MAPPING CURRENT STATE IN THE FIELD OF PREDICTION METHODS OF BUSINESS AND ECONOMIC CHARACTERISTICS ACROSS INDUSTRIES

[a]SIMONA HAŠKOVÁ, [b]JIŘÍ KUČERA, [c]RÓBERT KUCHÁR

Institute of Technology and Business in České Budějovice, School of Valuation and Expertness, Okružní 517/10, České Budějovice 37001, Czech Republic
email: [a]haskova@mail.vstecb.cz, [b]kuceraj@mail.vstecb.cz, [c]kuchar@mail.vstecb.cz

Abstract: The results of the prediction of business and economic characteristics provide valuable information to stakeholders (business owners and managers, investors, and shareholders). The aim of the paper is to provide a comprehensive overview on methods applied in practice for predicting significant business and economic variables. The research is structured into selected key industries for most of the world's economies. An extensive literary review of the scientific papers published over the last decade revealed that the most used prediction methods include ANN, GARCH combined with ARIMA. These are the methods strong enough to capture the specifics of the industries for the economic and business prediction purposes. The LS-SVM and ARIMA methods are used separately to a lesser extent. The other methods were used mainly for the purpose of vali-dation of their predicting applicability.

Keywords: Prediction, business and economic characteristics, prediction methods, biggest industries

1 Introduction

Reviewing, monitoring, inspecting and predicting are important tasks for management when evaluating the past and the prospects of enterprises. The concept of predictive models emerges as a very important issue both in practice and research studies. Prediction of values or a state is a challenging task, which might be impossible in some cases to reach. In terms of predicting business and economic variables, this refers mainly to predicting specific numerical values which, based on the subsequent analysis, enables to deduce specific conclusions/state. Several methods and models have been developed over the years, which are applicable provided that specified conditions are met; such methods enable predicting a value or a state with a certain degree of probability. Business and eco-nomic variables must be predicted regarding internal and external factors that fundamentally affect them.

For example, a value of shares can be affected by the situation on the financial market at a specific moment, which can be caused by different factors, such as the development in the value of precious metals, the change in exchange rates, etc. (Jeong & Kim, 2019). Recent impact of the COVID - 19 pandemic or the current Russia-Ukraine conflict are the prime examples of external factors whose ultimate impact on the share price is very difficult to predict (Sansa, 2020).

The outputs of prediction methods provide users with signals for business activities, measures to mitigate the negative effects of business cycles, the orientation of foreign trade, etc. Economic forecasts are the most problematic area in economic decision-making. In the first half of the 20th century, the main support was the analysis of past developments and estimates of the configuration of future factors (Brozyna et al., 2016). Later, the use of neural networks and data mining methods were added to the most frequently used quantitative methods (Scardapane & Wang, 2017). Currently, forecasts are influenced by methods based on fuzzy propositional logic, which allow reflecting the knowledge and experience of managers and economic experts (Ikram & Qamar, 2015).

The aim of the paper is to provide a comprehensive overview on prediction methods applied in practice for predicting significant business and economic characteristics in financial markets with a focus on currency exchange markets and precious metals markets, agriculture, transport, automotive and energy industry, and manufacturing enterprises. The procedure by clustering the prediction methods according to industries is made with the intention to find out the method/methods that are strong enough to capture the specifics of industries in the view of purposes for economic and business prediction.

2 Materials and Methods

Web of Science and SCOPUS databases of scientific articles published over the last decade are used to achieve the aim of the paper. The method of our research is a biblio-metric analysis of scientific articles with the aim to map the use of prediction methods to determine business and economic characteristics. The prediction methods are divided according to the specific industries they have been used. The monitored sectors are financial markets, exchange rates, precious metals, agriculture, transport, automotive, energy industry and manufacturing enterprises.

Furthermore, the analysis of the development trend of the most utilized predictive methods for estimating the future state of business and economic characteristics across sectors is carried out. The achieved results are presented by means of summary tables for better clarity.

