Neural Comput & Applic (2010) 19:1165–1195
DOI 10.1007/s00521-010-0362-z

ORIGINAL ARTICLE

A comparative survey of artificial intelligence applications in finance: artificial neural networks, expert system and hybrid intelligent systems

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Received: 22 April 2009 / Accepted: 30 March 2010 / Published online: 20 June 2010

Abstract Nowadays, many current real financial applications have nonlinear and uncertain behaviors which change across the time. Therefore, the need to solve highly nonlinear, time variant problems has been growing rapidly. These problems along with other problems of traditional models caused growing interest in artificial intelligent techniques. In this paper, comparative research review of three famous artificial intelligence techniques, i.e., artificial neural networks, expert systems and hybrid intelligence systems, in financial market has been done. A financial market also has been categorized on three domains: credit evaluation, portfolio management and financial prediction and planning. For each technique, most famous and especially recent researches have been discussed in comparative aspect. Results show that accuracy of these artificial intelligent methods is superior to that of traditional statistical methods in dealing with financial problems, especially regarding nonlinear patterns. However, this outperformance is not absolute.

Keywords Artificial neural networks · Expert system · Hybrid intelligent systems · Credit evaluation · Portfolio management · Financial prediction and planning

1 Introduction

The economic and, therefore, the social well-being of developing countries with fairly privatized economies are highly dependent on the behavior of a country's financial sector. The financial sector is a crucial building block for private sector development. It can also play a significant role in reducing risk and vulnerability and increasing the ability of individuals and households to access basic services, such as health and education, thus having a more direct impact on poverty reduction [1]. The importance of well-functioning financial institutions, and their role in promoting and enabling capital accumulation and economic development, has been understood during at least last century. During these years, researchers in many different areas aimed to facilitate financial sector affairs by making credit and other financial products available, predicting financial trends, simulating financial and investor's behavior, goal evaluation, asset portfolio management, pricing initial public offering, determining optimal capital structure, detecting regularities in security price movements, predicting defaults and bankruptcy, etc. (refer to [2–13]). In this regard, different methods have been used. Generally, these methods can be classified to parametric statistical methods (e.g., discriminant analysis and logistic regression), nonparametric statistical methods (e.g., k nearest neighbor and decision trees) and soft-computing approaches (e.g., artificial intelligent algorithms and rough sets). Recently, artificial intelligent methods (especially ANN) are the most popular tool used in financial markets. In this paper, the literature background of three famous artificial intelligence techniques, i.e., ANNs and ES along with hybrid intelligent methods in financial markets has been studied. ES was used because of its abilities like permanence, reproducibility, efficiency, consistency, documentation, completeness, timeliness, breadth and consistency of decision-making. NNs were used because of their numeric nature, no requirement to any data distribution assumptions (for inputs), capability of updating the data

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and being as free model estimators. The numeric nature of NNs is superior to nominal nature of symbolic manipulation techniques because in these techniques numeric data must be converted into nominal values before they can be used as input, and therefore there are the problems of losing information, inappropriate data intervals and different conversion methods leading to different mining results. But in NNs, we can input numeric data directly as input for processing. Second, in statistical techniques such as regression or discriminant analysis, we need data distribution assumptions for input data but in NNs there is no need to any data distribution assumptions for input data and therefore could apply to a wider collection of problems than statistical techniques. Third, NNs allow new data be added to a trained NN in order to update the previous training result. In contrast, many symbolic manipulation and statistical techniques are batch-oriented, which must have both new and old data submitted as a single batch to the model, in order to generate new mining results. In dynamic financial applications, NNs can accommodate new information without reprocessing old information. Finally, NNs are model-free estimators. This feature allows interaction effect among variables be captured without explicit model formulations from users. Basically, the more hidden layers in a NN, the more complicated the interaction effect can be modeled [14]. Finally, hybrid system was used because it capable us to combine the capabilities of different systems.

Regarding financial markets, for comparison simplicity, the author chose three most important artificial intelligence applicability domain, i.e., credit evaluation (credit scoring and ranking, credit risk analysis, bond rating, etc.), portfolio management (optimal portfolio selection, equity selection, asset portfolio selection, etc.) and financial prediction and planning (bankruptcy prediction, financial forecasting, stock and exchange rate prediction). The author tried to highlight most important studies that have been done in selected financial domains during the last 20 years with special attention to last 5 years. The main focus of this paper is to compare the performance of these three new methods with previous traditional methods and also with other intelligent methods. This paper has been organized as follows: In the second section, ANN definition and its applications in financial domain are detailed. In section three, ES applications in financial domains are presented and in fourth section, definition, classification and applications of hybrid intelligent systems (HISs) in financial domain are detailed. In the fifth section, conclusions are discussed. At the end, due to the complexity of the necessary abbreviations in this paper, especially in Tables 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, the key for their interpretation is presented in "Appendix A".

2 Artificial neural network applications in finance

Artificial neural networks are computational modeling tools that have recently emerged and found extensive acceptance in many disciplines for modeling complex real-world problems [15].

Inspired from biological nervous systems and brain structure, ANNs [16–18] have been, over the recent decades, central sources of inspiration for a large number of original techniques covering a vast field of applications [19–21]. From a general point of view, ANN could be seen as information processing systems which use learning and generalization capabilities and are very adaptive. Especially, as a result of their adaptability, ANN represent powerful solutions for subjective information processing [22], decision-making [23], forecasting [24] and related problems which became during the last decades central points of an ever-increasing range of real-world and industrial applications. Especially, in the recent years, because of many useful characteristics of NNs, they have become a popular tool for financial decision-making [14]. As a result, there are mixed research results concerning the ability of NNs in financial sector.

In this regard, various studies have been done to review and classify applications of NN in financial domain [7, 8, 25, 26]. For example, a classification proposed by [25], which states that the following potential corporate finance applications can be significantly improved with the adaptation to ANN technology: financial simulation, predicting investor's behavior, financial evaluation, credit approval, security and/or asset portfolio management, pricing initial public offerings and determining optimal capital structure. Another classification is proposed by [26], which list the following financial analysis task on which prototype NN-based decisions aids have been built: credit authorization screening, mortgage risk assessment, project management and bidding strategy, financial and economic forecasting, risk rating of exchange-traded, fixed income investments, detection of regularities in security price movements and prediction of default and bankruptcy. As stated before in this paper, we classify the application of NNs on financial domains as follows:

2.1 Credit evaluation

The method of evaluating the credit worthiness of a personal or corporate entity, applying for a credit and now referred to as credit scoring, was invented and used for the first time yet in the 1950s. Credit scoring problems are generally seen as a typical classification problem where objects will be categorized into one of predefined groups or classed based on a number of observed attributes related to that object. So far, different methods such as linear discrimination analysis, logistic regression and the recursive partitioning algorithm have been suggested to be used in credit scoring [27, 28] but with the growth and development of the credit industry and the large loan portfolios under management nowadays, the industry is frequently developing and using more accurate credit scoring models. This effort is leading to the investigation of new methods as artificial intelligence methods for credit scoring applications [27–29]. ANNs could be designed using the financial data of banking customers as the input vector and the actual decisions of the credit analyst as the desired output vector. The objective of the system would be to imitate the human expert in granting credit and setting credit limits. The system would then be able to deal with the diversity of input information without requiring that the information be restated [30]. Several examples in application of ANN to this domain exist. For example, Jensen used backpropagation NN (BPNN) for credit scoring. Applicant characteristics were described as input neurons receiving values representing the individuals' demographic and credit information. Three categories of payment history, delinquent, charged-off and paid-off, were used as the networks output neurons to depict the loan outcomes. He claimed that more traditional and much more costly, credit scoring method used by 82% of all banks, resulted in a 74% success rate while the accuracy of the proposed network is between 76 and 80%, although the sample size of Jensen was just composed of 125 loan applicants [31]. Lloyds Bowmaker Motor Finance Company also used ANN for financial decisions credit scoring of its cars. This company claimed that this network is 10% more successful than its previous system. Security Pacific bank also used ANN for little commercial loan scoring. The NN that was used by this bank was composed of one multilayer perceptron NN that been trained by backpropagation algorithm. The managers of this bank declared their satisfaction from using this system comparing to their old method [32]. Trinkle, in his Ph.D. report, compared the power of ANN with traditional statistic methods in credit scoring. He had two assumptions: first, if the classification power of ANN credit models exceeded that of traditionally developed models and second, if different connection weight interpretation techniques yielded final models with different classificatory power. The results of the research partially support the author's hypotheses [33]. In 2008, [34] proposed a multistage NN ensemble learning model to evaluate credit risk at the measurement level. The suggested model proceed following consequent stages: At the first, different training data subsets will be generated using a bagging sampling approach particularly for data shortage. In the second stage, by using training subsets obtained from first stage the different NN models will be created. In the third stage, these created models will be trained with different training datasets and accordingly the classification score and reliability value of neural classifier can be obtained. In the fourth stage, the appropriate ensemble members will be selected using decorrelation maximization. In the fifth stage, the reliability values of the selected NN models will be scaled into a unit interval by logistic transformation. In the final stage, the selected NN ensemble members are fused to obtain final classification result by means of reliability measurement. The authors also have used two credit datasets to verify the effectiveness of their proposed model. In the same year, Angelini et al. [35] developed two NN systems, one with a standard feed-forward network and other one with special purpose architecture. The system was validated with real-world data, obtained from Italian small businesses. They show that NNs can be strong in learning and estimating the default tendency of a borrower if careful data analysis, data preprocessing and proper training are performed.

In the comparison aspect, there are several studies that used ANN and tried to compare their methods to other conventional models. Results of these comparisons are generally in the favor of NNs. For example, [36] compared his proposed BPNN with backward selection process with classical LDA, LR and recursive partitioning analysis (as implemented in CART). He concluded that his proposed method performs better than other benchmarked models. The work done by [37] compared ANN with backpropagation with multiple discriminant analyses (MDA). They concluded that ANN performs better than MDA. In 2008, Abdou et al. [38] compared two credit scoring neural architecture, probabilistic NN (PNN) and multilayer perceptron (MLP), with discriminant analysis, probit analysis and logistic regression. Their results demonstrated that PNN and MLP perform better than other models. Also, [39] used ANN for credit measurement. They used data from different credit agents in different countries from 1989 up to 1999. Finally, they concluded that ANN perform much better for calibrating and predicting sovereign ratings relative to ordered probit modeling, which has been considered by the previous literature to be the most successful econometric approach. Also studies done by [40–48] concluded that ANN performs better than compared method. Table 1 presents the brief results of these comparisons. The studies in all of the tables in this paper have been ordered based on publication year (ascending). However, some researchers also indicate that performance of ANN is as same as or worse than benchmarked methods. For example Desai et al. [49] compared their proposed MLP-NN with linear discrimination analysis and logistic regression. They found that in classifying loan applicants to bad credit clients and good credit clients, ANN work better than LDA and work almost as same as logistic regression [49]. Another interesting work is done by West [29] who studies

Table 1 Brief results of comparisons in which ANN performs better in credit evaluation

Author/s	Domain	Method compared with	Result
[40]	Bond rating	BPNN with LR	ANN performs better
[41]	Bond rating	BPNN with LR	ANN performs better
[42]	Bond rating	BPNN with MDA	ANN performs better
[36]	Loan application and overdraft check	BPNN with LDA, LR, CART	ANN performs better
[43]	Loan application scoring	ANN with GMLC, FuzC	ANN performs better
[44]	Bond rating	BPNN with LR and MDA	ANN performs better
[45]	Bond rating	OPP approaches to BPNN with BPNN and MDA	OPP-BPNN performs better than others and BPNN better than MDA
[46]	Bond rating	BPNN with MDA	ANN performs better
[47]	Bond rating and house pricing	BPNN with RBF, LVQ and LR	ANN performs better followed by LR
[37]	Credit evaluation	BPNN with MDA	ANN performs better
[48]	Credit scoring	BPNN with LR, MDA, LS-SVMs	LS-SVMs and BPNN performs better
[39]	Sovereign credit ratings	BPNN with OPM	ANN performs better
[38]	Credit scoring	PNN and MLP versus DA, probit and LR	PPN and MLP perform better

the accuracy of credit scoring of five NN models: multilayer perceptron, mixture-of-experts, radial basis function, learning vector quantization and fuzzy adaptive resonance. He benchmarked the results against five other traditional methods including linear discriminant analysis, logistic regression, k nearest neighbor, kernel density estimation and decision trees. Results demonstrate that the multilayer perceptron may not be the most accurate NN model and that both the mixture-of-experts and radial basis function NN models should be considered for credit scoring applications. Also, between traditional methods, logistic regression is more accurate method and more accurate than NN models in average case. Also, [50] compared BPNN with LR for credit worthiness evaluation using 21.678 applicants (67% training and 33% validation) and found that ANN performs better on rural applicant while logistic regression is more accurate on urban applicant.

