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Review Article

Artificial neural networks in business: Two decades of research

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A R T I C L E I N F O

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In recent two decades, artificial neural networks have been extensively used in many business applications. Despite the growing number of research papers, only few studies have been presented focusing on the overview of published findings in this important and popular area. Moreover, the majority of these reviews were introduced more than 15 years ago. The aim of this work is to expand the range of earlier surveys and provide a systematic overview of neural network applications in business between 1994 and 2015. We have covered a total of 412 articles and classified them according to the year of publication, application area, type of neural network, learning algorithm, benchmark method, citations and journal. Our investigation revealed that most of the research has aimed at financial distress and bankruptcy problems, stock price forecasting, and decision support, with special attention to classification tasks. Besides conventional multilayer feedforward network with gradient descent backpropagation, various hybrid networks have been developed in order to improve the performance of standard models. Even though neural networks have been established as well-known method in business, there is enormous space for additional research in order to improve their functioning and increase our understanding of this influential area.

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1. Introduction

Artificial neural networks are computational structures designed to emulate the accumulation of knowledge in the biological central nervous system. Contrary to conventional computational techniques, they are able to solve nonlinear and ill-defined problems based on parallel composition. In last two decades, the utilization of artificial neural networks has largely increased in the field of business. This evolution has not only led to development of many different scientific applications, but also to intensive exploration of practical issues. The characteristics of artificial neural networks such as efficiency, robustness and adaptability make them a valuable tool for classification, decision support, financial analysis or credit scoring. Their success can be clearly demonstrated by a growing number of publications in prestigious journals.

Employment of neural networks in business, finance, or management has been reviewed by several authors from various points of view. Wong et al. [408] focused on neural networks business applications and surveyed 203 articles published during the period of 1988–1995. They categorized the available literature according to 12 categories, namely the year of publication, application area, means of development, etc. Wong and Selvi [407] concentrated on financial applications and reviewed 64 articles introduced between 1990 and 1996, concluding that the most applications have been published in bankruptcy prediction and stock performance forecasting. On the other hand, Vellido et al. [388] aimed in their study at applications related to management, marketing, or decision making and avoided financial uses such as bond ratings, derivatives, stock markets as well as macroeconomic predictions. Smith and Gupta [350] presented interesting developments in the use of artificial intelligence for the operations research problems. They emphasized the various types of neural network models which are applicable when solving business problems. Wong et al. [409] reviewed neural network application research in business between 1994 and 1998, stating that due to accessibility of raw data and overall complexity, financial applications could be one of the most common neural network research areas in the future.

Writing a comprehensive survey of business, operational, or manufacturing applications of neural networks would be demanding due to the extent of studies and their number. The purpose of this research is therefore to provide a review of the recent neural networks research purely in business. Various disciplines have been investigated, including accounting, costs monitoring, customer analysis, finance, marketing or sales. Articles dealing with manufacturing, process optimization, engineering or operational research have not been included. The study highlights the importance of this artificial intelligence method and provides description of recent research for both academics and practitioners. Our review not only emphasizes the historical progressions in the field of neural networks, but also discusses the prospective development in the neural network research in the examined area.

2. Research methodology

To identify relevant journal articles dealing with neural network applications in different areas of business we searched EBSCOhost, Google Scholar, JSTOR, Science Direct, SpringerLink, and Wiley Online Library databases for the period of 1994–2015 using combinations of keywords “neural networks” and “business”, “finance”, “corporate”, “stocks”, “capital”, “costs”, “financial analysis”, “accounting”, “bankruptcy”, “exchange rates”, “financial distress”, “inflation”, “marketing”, “customers”, and “bonds”. After search through the databases we performed an additional exhaustive review of all 125 identified journals.

We followed the modified criteria given in [409] determining that each article should introduce the utilization of neural network in given area and should have detailed description of the network type and learning algorithm. Every article had been carefully reviewed before it was incorporated into the survey. A large number of publications had not been included because given applications had primarily system design, operational, or engineering characteristics such as facility layout problems [45,380], intelligent manufacturing [25,39,150,345], job-shop scheduling [196,252], or process identification [14,256]. Each article was classified according to seven categories:

1. Year of publication.
2. Application area.
3. Type of neural network.
4. Learning algorithm.
5. Benchmark method.
6. Citations.
7. Journal.

It is essential to emphasize that the results of this review definitely do not include all applications of artificial neural networks in business and are based purely on information acquired from mentioned databases and identified influential journals. Working papers, conference proceedings unpublished in reputable journals, and non-English journals were not part of the study.

3. Results and discussion

We have identified a total of 412 suitable journal articles which presented appropriate artificial neural networks applications in various business disciplines. References [37,70,80,331,350,388,407–409] provided surveys of the neural network business applications, including accounting, finance, production, or economic research.

3.1. Year of publication

Large amount of research has been done in the last two decades. Fig. 1 introduces the distribution of published articles by year in period of 1994–2015. After decline in period between 2001 and 2003, the number of papers sharply increased and peaked in 2012

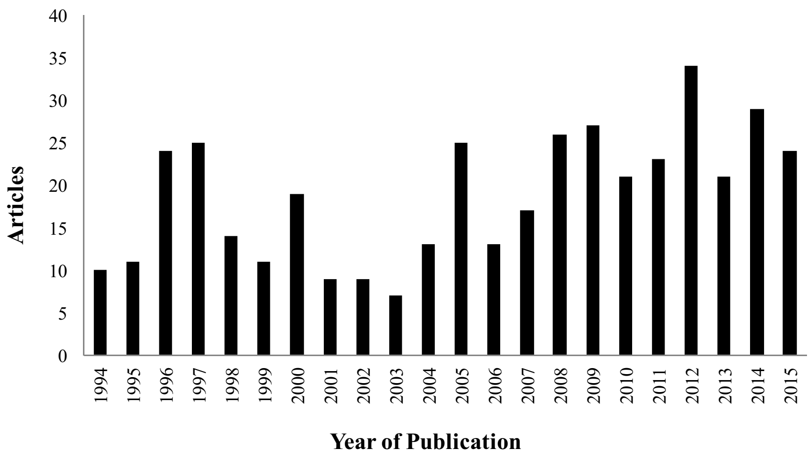

Fig. 1. Distribution of articles by year.

with 34 published articles. Recognized growth of neural networks business applications might be contributed to massive development and expansion of information technology in last decade which led to better applicability of artificial intelligence methods in scientific studies. Moreover, many software packages have been introduced that enable users with minimal programming skills to design and test neural networks for specific problems.

