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A review on the applications of neuro-fuzzy systems in business

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Abstract This paper presents a review of the application of neuro-fuzzy systems (NFS) in business on the basis of the research articles issued in various reputed international journals and conferences during 2005–2015. The use of NFS for tackling various real world problems in different business domains has diversified significantly during this period. In effect NFS has emerged as a dominant technique for addressing various difficult research problems in business. Based on a detailed review of these research papers we have identified finance, marketing, distribution, business planning, information systems, production and operations as the main business application domains of NFS during this period. This paper also discusses the impact of NFS in various business domains and the trend of this application based research during this period. This paper also surveys the various innovations in NFS methodologies employed by the researchers to deal with different business problems in each of these years. Moreover the paper includes some articles published during 2016 in several international journals to present the latest progress in the application of NFS in various business domains.

Keywords Business · Artificial intelligence · Neural networks · Neuro-fuzzy systems · Review

1 Introduction

Artificial intelligence (AI) has been used in a wide range of real life problems as depicted by a substantial amount of research done in this field during the recent past. AI techniques mainly include methods like artificial neural networks (ANN), fuzzy logic, genetic algorithms and various hybrid methods combining the various AI techniques such as NFS, Neuro-genetic

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systems etc. But the research in the last few years has revealed several drawbacks of the use of standalone AI techniques for handling the real world problems. The limitations are mainly due to the mass and vagueness of datasets, complexity of the real world problems, uncertain/unclear information or lack of enough information. As a result the research on the applications of AI techniques indicates a shift from the use of these traditional standalone AI methods towards employing hybrid systems which are obtained by integrating two or more different AI techniques by different methods.

ANN is a powerful technique for solving complex approximation and classification problems due to their high generalization capability, robust design, ability to handle the incomplete data and to learn and tune their parameters depending on a particular dataset using a learning algorithm. Even though ANN techniques possess these capabilities these have some limitations like the black box organization due to which their operation is not transparent to user, possibility of over-fitting and long training periods. On the other hand fuzzy logic provides a mathematical foundation for dealing with uncertainty in real world problems and the ability to represent the domain knowledge in the form of interpretable fuzzy if–then rules due to which the system is transparent and can reveal the stored functionality. But the operation of a fuzzy system is totally dependent on the expert designing it because a standalone fuzzy system can only utilize the knowledge encoded in it but is not able to learn and therefore is difficult to generalize. Therefore ANN and fuzzy systems are somewhat supplementary to each other as one of the techniques has the capabilities the other is lacking of. NFS combine these two AI techniques in various ways so that the learning ability of the connectionist neural networks is incorporated into the human like reasoning ability of the fuzzy systems. Due to the combined abilities and overcoming of the respective limitations of each of these two techniques these hybrid systems are able to solve difficult real world problems and have been successfully applied in student modeling, medical science, business, traffic control, and image processing.

NFS have also been successfully used in business and the application is expanding into different business domains like finance, production, marketing, business planning, human resource management (HRM) etc. The purpose of this paper is to present a review of the application of NFS in different business areas from 2005 to 2015 as a part of research on NFS in business. The review is based on the articles published in journals of various reputed publishing houses like Elsevier, ACM, Springer, IEEE, EBSCO etc. and articles from proceedings of various international conferences. On the basis of the scope of these articles in business, this paper broadly identifies production and operations, finance, business planning, marketing and distribution, human resource management and information systems as the main application domains of NFS during these years. Also this study discusses the various NFS methodologies currently used in business which can enable the interested researchers to understand the most advanced neuro-fuzzy techniques and their application in different business areas. Additionally the paper discusses the most recent research trends in the application of NFS in various business domains by including the relevant research articles published during year 2016 in some reputed international journals and conferences.

The organization of the paper is: Sect. 2 discusses the NFS methodology and their importance in business; Sects. 3 to 8 provide a detailed review of the NFS methodologies and research trends in finance, marketing and distribution, HRM, business planning, production/operations and information systems respectively during the last decade; Sect. 9 discusses the novel NFS methodologies introduced in business and newer business domains explored during 2005–2015 in addition to providing a summary of the results of this survey; Sect. 10 concludes the paper and also presents the applicable future research outline.

2 Neuro-fuzzy systems and their importance in business

As already explained in the introduction section NFS are a result of combining the neural network and fuzzy system concepts in order coalesce the advantages of both the techniques and address their respective limitations. There are in general multiple ways for combining ANN and fuzzy systems but in literature three types of NFS are described (Nauck et al. 1997; Vieira et al. 2004):

Cooperative NFS where the neural network part is used initially for determining the fuzzy sets and/or fuzzy rules and only the obtained fuzzy system is executed afterwards.

Concurrent NFS in which the neural network works concurrently with the fuzzy system providing input to fuzzy system or changing fuzzy system output.

Hybrid NFS in which a fuzzy system employs a learning technique inspired by the ANN technique to tune its parameters using pattern processing.

Among the three types of NFS the third type i.e, hybrid NFS has been widely applied to the real world problems as indicated by the vast literature on the applications of NFS. A number of implementations have been proposed for this type of NFS in literature like ANFIS (Jang 1993), NEFPROX (Nauck et al. 1997) etc. Most of these NFS are based on a multilayer ANN-like connectionist structure to represent the computations and dataflow in the fuzzy model in order to formalize the use of learning techniques. The connections in the network are organized in a way so as to represent the rule base of the underlying fuzzy system. The architecture of a typical 5-layered neuro-fuzzy system with n inputs x1 to x_n and m outputs y1 to y_m is shown in Fig. 1. The structure consists of:

Input layer that obtains the external inputs and sends them to next layer.

Fuzzification layer where each node represents a membership function so that each node outputs the fuzzified value of the corresponding input value based on the type of membership function for that variable.

Rule layer that represents the conjugation of the antecedents of each rule using some T-norm e.g. product, min etc.

Union layer used to integrate the fuzzy rules with similar consequents using some S-norm like sum, maximum etc.

Output or *defuzzification* layer where each node uses a de-fuzzification method to produce the final output. The output depends on the activation of each rule and the parameters of the membership function parameters if used for the output linguistic terms.

The various business problems usually involve decision making requiring accurate and interpretable models that convey the knowledge acquired from business environments in a human understandable way. NFS offer to represent the complex solutions in a natural language like representation in the form of interpretable fuzzy if-then rules which are easier to comprehend for the business personnel. Also NFS based on fuzzy set theory are flexible and efficient methods for solving the nonlinear and uncertain business problems like stock price prediction, sales forecasting etc. Different NFS methodologies have been successfully used in business and have been proved to be efficient than various other AI techniques used in business as indicated by the extensive literature review done by the authors.