In the same domain, [51] compared ANN with decision tree analysis and logistic regression for credit risk classification and they concluded that decision tree technique performs better than ANN (with 74.2% of accuracy) and ANN (with 73.4% of accuracy) performs better than logistic regression (with 71.1% of accuracy). In another work, [52] designed a support vector machine (SVM) for credit rating analyses and they compared it with ANN. The results showed that SVM performs as same as ANN. Work done by [53] show that genetic programming performs better than ANN in credit scoring. Also studies done by [54–56] are in this category of researches. Table 2 presents the brief results of these comparisons.

In another type of studies, researchers compared single ANN classifier with multiple ANN classifier such as work done by [57] that compared ensemble NNs versus single NN for credit risk classification and concluded that ensemble NNs perform better than single NN.

In 2008, also, [58] used ANN simultaneously to bankruptcy prediction and credit scoring. In their study, they investigated the performance of a single classifier as the baseline classifier to compare with multiple classifiers and diversified multiple classifier by using NN based on three data sets. Result showed that single classifier ANN generally performs better because, at the first, the divided training datasets may be too small to make the multiple classifiers and diversified multiple classifiers to perform worse.

Second, in the binary classification domain problem as credit scoring, single classifiers may be a more stable model. Table 3 presents the brief results of these comparisons.

2.2 Portfolio management

Determining optimal asset allocations for the broad categories of assets (such as stocks, bonds, cash, real estate) that suit investment of financial organizations across time horizon and risk tolerance is nowadays a crucial phenomenon based on the principle "Don't put all your eggs in one basket." Nowadays, the investors know properly that they should wisely diversify their portfolio. Given the unstructured nature of the portfolio manager's decision processes, the uncertainty of the economic environment and the diversity of information involved, this would be an appropriate domain for ANNs implementation [59]. In this regard, [60] designed a multilayer perceptron backpropagation ANN to predict prepayment rate of mortgage using correlation learning algorithm. In 1994, [61] designed an

Table 2 Brief results of comparisons in which ANN performs as same as or worse than other methods in credit evaluation

Author/s	Domain	Method compared with	Result
[54]	Consumer credit	ANN with LDA	The same performance
[49]	Credit scoring	MLP and Modular NN with LDA and LR	ANN perform better than LDA and almost as same as LR
[55]	Credit risk in consumer loan	BPNN, LDA, CART	Same performance but generally LDA as the best technique
[29]	Credit scoring	Five NN models: MLP, MOE, RBF, LVQ, and fuzzy adaptive resonance with LDA, LR, k-nn, kernel density estimation and CART	LR performs better than NN in average case
[50]	Credit worthiness	BPNN with LR	ANN performs better on rural applicant while LR is more accurate on urban applicant
[51]	Credit risk classification	Decision tree analysis and LR	Decision tree performs better than ANN and ANN performs better than LR
[52]	Credit rating analysis	ANN with SVM	Same performance
[53]	Credit scoring	GP with ANN, C4.5, CART, rough sets and LR	GP performs better
[56]	Corporate credit rating	BPNN with SVM, MDA and CBR	SVM performs better than other methods

Table 3 Brief results of comparisons in which single ANN compared with multiple ANN in credit evaluation

Author/s	Domain	Method compared with	Result
[57]	Credit risk classification	Ensemble NNs versus single NN	Ensemble ANN perform better
[58]	Credit scoring and bankruptcy prediction	Single classifier versus multiple ANN classifier	Single classifier ANN perform better

analog NNs for portfolio optimization under constraints. Meanwhile he also proposed a feed-forward NN for short-term equities prediction as a problem in nonlinear multi-channel time series forecasting. In [62], an ANN was used to economic analysis of risky project for acquisition. Based on the results of this network, the financial managers could decide more easily and safely in selecting the financial project comparing to conventional models. All of the surveyed comparison studies in this paper for portfolio management demonstrate that ANN performs better than other traditional methods, especially backpropagation NNs, such as work done by [63], which proposed an error correction NN for portfolio management that adapts the Black/Litterman portfolio optimization algorithm. The portfolio optimization is implemented such that (1) the allocations comply with investor's constraints and that (2) the risk of the portfolio can be controlled. They tested their method by constructing internationally diversified portfolios across 21 different financial markets of the G7 countries. They concluded that their approach outperforms conventional benchmark portfolio like mean–variance framework of Markowitz. Also, [64] compared BPNN with general property market and randomly selected portfolios methods for portfolio analysis and concluded that their proposed ANN method performs better. In the same domain, [65] used four different heuristic models (NN, tabu search, genetic algorithm and simulated annealing) in portfolio selection. Their results demonstrate that there are no much differences in using heuristic models to portfolio selection; just when portfolio is broad and investment risk is low using Hopfield NN is better. In the same domain, [66] used ANN to select suitable financial resource allocation in financial portfolio. The result of their studies demonstrates that their resource allocation ANN performs better than traditionally buy-and-hold trading. Although ANN performance is high but isn't complete and doesn't have 100% efficiency. Finally, in 2009, [67] compared mean–variance model with BPNN for portfolio optimization model and concluded that BPNN perform better. Other examples of this type of comparisons are [68, 69]. Table 4 presents the brief results of these comparisons.

2.3 Financial prediction and planning

Financial markets are complex nonlinear systems with subtleties and interactions difficult for humans to comprehend. This is why ANNs been used extensively in this area. ANNs could be designed to predict exchange markets, bank's liquidity, inflation and many other financial necessities. A lot of studies in this area has been done, for

Table 4 Brief results of comparison between ANN and other methods in portfolio management

Author/s	Domain	Method compared with	Result
[68]	Mortgages choice decision	ANN with probit	ANN performs better
[69]	Portfolio optimization	B&H strategy	ANN performs better
[63]	Portfolio management	Error correction ANN with mean–variance framework of Markowitz	ANN performs better
[64]	Portfolio selection	BPNN with general property market and randomly selected portfolios	ANN performs better
[65]	Portfolio selection	Hopfield NN with Tabu search, GA and SA	ANN performs relatively better
[66]	Portfolio resource allocation	Resource allocation ANN with B&H trading	ANN performs better
[67]	Portfolio optimization	BPNN with mean–variance model	ANN performs better

example, [70] used a single-layer feed-forward network to predict nonlinear regularities in asset price movements. The author focuses on the case of IBM common stock daily returns. This system was trained on 1,000 days of data and tested on 500 days of data and was trained for over 30 h using backpropagation without converging on a four MIPS machine. The result of studies was over-optimistic and over fitting. In another work, [71] designed two NN prototypes for credit card account performance prediction. One which emulates the decisions of the current risk assessment system, and another which attempts to predict the performance of credit card accounts based on the accounts historical data. The authors claimed that their proposed model can be useful in discovering the potential problems of credit card applicants at the very early stage of the credit account life cycle. Also, [72] used artificial intelligence techniques in analyzing post-bankruptcy resolutions using a sample of 59 Taiwanese firms in distress. They developed five-variable models based on ANN. Results showed that all of five ANN-based models have high degree of accuracy and stability. In the same year, Celik and Karatepe used NN in financial prediction. In their study, the performance of NNs in evaluating and forecasting banking crises has been examined. They found that ANNs which are capable of producing successful solutions for semi-structural and nonstructural problems can be used effectively in evaluating and forecasting banking crises [73].

In the comparison aspect, there are enormous studies in this area especially in recent years. The results of these studies are generally in favor of ANN when comparing to traditional methods like MDA, LR, random walk model, etc. For example, study done by [74] compare buy-and-hold strategy, conventional linear regression and the random walk model with NN models that use constant relevant variables in financial and economic variables selection. Results revealed that redeveloped NN models that use the recent relevant variables perform better. Also, [75] used NN to predict weekly Indian Rupee/US dollar exchange rate. They also compared the forecasting evaluation accuracy of NN with that of linear autoregressive and random walk models. Using six evaluation criteria (MAE, RMSE, MAPE, CORR, DA & SIGN), they found that NN has superior in-sample forecast than linear autoregressive and random walk models. Studies done by [76–91], [49], [92–104] are also in the same category, which concluded NNs have superior performance comparing to other traditional methods. Table 5 presents the brief results of these comparisons.

Some studies concluded that ANN has same performance compared to benchmarked methods, such as [105], which compared application of NN and regression techniques in performance and turnover prediction. In this study, NN techniques were compared with standard regression techniques in a selection context. The initial hypothesis state that the NN models perform better than standard regression techniques in predicting turnover and six objective job performance metrics using a standard pre-employment assessment battery. For regression models, ordinary least squares and LR were used. A several types of NN models were tested. All examined NN models were using supervised feed-forward backpropagation technique. Results indicated that neither regression techniques nor neural networking techniques consistently predicted turnover or job performance. Other examples are [106, 107]. Table 6 presents the brief results of these comparisons.