3 Literary research

Literary research provides overview of prediction methods that were used by authors in the key sectors of economy, i.e., in the sector of financial markets, agriculture, transport, automotive and energy industry and manufacturing enterprises. The issue of predictions is being addressed by investors, analysts, and the academic community. The “quality” of the prediction accuracy is based on the selection of the correct “prediction tool”. The most used methods successfully verified in practice are presented in the text below. According to Kliestik et al. (2021) earnings management is the most important topic in the field of financial management of a company. Managing the earnings of companies has a great im-pact on the accounting data of companies and subsequently can bring distorted results after applying prediction models to significant business and economic characteristics. Zenzerović (2010) has already dealt with the prediction of financial risks in several sec-tors.

3.1 Financial markets

Financial markets represent an environment that calls for predicting the development of prices, as evidenced by numerous publications listed in Web of Science. Price development of shares represents a subject, within which the prices prediction with a high degree of accuracy is valuable information for all stakeholders in the market. Gungor & Luger (2021) deal with the predictions of higher earnings per share. They used a model combining regression t-statistics and Monte Carlo resampling techniques to control error rate in resulting predictions. In the last decade, the financial sector has been using prediction methods based on artificial neural networks (ANN). Such methods work with clusters of input data based on which they predict further development of a target variable. In the is-sue of predicting stock prices using ANN, Wang et al. (2021) used bidirectional long-short term memory neural network (also referred to as BiLSTM). Chen (2019) deals with the prediction of continuous sustainability of businesses in relation to the development of capital markets; the predictive model was a decision tree (DT), specifically classification and regression model. The data tested were selected using the method of gradual regression and data mining using the artificial neural networks. It was found that the method of gradual regression for data selection combined with the classification and regression decision tree shows the best predictive ability. Zhang et al. (2021) use the method of Long Short-Term Memory Networks (LSTM) for the prediction of the development of stock prices. Compared to ANN, LSTM are more suitable for processing and predicting the development of non-linear and non-stationary numeric time series. Numeric time series may contain specific economic values, but might also include specific economic indicators, such as indexes, ratios, etc. LSTM can be supplemented by other indexes, such as price and volume indexes, which further improve its predictive ability. Based on training, LSTM can predict the sequence of other related events based on past events. Sadorsky (2021) states that the prediction of a specific value of stocks is a difficult task that is not practically possible to reach due to a large number of variables affecting their future price. Therefore, the author recommends limiting the prediction of stock prices to the prediction of the future trend of its development (upward or downward) using ANN. McMillan (2019) examines stock market predictions based on historical data on dividend payment. As dividends are paid at longer intervals than the value of stocks changes, this model shows a poor ability to make short-term stock prices predictions. In this respect, it is recommendable to use predictive models based on historical data of the average stock prices. It is thus a trend search method. According to Basak et al. (2019), the improved predictive ability of a model enables minimizing the investment risk. To predict stock price development, the authors recommend the method of random forest (RF) and DT boosted by the algorithm XGBoost (eXtreme Gradient Boosting) based on DT, which increases the speed and performance of these methods. Dai & Zhu (2019) focus on improving the predictive ability of specific methods by combining them. To predict the development of the capital market, they combined the method of sum-of-the-parts (SOP) and Ensemble Empirical Mode Decomposition (EEMD). Based on the results achieved, this combination appears to be a successful predictive tool. Ni & Xu (2021) developed a hybrid model of DCDNN (Dynamically convergent differential neural network) based on the model of RDNN (recurrent deep neural network) and DCC-GARCH (Dynamic conditional correlation generalized autoregressive conditional heteroskedasticity model), which combines both these models. To predict the development of stock market, Zhang et al. (2020) recommend the application of the model Support Vector Regression (SVR-ENANFIS) combined with ensemble adaptive neuro-fuzzy inference system of vector regression. Combining these two methods enables to make predictions of the stock market development in the long term, but only with a certain degree of probability and accuracy.