3 NFS in finance

Finance plays an important role in the profitability of a business both in short term and long term. Its functions mainly include planning, directing and coordinating activities like

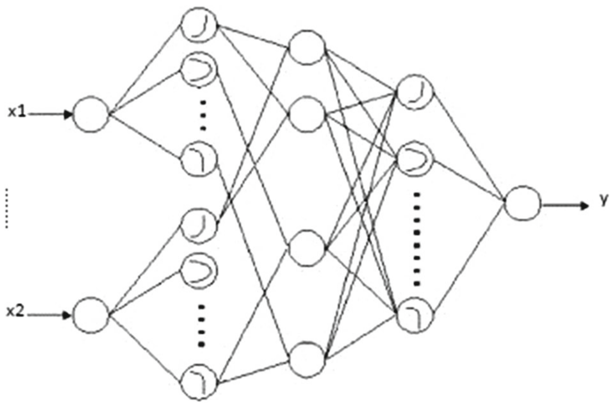


Fig. 1 Structure of a neuro-fuzzy system

accounting, insurance investing, banking, securities, management of debtors and other financial affairs in business. NFS have been widely used in this area during the 2005–2016 for the analysis of financial condition, debt risk assessment, fraud detection, stock trading, business failure prediction etc.

A number of authors have contributed innovations in the application of NFS for handling various real world financial problems since 2005. Xiong and Li (2005) performed a study to compare the performance of adaptive neuro-fuzzy inference system (ANFIS) and ANN in forecasting the annual excess returns. The methods used for this purpose also included the Fair-Shiller test. The authors used a simple trading strategy to find the profit generating ability based on trading on the forecasts from each technique. As per the study both ANFIS and ANN have good forecasting ability and none of the techniques dominates the other. Both the techniques performed better than the traditional statistical methods used in stock trading. Patel and Marwala (2006) presented a pattern classification method based on ANN, fuzzy inference system and ANFIS for aiding the investors in arriving at the financial decisions. The study recommended the stock quality selection component to investors for purchasing stocks, selling stocks or to hold the current invest position. The three types of designs considered were implemented by the authors with 16, 4 and 1 classifiers. Yao et al. (2007) introduced a novel method to select the best currency pair for selling and buying along with the right market timing in the foreign exchange portfolio management. NFS was used for forecasting the future buy/sell signals and then matching these signals across various currencies in order to optimize the trade returns. Various common technical indicators like moving averages, novel portfolio trade timing optimization etc were used to obtain an optimized buy/sell timetable.

A number of research studies were conducted based on using NFS in stock trading. Abbasi and Abouec (2008) used an ANFIS based model to investigate the trend of the stock price. The authors used four independent variables as system input and used two triangular shaped membership functions for each variable. The four independent variables were the traded stock volume, price to earnings ratio, dividend per share for long term period and closing price. The stock fluctuation was the dependent variable. The study showed the efficacy of applying ANFIS for stock trading. Kalban (2009) designed a neuro-fuzzy model which used the historical market data for forecasting the future price direction in order to find the best investment strategy. Authors merged the fuzzy reasoning with the pattern recognition capability of ANN. The innovativeness of the study was the application of this approach to high frequency finance involving forecasting at very high frequency using the intra-day data. The model also had the capability of monitoring various events and seasonality in dataset for eliminating the unwanted data. Later on Ching et al. (2010) designed a five layer self-organized neuro-fuzzy system for stock market prediction using technical indicators. The technical indicators included volume adjusted moving average (VAMA), ease of movement (EMV) and the stochastic oscillators (%K and %D). The authors showed that the forecasting accuracy of the proposed model was better than ANN and also could effectively attenuate the input error. In credit risk analysis area Yao et al. (2009) designed a fuzzy neural network based model for assessing the credit risk of commercial banks based on the credit assessment index system for commercial banks. The model was a six layer network having four inputs and the output was the credit risk for the bank. The fuzzy rule layer of this model did the needed adjustments corresponding to certain problem conditions. According to the study the performance of this hybrid system was better than the black-box ANN model in terms of the prediction error. Constantinescu et al. (2010) used a neuro-fuzzy approach for credit scoring problem in banking field. The authors took the various cost functions into consideration. This neuro-fuzzy system attuned the example dependent prices and classified the set of individuals into two classes, each class having a cost assigned to it. Later Tan et al. (2011) used ANFIS for stock trading problem. Authors supplemented this model with the Reinforcement learning. The system had the capability of identifying the variations in a primary trend to assist the trading and investment decisions. In addition the system had the ability to obtain the periods for moving average and momentum using RL paradigm and shift the cycle using ANFIS-RL to tackle the delay in forecast cycle. As per the study ANFIS outperformed DENFIS and RSPOP in terms of forecasting error and correlation.

Type-2 fuzzy systems were also used in several research studies. Liu et al. (2012b) showed the effectiveness of the type-2 NFS in stock price prediction. The type-2 rules were obtained using a self-constructing clustering method. The dataset was partitioned into clusters using input and output similarity tests and then a type-2 TSK rule was produced from each cluster for the system rule base. Least Square Estimation and Particle Swarm Optimization (PSO) methods were used to tune the parameters of the fuzzy rule base. Fallahzadeh and Montazeri (2013) presented a neuro-fuzzy system for forecasting the FOREX stock market. The hybrid system was based on the interval type-2 C-means clustering, MLP and interval type-2 fuzzy model. The authors used the back-resilent and back-propagation methods for faster model convergence. The performance of the system was assessed for the accuracy of the day-ahead stock price prediction as well as convergence time. The proposed system performance was compared with the C-means clustering based type-1 and FLANN based neuro-fuzzy systems.

Later on Hajialiakbari et al. (2013) presented a system based on ANFIS and Principal Component Analysis (PCA) to evaluate the impact of bad loans on the technical efficacy of commercial banks. The output of this model was the technical efficiency obtained with respect to bad loans, profit and cost. Guan et al. (2014) employed ANFIS to predict the value of the real estate property. The work also tackled various problems in previous such studies like limited sample size, lack of scrupulous sampling, poor testing and validation of the model. Several test scenarios were designed to test and contrast ANFIS and MRA (Multiple regression analysis). NFS was proved superior in all the test scenarios which indicated the promising potential of ANFIS in the field of estimating the real estate value. Mahmud and Meesad (2015) designed a novel recurrent error-based neuro-fuzzy system for forecasting stock price time series. The authors used the stock price momentum and time series prediction errors for adjusting this neuro-fuzzy system to obtain a steady stock price forecasting system with minimum forecasting error. This system was proved to be superior to ANFIS and ANN for the stock price time series prediction. Recently Maksimovic et al. (2016) used NFS for the prediction of economic growth rate. The study was based on the effect of manufacturing, agriculture, services and industry on the economic growth rate of a country. The researchers used the gross domestic product as the indicator for the economic growth.