Besides, some other studies compared application of several NNs together and with other traditional methods. For example [108] compared performance of backpropagation NNs with functional link backpropagation with sines NN, pruned backpropagation NN, predictive cumulative backpropagation NN, LDA, Logit, Probit, quadratic discriminant analysis and nonparametric discriminant analysis. The results showed that generally there is almost same performance, however, with small differences. In another study [109] compared the performance of SOFM, RBF-SOFM, LVQ with that of LDA, QDA, K-nn. He concluded that RBF-SOFM performs slightly better than other methods. In the same context, [110] compared generalized regression NN (GRNN) with buy-and-hold strategy, PNN level estimation NN, linear regression models and T-bill in

Table 5 Brief results of comparisons in which ANN performs better in financial prediction and planning

Author/s	Domain	Method compared with	Result
[76]	Bankruptcy prediction	ANN with MDA	ANN performs better
[77]	Bankruptcy prediction	BPNN with DA and LR	ANN performs better
[78]	Predicting thrift failures	BPNN with Logit	ANN performs better
[79]	Financial distress prediction	Cascade correlation NN with MDA	ANN performs better
[80]	Bank failure predictions	ANN with LDA, QDA, LR, k-nn, ID3	ANN performs better
[81]	Bankruptcy prediction	ANN with Logit	ANN performs better
[82]	Bankruptcy classification problem	ANN with MLR	ANN performs better
[83]	Bankruptcy prediction	BPNN with LDA	ANN performs better
[84]	Financial clustering	SOM-ANN with clustering techniques: single linkage, complete linkage, average linkage, centroid method, Ward's minimum variance, two-stage density linkage, and k-NN density linkage	SOM-ANN performs better
[85]	Bankruptcy prediction	BPNN with standard and multi Logit	ANN performs better
[86]	Asset value forecasting	BPNN with regression models	ANN performs better
[87]	Financial information classification	ANN with LDA and LR	ANN performs better
[88]	Index movement prediction	ANN with B&H strategy and naive prediction	ANN performs better
[89]	Going concern prediction	BPNN with MDA, Logit and probit	ANN performs better
[90]	Consumer price index forecasting	ANN with random walk model	ANN performs better
[91]	Bankruptcy prediction	ANN with LR	ANN performs better
[92]	Corporate failure prediction	BPNN with MDA	ANN performs better
[59]	Equity profitability	BPNN with regression and B&H strategy	ANN performs better
[93]	Financial time series forecasting	ANN with ARMA	ANN performs better
[94]	Post-bankruptcy analysis	ANN with Nikkei Dox average	ANN performs better
[95]	Bankruptcy prediction	ANN with MDA (Altman Z score)	ANN performs better
[96]	Taiwan stock index forecasting	PNN with B&H strategy, random walk model and the parametric GMM models	ANN performs better
[14]	Financial performance prediction	BPNN with minimum benchmark based on a highly diversified investment strategy	ANN performs better
[74]	Financial variables selection	ANN models that use constant relevant variables, B&H strategy, LR and random walk	ANN performs better
[97]	Stock exchange prediction	BPNN with four simple benchmark functions	ANN performs relatively better
[98]	Exchange rates forecasting	MLP and RBF with ARMA and ARMA-GARCH models	ANN performs better
[75]	Exchange rates forecasting	ANN with linear autoregressive and random walk models	ANN performs better
[99]	Capital structure modeling	BPNN with MRA	ANN performs better
[100]	Stock market movement forecasting	BPNN with adaptive exponential smoothing method	ANN performs better
[101]	Consumer loan default predicting	ANN with DA, LR and DEA-DA	DEA-DA and NN perform better
[102]	Financial information manipulation prediction	PNN with DA, LR, and probit	ANN performs better
[103]	Economic growth forecasting	BPNN with LR	ANN performs better
[104]	Global stock index forecasting	BP stochastic time effective NN with numerical experiment on the data of SAI, SBI, HSI, DJI, IXIC and SP500, and the validity of the volatility parameters of the Brownian motion	ANN performs better

Table 6 Brief results of comparisons in which ANN doesn't outperform other methods in financial prediction and planning

Author/s	Domain	Method compared with	Result
[106]	Corporate distress diagnosis	ANN with LDA	The same performance
[107]	Corporate failure prediction	BP-NN with LDA, QDA, k-nn, Logit and probit	The same performance
[105]	Performance and turnover prediction	ANN with regression techniques	None of them succeed

forecasting stock market returns. The result of their study showed that GRNN classification models perform better.

In 2009, [111] used several different NN techniques along with multivariate statistical and support vector machines methods to the bank failure prediction problem in a Turkey. Twenty financial ratios with six feature groups were selected as predictor variables in their study. Also four different data sets with different characteristics were developed. Each data set was also divided into training and validation sets. In the category of NNs, they used four different architectures: multilayer perceptron, competitive learning, self-organizing map and learning vector quantization. The multivariate statistical methods; multivariate discriminant analysis, k-means cluster analysis and logistic regression analysis were also tested. Experimental results were evaluated with respect to the correct accuracy performance of techniques. Results showed that multilayer perceptron and learning vector quantization can be considered as the most successful models in predicting the financial failure of banks. Other examples of this type of studies are done by [112, 113]. Table 7 presents the brief results of these comparisons.

In the last category of application of ANN in financial prediction and planning, several researchers compared the performance of one or several types of NNs with that of other types of NNs or other intelligent models. For example, study done by [114] showed that case-based reasoning performs better than refined probabilistic NN, arrayed probabilistic network (APN), backpropagation and recurrent NN (RNN) in stock market index forecasting. In another study [115] compared the performance of ensemble classifier NNs with single classifier NN in exchange rate prediction and concluded that ensemble NNs perform better. Also, [116] used MLP-NNs as a prediction model to compare comparing five well-known feature selection methods used in bankruptcy prediction: *t* test, correlation matrix, stepwise regression, principle component analysis (PCA) and factor analysis (FA). Examining prediction performance of these five models, he concluded that t test feature selection method outperforms the other ones. In another study, [117] designed a distance-based fuzzy time series for exchange rates forecasting and compared the performance of their proposed model with that of random walk model and the ANNs model. They concluded that their proposed model performs better than ANNs and random walk model. Also study done by [118] shows that between dynamic ridge polynomial NN (DRPNN) and Pi-Sigma NN and the ridge polynomial NN, DRPNN performs better in prediction of financial time series.

Finally, [119] compared the forecasting accuracy of NN weights estimated with backpropagation suggested by Zhang et al. [120] (who concluded outperformance of backpropagation NNs comparing to the forecasting accuracy of ARIMA and linear regression models) to genetic

Table 7 Brief results of comparisons between several ANN together and with other traditional methods in financial prediction and planning

Author/s	Domain	Method compared with	Result
[108]	Business failure prediction	BPNN with functional link BP-NN, pruned BPNN, predictive cumulative BPNN LDA, Log, probit, QDA and nonparametric DA	The same overall performance, however, small differences
[109]	Bankruptcy prediction	LDA, QDA, k-NN, SOFM, RBF-SOFM, LVQ	RBF-SOFM performs slightly better
[112]	Exchange rate forecasting	GRNN with MLP, ARIMA and random walk model	GRNN performs better
[110]	Stock market returns forecasting	GRNN with B & H strategy, PNN level estimation NN, LR and T-bill	ANN performs better
[113]	Foreign exchange accuracy rates forecasting	BPNN with three versions of recurrent NNs (RNN1, RNN2 and RNN3) and linear models	ANN performs better
[111]	Bank financial failures prediction	MLP, competitive learning, SOM and LVQ NNs with SVM, MDA, k-means cluster analysis and LR	MLP and LVQ perform better

Table 8 Brief results of comparisons between ANN model/s together or with other intelligent methods in financial prediction and planning

Author/s	Domain	Method compared with	Result
[114]	Stock market index forecasting	Refined PNN, APN, BPNN, RNN and CBR	CBR performs better
[121]	Bankruptcy prediction	Fully connected BPNN versus interconnected BPNN	Interconnected BPNN performs better
[115]	Exchange rate prediction	Ensemble NNs with single NN	Ensemble NNs perform better
[122]	Stock market prediction	Gradient descent with adaptive learning rate BP, gradient descent with momentum & adaptive learning rate BP, LM BP, BFGS BP, Quasi-Newton and RPROP BP	LM BPNN performs better
[120]	Earnings per share forecasting	BPNN with ARIMA and LR	BPNN performs better
[123]	Exchange rate prediction	CFLANN with FLANN and standard LMS based forecasting model	CFLANN perform better
[116]	Feature selection in bankruptcy prediction	*T* test, correlation matrix, stepwise regression, PCA and FA for feature selection in BPNN	*T* test method is best method for BPNN future selection
[117]	Exchange rate forecasting	Distance-based fuzzy time series with random walk model and ANN	Distance-based fuzzy time series perform better
[118]	Financial time series prediction	DRPNN with Pi-Sigma NN and the ridge polynomial NN	DRPNN performs better
[119]	Earnings per share forecasting	BPNN (suggested by [120]) with GA	GA performs better

algorithm in predicting future earnings per share based on fundamental signals. They finally concluded that GA performs better than BP procedure of [120]. Another example of this type of studies is done by [121–123]. Table 8 presents the brief results of these comparisons.

3 Expert system applications in financial domain

An ES is defined as a computer system, which contains a well-organized body of knowledge that imitates expert problem-solving skills in a limited domain of expertise. In other hand, rule-based ES is a computer program that is capable to use information in a knowledge base, using a set of inference procedures, to solve problems that are difficult enough to require significant human expertise for their solution [124]. The set of inference procedures are provided by a human expert in the particular area of interest, while the knowledge base is an accumulation of relevant data, facts, judgments and outcomes [125]. ES consists of three main components including the knowledge base, the inference engine and the user interface. Knowledge base contains the knowledge required to solve specific problem. Knowledge can be represented using a variety of representation techniques (e.g., semantic nets, frames, predicate logic), but the most commonly used technique is if–then rules, also known as production rules. The inference engine is employed during a consultation session, examines the status of the knowledge base, handles the content of the knowledge base and determines the order in which inferences are made and finally user interface part enables communication between system and user. It mainly includes screen displays, a consultation dialog and an explanation component [126]. The important features which distinct ES from other mathematical models could be summarized as follows [127]: (a) ES are not limited by rigid mathematical or analog schemes and can handle factual or heuristic knowledge; (b) The knowledge base can be continuously augmented as necessary with accumulating experience; (c) Ability to handle qualitative information; (d) Coping with uncertain, unreliable or even missing data; (e) The reflection of decision patterns of the users. Regarding these features, ES have been widely used in different areas especially in financial domains. There have been several studies on the use of ES in finance. In 1987, [128] presents a number of applications of ES in finance, investment, taxation, accounting and administration over the period 1977 through 1993, but points to the restrictions on the broader development of ES in business posed by the hardware limitations of the time. In 1995, [3] and [4] note that expert making tools in many businesses, document an extensive use of ES in various areas of finance such as investment analysis, stock market trading and financial planning. Also, [9] conducted a review regarding the usage of ES across general areas, including finance, over the period 1995 through 2004 and observed that ES provide a powerful and flexible means of obtaining solutions to a variety of problems and can be called upon as needed (when a human with expertise in the particular area may not be available). Main applications of ES in financial domain as follows:

3.1 Credit evaluation

The most important job of a loan officer is to decide on the conditions and the amount of a loan which should be paid to the customers. For performing this duty, he must track the customer's credit history and also check his previous and current financial status [2], the nature of this task is repetitive and unstructured. The benefits of using ES for credit analysis are speed and accuracy, both which far exceed human capacity. To improve the throughput and accuracy of loans granted and to insure greater consistency of loan review, several credit analysis ES have been developed. For example, American express uses ES to process unusual requests. It is designed to evaluate unusual credit requests from cardholders on a real time these requests had previously been evaluated manually with a 15% bad guess rate. Since the deployment of authorizer's assistant, the rate has dropped significantly to 4% [129]. In 1985, [130] designed a framework for ES to manage banking loans. In 1986 [131] developed a credit-evaluation ES using MuLISP which was conducted by the academy of economics in Wroclaw, Poland. The method which was used by this ES for credit granting look likes that of goal-directed backward chaining search used by Prolog.

In 1989, [132] designed a knowledge-based decision support system (KB/DSS) for financial analysis and planning called FINISM. This system used for credit analysis in some French industrial companies at the corporate finance level. The adaptability of the system has been increased by using the ES approach. In 2001 [133] designed an ES called ALEES (an agricultural loan evaluation ES) for agricultural loan evaluation. ALEES incorporate both qualitative and quantitative assessments in agricultural loan evaluation In 2003, [134] designed a credit evaluation and explanation expert system (CEEES) which was used for granting credit lines to applicant firms. This ES was programmed in Prolog. If the expected benefit be large enough to include both expected loss and generate sufficient revenue for the financial institution, the system will recommend credit granting, if not, the credit recommendation will be rejection. This system divides loan applicants to qualified and non qualified applicants. Finally, [135] used their ES [which is able to expose stages of VPRS Model (variable precision rough set model)] for credit ratings in large banks and investment companies in Europe and North America. Other examples are [136–138]. Table 9 demonstrates the application of ES in credit evaluation along with comparison made by author/s.