3.2. *Application area*

Throughout the investigated period authors have applied artificial neural networks to various problems including credit scoring [161,258,259], financial analysis [52,186], or stock performance prediction [89,162,166]. Table 1 presents the complete list of reviewed publications, while Fig. 2 shows the distribution of articles by field of application. The research emphasis has been particularly on financial distress and bankruptcy, corporate securities, decision support, and credit scoring. On the other hand, only few studies have been focusing on inflation, costs monitoring, and sales analysis. For instance, Shin et al. [344] compared conventional backpropagation neural network with support vector machines in corporate bankruptcy prediction problem, Kuo and Xue [235] proposed fuzzy neural network for the sake of sales forecasting, West et al. [401] employed multilayer feedforward network as a base classifier, and Chen et al. [175] compared multilayered network to logit in order to detect fraud litigation and assess significant risk factors. They argued that neural networks provide not only better forecasting accuracy, but also lower misclassification costs than logit. Jain and Nag [197] successfully focused on the pricing of IPO's and Koskivaara [228] documented reliable pattern recognition results in financial accounts auditing.

The possible explanation of papers distribution lies in the characteristics of problems in given areas which often consisted of classification, pattern recognition and time series prediction. The notion of potential financial reward in case of precise risk analysis, or stock price forecasting model may also make these explorations very attractive. Another reason is the availability of data. Neural networks capture the patterns in data by iteratively adjusting their synaptic weights in line with the learning algorithm. In order to achieve optimal performance, networks require relatively large data sets, and historical databases contain many examples of financial reports, customer credits, or security prices. Overall, we found wide differences in nature of data sources used as well as sample sizes. Although there is no optimal number of input patterns relative to the number of network free parameters, researches based on small samples usually did not provide significantly better results of neural networks comparing to conventional approaches. Primarily due to unavailability of data, several authors complemented real sample with a simulation or used solely artificial data [33,59].

Following subsections focus on key findings of reviewed articles with respect to the application area. It might be stated that utilization of neural networks significantly contributed to the development of business research and they demonstrated to be well suited to extract useful information from complex, nonlinear and often noisy data.

3.2.1. *Auditing and accounting*

Even though neural network models are able to handle categorical variables with more values, most authors in auditing and accounting focused on binary variables. Etheridge et al. [108] and Gaganis et al. [123] showed how various neural networks can decrease the costs of misclassification in auditor's judgment about financial viability of a client. While backpropagation and probability networks performed more reliably in categorizing non-failed banks in the sample (Type II error), categorical learning network was more successful in successfully classifying failed banks (Type I error). In general, models with smaller Type I error should be preferred, since incorrectly classifying a failed bank as healthy could be much more costly than vice versa. Even though further research of the costs in respect to the Type I and Type II errors might be desirable, obtained results provided additional evidence to Lenard et al. [264] who argued that hidden patterns of financial data strongly affect decision making process in auditing.

In the investigation of tax reports auditors look for questionable values in accounting and subsequently execute comprehensive inspection of specified errors. This type of task usually requires very experienced personnel. Chen et al. [178] therefore proposed an automatic detection method for analyzing mistaken tax reports in construction companies using several neural networks variations. They results indicated that multilayer feedforward networks reached the upper 70% successful recognition rate, despite the fact that their outcomes greatly depended on architecture, number of training epochs and selection of initial weights.

3.2.2. *Costs monitoring*

Costs prediction plays a crucial role in the business and product cycles. Despite small number of found applications, neural networks offered various advantages in costs estimation compared to traditional methods [428]. With real data, neural networks were able to extract knowledge and approximate costs functions, or to be modified and retrained using new data. Bode [59] estimated costs in manufacturing company without any assumptions about the shape

Table 1
Reviewed articles by area.

Auditing and accounting (14)	[55,92,108,123,149,151,178,228,245,264,277,353,367,371]
Costs monitoring (7)	[58,59,61,100,217,349,428]
Credit scoring (36)	[4,11,20,27,41,46,56,67,85,94,95,111,146,160,161,215,216,240,258,259,265,271,283,284,305,311,319,321,340, 361,369,374,400,414,433,434]
Customers metrics (24)	[32,34,49,63,82,91,138,144,145,157,173,191,192,214,221,246,260,261,281,306,343,373,402,412]
Decision support (37)	[5,12,24,29,48,68,69,84,96,102,112,117,118,124,131,133,135,148,187,224,234,250,270,285,292,316,320,324,339,341,356,365, 389,393,398,401,415]
Derivatives (28)	[19,23,47,66,99,113,121,125,127,142,164,174,188,199,226,230,231,249,268,302,336,354,378,382,390,396,403,436]
Exchange & interest rates (27)	[18,50,87,103,109,119,120,132,156,170,171,198,206,207,233,267,297,307,314,335,337,338,363,413,417,420,429]
Financial analysis (35)	[2,22,33,53,71,72,106,115,136,163,186,205,208,210,229,232,238,239,244,247,251,290,294,295,315,317,334,352,360,362, 364,375,397,424,427]
Financial distress & bankruptcy (75)	[8,13,16,17,30,31,38,40,60,62,64,65,74,77,78,86,90,97,98,107,128,129] [147,158,159,167,168,176,177,179–181,183,185,189,193,194] [201,203,204,212,213,218,220,223,227,243,253,254,257,266,274,288,308] [318,327–329,344,346,348,358,359,370,372,376,379,381,404,411,416] [419,421,426,430]
Fraud analysis (12)	[75,76,105,112,122,134,175,262,273,304,355,391]
Inflation (6)	[51,52,182,287,293,298]
Marketing (18)	[9,35,36,57,81,116,130,184,202,209,236,269,286,309,384,387,422,423]
Reviews of applications (9)	[37,70,80,331,350,388,407–409]
Sales (11)	[7,15,21,79,143,222,235,237,248,282,366]
Shares & bonds (73)	[3,6,26,28,42–44,54,73,83,88,89,93,101,104,110,114,126,137,139] [140,141,152,153,162,165,165,169,172,190,195,197,200,211,219,225,241] [242,255,263,272,275,276,278,279,291,296,299–301,303,310,312,322] [323,325,326,330,333,342,357,368,385,386,392,394,395,399,405,406,410,431,435]

of the costs function and Boussabaine and Kaka [61] forecasted complex nonlinear costs flow curve.