Almost all predictive methods deal with the issue of the frequency of the input data that need to be used to estimate future values. The goal is to achieve the highest possible accuracy for the longest time horizon possible. This issue was addressed by Lyocsa et al. (2021) in monitoring the development of stock prices based on the comparison of high-frequency and low-frequency data. The statistical testing of both datasets showed that high-frequency data can provide more accurate predictions only for a short period of time – the period of the coming month at most. For longer periods of time, the predictive models based on the low-frequency and high-frequency data show the same accuracy. Further on, the authors state that the selection of the data depends on the intention of researchers.

Due to the progress in the field of IT, the development of the state of financial markets can be predicted and evaluated using the combination of financial services and IT (the so-called FINTECH). FINTECH itself can be referred to as a new industrial framework (Knewtson & Rosenbaum, 2020). The use of FINTECH by institutions operating in the field of financial markets was discussed by Dwivedi et al. (2021). FINTECH is an excellent tool for collecting large volumes of data, which can then be analyzed. In this case, the use of a combination of artificial intelligence (AI) and machine learning (ML) is directly offered. Based on AI and ML, the development of financial data can subsequently be predicted, including the behavior of individual market participants (Nguyen et al., 2022). By means of ML, the solvency of borrowers can also be predicted based on data obtained through FINTECH (Kriebel & Stitz, 2022).

3.1.1 Exchange rates

The prediction of the exchange rates is an important part of analyses in financial markets. Exchange rates change depending on many external and internal factors. There-fore, it is difficult to predict their development with a high degree of accuracy. Due to their volatility, it is desirable to estimate their change at least several days in advance. Sun et al. (2018) argue that internal and external factors, which are usually turbulent in nature, can be partially included as a variable within the use of ANN or Least squares-Support vector machine (LS-SVM) for the prediction of the exchange rate. In terms of the performance of the predictive model LS-SVM is considered to be a more efficient short-term predictor. Ac-cording to Babu & Reddy (2014), the predictive ability of ANN can be improved by its combination with the ARIMA (Auto regressive integrated moving average) model. Furthermore, the authors point out that the hybrid predictive model can be used in many segments of financial market, e.g., for predicting the stock prices. The hybrid predictive model application was further tested on financial and non-financial data based on the time series (the development of energy prices, the occurrence of sunspots). Using the so-called Wavelet Neural Network (WNN) it was possible to identify and map the relationships between the factors affecting the development of exchange rates that help to im-prove the predictive power of ANN (Bekiros & Marcellino, 2013). In terms of predicting the development of exchange rates Abedin et al. (2021) propose the application of deep learn-ing, which integrates the regression of Bagging Ridge (BR) with Bi-directional Long Short-Term Memory (Bi-LSTM). This resulted in the method of Bi-LSTM BR, which showed a higher prediction accuracy. Rehman et al. (2014) used the model of Recurrent Cartesian Genetic Programming evolved Artificial Neural Network (RCGPANN); they showed that this model can predict exchange rates with up to 98.872% accuracy. Sevim et al. (2014) addressed early warnings about the upcoming currency crisis. They used ANN, DT and the LR model. As the dependent variable the financial stress index was used, as the independent variable 32 macroeconomic indicators were set. According to their results, the model is able to predict a currency crisis one year in advance with up to 95% accuracy. Pandey et al. (2018) recommend the BN artificial neural network training for predicting exchange rates using ANN advocating that this method can achieve better pre-diction accuracy.

As data on current exchange rates are available on many cloud storages Lin et al. (2013) proposed their use as data sources for predicting further development of prices in currency markets. For this purpose, they developed an Intelligent Prediction System (IPS). Premanode & Toumazou (2013) formulated a new algorithm – Empirical Mode Decom-position (EMD), which serves to improve the prediction of exchange rates based on sup-porting vector regression. This algorithm is able to smooth and reduce noise, while the model of supporting vector regression with a filtered dataset improves the prediction of exchange rates. The advantages of the application of the Kalman filter (KF) for the spot exchange rate prediction is addressed by Fronckova & Prazak (2020), whose analysis con-firmed the model´s good predictive ability.