As been presented in this table, most of developed ES have been compared to conventional methods and existing methods in financial sector. For example [133] compared his proposed ES with real evaluation of five loan officers in two different institutes. He concluded that ES performs better than these five loan officers. Also, [134] and [136] applied their ES to real-world problems and they got better results. The only work in which a rule-based ES has been compared to other intelligent techniques is done by [138]. They compared his proposed backpropagation ANN bond evaluation system with rule-based ES, linear regression, discriminant analysis, logistic analysis. He concluded that backpropagation ANN performs better than other models with 55% of accuracy followed by logistic analysis (43.1%), linear regression (36.21%), discriminant analysis (36.20%) and rule-based ES performs worst by 31% of accuracy.

3.2 Portfolio management

Having the current number of financial tools, the number of possible portfolio mixes that can be synthesized is

Table 9 Brief results of comparisons between ES and other methods in credit evaluation

Author/s	Domain	Method compared with	Result
[129]	Credit authorization	Conventional methods (manual banking methods)	ES performs better
[130]	Banking loan management	Conventional methods (real data)	ES performs better
[136]	Loan losses evaluation	Conventional methods (real-world implementation)	ES performs better
[132]	Credit analysis	Conventional methods (real data)	ES performs better
[137]	Credit card application assessment	Conventional methods (implementation in Nissho Electronic Corporation)	ES performs better
[138]	Bond rating	ANN with LR, DA, Logit and a rule-based system	ANN performs better
[133]	Agricultural loan evaluation	Conventional methods (comparing to real evaluation of 5 loan officers in 2 institutes)	ES performs better
[134]	Credit granting evaluation	Conventional methods (real-world implementation)	ES performs better
[135]	Credit rating	Conventional methods (real-world implementation)	Results differ with parameters variations

astronomical. To search for portfolio allocations that match the objectives and constraints of a fund manager is a hard and time-consuming process. A financial manager can delegate part of this task to an ES by connecting it to the financial databank [2]. In this regard, [139] designed a knowledge-based portfolio analysis for project evaluation. This ES which was designed for the ministry of science and technology of the republic of Slovenia was based on an adjusted portfolio matrix which determines the position of each project regarding their contents and feasibility. The model consists of a tree of criteria, supplemented by if–then rules.

Port-Man is another ES for portfolio management in banking system developed by [140]. The main goal of this ES was to give advices to personal investment in a bank. In general, the consultation process of Port-Man was consisted of four stages: information acquisition, product selection, choice refinement and customer and target frame.

The INVEX, suggested by [141], is an ES for investment management. This system helps investment decision maker and project analysts to choose a project for their investing portfolio. In another study, [125] designed an ES for portfolios of Australian and UK securitized property investments. They concluded that their proposed expert system outperforms general property market and randomly selected portfolios in select cases, although the outperformance was not statistically significant. Table 10 presents the application of expert system in portfolio management along with comparison made by author/s.

In portfolio management domain, like credit evaluation, proposed ES have been compared and validated by conventional methods like [140–142]. The reason why ES hasn't been compared to other methods is yield on the nature of these types of systems which is somehow different from that of other intelligent methods. This reason causes researchers to more compare their proposed ES to conventional methods like existing indexes, expert's opinion or real data. One of the most recent works is study done by [143] where they developed an ES, called PORSEL (PORtfolio SELection system), which uses a small set of rules to select stocks. This ES includes following three parts: the information center which provides representation of several technical indicators such as price trends; the fuzzy stock selector which evaluates the listed stocks and then assigns a mixed score to each stock and finally the portfolio constructor which generates the optimal portfolios for the selected stocks. The PORSEL also includes a user-friendly interface to change the rules during the run time. The results of simulation show that PORSEL outperformed the market almost every year during the testing period. They compared their proposed system with S & P 500 Index and concluded that the portfolios constructed by the new system consistently outperform the S & P 500 Index.

3.3 Financial prediction and planning

Another promising area of ES applications is financial prediction and planning. Many banks have used these types of systems in order to ameliorate their financial and trading operation. For example, the London-based Midland Bank uses an ES to manage its currency options and interest rate swap portfolios, as well as to price options and to provide general back-up and monitoring systems [2]. In 1989, [144] used ES for personal financial planning. He notes that the use of ES for financial planning by customers would give financial institutions both a product that the public would like and the means of gathering information which can be used to create cross-selling opportunities. FAME system proposed by [145] is an ES for financial marketing, which runs on Lisp and give financial marketing recommendations for mainframe computer business. In 1990, [146] also confront this issue (personal financial planning). They list eight systems which are in use in the USA for financial planning. Several of these systems provide reports which give recommendations for asset management, investment strategies, tax saving strategies and life insurance needs. They also note that "the pace of new financial product

Table 10 Brief results of comparisons between ES and other methods in portfolio management

Author/s	Domain	Method compared with	Result
[142]	Business loan portfolio management	Conventional methods	ES performs better
[140]	Portfolio analysis	Conventional methods	ES performs better
[139]	Portfolio analysis for project selection	Expert reviewers who answer questions on a special questionnaire	ES performs better
[141]	Investment advisory	Conventional methods	ES performs better
[143]	Investment analysis and valuation	S & P 500 Index	ES performs better
[125]	Investment portfolio	General property market and randomly selected portfolios	ES performs better, however, not statistically significant

introductions underpin the need for periodic updates of the expert system's knowledge base".

FINEVA (FINancian AVAaluation) is a multicriteria knowledge-based ES to assess firm performance and viability, which is developed using M4 ES shell. The inference engine of this ES uses both backward and forward chaining methods. The output of this system demonstrates the ranking of analyzed firms based on class of risk [147]. Also, The BANKSTRAT model is used to recommend on suitable marketing strategy for a retail bank. This system is capable to recommend micro and macro strategies based on detailed inputs which will be inputted by user and its knowledge base. In this model, user has also option to see the direct effects of his inputs in system's recommendations [148]. In 1998, [149] explored the use of a rule-based ES with real-time market indexes and stock quotes as input, to predict trends in order to maximize gains and minimize losses. This ES uses a set of forward chaining rule based on the comparison of past behavior and current real-time market data, coupled with the use of relative strength index to derive decisions for the purpose of daily-trading. The result of this study shows that within using a rule-based ES, it is possible to monitor fast-moving, real-time data to make profitable trade decisions. In another study, [150] developed a prototype ES for automation of financial ratio analysis. Their system is capable of performing five types of analysis: (1) liquidity, (2) leverage, (3) turnover, (4) profitability and (5) past performance. The output of the system is a list of conclusions and recommendations based on these analyses. In 2008, [151] suggested a knowledge system frame which encapsulate the structural and procedural decision knowledge, so that avoid unnecessary interference. They use Jess and Java interoperable computing for deployment and web enabling. They validated their system in supporting the expert's decision-making by conducting an empirical experimentation on 537 companies listed in the Taiwan stock exchange corporation. Table 11 presents the application of ES in financial prediction and planning along with comparison made by author/s.

In financial prediction and planning domain, several ES has been compared to conventional methods and also statistical methods. For example, [152] developed a rule-based ES for modeling the analysis of a saving and loan (S & L) analyst. In order to test their proposed ES, they compared its effectiveness with logit analysis of S & L bankruptcy. The result demonstrated that ES outperform logit in predicting traditional bankruptcy. In another research, [153] designed a medium-sized knowledge-based ES to choose an appropriate innovative financing technique(s) for transportation projects. They validated their proposed system's result with actual results obtained from transportation experts across the country. The tests indicate outperformance of ES. Also, in 2008, [154] investigated a new approach for forecasting the performance of mutual funds in Greece. They performed and validated this work with an application of a variation of the Theta model on a time series composed of the daily values of mutual funds. In comparison with existing conventional methods this ES performs better. One year later, [155] developed an ES for corporate financial rating which integrates two different knowledge bases, into one complete ES. The first one is Protégé, which is domain knowledge base, and second one is JESS, which is operational knowledge base. The performance of this system was validated by authors through its application to actual financial statements of several companies of Taiwan stock market. Other examples are [156–160].

Table 11 Brief results of comparisons between ES and other methods in financial prediction and planning

Author/s	Domain	Method compared with	Result
[156]	Banking fraud detection	Conventional methods	ES performs better
[152]	Bankruptcy prediction	Logit	ES performs better
[145]	Financial marketing consultant	Conventional methods	ES performs better
[157]	Audit planning	Conventional methods	ES performs better
[158]	Accounting management	Conventional methods	ES performs better
[159]	Audit planning	Conventional methods	ES performs better
[160]	Mortgage arrears problems	Conventional methods	ES performs better
[153]	Transportation financing techniques	Conventional methods (Expert's recommendation)	ES performs better
[150]	Financial ratio analysis	Conventional methods	ES performs better
[151]	Financial decision knowledge management	Conventional methods	ES performs better
[154]	Forecasting mutual funds	Conventional methods	ES performs better
[155]	Corporate financial rating	Conventional methods	ES performs better

4 Hybrid intelligent systems

If much is still to discover about how the animal's brain trains and self-organizes itself in order to process and mining so various and so complex information, a number of recent advances in "neurobiology" allow already highlighting some of key mechanisms of this marvels machine. Among them one can emphasizes brain's "modular" structure and its "hybridization" (e.g., mixing different functions in order to perform a complex task) capabilities. In fact, if our simple and inappropriate binary technology remains too primitive to achieve the processing ability of these marvels mechanisms, a number of those highlighted points could already be sources of inspiration for designing new approaches emerging higher levels of artificial intelligence by smart methods' hybridization [161, 162]. HIS is an efficient and robust learning system which combines the complementary features and overcomes the weaknesses of the representation and processing capabilities of symbolic and nonsymbolic learning paradigms [163]. In another word, HIS is a system that integrates intelligent techniques to problem-solving [164]. HIS not only represents the combination of different intelligent techniques but also integrates intelligent techniques with conventional computer systems and spreadsheets and databases [165]. According to [164], three main reasons for creating hybrid systems are as follows: technique enhancement, multiplicity of application tasks and realizing multifunctionality. The degree of interaction between the two modules in hybrid models could be varied from loosely coupled (stand alone models), transformational models, tightly coupled models to fully coupled models. A stand alone hybrid intelligent model has two separate components, e.g., an ES and an artificial NN, where there is no interaction between them [166]. Cheng et al. used this architecture to do semantic analysis of knowledge base's queries [167]. Transformational models are another type of loosely coupled models. They have similar characteristics to the stand alone models where the two modules do not share any of their internal data structure. However, transformational models are sequential in their operational nature. A transformational model usually starts up with one component (e.g., ANNs) and ends up with the other one (e.g., ES) [166]. Gelfand et al. [168] integrated knowledge-based systems and NNs for robotic skill, based on transformational models. In tightly coupled models, the two components of the model use part but not all of their internal data structure to communicate instead of using external data files [166]. The system designed by [169] for syntax parser, used this architecture. Fully coupled models represent hybrid architecture of dual nature (i.e., the architecture can be viewed as an ES or as a NN architecture) and still have the unique features of both paradigms [126]. For example the system which designed by [170] for spoken language analysis was based on this architecture.

4.1 Financial application of hybrid intelligent systems

Based on the literature review that has been done in this paper, generally the applications of HISs in three financial domains are highlighted: credit evaluation and portfolio management and financial prediction and planning.