Even though the neural network models often proved as capable of cost estimating [100,217], authors usually emphasized the experimental nature of their research as neural network theory does not provide general methodology for the design of the topology, and setting of control variables such as learning rate and momentum. Determining the number of hidden neurons, hidden layers, or selection of learning algorithm is commonly the trial and error approach, and there is no guarantee that the chosen setting is the best.

3.2.3. Credit scoring

The credit financing has been rapidly increasing in last two decades and neural networks emerged as a useful technique in quantitative assessment of the creditworthiness of subjects applying for loans. Brown and Mues [61] compared various approaches that can be used for imbalanced credit scoring data sets, Blanco et al. [56] implemented neural networks for credit scoring of microfinance industry, and Leong [265] proposed Bayesian network model to address real-time credit scoring implementation issues. Emotional neural networks have been suggested as suitable tool for credit analysis as well [216]. Despite successful applications, there is a couple of issues when using neural networks in credit scoring including preprocessing of the input data, or determination of ratio of training-to-validation samples. For instance, Khashman [215] suggested 50%: 50%, while Tsai and Wu [374] used 70%: 30% training-to-validation sample ratio. Empirical evidence also indicates that multilayer feedforward networks trained by more sophisticated algorithms performed significantly better than networks trained by ordinary gradient descent which might have been caused by imbalanced rejected/approved samples in the datasets [336,433]. Despite several performance measures used, additional research in credit scoring applications would be beneficial to precisely estimate the costs of misclassification when evaluating the performance of various neural network alternatives.

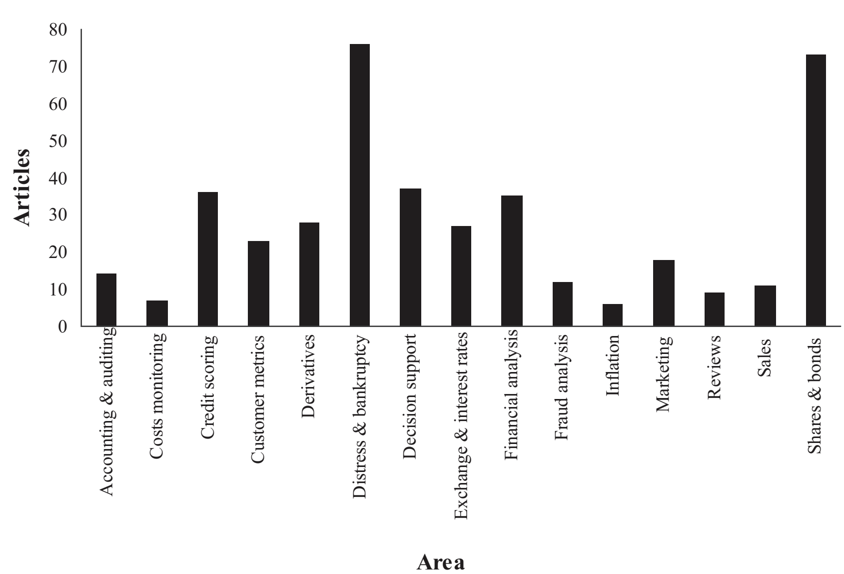

Fig. 2. Distribution of articles by area.

3.2.4. Customer metrics

In the field of customer behavior, the value of neural networks consisted in their capability to emulate the operation of human brain and precisely estimate behavior based on product characteristics without assumptions about relationships among input variables. Wide range of neural networks applications in this area included customer satisfaction analysis [214,246], heterogeneity research [145], or forecasting of expenditures [192]. Lee and Shih [260] and Lee et al. [261] focused on consumer behavior in seeking medical services, while Baesens et al. [34] identified the slope of the customer lifecycles. They presented Bayesian network as probabilistic white-box technique that is able to capture high-order relationships between sets of variables in binary classification. In fact, majority of customer analysis articles in our survey adopted neural networks for classification purposes. Networks usually demonstrated good discriminatory power and often provided better results when compared with conventional methods [32,402].

3.2.5. Decision support

Every business activity is affected by various essential decisions. To have a reliable decision support system in which models can deal with uncertainty is becoming an essential issue for companies in current fluctuating environment. Comparing to previous surveys of neural networks in business, we found a large increase in decision support applications. In reviewed articles neural networks provided a number of advantages over traditional models, particularly in case of nonlinear and complex data [148,187,250]. Li et al. [270] proposed intelligent generator of future scenarios for future business planning which overcame limitations of conventional methods in terms of learning ability. Thieme et al. [365] successfully compared neural networks with ordinary least squares and discriminant analysis in new product development decisions, while West et al. [401] focused on financial decision applications.

On the other hand, neural networks in decision support systems suffered from some imperfections of their own. They did not provide substantive insights regarding the impact of inputs, had many control parameters to set, or they might have lost their generalization ability in case of overtraining [316]. The quality of models therefore considerably depended on experience of the researcher.