3.1.2 Precious metals

Precious metals have the status of a long-term store of value and are thus a frequent choice of investors. Most often investors target their investments in gold, silver, palladium, and platinum. Bouri et al. (2021) examined the volatility of gold using the model of Heterogeneous Autoregressive realized Variance (HAR-RV), which works with high-frequency data. The prediction of precious metal volatility was also addressed by Naeem et al. (2019). Based on their conclusions, the model of Markov-switching GARCH (MSGARCH) can be used for predicting the volatility of all types of precious metals. Their analysis showed a high prediction of the model accuracy. Demiralay & Ulusov (2014) predict the values of four main types of precious metals (gold, silver, platinum, and palladium) using non-linear long-term memory volatility models, namely fractionally integrated generalized autoregressive conditional heteroscedastic model (FIGARCH), fractionally integrated asymmetric power autoregressive conditional heteroscedastic model (FIAPARCH) and hyperbolic generalized autoregressive conditional heteroscedastic model (HYGARCH) under normal and Student´s t-distribution of the data. Long-term memory volatility models within Student´s t-distribution of the data work well for the prediction of the development of precious metals´ value for the next day. Ranganai & Kubheka (2016) examined the development of platinum and palladium value using models based on long-term memory, which were the models of FIGARCH, autoregressive fractionally integrated moving average (ARFIMA)-FIEGARCH, ARFIMA-FIAPARCH, and ARFI-MA-HYGARCH.

Gaspareniene et al. (2018) analyzed the technical possibilities of predicting the prices of gold using the ARIMA predictive model. They confirm that this model is only suitable for predicting the development of the price of gold in the short term, specifically, in the one-year horizon. The development of the price of gold is closely related to the development of the price of other commodities. Chandar et al. (2016) predicted the development of the value of gold based on the development of the values of silver, oil, S&P500, and ex-change rates. The prediction model used was the multilayer neural network Extreme Learning Machine (ELM). This type of artificial neural network shows better performance than other types of artificial neural networks due to its good ability to learn. El-Rashidy (2021) points out that the value of gold can fluctuate within very short time intervals (5, 10, 15, 30, and 60 minutes). For these short periods, the value can be predicted using the wrapper selection method (WSM) combined with ANN and genetic algorithm (GA). Brabenec et al. (2020) used five methods of time series smoothing to the value of gold prediction, namely ANN, DT, gradient boosted tree (GBT), LR, and the nearest neighbor method. These methods enabled the authors to estimate the development of the price of gold for the next calendar year.

3.2 Agriculture

Agriculture is focused on food production, animal husbandry, and soil cultivation. The volumes of production represent important indicators of each country´s economic development. Therefore, the choice of the right prediction methods to estimate the development of economic characteristics in this industry is an essential part of planning and budgeting. The prediction of possible financial distress of companies operating in agriculture is addressed, e.g., by Klepáč & Hampel (2017). Analyses showed that the best results were achieved using the method of logistic regression (LR), Support vector machines (SVM) RBF ANOVA core, DT, and Adaptive boosting based on DT. The prediction accuracy of all these models decreases with the growing distance from bankruptcy. DT and Adaptive boosting enable higher accuracy for stress prediction compared to the methods of SVM and logit. A traditional method of predicting bankruptcy is Altmann Z-Score developed in 1968. Boda & Uradnicek (2019) compared Altmann Z-Score with the CH-index (Chrastinova's index) and G-index (Guroik's index) in a sample of agricultural companies operating in Slovakia. Comparing the two models mentioned above, Altmann Z-Score is considered to be a more modern predicting method of possible bankruptcy, G-index enables the same results despite its obsolescence. According to Almamy et al. (2016), the predictive power of Z-Score is different when used for the prediction of the development of agricultural companies in various countries. Therefore, a modified model of Z-Score was developed for agricultural companies in Great Britain, which considers the cash flow of the company in the calculation. The modified model is called J-UK Model; according to the current tests, it achieves the same accuracy results as the Taffler‘s model. Bai et al. (2019) state that bankruptcy and monitoring of sustainable economic stability of agricultural companies can be predicted using fuzzy theory and fuzzy c-means. Liu & Wu (2018) used the same method for the bankruptcy prediction of agricultural companies. They deter-mined that bankruptcy can be estimated by the methods of LR, DT, ANN, and supporting vector network. Huang et al. (2015) add that financial failure can be predicted using the data envelope analysis. They also demonstrated the use of an improved method integrating the super-efficiency of data envelope analysis. This method excludes the evaluated data envelope analysis from the reference set; efficient data envelope analyses may have an efficiency score higher or equal to 1. It is also able to generate more meaningful correlations and measure central trends in an empirical application with more effective units for which such units would achieve the same score otherwise (Avkiran, 2011). In the case of agriculture, seasonal fluctuations should be taken into account. The fluctuations may negatively affect the accuracy of the predictive models that are not able to consider them. Chen et al. (2020) used the Gray Seasonal Model (GSM) for accurate estimations of seasonal fluctuations in the observed sequence and obtaining better-predicted values. The results of their study show that the accuracy obtained is relatively high. The authors thus state that the GSM method is generally becoming a new method to be used for seasonal data prediction.