4.1.1 Credit evaluation

To evaluate financial credit, banks and financial institute use many techniques such as judgmental systems, statistical models, or simply intuitive experience. In recent years, HISs have attracted the growing interest of researchers. For example, in 1997, [171] used combination of neural network and fuzzy system. In the proposed system, the fuzzy part was used as a special case neural network units like RBF and sigmoidal neurons, to ameliorate credit rating. Hsieh [172] used a hybrid mining approach to design a credit scoring model, based on clustering and NN techniques. He used clustering techniques to preprocess the input samples in order to indicate unrepresentative samples into isolated and inconsistent clusters, and used NNs to construct the credit scoring model. He used two real-world credit data sets in his proposed model. The result indicated that clustering is valuable in building networks of high effectiveness. In another study, [173] used designed a hybrid system to model the credit rating process of small financial enterprises. In their fuzzy adaptive network, they first used fuzzy numbers to represent the data of the credit rating problem. In the next stage, they construct the FAN network based on inference rules. Finally, they trained or learned the network by using the fuzzy number training data. The main advantages of the proposed network are the ability for linguistic representation, linguistic aggregation and the learning ability of the NN. In 2010, [174] designed a HIS for credit risk evaluation using four-stage SVM-based multiagent ensemble learning approach. In the first stage, the first dataset is divided into training subset, which is in-sample data, and testing subset, which is out-of-sample data, for training and verification. In the second stage, several different SVM learning paradigms are designed as intelligent agents for credit risk evaluation. In the third stage, they trained multiple individual SVM agents with training subsets. In the same stage they also obtained corresponding evaluation results. In the fourth and final stage, ensemble results are obtained by aggregation of all individual results produced by multiple SVM agents in the previous stage. They validated their hybrid system with corporate credit card application approval dataset. Also, [175] used fuzzy TOPSIS system for quick credibility scoring. This hybrid system is supposed to be used by the banks when they want to determine whether an applicant firm is worth a detailed credit check or not. They validated their proposed hybrid system with real cases.

The results of comparing hybrid credit based intelligent models to single linear and nonlinear models are encouraging. Several different models have been designed specially in last 5 years. Most of these models have been compared with traditional models. For example [176] compared the performance of adaptive neuro-fuzzy inference systems (ANFIS) with that of MDA model to identify bad credit applications. Using a modeling sample (500 observations from nine credit unions) and a test sample (290 observations from nine credit unions), they found that neuro-fuzzy system performs better than the multiple discriminant analysis approach in identifying bad credit applications. Further, they found that neuro-fuzzy systems are more tolerant of imprecise data and can model nonlinear functions of arbitrary complexity. In another research, [177] used two different fuzzy learning paradigms to train classifiers in credit scoring: boosted genetic fuzzy classifier and fuzzy NN. Boosted genetic fuzzy classifier uses evolutionary optimization and boosting, in order to learn fuzzy classification rules. In other side, fuzzy NN uses a fuzzy variant of the classic backpropagation learning algorithm. By using real credit data in their experiments they compared performance of these two methods with each other and with C4.5 decision tree induction algorithm. They finally showed that the boosted genetic fuzzy classifier performs better than two other methods. Other examples for this type of comparison are [178–181]. Table 12 presents the brief results of HISs applications in credit evaluation along with related comparisons.

Some researchers also compared their HIS with not only traditional system but also with intelligent methods especially NNs. For example, Lee et al. used backpropagation NNs along with traditional discriminant analysis approach for credit scoring. They performed credit scoring on bank credit card data set in two stages. In the first stage, they used discriminant analyses for credit scoring and at the next stage the output of the first stage was used as input to NN. The result showed that the proposed hybrid approach converges much faster than the conventional NNs model. In addition, the credit scoring accuracies increase in terms of the proposed methodology and outperform traditional discriminant analysis and logistic regression approaches [182]. Lee and Chen used same procedure. To build the credit scoring model, at the first, they used MARS and afterward they used the obtained significant variables as the input nodes of the NN models. The result demonstrated that the proposed hybrid approach outperforms the results using discriminant analysis, logistic regression, ANNs and MARS [183]. In 2007, [184] proposed a neural logic networks with the help of genetic programming methods which was trained adaptively through an innovative scheme. They tested their proposed method on two different real cases, first on the classification of credit applicants for consumer loans in a German bank and the second on the credit-scoring decision-making process in an Australian bank. They also compared their method to C4.5 (well-known inductive machine learning method) and 22 existing competitive methods including backpropagation networks, LVQ, discriminant analysis, K-nn, logical discriminant and 18 competitive methods. Results demonstrated that proposed methodology outperforms all of other methods, while it also produces handy decision rules, short in length and transparent in meaning and use. In 2009, [185] by two-stage hybrid models of logistic regression-ANN demonstrated that this model outperforms logistic regression, logarithm logistic regression and ANN approaches, providing an alternative in handling credit risk modeling which have assessment implications for analysts, practitioners and regulators. In the same year, [186] presents a reassigning credit scoring model (RCSM) involving two stages. Classification stage and reassign stage. The first

Table 12 Brief results of comparisons in which HIS/s compared with traditional methods in credit evaluation

Author/s	Domain	Hybrid method/s used	Method/s compared with	Result
[176]	Consumer loans evaluation	ANFIS	MDA	Hybrid model performs better
[177]	Credit scoring	Neuro-fuzzy and boosted fuzzy-genetic	C4.5 decision tree (rules) induction algorithm	Boosted Fuzzy-genetic performs better
[178]	Credit-risk data	MDD using NNs (Ordinary BPNN, Neurorule NN and Trepan NN)	C4.5, EODG	Hybrid model performs better
[179]	Sovereign credit ratings	Ordinary LR, intrinsically linear regression kernel based learning SVM	Real data comparison	Hybrid model performs better
[180]	Credit scoring	Rule extraction from SVM	C 4.5, Logit	Hybrid model performs better
[181]	Consumer credit scoring	GA with Kohonen ANN and BPNN	LR	Hybrid model performs better

stage builds an ANN-based credit scoring model in order to classify applicants into accepted or rejected credits. The second stage which uses CBR-based classification technique, tries to reduce the type I error by reassigning the rejected good credit applicants to the conditional accepted class. To demonstrate the effectiveness of proposed model, RCSM was performed on a credit card dataset obtained from UCI repository. They reported that the proposed model not only proved more accurate credit scoring than linear discriminant analysis, logistic regression and NNs, but also helps to increase business revenue by decreasing the type I and type II error of credit scoring system. Finally in 2009 [28] designed a credit ranking HIS using ES and ANNs. They compared results of their system with traditional methods which have been used in 6 different banking branches. Using several evaluation measures (MSE, MDA, RMSE, MAPE, MPE, correlation and *T*-test), they concluded high accuracy of their proposed HIS comparing to ES and traditional methods used by loan officers in real banking system. Other examples for this type of comparison are [187–190]. Table 13 presents the brief results of these comparisons.

Some studies compared their proposed hybrid system with single nonlinear methods or with another type of hybrid systems. For example, [191] suggested a particle swarm optimization (SPSO) approach for training feed-forward NNs for credit scoring. They applied successfully their method to real credit problems. Results showed that the proposed method outperforms backpropagation, genetic algorithm and SPSO. Laha [192] proposed a fuzzy rule-based classifiers for credit scoring. In his method at the first, the rule base is learned using a SOM-based method from the training data. Then, the fuzzy k-NN rule is incorporated for more powerful and qualitatively better classification. One of the capabilities of this mode is in demonstrating the commercial constraints. He also concluded that his proposed system outperforms fuzzy rule-based system. Finally, in 2010, [193] proposed an ensemble approach busing NN, Bayesian network and SVM classifiers. In their method, at the first they built individual classifier using class-wise bagging as a data augmentation strategy to obtain good generalization performance and in the second stage, the final outputs were decided by a confidence-weighted voting ensemble strategy. They concluded that their proposed ensemble approach performs much better than individual models and the conventional ensemble classifiers. Other examples for this type of comparison are [194, 195]. Table 14 presents the brief results of these comparisons.

As mentioned in all of the above studies, always hybrid credit-based systems perform better than compared methods except in work done by [194] and [195]. In 1999, [194] used neural-fuzzy system to ameliorate credit evaluation decisions. Using in three different cases, they stated that, the neuro-fuzzy systems provide a more transparent rule-based system for classification. However, despite these advantages, ANNs were found to significantly outperform the neuro-fuzzy system in all three cases. In 2005, [195]

Table 13 Brief results of comparisons in which HIS/s compared with traditional and single intelligent methods in credit evaluation

Author/s	Domain	Hybrid method/s used	Method/s compared with	Result
[187]	Credit and bond rating of firms	CBR, nearest neighbor matching algorithm, GA	MDA, ID3, and CBR	Hybrid model performs better
[182]	Credit scoring	BPNN with LDA	Conventional BPNN, LDA and LR	Hybrid model performs better
[183]	Credit scoring	MDRS with BPNN	Conventional DA, LR, ANN and MARS	Hybrid model performs better
[184]	Consumer loan and credit scoring	Neural logic networks and GP	C 4.5, BPNN, K-nn, LVQ, and 18 competitive methods	Hybrid model performs better
[188]	Credit scoring	SVM and GA	Conventional ANN, GP and C4.5	Hybrid model performs better
[189]	Credit scoring	Evolutionary and descriptive genetic- fuzzy rule-based classifier	Fisher, Bayes, ANN, C 4.5	Hybrid model relatively performs better
[190]	Consumer credit mining	Hybrid SVM technique, CART, MARS and grid search	Separate CART, MARS and SVM	Hybrid models performs better
[28]	Credit ranking	ES and BPNN	ES and conventional banking methods	Hybrid model performs better
[185]	Credit risk in banking	LR-ANN	LR, logarithm LR, and ANN	Hybrid model performs better
[186]	Credit scoring	ANN, CBR and MARS	LDA, LR, and ANN	Hybrid model performs better

Table 14 Brief results of comparisons in which HIS/s compared with single intelligent methods or other HIS/s in credit evaluation

Author/s	Domain	Hybrid method/s used	Method/s compared with	Result
[194]	Credit risk evaluation	Fuzzy NN	ANN	ANN performs better
[195]	Credit approval	CART basis artificial neuro-fuzzy system	MLP- BPNN	ANN performs better
[191]	Credit scoring	SPSO and feed-forward NN	Conventional BPNN, GA and SPSO	Hybrid model performs better
[192]	Credit scoring	FRKNN method	FRB	FRKNN model performs better
[193]	Credit scoring analysis	Ensemble classifier: discretize continuous values; ANN, SVM and Bayesian network	Conventional classifier and individual NN, BN, and SVM classifiers	Ensemble classifier performs better

designed a CART basis artificial neuro-fuzzy system for credit approval and he compared his proposed system with multilayer perceptron NN using backpropagation. The results showed that NN outperform ANFIS in classification accuracy. He stated that this is because of loss of information during fuzzification and defuzzification of categorical inputs and outputs, respectively, in hybrid system.