3.2.6. Derivatives

The most intensively examined area in the financial derivatives applications was the pricing of options [47,174,226]. Since neural networks estimated price solely relying on historical data, they did not suffer from systematic biases resulting from simplified assumptions of standard pricing techniques such as Black-Scholes model. Moreover, they were easier to implement and had good out-of-sample performance [19,396]. Neural networks often achieved plausible forecasting outcomes despite the complexity and interconnected nature of financial derivatives markets. However, several authors suggested preprocessing the input data to generate sound predictions [142].

3.2.7. Exchange and interest rates

Exchange rate markets are highly complex structures with limited information about the underlying forces influencing the data. Various types of neural networks architectures and learning algorithms have therefore been applied to predict the magnitude and direction of shifts in exchange rates. Davis et al. [87] compared backpropagation, linear vector quantization, genetic reinforcement learning to forecast CAD-USD daily returns, Tenti [363] used recurrent network to forecast Deutsche mark, and radial basis function ensemble model was proposed by Yu et al. [420]. The substantial risk of convergence to a local minimum rather than to the global minimum was a highlighted problem under the conventional neural network framework. Hybrid networks, integrating additional methods into neural network environment, were therefore repeatedly tested with promising results [109,297,335]. Considering the analyzed samples, the most frequently investigated currencies in our survey were USD, EUR, GBP and JPY.

3.2.8. Financial analysis

In the field of financial analysis, Abdou et al. [2] explored determinants of capital structure in retail industry, Chiang et al. [186] analyzed net asset value of mutual fund, and Kryzanowski and Galler [232] examined financial statements of small businesses. Cao and Parry [72], Etemadi et al. [106] and Zhang et al. [427] concluded that neural networks can significantly improve earnings per share forecast accuracy. Their findings also indicate that models consisting only of lagged dependent variables had lower explanatory power than models that included fundamental accounting variables. It is worth to notice that sample sizes in financial analysis applications were usually smaller than in case of other business disciplines [290].

3.2.9. Financial distress and bankruptcy

Although conventional classification methods are very popular in financial distress and bankruptcy research, neural networks have been widely used to design bankruptcy models as well. More than on studying the role of particular input variables [98], majority of authors focused on improving the overall accuracy of prediction [147,167,253,374]. Usually a number of ratios were used to assess the performance and financial health of companies [16,404]. The most commonly used network was the multilayer feedforward network with gradient descent learning despite its local search nature. Several authors therefore recommended the integration of neural networks and metaheuristic techniques to reach a better performance in bankruptcy prediction tasks [159,168,201]. Fig. 3 indicates the summary of reviewed financial distress and bankruptcy articles according to the year of publication. It might be emphasized that the utilization of neural networks in the field increased particularly after the period of financial crisis and again after sovereign debt crisis in Europe.

3.2.10. Fraud analysis

Effectiveness of neural networks in financial fraud classification has been examined by several authors. Green and Choi [134] and Chen et al. [175] successfully employed conventional backpropagation neural network as a financial fraud assessment and detection tool, while Lei and Ghorbani [262] proposed clustering algorithms for fraudulent behavior in e-Commerce companies based on improved and supervised improved competitive learning. Estévez et al. [105] developed real-time fraud detection system for telecommunication company customers using neural network for prediction module and fuzzy rules for the classification module. Several classification techniques and their ensembles were compared by Song et al. [355] to evaluate the risk of financial statement fraud. Even though the ensemble of classifiers outperformed individual methods, neural networks and support vector machines considerably outclassed logistic regression and decision trees in average accuracy, composite error rate and area under the curve. Also outcomes of other reviewed applications in the field of fraud analysis indicated that properly trained and configured neural networks were able to make consistently correct classifications and generalizations.

3.2.11. Inflation

In case of inflation forecasting, our evidence suggests that neural networks were more than competitive with other applied models. To prove their value, authors have tested different types of out-of-sample performance metrics such as mean squared error,

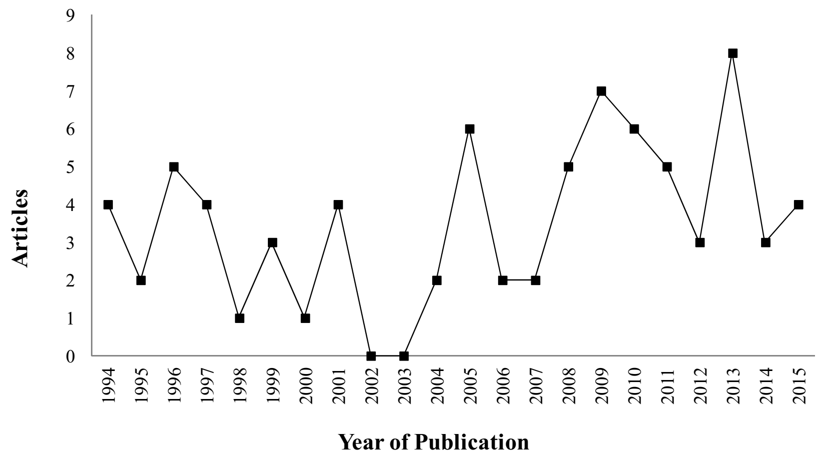

Fig. 3. Distribution of financial distress and bankruptcy articles by year.

Diebold-Mariano test for competing models, or Pesaran and Timmermann test of directional accuracy of the signs of forecasts. McAdam and McNelis [287] reported high degree of robustness in results obtained by neural networks, and Binner et al. [52] compared performance of recurrent networks with Markov switching autoregressive model capturing predictable nonlinearity in inflation data. Chen et al. [182] explored asymptotic properties of neural networks with different activation functions. They stated that all proposed models outperformed benchmark linear technique in terms of both mean squared error and absolute deviation error. Among other traditional performance measures, root mean squared error, mean absolute error, mean absolute percentage error, or coefficient of determination were often used [51,293].

3.2.12. Marketing

One of the main areas in marketing research is the market segmentation. Bloom [57] introduced self-organizing map for segmenting the international tourist market, Fish et al. [116] focused on segments in the industrial marketing, and Cuadros and Domínguez [82] calculated customer lifetime value, loyalty and consequently identified client segments. In most of segmentation studies self-organizing maps were utilized and authors often stressed their advantage in interpreting the informational value of input data.