Besides the above studies, a number of research articles based on the application of NFS in finance were published during 2005–2015. The focus was mainly on the applicability of NFS for stock market prediction, credit scoring, economic crisis forecasting, exchange rate forecasting, risk analysis etc. The stock market prediction was the most popular application in finance during the period. As per this study various NFS methodologies like ANFIS, type-2 NFS and simple neuro-fuzzy inference systems like Mamdani type NFS but ANFIS was the most dominant technique in finance with better performance than other NFS techniques. Table 1 lists the authors, methodologies and application area of the articles published in this area during 2005–2014.

4 NFS in marketing and distribution

Marketing and distribution have a direct effect on the sales and profitability of a business and are an important link between manufacturers and customers. The main purpose of the marketing and distribution area is that the products or the services which a business deals in reach the end users effectively and efficiently. NFS were used successfully in this business area since 2005 for price prediction, sales forecasting, supply chain evaluation, demand variability, new product profitability assessment etc. Below is a brief description of the research employing NFS in this domain since year 2005.

As per this survey in 2005 no important study was done on the application of NFS in this business field. But in the later year Amjady (2006) presented a neuro-fuzzy method for price forecasting in electricity markets. This neuro-fuzzy model had an inter layer connected and feed forward design. It used a novel hyper cubic training method. The purpose of the study was to forecast the day-ahead market clearing prices on hourly basis in electricity markets. The study deduced that the proposed neuro-fuzzy model gave more accurate results than ARIMA, MLP and Radial Basis Function (RBF) network on the basis of forecasting errors. Chang et al. (2007b) applied a Weighted Evolving Fuzzy Neural Network (WEFuNN) for the problem of PCB sale prediction. The researchers used Grey Relation Analysis for selecting a combination of the key factors most affecting this sales forecasting problem. In addition Winter's exponential smoothing technique was applied to predict the influence of PCB sales tendency and seasonal effects while taking into account the time serial factor. The performance of WEFuNN was shown to be 2.11% better than other methods.

Some significant studies used ANFIS during 2009–2010 in this business field. Didehkhani et al. (2009) used an ANFIS for evaluating flexibility in a supply chain, using attributes such as operation, new product and responsiveness. The model was intended to assist managers in performing gap analysis between desired flexibility level and the existent one. Wu et al. (2009) presented an ANFIS based expert system for car price forecasting. The mark of the car, engine style and manufacture year were used as the input factors for price forecasting. The authors demonstrated the usefulness of ANFIS in price forecasting using a performance comparison with ANN. In another study Kaynar et al. (2010) applied four methods viz. ARIMA, MLP, RBFN and ANFIS to forecast the weekly consumption of natural gas. Based on the root mean square error (RMSE) MLP performed better than RBFN, subtractive clustering based ANFIS performed better than grid partitioning based one. MLP, RBFN and ANFIS performed better than ARIMA. Furthermore ANFIS showed faster convergence than all other methods.

Table 1 NFS in finance

Authors/date	Methodology	Application
Fallahzadeh and Montazeri (2013)	Interval type-2 neuro-fuzzy system	Foreign exchange rate forecasting
Nhu et al. (2013)	ANFIS and firefly algorithm	Stock price prediction
Yang et al. (2011)	ANFIS	Credit risk assessment
Nair et al. (2010)	ANFIS, decision tree,	Stock market prediction
Tan et al. (2011)	ANFIS and reinforcement learning	Stock trading
Liu et al. (2012b)	Type-2 fuzzy system	Stock trading
Guresen et al. (2011)	Neuro-fuzzy inference system (NFIS)	Stock market index prediction
Meesad and Srikhacha (2008)	NFIS and support vector guideline system	Stock trading
Atsalakis and Dimitrakakis (2011)	NFIS and Elliot wave theory	Stock trading
Radeerom et al. (2012)	NFIS	Stock index prediction
Chen et al. (2013)	Logistic regression analysis and ANFIS	stock trading
Alizadeh et al. (2010)	ANFIS	Stock portfolio analysis
Li et al. (2011)	Self-organizing neuro-fuzzy system and PSO	Exchange rate forecasting
Jin (2011)	ANFIS and multiple linear regression	Efficient risk allocation
Ching et al. (2010)	Five layer neuro-fuzzy system	Stock market dynamics forecasting
Banik and Khan (2012)	ANFIS, ARIMA and ANN	Stock market index prediction
Atsalakis et al. (2007)	ANFIS	Exchange rate forecasting
Khashei et al. (2013)	NFIS	Credit risk analysis
Sreekantha and Kulkarni (2012)	NFIS	Credit risk evaluation
Boyacioglu and Derya (2010)	ANFIS	Stock trading
Yao et al. (2009)	NFIS	Credit risk analysis
Ho et al. (2010)	Evolving Mamdani–Takagi-Sugeno NFS	Stock trading
Radeerom and Kulthon (2013)	NFIS	Stock trading
Xiong (2010)	PSO and NFS	Credit risk forecasting
Svalina et al. (2013)	ANFIS	Stock trading
Hajialiakbari et al. (2013)	PCA and ANFIS	Bad loan assessment
Constantinescu et al. (2010)	NFIS	Credit scoring
Sekar (2011)	NFIS	Stock trading
Cuong and Chien (2011)	ANFIS	Stock price prediction
Kalban (2009)	ANFIS	Financial trading and forecasting
Vella and Ng (2014)	ANN, ANFIS and DENFIS	Stock market intraday trading

Table 1 continued

Authors/Date	Methodology	Application
Tan et al. (2008)	NFIS	Stock trading
Khashei and Bijari (2014)	ARIMA and NFS	Financial time series forecasting
Abbasi and Abouec (2008)	ANFIS	Stock price prediction
Gunasekaran and Ramaswam (2014)	ANFIS and CAPM	Stock portfolio optimization
Guan et al. (2014)	ANFIS	Real estate value forecasting
Chang et al. (2007a, b)	ANFIS	Import forecasting
Bagheri et al. (2014)	ANFIS and quantum-behaved PSO	Financial forecasting
Li and Xiong (2005)	NFIS	Stock market forecasting
Xiong and Li (2005)	ANFIS	Credit scoring
Trinkle (2005)	ANFIS and ARIMA	Stock return forecasting
Patel and Marwala (2006)	ANFIS	Financial decision making
Liu et al. (2006)	NFIS	Real estate price prediction
Lee et al. (2006)	NFIS	Bank failure analysis
Ang and Quek (2006)	NFIS	Stock trading
Banik et al. (2007)	ANFIS	Stock price prediction
Yao et al. (2007)	NFIS	Foreign exchange portfolio management
Chai and Lim (2007a, b)	NFIS	Economic turning point forecasting