3.3 Transport

Transport is related to a large volume of data of both economic and non-economic nature. According to Zhou et al. (2015), the economic parameters of a business can be predicted using the method of data mining (DM). Brozyna et al. (2016) used classic linear discriminant analysis (LDA) and LR to predict the bankruptcy of businesses operating in the transport sector. They also applied predictive models based on classification trees and the nearest neighbor method. Based on the statistical verification, it can be stated that these predictive models show high prediction accuracy. In the case of the lack of accounting data, which represents the input information for predicting the development of a business over time, it is possible to use probability models (PM) (Kuhi, et al. 2015). Weytjens et al. (2021) recommend the use of classical predictive methods, ARIMA and Face-book Prophet (FP) for predicting cash flows in transport companies. Wang et al. (2017) use BNN (Bayesian Neural Networks) for the possible bankruptcy of transport companies' prediction; they point out that due to its predictive power this method should be included as the standard indicator of the financial health of transport and other companies.

Bankruptcy risk in the transport sector poses a big risk of disrupting the capability of international trade. For predicting the possible bankruptcy of airlines, Mathani & Garg (2018) suggested using the multi-criteria decision making (MCDM) method based on the fuzzy AHP (Fuzzy Analytical Hierarchical Processing). Sedláčková & Švecová (2019) analyzed the risk of airline bankruptcy utilizing the specific bankruptcy and solvency models IN05 and Kralicek´s Q-test (Q-Test).

3.4 Automotive

The ZEW market sentiment indicator (ZEW index) can be used as a model for predicting the development in the automotive sector. The ZEW index provides more accurate predictions if used on a complex model of tested data. This indicator can be used to predict the upcoming bankruptcy of automobile companies three months ahead (Homolka & Pavelková, 2018). In automotive, various models of machine learning (ML) are applied to optimize the costs of production. They mainly include the application of vector regression (VR), optimized supporting vector regression (OSVR) (using a genetic algorithm), the methods of RF and EGB, and the method of deep learning (El Mazgualdi et al., 2020). In terms of making decisions to reduce the product failure rate, a decision support system (DSS) is used (Unver et al., 2020). Lessmann & Voss (2017) examined the usage of predictive models to determine the selling prices of used cars. They found that when predicting the selling price of this product, it is necessary to avoid LR and apply RF instead. In contrast, Zainudin et al. (2021) argue otherwise. According to the authors, it is necessary to apply regression models to estimate specific variables that have a major impact on the generation of revenues. For this purpose, Panel Regression Analysis (PRA) was used.