Baesens [34], Crone et al. [81], and Olson and Chae [309] aimed their attention at direct marketing, while Gómez-Pérez et al. [130] searched an optimal policy for a marketing campaign. They confronted self-organizing map with multilayer feedforward network and argued that map allows an intuitive representation of results, therefore is more straightforward to understand. On the other hand, feedforward network was more powerful, since its generalization process was more robust than in case of self-organizing map.

3.2.13. Sales

Similar to many business time series, sales data exhibits strong trends and seasonal patterns. For that reason standard models often lack the extrapolation abilities and lead to disturbances in plans of production. Thomassey and Happiette [366] therefore designed a neural network automated sales prediction system based on data from textile distributor. Ansuj et al. [21] argued that conventional backpropagation network outperformed ARIMA model with interventions and provided better forecasts, while out-of-sample forecasting performance of different models for retail sales was presented by Alon et al. [15]. Kuo and Xue [235] and Kuo et al. [237] focused on integration of conventional and fuzzy neural networks to improve solution of sales prediction problem under promotion.

3.2.14. Shares and bonds

Due to the potential of high profits, prediction of share prices is of great interest not only to academic researches, but also to traders and investors. During the investigated period, a number of neural network models have been presented in attempt to overcome conventional statistical techniques and precisely forecast price movements. O'Connor and Madden [303] developed multilayer feedforward network to evaluate the external factors such as commodity prices and exchange rates in predicting equity prices. Cao et al. [73] compared neural network to Fama and French's model, whereas Quah [322] focused on neuro-fuzzy inference systems and general growing and pruning radial basis function. Several approaches have also been suggested to improve the performance of neural networks in stock markets prediction, including normalization of data, use of hyperbolic tangent instead of logistic activation function, addition of hidden neurons and hidden layers, or integration with metaheuristic methods [68,83,137,405,431].

Despite the global importance of debt financing and good availability of data, only few neural network studies aimed their attention at bonds. Kwon et al. [240] and Maher and Sen [283] examined bond ratings, but there still exists enormous space for further research considering initial offerings, yield curves, relationships among government obligations, or price forecasting.

3.3. Neural networks

Analyzed business application has shown that almost all types of neural networks have been utilized in our survey, but most of reviewed articles applied networks with supervised learning. However, many business tasks are uncertain and do not have target output examples. Additional research is therefore needed in the area of unsupervised learning which could be more appropriate in such circumstances. In general, it can be concluded that use of the specific type of neural network and selection of particular learning algorithm highly depended on explored problem.

3.3.1. Type of neural network

Considering the type of the network, the most popular sort in the study was multilayer feedforward network, which neurons are organized into series of layers and information signal flows through the network solely in one direction, from the input layer to the output layer. Multilayer feedforward networks have been used in all application areas and only small number of business studies has utilized other types of networks.

Among the noteworthy alternative approaches, adaptive resonance theory have been used in customer analysis [173,343],

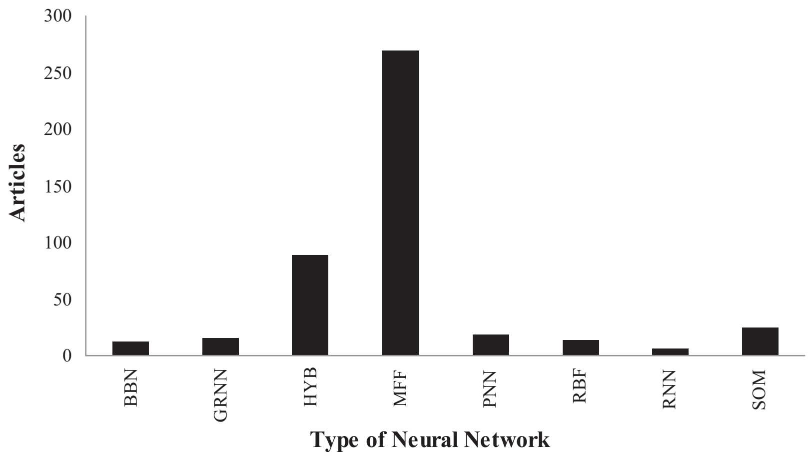

Fig. 4. Distribution of articles by applied neural network. BBN, Bayesian belief neural network; GRNN, generalized regression neural network; HYB, hybrid neural network; MFF, multilayer feedforward neural network; PNN, probabilistic neural network; RBF, radial basis function; RNN, recurrent neural network; SOM, self-organizing map.

generalized regression network estimated stock prices and focused on capital structure and earnings management [2,3,149], probabilistic network forecasted financial distress and marketing timing [107,184,411], radial basis functions evaluated risky projects and performed credit scoring [33,183,400], and self-organizing maps monitored marketing campaigns, shares, or investigated the relationship between innovativeness and participation of customers [96,130,139]. Fig. 4 shows the distribution of reviewed articles by mostly applied type of network. The total number of network types is significantly higher than number of journal articles, since often more networks have been considered for the same task in particular paper.

3.3.2. Learning algorithm

The process by which neural network updates its free parameters to capture the patterns in the presented sample is called the learning. Particular learning algorithms differ from each other in the manner in which the modifications are made. The most common learning algorithm in reviewed business applications was the backpropagation learning performed by gradient descent search. In this method, the adjustments applied to synaptic weights are in the opposite direction to the gradient vector. Even though this technique is considered as rather inefficient, its popularity is presumably caused by simplicity, universality, and good availability in statistical software. Comparing to gradient descent, faster convergence was often achieved by conjugate gradient methods [2,167]. Moreover, several more sophisticated methods for feedforward networks were found throughout the review such as Self-Scaling Parallel Quasi-Newton algorithm [435], or Levenberg–Marquardt algorithm [28,102,293] which is a combination of Gauss-Newton optimization rule and gradient descent. Various metaheuristic and global optimization methods were implemented into the learning process as well [193,235,273]. Fig. 5 presents the most applied learning algorithms in our survey.