Later on Holimchayachotikul et al. (2010) proposed a predictive system based on neuro-fuzzy concept, multi-criteria decision attributes and B2B supply chain (B2B-SC) performance evaluation system for supply chain. In the proposed model the neuro-fuzzy system could be adjusted by the human perception and judgment related to the supply chain context. Authors used the neuro-fuzzy method to fabricate a collaborative performance with the forward looking ability and linguistic rules to help managers comprehend the method to put the collaborative performance directions in another time. Kaiser et al. (2011) presented a warning system for the online market research which helped in the identification of the critical situations in online opinion framing based on a neuro-fuzzy approach. This system used a knowledge base that stored product-related success values, online opinions and patterns of social interaction. The system was shown to perform better than other alternative methods used in the study. Dimitrios and Mantas (2012) compared MLP, RBF and ANFIS for their accuracy and speed of convergence sales forecasting of medical products. Among the various methods ANFIS was the best method due to its implementation speed and simplicity. Chan et al. (2012) designed a methodology based on neuro-fuzzy approach for generating a customer satisfaction model. Authors applied a rule mining method for extracting the important rules from the fuzzy rule base which indicated the important customer requirements for a given new product. Using these significant rules a customer satisfaction model was built. The experiments showed that the hybrid approach outperformed the statistical regression methods on the basis of mean absolute error and variance of errors. Hiziroglu (2013) used a neuro-fuzzy approach to obtain the non-strict customer segments as per their purchasing behavior, frequency, recency and monetary value. The study applied a two-stage clustering method for customer segmentation. According to the chosen validity indices the study showed that the proposed hybrid system gave better managerial implications and insights than the traditional methods into this problem. Later Özkana and İnalb (2014) employed ANFIS in supplier selection and evaluation process. In order to assist the decision makers in supplier evaluation, ANFIS was used to discover the reliable suppliers. Several datasets containing various attributes of suppliers and their scores were used as inputs to ANFIS. MSE (mean square error) and linear regression analysis (R-value) were used for assessing the performance of the models. In addition to the above studies NFS were used for a number of other applications in this domain during 2015 viz. sales forecasting (Rajab and Sharma 2015), gold price prediction (Christina and Umbara 2015) and so on.

In most of the studies reviewed for this period NFS were proved to be better than other AI and traditional statistical techniques in addressing different problems in marketing and distribution. Besides these a number of authors have contributed in this area during 2006–2014, the list is provided in Table 2.

5 NFS in human resource management

Neuro-fuzzy systems were also introduced in the field of HRM during recent past. HRM is concerned with the proper and maximum utilization of human resource in an organization. In the last years AI techniques have been used to assist in decision making used in various unstructured processes of HRM like training, staffing, maintenance and motivation of human resources in an organization. But the application of NFS has not been so popular in HRM which is indicated by only few number of research papers published in this category since 2005. Some articles used NFS for the very uncertain problem of applicant selection for jobs. Doctor et al. (2009) proposed a neuro-fuzzy system to efficiently shortlist the submitted resumes of the candidates from a large database of applications to produce a fair and consistent resume ranking policy. The study used an innovative method to deal with the uncertainties and inconsistencies in the decisions of experts while also determining the key skills based on the experts' decisions and preferences for ranking the applicants. Few papers also used NFS for the problem of determining the employee absenteeism at a workplace. Martiniano et al. (2012) used a neuro-fuzzy system to forecast the absenteeism of employees at work. The experimental dataset contained the details of absences for the employees of a courier company. Avasilcai and Pislaru (2013) employed ANFIS to provide a solution for the staff management problem using the linguistic variables as system inputs. The model was intended optimize the decision making process of job assignment within a firm. Macwan and Sajja (2013) proposed the architecture of a NFS based intelligent system to assist in the performance evaluation of the employees of an organization. The performance appraisal system removed any psychological elements that had a negative impact on the unbiased evaluation of the employees. The authors also discussed the different features that affect the performance evaluation process. As per the literature survey conducted by the authors no significant studies were conducted on the application of NFS in this field in 2015 and 2016. Table 3 displays the list of articles in this area during 2005–2014.

6 NFS in production and operations

NFS were used for a wide range of applications in productions and operations and are getting more and more popular in this area of business. Productions and operations have

Table 2 NFS in marketing/distribution

Authors/date	Methodology	Application
Wu et al. (2009)	ANFIS	Price forecasting
Nazari-Shirkouhi et al. (2013)	ANFIS	Customer satisfaction
Chan et al. (2012)	NFIS	Customer satisfaction
Kwong and Chan (2009)	NFIS	Customer satisfaction
Holimchayachotikul et al. (2010)	NFIS	Supply chain evaluation
Tozan and Vayvay (2009)	ANFIS and grey forecasting	Demand variability
Hiziroglu (2013)	NFIS	Customer segmentation
Pousinho et al. (2012)	ANFIS and PSO	Electricity Price forecasting
Azadeh et al. (2011)	ANFIS and stochastic frontier analysis	Natural gas consumption forecast
Catalão et al. (2011)	Neuro-fuzzy and wavelet transform	Electricity price forecasting
Gumus et al. (2009)	NFIS and mixed integer linear programming	Supply chain design
Azadeh et al. (2013)	ANFIS, fuzzy data envelopment analysis(FDEA)	Natural gas consumption forecast
Wang et al. (2010)	NFIS	Demand variability prediction
Kaynar et al. (2010)	ANFIS, ANN and ARIMA	Natural gas consumption prediction
Chiroma et al. (2013)	Co-active neuro-fuzzy system	Oil price prediction
Nilashi et al. (2011)	ANFIS	e-commerce
Didehkhani et al. (2009)	ANFIS	supply chain assessment
Kaiser et al. (2011)	NFIS	online market research
Gerek (2014)	ANFIS-GP and ANFIS-SC	House price estimation
Xiao et al. (2014)	ANFIS, IPSO and SSA	Air transport demand forecasting
Latif et al. (2014)	ANFIS, genetic algorithm	Supply-chain ordering
Azadeh et al. (2014)	NFIS and fuzzy linear regression (FLR)	House price estimation
Özkana and İnalb (2014)	ANFIS	Marketing decision making
Amjady (2006)	NFIS	Price forecasting
Chang et al. (2007b)	Evolving fuzzy neural network	Sales forecasting