Automotive, as well as other sectors, see the importance of sales and turnover. In the automotive sector, it may refer to selling automobiles as final products as well as specific spare parts and components. Türkbayragi et al. (2022) predicted the development of selling spare parts and components using ANN and multiple linear regression (MLR). Sangasoongsong et al.

(2012) identified specific economic ratios whose values change in dependence on the volume of sales. This was achieved utilizing the vector error correction model (VECM). Selling automotive spare parts is also dealt with dismantling companies. For these companies, the prediction of demand for older dismantled automobile spare parts is of great importance. According to Czwajda et al. (2019), the future demand for spare parts can be predicted using the method of market prediction. For demand prediction of dismantled automobile spare parts Modified Croston’s method (MCM), which is based on Holt´s double exponential smoothing was used by Altay et al. (2008). Kosacka et al. (2016) added that dismantling companies represent a large part of enterprises operating in the automotive sector. For such companies, the key issue is usually to determine a bid price for a specific dismantled spare part. For this purpose, they developed a tool to set bid prices on the basis of the business process model and notation diagram (BPMN) and Unified Modelling Language (UML).

3.5 Energy industry

The predictive ability is highly important for energy companies so that they can respond to the upcoming changes in industrial structures well in advance. Kerhel & Sick (2014) dealt with the evaluation of economic and technological predictive competencies of German energy companies. Their results indicate that large energy providers make high-quality economic predictions; however, they are less able to make valid predictions in terms of renewable resources due to the current unstable political frameworks. Companies using renewable energy resources do not have to face these difficulties but show low-er accuracy of economic predictions. The energy industry and its development significantly influence other manufacturing and non-manufacturing sectors. Zheng et al. (2018) dealt with the prediction of the capital intensity of the energy industry. Based on the Cobb-Douglas production function, they created a model of the capital and labor force indicator at the level of industry and subsequently modified it by implementing the method of estimating and predicting of non-linear grey Bernoulli model (NGBM). This model can be applied even in the case of a sudden transformation of the energy industry. Scalzer et al. (2019) argue that possible financial distress of energy companies can be predicted by specific financial ratios. Specifically, ROE, immediate liquidity (IL), and current liquidity (CR) were identified as the best predictors. Angilella & Pappalardo (2021) dealt with predicting the possible bankruptcy of energy companies using a non-parametric model for multi-criteria decision-making (MDCA), a model of Multi-group Hierarchy Discriminant (M.H.DIS) utilizing the application of a better MCDA approach, specifically Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE II).

As for wind energy, its sustainability requires correct and professional prediction of the development of investment safety in real-time. Yan & Hong (2021) thus present a predictive model based on combining Grey relational analysis based on the technique for or-der preference by similarity to an ideal solution (GRA-TOPSIS) and a modified bat algorithm with weighted least squares support vector machine (MBA-WLSSVM). Rotela et al. (2019) use the predictive model of Monte Carlo and ANN to identify variables that most affect the development of investments in the projects of wind power plants over time.

3.6 Manufacturing enterprises

Manufacturing enterprises represent one of the largest sectors in many countries. Their activities affect many other aspects, such as the environment, employment rate, GDP development, etc. In many sectors, significant business and economic characteristics are predicted based on large datasets. Yadegaridehkordi et al. (2019) dealt with the possibility of using large datasets containing accounting data of manufacturing companies for predicting their performance using the method of Decision-making trial and Evaluation laboratory (DEMATEL) - Adaptive neuro-fuzzy inference systems (ANFIS).

Javaid & Javid (2018) tested the predictive ability to go concern models in creditor-oriented manufacturing companies. As the first step, they performed the analysis of standard bankruptcy and liquidity models, which was followed by their revision. As the second step, a going concern prediction model was developed using multiple discriminant analysis (MDA). Based on the results achieved, the MDA predictive model appears to be a reliable model for predicting the going concern principle of a company.