Consistent with our expectations, Levenberg–Marquardt algorithm usually provided the best outcomes comparing to other conventional techniques, and required the smallest number of training epochs. But because of its computational demand, Quasi-Newton methods and conjugate gradient were better suited in cases of larger networks [56,163].

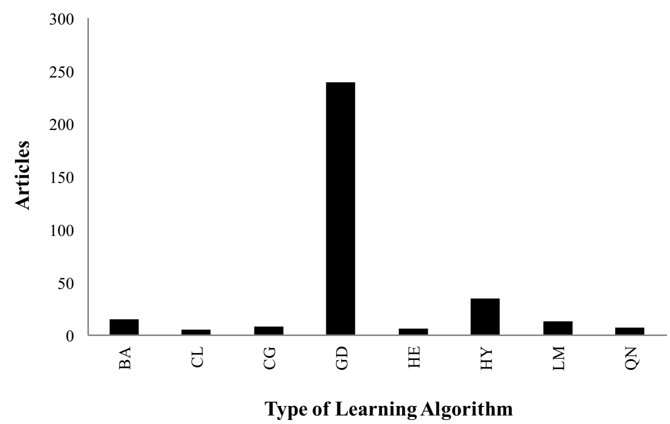

Fig. 5. Most applied learning algorithms. BA, Bayesian learning; CL, competitive learning; CG, conjugate gradient; GD, gradient descent; HE, Hebbian learning; HY, hybrid learning; LM, Levenberg–Marquardt algorithm; QN, Quasi-Newton algorithms.

3.4. Hybridization

Among features that had considerable impact on the performance of artificial neural networks might be included local minimum problem, selection of network topology and initial weights, or choice of control parameters. Common multilayer feedforward network trained by backpropagation often ensure convergence only to a local minimum of error function, depending on the set of initial weights. The integration of neural networks with secondary artificial intelligence and metaheuristic methods such as fuzzy logic [102,139,273,368], genetic algorithms [119,132,234,311], bee colony algorithm [153,154], or artificial immune systems [191] have therefore been proposed in order to eliminate this drawback and improve network performance and applicability for particular tasks. Jeong et al. [201] tuned various architecture parameters of neural network applying genetic algorithms and generalized additive model, while Chen [177] introduced the concept of self-organizing feature map optimization, fuzzy, and hyper-rectangular composite neural network. An adaptive neural network based fuzzy inference system was tested by Trinkle [368].

According to reviewed papers, the group of hybrid networks may be methodologically distributed into two fractions based on their focus: (1) dealing with learning process, (2) dealing with network architecture. Our research found than in 412 articles 89 hybrid networks were used. Obtained results suggest that performance of hybrid networks integrating other artificial intelligence algorithms into neural network framework, had almost always been superior to ordinary statistical methods as well as gradient-based multilayer feedforward networks [28,184,396,419]. Fig. 6 introduces the

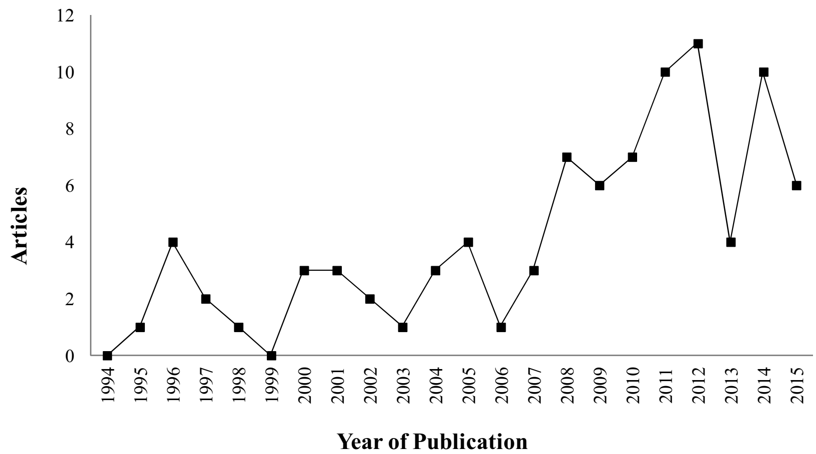

Fig. 6. Distribution of articles using hybrid neural network by year.

distribution of hybrid neural networks in business and finance papers by year in the period of 1994–2015.

The growing popularity of novel hybrid methods confirms that they are able to overcome several difficulties of conventional neural networks, and achieve better results. However, many other artificial intelligence methods such as simulated annealing [1,332,351], particle swarm optimization [289,377,425,432], tabu search [10,155,383,418], or ant colony optimization [280,313,347], have been successfully utilized in different research areas like engineering and operational research in order to improve their performance and efficiency. Further integration of neural networks with these artificial intelligence algorithms might therefore result into additional valuable applications in business disciplines as well.

3.5. Benchmark method

Even though the bankruptcy analysis, or stock prices prediction have been intensively examined by conventional methods such as linear regression, GARCH, or discriminant analysis, the nature of neural networks enables them to obtain better results without obligatory statistical assumption in terms of independence among variables, linearity, normality of residuals, etc. The most common benchmark methods identified in our research are discriminant analysis [189,318], linear regression [149,192], logit [402,419] and ARIMA [51,312] (Fig. 7).

Comparing with standard statistical and econometric techniques, neural networks have often reached a better performance in terms of mean squared error, determination coefficient, or prediction and classification accuracy. However, significant advantage of conventional models is their transparency and capability to comprehensibly interpret received results. Often it is very difficult to document how these specific results have been obtained and support given outcomes with underlying economic theory. Due to the complex and parallel nature of neural networks, there is no explanatory value of synaptic weights in hidden layers, and it is almost impossible to interpret relationships between inputs and outputs. Several researchers therefore recommended to use combination of both neural networks and conventional approaches [16]

3.6. Citations

Number of citations contain certain information about what researchers are interested in at a particular time. Even thought the probability of being cited depends on various factors such as publication time, journal accessibility, or field, citation count is an attractive measure for the evaluation of scientific performance. To estimate the impact of reviewed papers in terms of citations we used Google Scholar database. Fig. 8 shows the distribution of citations by year the cited article was introduced. Despite the fact that we do not offer a comprehensive review of the general literature on neural networks, the chart indicates when the most notable findings and innovations in business were presented. It is not surprising that formerly published literature has been cited more than newer articles, however, influential papers dealing with stock market returns, credit scoring, bankruptcy and financial time series forecasting [104,258,288,344,424] significantly increased the citation number of publications originated in year 2005. Table 2 introduces the most cited papers according to the year of publication, number of citations, share on total number of citations, journal, and area of research.