Table 3 NFS in HRM

Authors/date	Methodology	Application
Macwan and Sajja (2013)	NFIS	Human resource retention
Martiniano et al. (2012)	ANFIS	Employee absenteeism prediction
Doctor et al. (2009)	NFIS	Applicant ranking
Avasilcai and Pislaru (2013)	Neuro-fuzzy system	Employee Job Assignation

an essential role in business for increasing the productivity and efficiency. Production is needed to churn the inputs into the desired outputs. Operations Management has to deal with planning, execution and administration of activities in production. During 2005–2015, as is evident form the amount of relevant published literature application of NFS in this field achieved a huge attention in this field. NFS were used for production process control, planning, tool wear monitoring, machine fault diagnosis, job-shop scheduling, robot control, supplier selection and number of other functions. A brief account of the contribution of some studies in this area since 2005 is given next.

Chatterjee et al. (2005) developed a neuro-fuzzy and PSO based system as a building block of a robot system controlled by means of voice commands. The system outputs were the crisp control signals for the robot system and inputs were the spoken commands from the user. In order to identify various important directives from a running statement Hidden Markov Model based automatic speech recognizers were devised. The study applied this system for controlling motion and navigation of a mobile robot. Later Palluat et al. (2006) developed a neuro-fuzzy framework for monitoring a flexible manufacture system. The framework was composed of a neuro-fuzzy diagnostic tool and a dynamic ANN detection tool. The learning capability of the system was employed to tune the monitoring aid system. For the uncertainties in the maintenance knowledge the system gave a fuzzy characterization of each cause.

ANFIS was used in a number of real world problems in this field. Kurnaz et al. (2007) used ANFIS as a flight controller of an unmanned airborne vehicle. For the control of speed, roll angle and altitude three fuzzy logic modules were designed. The model was used in simulations to assess the potential and performance of the controller. For getting the visual output Microsoft Flight Simulator and Flight-Gear Flight simulator were used which could aid in evaluating the controllers. Akhlaghi (2008) proposed an ANFIS and Independent Component Analysis (ICA) based system for the online fault diagnosis of a intricate dynamical system. ICA was employed to obtain the various salient features of the raw datasets. The essential features from datasets were used as the inputs to the ANFIS using ICA. The study used an ANFIS component for each type of fault in order to fasten the training of the system and to reduce the system complexity. Samhouri et al. (2009) designed an intelligent machine state monitoring system using ANFIS and ANN. Several combinations of the vibration time signals like variance, kurtosis, skewness, etc were used as input. The output was the forecasted fault type. ANFIS which used trapezoidal membership function achieved a forecasting accuracy of 95% and ANN based on cascade forward back-propagation yielded an accuracy of 99%. Fazel Zarandi and Ahmadpour (2009) proposed a fuzzy multi-agent system for steel making processes. Authors used ANFIS to generate agents' knowledge bases. Moreover in this multi-agent model contract net protocol was used as a negotiation protocol. The proposed system consisted of autonomous, heterogeneous and cognitive agents. Each agent locally executed the assigned task while cooperating with the other components. The fuzzy systems enabled the whole multi-agent system to work in the same way as the real world model.

Later on Havangi et al. (2010) designed Adaptive Neuro-Fuzzy Extended Kalman Filtering (ANFEKF) for robot localization. ANFIS part was used for monitoring performance of the Extended Kalman Filter which was used in localization of a mobile robot by adjusting the matrices of noise covariance for decreasing the inconsistency between the actual and theoretical covariance of the innovation sequences. The experimental results showed that the AFEKF based localization is better than standalone EKF. GüNeri et al. (2011) developed a new method using ANFIS for the supplier selection problem. Using ANFIS various criteria for the problem were reduced and based on the selected criteria and output needed, ANFIS configuration was chosen. The output of the model was the value of each supplier's sales. The authors showed that the ANFIS performed better than multiple regression. Gajate et al.

(2012) demonstrated the use of various neuro-fuzzy techniques for tool wear monitoring. Three types of neuro-fuzzy models viz. transductive, inductive, and evolving were used. This comparative study demonstrated that the Transductive neuro-fuzzy model gave better performance for detecting tool wear than inductive neuro-fuzzy model and evolving neuro-fuzzy model with lesser prediction error and fewer rules. Fazlollahtabar and Mahdavi-Amiri (2013) presented a cost estimation model based on the fuzzy rule back-propagation network for estimating the cost under uncertainty in a job-shop automated production system. For finding the most useful fuzzy rules multiple regression analysis (MRA) was used. The potential of the model for cost estimation under uncertainty was illustrated by applying the model to a theoretical numerical example. Zahin et al. (2013) used ANFIS for power demand prediction in the scenario of power production. The authors used year, amount of rainfall, irrigation season and temperature as input parameters from the dataset of electricity demand for a period of five years. The study proved that ANFIS performed better than both the traditional seasonal forecasting and ANN in terms of different error measures. In another study Azmi et al. (2013) developed a system using neuro-fuzzy approach and MRA for predicting and the monitoring wear on a carbide tool while end milling. The study showed that although MRA gave acceptable performance for prediction but using fuzzy model yields marked improvements in the prediction accuracy particularly for the nonlinear functional relationships. This system was also useful in a well timed decision to perform tool-reconditioning or tool replacement. Later Aksoy et al. (2014) applied ANFIS for demand prediction in an apparel industry. The input and output of the system was based on the requirements of apparel producers and literature research. The scope of the prediction was one month. Real application of this system was performed and the testing was done on the apparel manufacturers' real demand values. The experimental work showed the suitability of ANFIS for demand forecasting which gave better accuracy of prediction.

During 2015 and 2016 also NFS were used in various domains of production/operations. In 2015 NFS were used for predicting fabric wrinkle recovery (Hussain et al. 2015), inventory level forecasting (Kumar et al. 2015) and meat production domain Zhang et al. (2015). In 2016 in a study (Anicic and Jovic 2016) ANFIS was used for estimating the power coefficient value of ducted tidal turbines useful in the improving power quality obtained from tidal current turbines. The study applied conventional back propagation for tuning the ANFIS parameters and showed the effectiveness of this method in tidal energy production. In addition some more studies involved NFS in energy production viz. solar energy production (Jovic et al. 2016a) and wind energy (Jovic et al. 2016b).