4.1.2 Portfolio management

Portfolio management is a vital and important activity in many organizations which is engaged with a complex and difficult process that involves many decision-making situations. Decision-making for retaining or giving up a financial projects needs special process which should consider numerous conflicting criteria. Although there are many studies available to assist decision-makers in doing the process of portfolio selection, there are less hybrid frameworks that one can use to systematically do the portfolio selection till few years ago [196]. But during the last years, portfolio selection theory using HISs has been well developed and widely applied. Within this framework, several hybrid portfolio selection models have been proposed. One of the first attempts was made by [197]. He applied fuzzy logic and NNs to stock portfolio selection. He reported that the proposed model correctly identified 65% of all price turning points. In 2004, [196] integrated fuzzy theory into strategic portfolio selection based on the concepts of decision support system, to solve portfolio selection problem. Their framework helps managers to select projects for portfolio management by providing them a flexible, expandable and interactive DSS. A real-world case based on GE (General Electric) matrix and 3Cs (Corporation, Customer, Competitors) model was used by authors to test their proposed method. In another work, [198] proposed a portfolio selection model in which triangular fuzzy numbers represents future return rates and future risks of mutual funds. At first, they proposed a cluster analysis to categorize the large amount of equity mutual funds into several groups. In the next step, they proposed fuzzy optimization model to determine the optimal investment proportion of each cluster. They finally claimed that the optimal investment proportions can thus be determined, according to different confidence levels. In the same domain, [199] proposed a fuzzy neural system for portfolio balancing using the generic self-organizing fuzzy NN (GenSoFNN). In their model, they used supervised learning approach in the network in order to detect inflection points in the stock price cycles. In addition, they employed a modified locally weighted regression algorithm to smooth the stock cycles. The authors evaluated their proposed hybrid system with experiments conducted using 23 stocks from the New York stock exchange and NASDAQ. Results showed an average profit return of 65.66%. The authors claimed that their proposed system can be used as an efficient trading solution, and it can provide decision support in trading via its generated rules.

Comparing to credit evaluation and financial prediction and planning much less comparative works has been done on this area. But interestingly during the last 4 years much more attention has been paid to hybrid portfolio management systems. Like credit evaluation, again, results of most of comparison are in favor of hybrid portfolio management systems. For example, [200] proposed a new hybrid intelligent algorithm based on new definition of risk in order to solve portfolio selection problem. In his proposed neuro-fuzzy system, he employed NNs to calculate the expected value and the chance value to reduce the computational work and speed up the process of solution when compared with the random fuzzy simulation. One year later, in 2008, [201] proposed NN-based mean–variance–skewness model for portfolio selection based on integrating Lagrange multiplier theory in optimization and RBF. They used 3 stock market reputable indexes (S & P 500, FTSE 100, Nikkie 225) for testing and evaluating their proposed models. Their experimental result show that, for all examined investor risk preferences and investment assets, the proposed model is a fast and efficient way of solving the trade-off in the mean–variance–skewness portfolio problem. They also concluded that their proposed model outperforms random walk (RW) model, adaptive exponential smoothing (AES) model, autoregressive integrated moving average (ARIMA) model and multilayer feed-forward NN (MLFNN) model. Recently, in 2009 [202] designed a hybrid intelligent algorithm by integrating simulated annealing algorithm, NN and fuzzy simulation techniques in order to solve portfolio selection problems. In this model, NN is used to approximate the expected value and variance for fuzzy returns and the fuzzy simulation is used to generate the training data for NN. They also performed some comparisons between their model and genetic algorithm. They concluded that the hybrid intelligent algorithm is robust and more effective than genetic algorithm in portfolio selection. Specially, the hybrid model reduces the running time significantly for large size problems. In the same year, [203] proposed a multibrands portfolio optimization model based on genetic network programming (GNP) with control nodes. Their optimization model which consists technical analysis rules, are trained to generate trading advice. They performed some experiments on the Japanese stock market and they concluded that their proposed method outperforms other traditional models in terms of both accuracy and efficiency. They also compared their proposed model with the conventional GNP-based methods, GA and buy and hold method and concluded that it can obtain much higher profits than these methods. However, there is some exception for outperformance of hybrid portfolio management comparing to other methods. For example, [204] used Q-learning algorithm, to solve some asset allocation sequential decision problems. They proposed two neural-based online trading approaches and carried out some empirical comparisons with Q-learning and with a neural forecast-based trading model. They validated their proposed system with models such as risk-free investment, buy and hold strategy, Sharpe ratio maximization and differential Sharpe ratio. They concluded that neural-based Q-learning is competitive; however, the experimental results were not very conclusive. Also, in 2008, [205] compares the performance of three soft-computing models in equity selection: MLP-NN, ANFIS and general growing and pruning radial basis function (GGAP-RBF). He also proposed how equities can be selected systematically by using relative operating characteristics (ROC) curve. The results of this comparison demonstrated that GGAP-RBF has huge time complexity when compared to MLP and ANFIS. Besides, GGAP-RBF does not outperform MLP and ANFIS in recall rate. He also claimed that there is positive relationship between predictions of the trained networks with the equities appreciation, which could result in better earnings for investment. Another example in this area is [206]. Table 15 presents the brief results of these comparisons.

4.1.3 *Financial prediction and planning*

The key to successful financial forecasting is achieving best results with minimum required input data. In comparison with other domains, the use of hybrid artificial intelligent systems in financial prediction is much more because hybrid systems capable us to combine the capabilities of different systems with different abilities. In this area, Kuo et al. designed a system for stock market forecasting that concerned qualitative and quantitative factors simultaneously. This system was composed of integrating NN for quantitative factors and fuzzy Delphi model for

Table 15 Brief results of comparisons in which HIS/s compared with other methods in portfolio management

Author/s	Domain	Hybrid method/s used	Method/s compared with	Result
[206]	Portfolio management	Standard statistical (polynomial classifiers) methods and NN	DA	Hybrid methods performs better
[204]	Portfolio management	Gaussian RBF, neural-based Q-learning	Risk-free investment, B&H strategy, Sharpe ratio maximization, Differential Sharpe ratio	Hybrid method is competitive approach, although not overall superior to alternative ones
[200]	Optimal portfolio selection	Neuro-fuzzy system	Fuzzy simulation	Hybrid model performs better
[201]	Portfolio selection	Lagrange multiplier theory and RBF network-based mean–variance–skewness	Random walk model, AES model, ARIMA and MLFNN	Hybrid methods performs better
[205]	Equities selection	Adaptive ANFIS	MLP, general growing and pruning RBF	MLP performs better in case of accuracy
[202]	Portfolio selection	SA, ANN and fuzzy simulation techniques and GA	GA	Hybrid models performs better
[203]	Portfolio optimization	Technical analysis rules, GNP with control nodes	Conventional GNP-based methods, GA and B&H method	Hybrid models performs better

qualitative factors. They used their system in Taiwan stock market and got acceptable results [207]. In another study, [208] developed a rule-based ES for financial forecasting. They merged fuzzy logic and rule induction to develop a system with generalization capability and high comprehensibility. The result of system implementation was promising. In [209] Rizzi et al. simulate ECB (European Central Bank) decisions and also forecast short-term Euro rate with an adaptive fuzzy ES. The use of an ES allowed them for modeling the ECB behavior with the use of wider scope of knowledge. The system has been tested on the economic and financial time series going from the January 1999 to September 2000. The system's correct prediction was estimated to overall 70% and, considering the complexity of the task, the results obtained were promising. Also Zhang and Wan proposed the statistical fuzzy interval NN to predict statistical fuzzy knowledge discovery and the currency exchange rate. Their statistical interval data sets were consisting of week-based averages, maximum errors of estimate and standard deviations. They used these data to train the fuzzy interval NN to discover fuzzy if–then rules. The output of the fuzzy interval NN was an interval value with certain percent confidence. Simulations were performed in terms of the exchange rates between US Dollar and other Japanese Yen, British Pound and Hong Kong Dollar. The simulation results showed that the fuzzy interval NN can provide more tolerant prediction results [210].

In 2008, [211] proposed a model of forecasting the domestic debt (MFDD). In their model they applied ANFIS to some macroeconomic variables of the Turkish economy. They claimed that their MFDD model has a high power of forecasting and strong estimation capability. One year later, [12] surveyed more than 100 related published articles that focus on neural and neuro-fuzzy techniques derived and applied to forecast stock markets. Their classifications were made in terms of input data, forecasting methodology and performance evaluation and measures. They reported that soft-computing techniques are widely accepted to studying and evaluating stock market behavior. In the same year, [212] used a fuzzy multiple criteria decision-making (FMCDM) approach for evaluating banking performance. They used expert questionnaires to choose evaluation indexes. In addition, the relative weights of the selected evaluation indexes were calculated by fuzzy analytic hierarchy process (FAHP). And the three MCDM analytical tools of SAW (simple average weight), TOPSIS (technique for order preference by similarity to ideal solution method), and VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) were, respectively, used to rank the banking performance. The result of their study shows that the proposed model could be a useful and effective assessment tool. In the same domain, [213] proposed a regularized least squares fuzzy support vector regression (RLFSVR) for financial forecasting which is using knowledge of the noisy and nonstationary financial time series data samples, to ameliorate generalization. RLFSVR needs only a single matrix inversion to find the regressor, regardless of the kernel used. The authors concluded the efficacy of the regressor by several experiments. Also, [214] proposed a pseudo-outer product fuzzy NN to predict bank failure using the compositional rule of inference and singleton fuzzifier (POPFNN-CRI(S)) model. They evaluated the performance of their suggested model by using classification rate of 3636 US banks observed over a 21-year period. In 2009, [215] Integrated piecewise linear representation (PLR) with BPNN to predict stock's trading point. BPNN was used for supervised training of the model and also genetic algorithm was used to improve the threshold value of the PLR. They concluded that their proposed system can at the first make significant amounts of profit on stocks with different variations and also is very effective in prediction of the future trading points of a specific stock.

Like NNs, HISs have been also applied and compared with other methods by many researchers in financial predicting and planning. These applications are mostly in the domain of bankruptcy prediction (which could be also categorized as credit evaluation), stock prediction, exchange rate prediction and financial time series forecasting. It is not surprise to see those results of comparison between proposed HISs and other traditional and single intelligent models is in favor of hybrid systems because they are supposed to use capabilities of different separate systems. However, there are some exceptions. Because of diversification of these studies we classify them as follows:

Comparison between HIS/s and traditional and statistical model/s: Chen and Leung proposed an adaptive forecasting approach which combines the strengths of NNs and multivariate econometric models for error correction in foreign exchange forecasting and trading. This hybrid approach contained two forecasting stages. In the first stage, a time series model (multivariate transfer function (MTF), generalized method of moments (GMM) and Bayesian vector autoregression (BVAR)) generates estimates of the exchange rates. In the second stage, general regression NN is used to correct the errors of the estimates. A number of tests and statistical measures were then applied to compare the performances of the two-stage models (with error correction by NN) with those of the single-stage models (without error correction by NN). Both empirical and trading simulation experiments showed that the proposed hybrid approach not only produces better exchange rate forecasts but also results in higher investment returns than the single-stage models [216]. Using SVM and PNN, in 2009, [217] proposed a method to predict financial information manipulation. In their work, test performance of classification accuracy, sensitivity and specificity statistics for PNN and SVM are compared with the results of discriminant analysis, probability classifiers and logistics regression. They found that the performance of SVM and PNN are higher than that of the other classifiers. In the same year, [218] tried to provide an alternative for bankruptcy prediction using neuro-fuzzy system, a hybrid approach combining the functionality of fuzzy logic and the learning ability of NNs. Their empirical results show that neuro-fuzzy demonstrates a better accuracy rate, lower misclassification cost and higher detecting power than does logistic regression.

Also, [219] designed new hybrid intelligent system for option pricing by integrating new hybrid asymmetric volatility approach and ANNs option-pricing model in order to improve forecasting ability of derivative securities price using Grey-GJR–GARCH approach. They concluded that in the ANN option-pricing model, the Grey-GJR–GARCH volatility provides higher predictability than other volatility approaches. Other examples of this type of comparisons are done by [220–231]. Table 16 presents the brief results of these comparisons.

