survival model in oral squamous cell carcinoma based on clinicopathological parameters, molecular markers and support vector machines. *Expert Syst. Appl.* **2013**, *40*, 4770–4776. [[CrossRef](#)]
60. Tibshirani, R. Regression Shrinkage and Selection via the lasso. *J. R. Stat. Soc.* **1996**, *58*, 267–288. [[CrossRef](#)]
61. Berkson, J. Application of the Logistic Function to Bio-assay. *J. Am. Stat. Assoc.* **1944**, *9*, 357–365.
62. van de Schoot, R.; Depaoli, S.; King, R. Bayesian statistics and modelling. *Nat. Rev. Methods Prim.* **2021**, *1*, 1. [[CrossRef](#)]
63. Bianchi, C.; Cleur, E.M. Indirect estimation of stochastic differential equation models: Some computational experiments. *Comput. Econ.* **1996**, *9*, 257–274. [[CrossRef](#)]
64. Liu, Y.; Yang, A.; Zhang, J. An Optimal Stopping Problem of Detecting Entry Points for Trading Modeled by Geometric Brownian Motion. *Comput. Econ.* **2020**, *55*, 827–843. [[CrossRef](#)]
65. Meyer, Y. *Wavelets and Operators*; Cambridge University Press: Cambridge, UK, 1992.
66. Black, F.; Scholes, M. The Pricing of Options and Corporate Liabilities. *J. Polit. Econ.* **1973**, *81*, 637–654. [[CrossRef](#)]
67. Powell, S.G. The target capacity utilization model of OPEC and the dynamics of the world oil market. *Energy J.* **1990**, *11*, 26–63. [[CrossRef](#)]
68. Neusser, K. Autoregressive Moving-Average Models. In *Time Series Econometrics*; Springer: Cham, Switzerland, 2016.
69. Chu, K.Y. Short-Run Forecasting of Commodity Prices: An Application of Autoregressive Moving Average Models. *IMF Econ. Rev.* **1978**, *25*, 90–111. [[CrossRef](#)]
70. Yang, L.; Rolf, T. Non- and Semiparametric Identification of Seasonal Nonlinear Autoregression Models. *Econ. Theory* **2002**, *18*, 1408–1448. [[CrossRef](#)]
71. Rabbani, M.B.A.; Musarat, M.A.; Alaloul, W.S. A Comparison Between Seasonal Autoregressive Integrated Moving Average (SARIMA) and Exponential Smoothing (ES) Based on Time Series Model for Forecasting Road Accidents. *Arab. J. Sci. Eng.* **2021**, *46*, 11113–11138. [[CrossRef](#)]
72. García, M.V.R.; Krzemień, A.; del Campo, M.A.M.; García-Miranda, C.E.; Lasheras, F.S. Rare earth elements price forecasting by means of transgenic time series developed with ARIMA models. *Resour. Policy* **2018**, *59*, 95–102. [[CrossRef](#)]
73. Tamba, J.G.; Essiane, S.N.; Sapnken, F.; Koffi, F.; Nsouandele, J.L.; Soldo, B.; Njomo, D. Forecasting Natural Gas: A Literature Survey. *Int. J. Energy Econ. Policy* **2018**, *8*, 216–249.
74. Lago, J.; Marcjasz, G.; de Schutter, B.; Weron, R. Forecasting day-ahead electricity prices: A review of state-of-the-art algorithms, best practices and an open-access benchmark. *Appl. Energy* **2021**, *293*, 116983. [[CrossRef](#)]
75. Weron, R. Electricity price forecasting: A review of the state-of-the-art with a look into the future. *Int. J. Forecast.* **2014**, *30*, 1030–1081. [[CrossRef](#)]
76. Singh, N.; Mohanty, S.R. A Review of Price Forecasting Problem and Techniques in Deregulated Electricity Markets. *J. Power Energy Eng.* **2015**, *3*, 1–19. [[CrossRef](#)]
77. Acaroğlu, H.; Márquez, F.P.G. Comprehensive Review on Electricity Market Price and Load Forecasting Based on Wind Energy. *Energies* **2021**, *14*, 7473. [[CrossRef](#)]
78. Kumbure, M.M.; Lohrmann, C.; Luukka, P.; Porras, J. Machine learning techniques and data for stock market forecasting: A literature review. *Expert Syst. Appl.* **2022**, *197*, 116659. [[CrossRef](#)]
79. Thakkar, A.; Chaudhari, K. A comprehensive survey on deep neural networks for stock market: The need, challenges, and future directions. *Expert Syst. Appl.* **2021**, *177*, 114800. [[CrossRef](#)]