Majority of the above studies show that NFS can be efficiently used in adressing various problems in production and operations. The detail regarding the significant published research articles in this field during period 2005–2014 is presented in Table 4. It is apparent from the table the application of NFS has spanned almost all the key areas of productions and operations. Although control system modeling was the most popular field where NFS were used but robot system control was the most popular application in this sub-domain. Among the various neuro-fuzzy modeling techniques, NFS based on mamdani and sugeno based fuzzy models were mostly preferred by the researchers. Also type-2 fuzzy systems were introduced successfully in many domains of production and operations.

Table 4 NFS in production/operations

Authors/Date	Methodology	Application
Fazlollahtabar and Mahdavi-Amiri (2013)	NFIS	Jobshop cost estimation
Gajate et al. (2010)	NFIS	Process Tool wear monitoring
Xu and Zhang (2011)	Dynamic neuro-fuzzy	Aircraft Intelligent landing control
Oğuz et al. (2012)	ANFIS	Power generation system
Zarandi and Ahmadpour (2009)	ANFIS	Steel making process
GüNeri et al. (2011)	ANFIS	Supplier selection
Dimitrov (2011)	NFIS	Industrial fault diagnosis
Rafik et al. (2011)	TSK/Mamdani NFIS	Fault diagnosis and prognosis
Sadeghian and Fatehi (2011)	Locally linear neuro-fuzzy system (LOLIMOT)	Fault identification
Rigatos (2009)	NFIS	DC motor control
Gajate et al. (2012)	NFIS	Tool wear prediction
Samhouri et al. (2009)	ANFIS	Machine monitoring system
Azmi et al. (2013)	Multiple regression, neuro-fuzzy modeling	Tool wear prediction
Liu et al. (2013)	Sequential forward search(SFS), ANFIS	Tapping Process monitoring
Kayacan et al. (2012)	ANFIS	Robot control
Shi et al. (2009)	NFIS and lyapnuov approach	Batch process control
Akhlaghi (2008)	ANFIS	System fault diagnosis
de Carvalho Alves et al. (2009)	NFIS	Machine operational performance
Tran and Yang (2010)	Classification and regression trees (CART) and ANFIS	Machine condition prognosis
Tarjoman and Za (2009)	NFIS	Chaotic robot prediction
Zhu et al. (2009)	NFIS	Robot navigation control
Chung and Jun (2009)	NFIS	Mobile robot control
Zheng et al. (2010)	Generalized dynamic fuzzy neural network (GDFNN)	Underwater robot control
Ferreira et al. (2009)	TSK NFIS	Robot controller
Abiyev and Kaynak (2008)	Fuzzy wavelet neural network, GA	Plant control
Nurmaini and Norhayati (2009)	Interval type-2 NFIS	Robot navigation controller
Khaldoun and Al-Din (2009)	NFIS	Robot navigation system
Demirli and Khoshnejad (2009)	NFIS	Sensor based robot controller
Toledo-Moreo et al. (2010)	Dynamic fuzzy adaptive system art	Road vehicle Maneuver Prediction
Martin and Emami (2010)	NFIS	Robot control
Areed et al. (2010)	ANFIS	Induction motor control
Kurnaz et al. (2010)	ANFIS	Air vehicle flight control
Dybkowski and Szabat (2010)	NFIS	Induction motor control
Adhyaru et al. (2010)	ANFIS	Robotic manipulator control
Wang and Chiu (2010)	ANFIS	Robot parking controller
Kurnaz et al. (2007)	ANFIS	Unmanned vehicle control
SahIn and Tinkir (2010)	ANFIS	Robot trajectory control

Table 4 continued

Authors/Date	Methodology	Application
Havangi et al. (2010)	ANFIS, extended Kalman filtering (EKF)	Robot localization
Budiharto et al. (2010)	ANFIS	Servant robot control
Karunarathne and Knowles (2010)	ANFIS	Ariel vehicle power management
Javadi-Moghaddam and Bagheri (2010)	Adaptive neuro-fuzzy sliding mode genetic algorithm (ANFSGA)	Vehicle control system
Chen et al. (2012)	ANFIS, High order particle filtering	Machine remaining life prediction
Obe and Dumitrache (2012)	ANFIS	Mobile robot control
Kharmandar and Khayyat (2011)	NFIS	Robot manipulator control
Jang (2011)	Lyapunov theory and NFS	Robot control
Dimitrios et al. (2011)	Three layer neuro-fuzzy network	Robot manipulator control
Leia et al. (2008)	ANFIS	Fault diagnosis
Erdem (2011)	NFIS	Sumo robot control
Sadighi and Kim (2011)	ANFIS	Smart material actuator
Behrouznia et al. (2011)	ANFIS	Manufacturing lead time prediction
Mahdaoui et al. (2011)	Temporal NFS	Manufacturing system monitoring
Toloie-Eshlaghy et al. (2011)	ANFIS	Vehicle tire reliability prediction
Sithu and Thein (2011)	NFIS	Virtual machine controlling
Sathiyasekar et al. (2011)	NFIS	Machine insulation quality prediction
Douiri et al. (2011)	NFIS	Induction machine control
Chen et al. (2011)	ANFIS	Machine condition control
Cui (2011)	ANFIS and PCA	Surface roughness modelling
Kumar and Dhama (2012)	NFIS	Intelligent Robot control
Kumar et al. (2012)	NFIS	Robot arm control
Lakshmi and Mashuq-un-Nabi (2012)	ANFIS	Robot arm control
Mohanty and Parhi (2014)	ANFIS	Robot controller
Liu et al. (2012a, b)	NFIS and genetic algorithm	Vehicle control and warning system
Kothandaraman and Ponnusamy (2012)	PSO-ANFIS	Vehicle suspension system controller
Bin et al. (2012)	NFIS	Vehicle-manipulator system control
Melingui et al. (2014)	NFIS	Mobile robot controller
Zerfa and Nouibat (2013)	NFIS	Robot navigation
Lei et al. (2007)	ANFIS and GA	Fault diagnosis
Braik et al. (2013)	ANFIS	Manufacturing process automation
Zahedia et al. (2012)	ANFIS	Electricity demand estimation
Marwala and Twala (2014)	ARIMA and ANFIS	Electricity consumption forecasting
Seker et al. (2013)	NFIS	Process planning and scheduling
Aksoy et al. (2014)	ANFIS	Demand forecasting
Cherroun et al. (2014)	NFIS	Mobile robot control
Abhaya et al. (2014)	NFIS	Industrial robot system control