Comparison between HIS/s and single intelligent model/s: Thammano used a neuro-fuzzy model for forecasting future value of main governmental bank of Thailand. The inputs of network were final price of current month and previous 3 months and also were ROE (return on equity), ROA (return on assets) and P/E (price-to-earnings ratio) ratios. Model's output was the next 3 month stock price. They concluded neuro-fuzzy system perform better than backpropagation algorithm in this sort of predictions [232]. In 2009, [233] investigate the performance of different NNs architecture in government bond yields forecasting. They chose four different structures for their study: resilient propagation (RPROP), radial basis function neural network (RBFNN), ANFIS and BPNN. They concluded that at the first the number of nodes in the hidden layer is insensitive to the prediction; second, the recommended number of input nodes is five.

Table 16 Brief results of comparisons in which HIS/s compared with traditional methods in financial planning and prediction

Author/s	Domain	Hybrid method/s used	Method/s compared with	Result
[220]	Bankruptcy prediction	NN and GA	Logit	Hybrid model performs better
[221]	Financial forecasting	ANN, kernel function approach and the recursive prediction error	Classical statistical methods	Hybrid model performs better
[222]	Bankruptcy prediction	Hybrid clustering ANN	MDA	Hybrid model performs better
[216]	Foreign exchange forecasting and trading correction	Time series model and GRNN	Multivariate transfer function, GMM, and Bayesian vector autoregression without ANN error correction	Hybrid model performs better
[223]	Bankruptcy prediction	Neural logic networks into GP	Rough sets, DA, Logit	Hybrid model performs better
[224]	Stock market forecasting	HMM, ANN and GA	Conventional HMM, ARIMA	Hybrid model performs better
[225]	Stock trading	VAMA and EMV indicator with GRNN	VAMA and EMV indicator	Hybrid system performs better
[226]	Exchange rate prediction	Temporal SOM and SVR and GA	GRACH model	Hybrid models performs better
[227]	Stock price forecasting	Rule-based trading agents and GA	ARIMA and LR	Hybrid models performs better
[218]	Corporate bankruptcy	Neuro-fuzzy	LR	Hybrid models performs better
[228]	Stock exchange forecasting	GRACH model with ANN	GRACH model	Hybrid models performs better
[229]	Financial market trading system	HiCEFS: ISMF and HCGA	B&H strategy, trading system without and also without prediction and also with other predictive models (EFuNN, DENFIS and RSPOP)	Hybrid model performs better
[219]	Forecasting model for stock index option price	GJR-GARCH and ANN	GARCH and conventional GJR– GARCH	Hybrid model performs better
[230]	Real state valuation	CBR and ANN	MRA	Hybrid model performs better
[217]	Financial information manipulation prediction	SVM and PNN	DA, probability classifiers and LR	Hybrid model performs better
[231]	Exchange rates and stock returns	TAR-VEC-MLP, TAR-VEC-RBF and TAR-VEC-RHE models	TAR-VEC model	TAR-VEC-RBF performs the best

Third, more training samples do enhance forecasting performance; fourth, the performance of RBFNN is the best, followed by ANFIS and RPROP, SVR, and then BPNN, fifth; BPNN is efficient but not the best approach and finally they proposed RBFNN with five input nodes, six center nodes in the hidden layer and one output node as a useful predicting approach in government bond yield.

Other examples of this type of comparisons are done by [234–244]. Table 17 presents the brief results of these comparisons.

Comparison between HIS/s and with not only single intelligent models but also traditional method/s: In 1996, [245] suggested the hybrid model of discriminant analysis, NN, and case-based forecasting system to bankruptcy prediction. The results demonstrate that the hybrid model outperforms the three independent prediction techniques. Tung et al. used a neural-fuzzy-based early warning system for predicting bank failures called GenSo-EWS. Bank failures were predicted based on a population of 3635 US banks observed over a 21-year period. The performance of the GenSoFNN-CRI(S) network is subsequently benchmarked against that of the Cox's proportional hazards model, the MLP and the modified cerebellar model articulation controller (MCMAC). Three sets of experiments were performed—bank failure classification based on the last available financial record and prediction using financial records one and 2 years prior to the last available financial statements. The performance of this system in predicting banking failure is encouraging [246]. In 2010, [247] proposed a hybrid forecasting method called hybrid2CBR (H2CBR) which was designed by integrating six hybrid CBR modules. Six out-ranking preference functions with the algorithm of k-NN inside CBR were combined and modified to build these hybrid CBR modules They used a trial-and-error iterative process to identify the optimal hybrid CBR module in their proposed hybrid method. They finally compared their proposed system with classical CBR algorithm based on the Euclidean metric, LR and MDA. They concluded that the predictive performance of the H2CBR system is promising and also the most preferred hybrid CBR for short-term bank failure prediction of Chinese listed companies is based on the ranking-order preference function. Other examples of this type of comparisons are done by [248–266]. Table 18 presents the brief results of these comparisons.

Table 17 Brief results of comparisons in which HIS/s compared with single intelligent methods in financial planning and prediction

Author/s	Domain	Hybrid method/s used	Method/s compared with	Result
[234]	Future fiscal well-being classification	BPNN and GA	BPNN	Hybrid model performs better
[232]	Future banking value forecasting	Neuro-fuzzy model	BPNN	Hybrid model performs better
[235]	Temporal patterns in stock markets detection	1. ATNNs with GA 2. TNNs with GA	Conventional ATNN, TDNN and RNN	Hybrid model performs better
[236]	Corporate financial distress prediction	SVM and LR	Conventional SVM	Hybrid model performs better
[237]	Exploring financial internal mechanism of warrant	Integrating Black–Scholes pricing method and grey theory into a GA-based BPNN	Conventional BPNN	Hybrid model performs better
[238]	Financial investment decision support	Integrating K-chart technical analysis, discrete wavelet transform and a novel two-level SOM network	Conventional SOM	Hybrid model performs better
[239]	Stock market prediction	Improved bacterial chemo taxis optimization and BPNN	BPNN	Hybrid models performs better
[240]	Stock price forecasting	SOM and then SVR	Conventional SVR model	Hybrid models performs better
[241]	Earnings management prediction	ANN and decision trees model	Conventional ANN	Hybrid models performs better
[242]	Bankruptcy prediction	Hybrid case-based reasoning and GA approach	Conventional CBR	Hybrid models performs better
[243]	Budget allocation	FAHP	ANN	Hybrid models performs better
[244]	Stock trend prediction	SVM with F-score and F_SSFS	BPNN along with three commonly used feature selection methods	Hybrid models performs better
[233]	Government bond yields forecasting	ANFIS	RPROP, RBF NN and BPNN	RBF NN performs better

Table 18 Brief results of comparisons in which HIS/s compared with single intelligent and traditional methods in financial planning and prediction

Author/s	Domain	Hybrid method/s used	Method/s compared with	Result
[248]	Financial classification	BPNN and LDA	Conventional LDA and BPNN	Hybrid model performs better
[245]	Bankruptcy prediction	Hybrid DA, NN, and CBR	Conventional DA, ANN, and CBR	Hybrid model performs better
[249]	Bankruptcy prediction	NN, Logit, C4.5, DA and MARS	DA, Log, MARS, C4.5 and conventional NN	Hybrid model performs better
[250]	Sales forecasting	BPNN and fuzzy NN	ARMA and conventional BPNN	Hybrid model performs better
[246]	Bank failures prediction	Neuro-fuzzy model	Cox's proportional hazards model, MLP and modified CMAC	Hybrid model performs better
[251]	Stock index forecasting	Genetic-neural model	B&H strategy and locally RNN	Hybrid model performs better
[252]	Financial forecasting	RCBR	Random walk and standard CBR models	Hybrid model performs better
[253]	Bankruptcy prediction	FLN, fuzzy measures an GA	DA, probit, Logit, quadratic interval Logit, SLP, MLP, and traditional FLN	Hybrid model performs better
[254]	Corporate failure prediction	GA with DA, LR and ANN	Conventional GA, DA, LR, and ANN	Hybrid model performs better
[255]	Stock market index forecasting	GA-based optimal time-scale feature extractions SVM	ANN, pure SVMs or traditional GARCH models	Hybrid model performs better
[256]	Bank performance prediction	Ensemble MLFF-BPNN, PNN, RBF, SVM, CART and a fuzzy rule-based classifier and using GRNN and GA for training	Its constituent models and MDA and human judgment	Hybrid model performs better
[257]	Financial distress analysis	MLP, Choquet fuzzy integral and GA	DA, SLP, probit method, Logit and MLP	Hybrid model performs better
[258]	Stock market forecasting	HMM and fuzzy model	ARIMA, ANN and another HMM-based forecasting model	Hybrid models performs better
[259]	Bankruptcy prediction	ELECTRE-based SLM and GA	LDA, LR, probit method, traditional SLP, MLP, SVM, ELECTRE TRI method and fuzzy integral-based FLN	Hybrid models performs better
[260]	Financial time series forecasting	Independent component analysis and SVR	SVR model with nonfiltered forecasting variables and a random walk model	Hybrid models performs better
[261]	Financial distress prediction	MDA, Logit, ANN, DT, SVM and CBR	Conventional MDA, Logit, NNs, DT, SVM, and CBR	Hybrid models performs better
[262]	Price information evaluation and prediction	Adapted-CBR	Un-adapted-CBR approach, CART, ANN and LR	Adapted-CBR performs better
[263]	Financial distress prediction	CBR prediction method based on outranking relations	MDA, Logit, NN, SVM, DT, basic CBR, and grey CBR	Hybrid model performs better
[264]	Bankruptcy prediction	Integration of MDA, LR, ANN, and decision trees induction	Conventional MDA, LR, ANN, and decision trees induction models	Hybrid model performs better
[265]	Business failure prediction	Hybrid Gaussian CBR system	Conventional MDA, LR, and two classical CBR	Hybrid model performs better
[266]	Bankruptcy prediction	Fuzzy RBF NNs	Logit, quadratic interval Logit (including defuzzy), BPNN	Hybrid system performs better
[247]	Business failure prediction	Hybrid^2 CBR based (constructed by integrating six hybrid CBR modules) whose heart is the k-NN algorithm	Classical CBR algorithm based on the Euclidean metric, LR and MDA	Hybrid system performs better

Table 19 Brief results of comparisons in which HIS/s compared with other HIS/s in financial planning and prediction

Author/s	Domain	Hybrid method/s used	Method/s compared with	Result
[269]	Bankruptcy prediction	SOFM (SOFM-BP)-assisted NN	MDA-assisted NN, and an ID3-assisted NN	Proposed hybrid model performs better
[267]	Financial forecasting	ANN and GA with instance selection algorithm	ANN and GA without instance selection algorithm	Proposed hybrid model performs better
[270]	Financial evaluation of corporation	Regular RBF with 3 layers, GA in all the layers	Neuro-genetic forms of RBF	Proposed hybrid system performs better
[271]	Financial forecasting	Candlestick method based on GRNN with rule-based fuzzy gating network	Candlestick method based on GRNN with simple gating network	Proposed hybrid model performs better
[268]	Business failure prediction	DEA, rough set and support vector machines	Hybrid approach rough set and BPNN	Proposed hybrid model performs better

Table 20 Brief results of comparisons in which HIS/s compared with single intelligent methods and other HIS/s in financial planning and prediction