Out of 25,649 citations, 20 most cited articles reached 8054 citations (31.40%). While first 125 papers obtained 20,237 (78.90%) citations, remaining 250 papers were cited only 5412 (21.1%) times. Explored article had 68.4 citations in average. Almost 3.4% of total citations registered the notable work of Altman et al. [16] who compared traditional statistical models with artificial neural networks in corporate distress classification and prediction.

3.7. Journal

Our survey found that from the total number of 125 identified journals, first six journal have published 201 (53.60%) papers and obtained 16,428 (58.71%) citations. Large number of involved journals indicates that the contribution of neural networks is scattered across a wide range of different business applications. Vast majority (25.73%) of the examined articles on neural networks in business were published in Expert Systems with Applications, followed by Intelligent Systems in Accounting, Finance and Management (6.07%), and European Journal of Operational Research (4.85%). Table 3 summarizes the most occurring academic periodicals in our review according to number of articles, citations and impact factor.

It is given by the characteristics of neural networks that almost all listed journals focus primarily on real-world applications and do not excessively investigate underlying economic and financial theory. It is worth to notice that in last two years, more than 20 new journals have joined the group with one or two neural network business applications, including Applied Intelligence, Resources Policy, or The European Journal of Finance. In following years we might expect further growth of the list, since due to the availability of data, neural network utilizations are anticipated in human

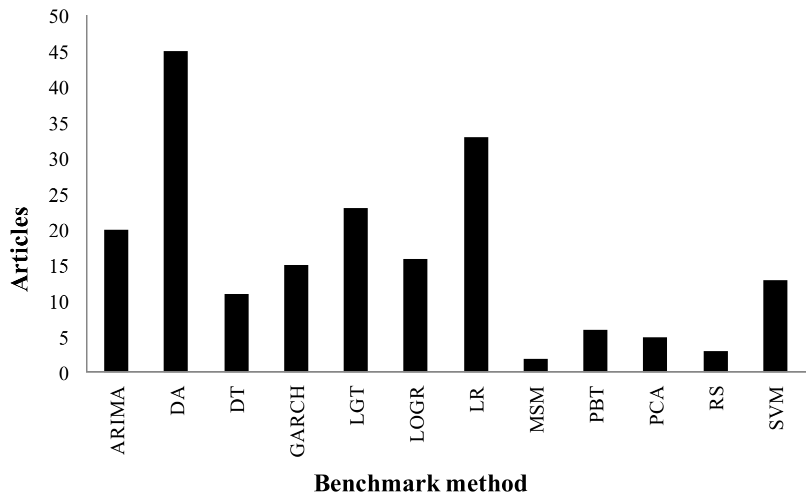

Fig. 7. Distribution of articles by benchmark method. ARIMA, autoregressive integrated moving average; DA, discriminant analysis; DT, decision trees; GARCH, generalized autoregressive conditional heteroskedasticity; LGT, logit; LOGR, logistic regression; LR, linear regression; MSM, Markow switching model; PBT, probit; PCA, principal component analysis; RS, rough sets; SVM, support vector machines.

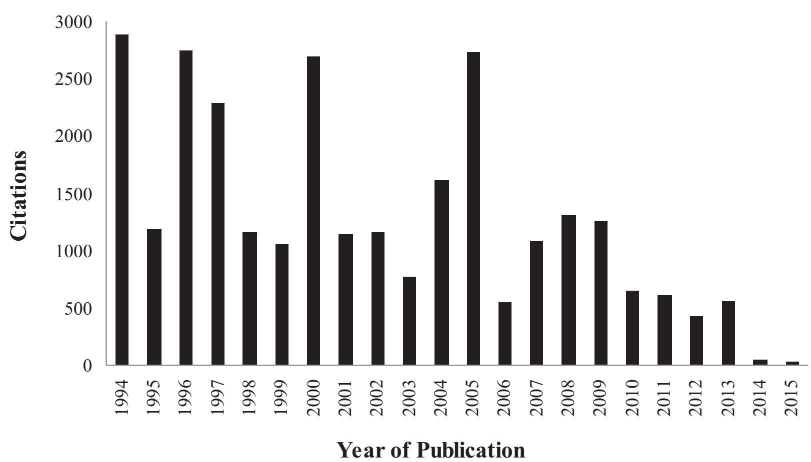

Fig. 8. Distribution of citations by year of publication.

Table 2
The most cited papers.