Table 4 continued

Authors/Date	Methodology	Application
Abbasi and Asgari (2014)	Fuzzy-Delphi method and ANFIS	Supplier selection
Pham and Fahmy (2005)	Inductive learning and NFIS	Robot trajectory tracking
Chatterjee et al. (2005)	PSO and NFIS	Robot control
Sainz et al. (2005)	Neuro-fuzzy art	Fault detection
Li et al. (2005)	NFIS	Job-shop scheduling
Ye et al. (2006)	ANFIS	Fault diagnostics
Palluat et al. (2006)	NFIS	Flexible production system
Zio and Gola (2006)	NFIS	Fault detection

7 NFS in business planning

Business planning also called strategic planning is one of the key units of any business which deals with planning of different aspects of a business. The use of AI techniques in business planning is in fact not new. AI methods have been used in this field for business planning for real time and stressful decision problems, facilitating up-to-date information, decreasing information overload and a number of other problems. As other AI techniques NFS were used in automating various business planning problems, especially decision making problems with high uncertainty. But as the NFS application in HRM the usage of NFS in business planning has not been much widespread which is reflected by small number of research articles published in this category during the last decade. The briefing of some studies in this field is given below.

Moayer and Bahri (2009) developed a hybrid intelligent system for generating scenarios in order to cope with the linguistic expression of experts and data shortage in scenario planning. ANFIS was used to deal with the uncertain inputs. The given methodology comprised of few steps: first the internal and external variable scope was defined, then the rules from the experts were determined and lastly ANFIS was built. The authors also gave two case studies for establishing the applicability of the hybrid scenario generator for facilitating business strategic planning. Later Akerkar and Sajja (2010) gave the layout of a neuro-fuzzy based business advisory system. ANN was used to analyze the data and parameters from the environment for small-scale business selection and then fuzzy rules were generated appropriately. Same year Chakrabarti and Basu (2010) discussed gain sensing based on the prediction based techniques. Sequence of gain pattern was verified by using statistical analysis of fuzzy value assignment. The study achieved stable gain condition by using the K-means clustering. Also the concept of 3D based gain sensing was introduced. Khatibi et al. (2011) introduced a neuro-fuzzy technique in project management for the scenario planning for dealing with the poorly defined methods, uncertainties due to the external factors and shifting business objectives. Also RBF was used for learning various situations in project management. More recently Azadeh et al. (2015) proposed an ANFIS based framework for forecasting the credibility of business partners in a mutual business relationship. The output of the system was the trust value with three values viz. low, medium or high based on monthly interaction of two business agents. The authors evaluated the ANFIS performance using mean absolute percentage error. The error values indicated the efficiency of ANFIS for this business prediction problem. Besides these NFS was used in novel applications areas like forecasting intellectual capital

Table 5 NFS in business planning

Authors/date	Methodology	Application
Chakrabarti and Basu (2010)	k-means clustering, neuro-fuzzy system	Business planning
Akerkar and Sajja (2010)	Neuro-fuzzy system	Business advisory system
Moayer and Bahri (2009)	ANFIS	Business strategic planning
Khatibi et al. (2011)	Radial basis neuro-fuzzy	Business scenario planning
Setlak (2008)	NFS	Decision support system

(Ahmad et al. 2015) and enterprise resource planning (Gupta and Naqvi 2015) in year 2015. A list of articles published in this area during period 2005–2014 has been presented in Table 5.

8 NFS in information systems

These days information systems is an integral part of business necessary for data management, communication, inventory management, customer relationship management, and many other important functions. During the last years NFS were used for problems like information retrieval, software fault proneness, software cost estimation, software quality evaluation etc.

Sandhu and Singh (2005) used neuro-fuzzy system to forecast the quality of the reusable software components. For predicting the reusability of various software components several design and coding phase metrics were used. The attributes used as inputs to the system were reuse frequency, cyclometic complexity, coupling and regularity volume. The output was the reusability of the software component. The neural network part of the system was used to learn the associations based on the input data which were then used to refine the fuzzy rules of the rule base.

A number of important studies were devoted to the application of NFS in software cost estimation. Huang et al. (2006) presented a novel neuro-fuzzy model for software cost estimation. The authors used neuro-fuzzy system to handle the relationships among different contributing factors and for isolating the effects of these factors. After that a neuro-fuzzy bank was applied to calibrate the various parameters of these contributing factors. The experimental results showed the usability of this model in predicting the software cost. Yang et al. (2007) proposed a neuro-fuzzy model for assessing software quality. The model could deal with the knowledge from the experts or similar projects and objective data from the software development process. This enabled to predict the software quality during the early stages of the software development process. Later Wong et al. (2009) applied neuro-fuzzy method to the backfiring and categorical data size estimation. The aim was to evaluate the performance of neuro-fuzzy approach for software cost estimation. According to the study neuro-fuzzy system provided a minimal improvement in the software cost estimation over the backfiring sizing method. Du and Capretz (2010) combined the neuro-fuzzy technique and the SEER-SEM for the effort estimation of software development process. The study combined the neuro-fuzzy technique with various effort estimation models. The model performance was evaluated using industrial data and various published software projects. The combined neuro-fuzzy and SEER-SEM model gave improved estimation results than using only SEER-SEM algorithmic estimation models. Later on Misra et al. (2012) used a neuro-fuzzy system for predicting the software development cost based on software size estimate. In this study 22 software cost drivers were used as inputs to the neuro-fuzzy model. These cost drivers were

Table 6 NFS in information systems

Author/date	Methodology	Application
Wong et al. (2009)	Neuro-fuzzy approach	Software size estimation
Quintero et al. (2009)	Sugeno-fuzzy inference system	Intelligent environment control
Nawaz and Khanum (2011)	Ranked neuro-fuzzy system	Information retrieval
Sree (2012)	NFIS	Software Effort estimation
Rao and Seetha Ramaih (2013)	NFIS	Software cost estimation
Peer and Malhotra (2013)	ANFIS	Software fault proneness
Mewada et al. (2013)	ANFIS	Software evaluation
Rani and Salaria (2013)	Neuro-fuzzy approach	Software risk estimation
Du et al. (2013)	NFIS	Software cost estimation
Du and Capretz (2010)	NFIS and SEER-SEM	Software effort estimation
Saxena Singh (2012)	NFIS	Software effort estimation
Marza et al. (2008)	NFIS	Development time estimation
Misra et al. (2012)	NFIS	Software cost/effort estimation
Momeni et al. (2014)	ANFIS	Quality requirement prioritization
Beldjehem (2010)	NFIS	Software quality prediction
Momeni and Yavari (2014)	ANFIS	Software complexity evaluation
Sandhu and Singh (2005)	NFIS	Software quality prediction
Huang et al. (2006)	NFIS	Software effort estimation
Yang et al. (2007)	NFIS	Software quality prediction

5 scale inputs and 17 effort multipliers which affect cost of the software. Based on these cost drivers model produced Adjustment Rating Factors (ARF). The ARF and the numerical values obtained from ARF were then passed to the COCOMO model that finally carried out the cost estimation process. The results of the experiment were evaluated using RMSE.