Author/s	Domain	Hybrid method/s used	Method/s compared with	Result
[275]	Bankruptcy prediction	GA-NN	LDA-NN and, Logit analysis-NN	GA-NN performs better
[276]	Predicting bank failures	Fuzzy CMAC, Fuzzy logic and ANN	CPH model and GenSoFNN-CRI(S) (another fuzzy neural approach) network, FHFSLMS	Hybrid model performs better
[277]	Stock index forecasting	Bivariate NNs with fuzzy time series forecasting substitutes	Bivariate and univariate conventional RL, ANN and ANN-based fuzzy time series and univariate ANN with fuzzy time series forecasting substitutes	Proposed bivariate hybrid model performs better
[272]	Forecasting KSE100 index	1.ANN- ARIMA 2. ANN-ARCH/GARCH	Conventional ARIMA, ARCH/GARCH and ANN	Second hybrid model performs better
[273]	Stock price prediction	Hybrid BPNN, SVM and ANFIS	Separate BPNN, SVM and ANFIS	Hybrid model performs better
[274]	Stock market prediction	Rough set theory and multiorder fuzzy time series	Weighted fuzzy time series models, high-order fuzzy time series, the partial autocorrelation function and autoregressive models	Hybrid model performs better
[278]	Predicting financial activity rate	CBR augmented with GA and the fuzzy k nearest neighbor	Conventional CBR, CBR with AHP weighted k-NN, CBR with GA weighted, CBR with weighted k-NN, CBR weighted by expert	Proposed hybrid model performs better

Comparison between HIS/s and other hybrid approach: In this domain, [267] proposed a hybrid system for financial forecasting using ANNs and genetic algorithm with instance selection algorithm. He compared his proposed hybrid system with the same hybrid system but without instance selection algorithm and concluded that proposed system performs better. In 2010, [268] used DEA-RST-SVM approach to predict business failure. They intended to integrate rough set theory (RST) with SVM technique to increase the accuracy of the prediction of business failure. In their proposed model, data envelopment analysis (DEA) is used as to evaluate the input–output efficiency. The model was verified by comparing to hybrid BPNN with RST model. The results show that DEA do provide valuable information in business failure predictions and the proposed RST-SVM outperforms RST-BPNN model. Other examples of this type of comparisons are done by [269–271]. Table 19 presents the brief results of these comparisons.

Comparison between HIS/s and not only other hybrid approaches but also single intelligent systems: In 2008, [272] proposed two different hybrid financial system to model Karachi stock exchange index data, KSE100, for short-term prediction. The first one is combination between

ANNs and ARIMA and the second one is combination between ANN and autoregressive conditional heteroskedasticity/generalized autoregressive conditional heteroskedasticity (ARCH/GARCH) models. They compared ANN with ARIMA and ARCH/GARCH on the basis of forecast mean square error (FMSE). The result demonstrated that ANN outperforms ARIMA and ARCH/GARCH models. Also they compared their two proposed hybrid financial models and concluded that ANN-ARCH/GARCH outperforms ANN and ANN-ARIMA in forecasting KSE100 index. One year later, [273] compared performance of hybrid prediction approaches with combining BPNN, ANFIS and SVM methods with single approach in stock price prediction. The result verified that hybrid approach had considerately a better performance than separate BPNN, SVM and ANFIS methods. In the same year, [274] proposed a hybrid model based on multiorder fuzzy time series, which uses rough sets theory and an adaptive expectation model. Rough sets theory was used in order to mine fuzzy logical relationship from time series and the adaptive expectation model was used in order to adjust forecasting results to improve forecasting accuracy. They compared their proposed model with weighted fuzzy time series models and high-order fuzzy time series. Besides, to compare with conventional statistic method, the partial autocorrelation function and autoregressive models are utilized to estimate the time lags periods within the databases. Based on comparison results, they reported that the proposed model can effectively improve the forecasting performance and outperforms other models. Other examples of this type of comparisons are done by [275–278]. Table 20 presents the brief results of these comparisons.

5 Conclusion

The need to solve highly nonlinear, time variant problems has been growing rapidly as many of nowadays as many current applications in the real world have nonlinear and uncertain behavior which changes with time. Conventional and traditional mathematical model based techniques can effectively address linear, time invariant problems and model based techniques can also solve more complex nonlinear time variant problems, but only in a limited way. These problems along with other problem of traditional models caused growing interest in artificial intelligent techniques such as fuzzy logic, NNs, genetic algorithms, ES, and recently HISs [279]. In this paper comparative research review of three famous artificial intelligence techniques, i.e., ANNs, ES and hybrid intelligence systems in financial market have been done. A financial market also has been categorized on three domains: credit evaluation, portfolio management and financial prediction and planning. For each technique most famous and especially recent researches have been discussed in comparative aspect. However, due to a variety of research design and evaluation criteria, it is difficult to compare the results of different studies.

Regarding application of ES in financial domain, I couldn't find many works in which ES has been compared to other common used linear and nonlinear models. These sort of systems have been generally validated by real experts or existing real data. However, they are more practical than traditional statistical methods (e.g., [152]) but they cannot compete with other intelligent methods like NNs and HISs (e.g., [28], [138]). The reason may returns back to the nature of ES. Despite the significant strength of ES, like permanence, reproducibility, efficiency, consistency, documentation, completeness, timeliness, breadth, consistency of decision-making, ES provide a prescription and not a prediction. That means that if a goal is given then, a knowledge-based ES suggests a course of action, while a simulation model predicts the consequences of a selected course of action under some experimental conditions [280]. The ES couldn't improve the result of experience and they just could move onto the next, if/then rule. Another problem of ES comparing to other intelligent technique, especially NNs, is that nonlinear relationships couldn't be identified by them.

Regarding NNs, the empirical results of these comparative studies indicate that the success of NNs in financial domain, especially in financial prediction and planning, is very encouraging. (However, while NNs often outperform the more traditional and statistical approaches but this is not always the case. There are some studies in which other traditional methods (e.g., [56]), or intelligent approach (e.g., [53]) outperforms NNs.) This success is due to some unique characteristics of NNs in financial market like their numeric nature, no requirement to any data distribution assumptions (for inputs) and model estimators and finally, their capability to update the data. Despite this success, this paper could not conclude that NNs are very accurate techniques in financial market because at the first, among these studies, BPNN is the most popular NN training technique. However, BPNN suffers from the potential problems. One of the problems of BPNN is local minimum convergence. Because the gradient search process proceeds in a point-to-point mode and is intrinsically local in scope, convergence to local rather than global minima is a very possibility [58]. Also BP training method is very slow and takes too much time to converge. Besides, it can over fit the training data [233]. Secondly, it is difficult, if not impossible, to determine the proper size and structure of a neural net to solve a given problem. Therefore, the architectural parameters are generally designed by researchers and via trial and errors and since these parameters determine outputs of NNs, their accuracy and performance are subject to numerous errors. Also sometimes NNs are incapable to recognize patterns and establish relevant relationships between various factors, which are important reasons to reduce their performance. Finally, NNs learn based on past occurrences, which may not be repeated [281], especially in financial markets and in current financial crisis. When, for researchers, such problems matter, an alternative to NNs could be hybrid approach. Hybrid systems are supposed to be right choice among other linear and nonlinear techniques because they capable us to combine the capabilities of different systems. This integration aims at overcoming limitations of individual techniques through hybridization or fusion of various techniques. Due to the complementary features and strengths of different systems, the trend in the design of hybrid system is to merge single techniques to more powerful integrated system, to overcome their individual weakness. However, using hybrid systems couldn't guaranty well performance of system because the right choice of integration models and also parameterization remain important problems. Due to these problems in some financial application, we can see outperformance of single techniques to hybrid techniques such as [194], [195] and [233]. Despite comparative approach, according to the results we can generally conclude that high percentage of previous studies reported that the accuracy of these artificial intelligent methods is superior to that of traditional and statistical methods in dealing with financial problems (as financial decision-makers in many areas of financial management must constantly deal with unstructured problems), especially in regard to nonlinear patterns ([30], [49], [194], [176]) and can broadly replace previous traditional methods. However, the application of these approaches is highly limited to parametric versions of nonlinear models.

Appendix A

See Table 21.

Table 21 Abbreviation keys (alphabetical order)

Abbreviation	Interpretation	Abbreviation	Abbreviation
AES	Adaptive exponential smoothing	GRNN	General regression neural network
ANFIS	Adaptive neuro-fuzzy inference systems	HCGA	Hierarchical coevolutionary genetic algorithm
ANN	Artificial neural networks	HiCEFS	Hierarchical coevolutionary fuzzy system
APN	Arrayed probabilistic network	HIS	Hybrid intelligent system
ARCH	Autoregressive conditional heteroskedasticity	HMM	Hidden markov model
ARIMA	Autoregressive integrated moving average	ID3	Inductive dichotomizer 3
ARMA	Auto regressive moving average	ISMF	Irregular shaped membership function
ATNNs	Adaptive time delay NN	K-nn	K nearest neighbor
B&H	Buy and hold	LDA	Linear discriminant analysis
BFGS	Broyden–Fletcher–Goldfarb–Shanno	LM	Levenberg–Marquardt
BPNN	Backpropagation neural networks	LMS	Least mean square
C4.5	Extension of CART and ID3	LR	Logistic regression
CART	Classification and regression trees	LS-SVMs	Least squares support vector machines
CBR	Case-based reasoning	LVQ	Learning vector quantization
CFLANN	Cascaded functional link ANN	MARS	Multivariate adaptive regression splines
CMAC	Cerebellar model articulation controller	MDA	Multiple discriminant analyses
CPH	Cox's proportional hazard	MDD	Multivalued decision diagrams
DRPNN	Dynamic ridge polynomial neural network	MDRS	Multifactor dimensionality reduction splines
DA	Discriminant analysis	MLFF	Multilayer Feed Forward
DEA	Data envelopment analysis	MLR	Multiple linear regression
DENFIS	Dynamic evolving neural-fuzzy inference system	MLP	Multilayer perceptron
DT	Decision Tree	MOE	Mixture-of-experts
ELECTRE	ELimination Et Choix Traduisant la REalité	NN	Neural network
ELECTRE TRI	ELECTRE Tree	OPM	Ordered probit Modeling

Table 21 continued

Abbreviation	Interpretation	Abbreviation	Abbreviation
EFuNN	Evolving fuzzy neural network	OPP	Ordinal pairwise partitioning
EMV	Ease of movement	PCA	Principle component analysis
EODG	Entropy-based oblivious decision graphs	PNN	Probabilistic neural networks
ES	Expert system	QDA	Quadratic discriminant analyses
FA	Factor analysis	RBF	Radial basis functions
FAHP	Fuzzy analytic hierarchy process	RCBR	Regression case-based reasoning
FAN	Fuzzy adaptive network	RHE	Recurrent hybrid elman
FHFSLMS	Functional hippocampal fuzzy semantic learning memory structure	RNN	Recurrent neural networks
FLANN	Functional link ANN	RPROP	Resilient propagation
FRB	Fuzzy rule based	RSPOP	Rough set–based pseudo-outer product
FRKNN	Fuzzy rule-based K-NN	RST	Rough set theory
F_SSFS	Supported sequential forward search	SA	Simulated annealing
FuzC	Fuzzy classifier	SOM	Self-organizing map
GJR	Glosten–Jagannathan–Runkle	SPSO	Particle swarm optimization
GMLC	Gaussian maximum likelihood classification	SVM	Support vector machine
GMM	Generalized methods of moments	SVR	Support vector regression
GNP	Genetic network programming	TAR-VEC	Threshold autoregressive vector error correction
GP	Genetic programming	TDNNs	Time delay NN
GRACH	Generalized auto regressive conditional heteroskedasticity	VAMA	Volume-adjusted moving average

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