Ferencek et al. (2020) point out that manufacturing companies must have sufficient financial reserves to be able to resolve possible customer complaints concerning their products under guarantee, whose repair is paid for by the company. The authors state that for the needs of manufacturing companies, prediction methods based on the simulation of discrete events and time series and predictive models of machine learning were used in the past to determine the necessary financial reserves. They thus extend the range of applicable prediction methods with a set of predictive models of deep learning (ANN). Klepáč & Hampel (2018) deal with a bankruptcy prediction of manufacturing companies. For this purpose, they recommend the SVM method with spline core, hyperbolic tangent, and RBF ANOVA, DT, and RF.

Csikosova et al. (2019) emphasize the need to combine predictive models, especially the older ones since the accuracy of the models gets worse due to the development of the economic environment. The models include Altman Z-Score, Taffler´s index, Springate model, and IN index, which are based on multidimensional discriminant analysis.

4 Summary tables

A comprehensive overview of the models that were and have been used for predicting the development of values/status in the examined sectors is presented in Table 1.

Table 1: Overview of models and methods used for predicting business and economic character-istics in a specific field

Research field	Predictive model and method used	Source	Year
Financial markets	t-test, Monte Carlo	Gungor & Luger	2021
	ANN-BilSTM	Wang et al.	2021
	Classification and regression DT	Chen	2019
	LSTM	Zhang et al.	2021
	ANN	Sadorsky	2021
	RF, DT+XGBoost	Basak et al.	2019
	SOP+EEMD	Dai & Zhu	2019
	DCDNN	Ni & Xu	2021
	SVR-ENAFIS	Zhang et al.	2020
	AI, ML	Nguyen et al	2022
Exchange rates	LS-SVM and ANN	Sun et al.	2018
	ANN+ARIMA	Babu & Reddy	2014
	WNN	Bekiros & Marcellino	2013
	Bi-LSTM BR	Abedin et al.	2021
	RCGPANN	Rehman et al.	2014
	ANN, DT and LR	Sevim et al.	2014
	BN	Pandey et al.	2018
	IPS	Lin et al.	2013
	EMD	Premanode & Toumazou	2013
	KF	Frončková & Pražák	2020
Precious metals	HAR-RV	Bouri et al.	2021
	MSGARCH	Naeem et al.	2019
	FIGARCH, FIAPARCH and HYGARCH	Demiralay & Ulusov	2014
	FIGARCH, ARFIMA-FIEGARCH, ARFIMA-FIAPARCH and ARFIMA-HYGARCH	Ranganai & Kubheka	2016
	ARIMA	Gaspareniene et al.	2018
	ELM	Chandar et al.	2016
	WSM+ANN+GA	El-Rashidy	2021
	ANN, DT, GBT, LR and Nearest Neighbor	Brabenec et al.	2020
Agriculture	LR, SVM+RBF ANOVA, DT, Adaptive boosting based on DT	Klepáč & Hampel	2017
	CH-index, G-index	Boda & Uradnicek	2019
	J-UK Model	Alama et al.	2015
	Fuzzy c-means	Bai et al.	2019
	Fuzzy c-means	Liu & Wu	2018

	GSM	Chen et al.	2020
Transport	DM	Zhou et al.	2015
	PM	Kuhi et al.	2015
	ARIMA and FP	Weytjens et al.	2021
	BNN	Wang et al.	2017
	LDA and LR	Brozyna et al.	2016
	MDCM/Fuzzy AHP	Mathani & Garg	2018
	IN05 and Q-Test	Sedláčková & Švecová	2019
Automotive	ZEW index	Homolka & Pavelková	2018
	ML, VR, OSVR, RF and EGB	El Mazgualdi et al.	2020
	DSS	Unver et al.	2020
	RF	Lessmann & Voss	2017
	PRA	Zainudin et al.	2021
	ANN and MLR	Türkbayragi et al.	2022
	VECM	Sa-ngasoongsong et al.	2012
	Prediction markets	Czwajda et al.	2019
	MCM	Altay et al.	2008
	BPMN and UML	Kosacka et al.	2016
Energy industry	HBGM	Zheng et al.	2018
	ROA, IL, CR	Scalzer et al.	2019
	MCDM, M.H.DIS and PROMETHEE II	Angilella & Pappalardo	2021
	GRA-TOPSIS and MBA-WLSSVM	Yan & Hong	2021
	Monte Carlo and ANN	Roleta et al.	2019
Manufacturing companies	DEMATEL-ANFIS	Yadegaridehkordi et al.	2019
	MDA	Javaid & Javid	2018
	ANN	Ferencek et al.	2020
	SVM	Klepáč & Hampel	2018

Source: Authors.