Article	Year	Citations	Total (%)	Journal	Area
Altman et al. [16]	1994	945	3.38	Journal of Banking & Finance	Distress & bankruptcy
Huang et al. [161]	2004	632	2.26	Decision Support Systems	Credit scoring
Wilson and Sharda [404]	1994	610	2.18	Decision Support Systems	Distress & bankruptcy
West [400]	2000	605	2.16	Computers Operations Research	Credit scoring
Hutchinson et al. [164]	1994	564	2.02	The Journal of Finance	Derivatives
Kaastra and Boyd [208]	1996	560	2.00	Neurocomputing	Financial analysis
Atiya [30]	2001	500	1.79	IEEE Transactions on Neural Networks	Distress & bankruptcy
Shin et al. [344]	2005	456	1.63	Expert Systems with Applications	Distress & bankruptcy
Min and Lee [288]	2005	267	0.95	Expert Systems with Applications	Distress & bankruptcy
Zhang et al. [426]	1999	455	1.63	European Journal of Operational Research	Distress & bankruptcy
Desai et al. [95]	1996	407	1.45	European Journal of Operational Research	Credit scoring
Vellido et al. [388]	1999	407	1.45	Expert Systems with Applications	Review
Kuan and Liu [233]	1995	370	1.32	Journal of Applied Econometrics	Exchange & interest rates
Zhang and Qi [424]	2005	375	1.34	European Journal of Operational Research	Financial analysis
Huang et al. [160]	2007	369	1.32	Expert Systems with Applications	Credit scoring
Ahn et al. [8]	2000	342	1.22	Expert Systems with Applications	Distress & bankruptcy
Chen et al. [172]	2003	289	1.03	Computers Operations Research	Stocks & bonds
Refenes et al. [301]	1994	272	0.97	Neural Networks	Stocks & bonds
Yao and Tan [417]	2000	266	0.95	Neurocomputing	Exchange & interest rates
Lee et al. [259]	2002	263	0.94	Expert Systems with Applications	Credit scoring

Table 3
The most occurring journals.

Journal	Papers	Total (%)	Citations	Total (%)	IF
Accounting, Management and Information Technologies	2	0.49	13	0.05	n.a.
Advanced Engineering Informatics	2	0.49	113	0.40	1.63
Applied Soft Computing	9	2.18	299	1.07	2.81
Computational Economics	3	0.73	187	0.67	0.52
Computers in Industry	3	0.73	86	0.31	1.29
Computers Industrial Engineering	5	1.21	235	0.84	1.78
Computers Mathematics with Applications	2	0.49	68	0.24	1.70
Computers Operations Research	14	3.40	2327	8.32	1.86
Decision Sciences	8	1.94	458	1.64	1.35
Decision Support Systems	17	4.13	2768	9.89	2.31
Economic Modelling	7	1.70	67	0.24	0.83
Economics Letters	3	0.73	221	0.79	0.51
European Journal of Operational Research	20	4.85	2362	8.44	2.36
Expert Systems with Applications	106	25.73	6774	24.21	2.24
IEEE Transactions on Neural Networks	4	0.97	824	2.94	2.63
Information and Management	2	0.49	202	0.72	1.87
Information Sciences	2	0.49	117	0.42	4.04
Intelligent Systems in Accounting, Finance and Management	25	6.07	895	3.20	n.a.
International Journal of Forecasting	4	0.97	357	1.28	1.33
International Journal of Production Economics	3	0.73	118	0.42	2.75
International Review of Financial Analysis	2	0.49	73	0.26	0.88
Journal of Banking & Finance	4	0.97	1004	3.59	1.30
Journal of Business Research	3	0.73	410	1.47	1.48
Journal of Econometrics	2	0.49	212	0.76	1.60
Journal of Economic Dynamics and Control	2	0.49	40	0.14	1.02
Journal of Forecasting	10	2.43	569	2.03	0.71
Journal of Interactive Marketing	3	0.73	267	0.95	2.77
Journal of International Financial Markets, Institutions and Money	3	0.73	59	0.21	1.24
Journal of the Operational Research Society	3	0.73	186	0.66	0.95
Knowledge-Based Systems	9	2.18	397	1.42	2.95
Neural Computing and Applications	4	0.97	53	0.19	1.57
Neural Networks	3	0.73	357	1.28	2.71
Neurocomputing	19	4.61	1302	4.65	2.08
Omega	3	0.73	340	1.22	4.38
Procedia Computer Science	7	1.70	12	0.04	n.a.
Systems Engineering-Theory Practice	2	0.49	81	0.29	n.a.
The Quarterly Review of Economics and Finance	2	0.49	124	0.44	n.a.

resources, corporate governance, and corporate social responsibility.

4. Conclusion

Artificial neural networks have been taken an enormous attention in last two decades. Much of the research has focused on various business disciplines, however, only a small number of surveys have been published in this area. Presented paper has examined 412 neural network applications in different areas of business published between 1994 and 2015 in well-known influential journals. Even though investigated authors have successfully applied neural networks to miscellaneous task, our results indicate that the most frequently examined issues occurring in our study were financial distress and bankruptcy analysis, stock price prediction, and credit scoring. It is interesting that the average number of financial analysis and derivatives articles stayed approximately the same throughout the examined period. On the other hand, research on shares, marketing, financial distress, and credit scoring has significantly increased compared to the early years of our survey. Particularly high-frequency time series and realized volatility have been favored in recent works. Despite the fact that some of the major problems in business have been addressed by neural networks, there still exist areas of potential applications which have not been fully investigated. This is primarily true not only for sectors where qualitative nature of problems implies modeling difficulties, but also for areas with precise data such as costs, bonds and debt financing.

Most of the papers in which various benchmark techniques were compared argued that neural networks outperformed conventional approaches such as discriminant analysis and linear regression, while proposed hybrid networks with secondary method performed usually better than traditional feedforward network trained by gradient based techniques. The hybridization of neural networks was a very popular phenomenon in investigated business disciplines. Even though that specific hybrid networks might work well only for particular tasks, our survey suggests that proper integration of metaheuristic methods into the neural network methodology might be a key for achieving the optimal performance. In general, neural networks have been successfully applied in wide range of business tasks and were able to detect complex and nonlinear relationships without requiring any specific assumptions about the distribution or characteristics of the data. According to reviewed articles, the lack of formal background and the explanatory abilities are the two essential problems that have to be resolved to improve the neural network business studies. The further research therefore should focus on universal guidelines and general methodology for the setting of control variables, selection of hidden layers and overall design of the topology, since the quality of models reviewed in this study considerably depended on experiences of the researchers. Moreover, robust measures that could assess the relevance of individual explanatory variables are very desirable, since researchers are currently still careful with interpretation of their results and perform their validation using conventional methods.

We are convinced that research on artificial neural networks in business has still much to offer. With their undisputed advantages, general availability of data, and increasing user-friendliness of software packages, neural networks will surely attract more authors and offer additional possibilities for applications.

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