Table 1 shows that many predictive models have been used in all fields under review. The literary research revealed models´ repetition in specific areas. The most frequently used prediction method is ANN, which has been applied 16 times in total. The second most frequently used model is GARCH; together with its other combination with the ARIMA model, it has been applied 8 times. This method is followed by DT, which has been applied 5 times. Other methods, that should be mentioned, include LS-SVM and ARIMA, which, for the purpose of the prediction, have been applied 3 times. It is also obvious that various authors tried to apply the other prediction methods, but only randomly in order to find out whether these methods could be used for prediction purposes.

Subsequently, the results of the bibliometric analysis were arranged ascending ac-cording to the publication year in order to reveal the development trend of the most utilized models and methods to determine business and economic characteristics across sectors. The results are presented in Table 2.

Table 2: Overview of the most utilized models and methods used for predicting business and economic characteristics across sectors

Predictive model and method used	Year
MCM	2008
VECM	2012
WNN	2013
IPS	2013
EMD	2013
ANN+ARIMA	2014
ANN, DT and LR	2014
FIGARCH, FIAPARCH and HYGARCH	2014
FIGARCH, ARFIMA-FIEGARCH, ARFIMA-FIAPARCH and ARFIMA-HYGARCH	2016
LR, SVM+RBF ANOVA, DT, Adaptive boosting based on DT	2017
LS-SVM and ANN	2018
ARIMA	2018
Classification and regression DT	2019
RF, DT+XGBoost	2019
MSGARCH	2019
Monte Carlo and ANN	2019
ANN, DT, GBT, LR and Nearest Neighbor	2020
ANN	2020
ANN-BilSTM	2021
ANN	2021
WSM+ANN+GA	2021
ARIMA and FP	2021
AI, ML	2022
ANN and MLR	2022

Source: Authors.

From Table 2 we can see that in the first decade of 2020 the predictive models were used, which required large interventions on the part of their users and, from this point of view, were more demanding. Over time, in hand with the development in the field of IT, the predictive models based on sophisticated procedures of artificial intelligence (mainly ANN) have been increasingly used. These models proved to be able to provide the user with accurate predictions of the business and economic characteristics, regardless of the industry in which they are used. Moreover, they proved to be user-friendly.

5 Conclusions

In many economic areas, several models are used to predict business and economic variables. The aim of the paper was to provide a comprehensive overview of prediction methods published over the last decade in scientific papers. Specifically, the authors dealt with the applicability of predictive models in the financial markets with a focus on the currency markets and precious metal markets, of the companies operating in agriculture, transport, automotive, energy industry, and manufacturing companies.

In terms of the development of financial markets, currency markets, and precious metal markets, the most frequently applied method is the ANN; this method is intended for non-linear time series prediction, which corresponds with the situation in these markets. We found that in the other sectors under review some authors, dealing with the issue of predictions, try to prove the applicability of selected models. In general, the most frequently used methods for the prediction of business and economic characteristics are ANN and GARCH combined with ARIMA; the models LS-SVM and ARIMA are used to a lesser extent. These are the methods strong enough to capture the specifics of the industries for economic and business prediction purposes. The use of ANN-based predictive methods and its hybrid versions was made possible by large and increasingly rapid developments in the field of IT.

Further research will be focused on the verification of the application of not often ap-plied methods (e.g., fuzzy approach) in predicting specific economic and business characteristics. The following research into ANN-based prediction methods could increase awareness of these sophisticated prediction methods within industries and their use for future analyses.

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