In a study Peer and Malhotra (2013) used ANFIS to predict the change prone classes in software during the early software development phases for efficiently drawing a strategy for allocating resources during testing. The authors framed the relationship between the change susceptibility and object oriented metrics. For depicting the model effectiveness, area under the Receiver Operating Characteristic (ROC) technique was used. The study also compared the performance of ANFIS with other techniques like bagging, decision trees and logistic regression which showed that out of the different techniques applied ANFIS provided the best performance. Later Momeni et al. (2014) used ANFIS for analyzing the complexity of the aspect oriented software. The input parameters included the complexity of attributes, nested components and operations and the output was the estimated complexity of the software component. Three aspect oriented languages viz. CaesarJ, AspectJ and Hyper/J were considered. The output complexity of the software component was divided into six classes. The RMSE value for ANFIS was 0.6309 which was better than non-adaptive fuzzy method. Some more articles were published during 2005–2014 for software fault proneness, intelligent environment control, effort estimation, software quality prediction, risk estimation etc. as indicated in Table 6.

In 2015 NFS were mainly used in the field of software development domain with focus mainly on assisting in the software project cost estimation. Ho et al. (2015) presented a generic neuro-fuzzy framework which could be used for software cost and quality estimation and also for project risk analysis. The system did not depend on the type and nature of estimation. The authors used COCOMO, analysis of variance (ANOVA) and function point analysis as algorithmic models along with neuro-fuzzy system. The proposed model gave more precise estimation than using only the algorithmic models. In 2015 some more studies used NFS in software project development (Garcia-Diaz et al. 2015; Kotaiah et al. 2015).

9 Summary, discussion and limitations

The review of the research articles based on the application of neuro-fuzzy systems for real world business problems during the period 2005–2015 indicates that NFS can be effectively used in business domains. In most of these research articles neuro-fuzzy methods have been compared with other AI and various statistical methods and were proved to be superior in addressing different business problems. The researchers used variety of neuro-fuzzy methodologies and learning techniques depending on their expertise, research interest and abilities and also problem domains. The review indicates much diversification in the use of neuro-fuzzy techniques. But among the various neuro-fuzzy techniques some techniques like ANFIS have been more favored by the researchers. As per the study ANFIS has been the most popular and successful neuro-fuzzy technique during the last decade. Of the many NFS methodologies, ANFIS has been used in diverse applications in different business areas. In the same manner among the various business domains NFS have been more prevalent in some of the business domains. As per our study during 2005–2015 NFS were used in nearly all the business domains but were more popular in production, operations, finance, marketing and distribution. Various real world business problems like robot control, stock trading, price and sales forecasting were the focal application of NFS in business during the last years. As per our survey the research done on the application of NFS in some business domains like HRM, business planning, accounting and auditing was limited. The usage pattern of NFS in various business domains has changed since 2005 and before, newer NFS methodologies were developed and were assessed for performance in handling various real world business problems. From year 2005 to 2008 NFS were not a popular AI technique being restricted mainly to stock price prediction, robot control, software cost estimation and credit analysis. During 2009, 2010 and 2011 the focus shifted towards using higher order fuzzy systems in particular type-2 fuzzy systems and on combining the neuro-fuzzy techniques with other intelligent systems for optimizing performance. During 2012-2015 improving the performance of neuro-fuzzy systems in terms of various prediction error measures for different applications remained the main focus. Besides some new real world business problems like software requirement prioritization were explored. Table 7 provides an outline of the yearly developments from 2005 to 2015 in the neuro-fuzzy methodologies and the trend of the usage pattern of NFS in different business domains.

In Fig. 2 the impact of NFS on various business domains during period 2005–2015 has been given. Form the figure it is apparent that the production and operations was the dominant application area during this period followed by finance and then marketing and distribution. NFS being most prevalent in production and operations is obvious as fuzzy systems are an established efficient technology in this domain for control, fault detection and diagnosis, scheduling, supervision, etc. since the fuzzy boom of 1990s (Bellon et al. 1992; Seising 2012). During 2005–2010 NFS were mostly used in robotics in this business domain which was due to the reason that NFS provided a means to cope with the uncertainties in the unstructured environments in which robots operate (Alavandar and Nigam 2008). Figure 3 gives year wise

Table 7 Year wise progress in NFS application based research in business

2005	In finance Credit scoring was the main application of NFS and ANFIS was the main technique used. In HRM, marketing and distribution NFS were not as popular. A model using neuro-fuzzy approach was introduced to software quality prediction. NFS were popular in production and operations for job shop scheduling, robot control and fault identification. A PSO based neuro-fuzzy system was used for robot control where PSO technique was used for training the neuro-fuzzy system to convey crisp control signals for robot navigation
2006	NFS were applied in handling various real world financial problems like real estate value prediction, financial decision making, stock trading, and bank failure prediction. In marketing and distribution domain a neuro-fuzzy system was used for price forecasting. A neuro-fuzzy system was used in software effort estimation to handle dependencies among various factors affecting the software cost and to fine tune parameters of these factors. In production and operations neuro-fuzzy approach was used mainly in fault diagnosis, flexible production system and machine control. In addition ANFIS was introduced to machine fault detection
2007	Neuro-fuzzy technique was introduced to predicting the economic turning point and foreign exchange in finance. An evolving neuro-fuzzy system was used for sales forecasting. This system could deal with the data from the software development process and the knowledge from experts and identical projects. In production and operations NFS were mostly applied in fault diagnosis and vehicle control
2008	In finance NFS were mostly used in stock trading. In HRM, marketing and distribution no important research employing NFS was done. In production and operations fault diagnosis was the main application of NFS. A fuzzy wavelet neural network was applied for flight control of an unmanned aerial vehicle. A business decision support system based on neuro-fuzzy technique was introduced to managerial decision making process
2009	In finance the use of NFS was restricted to stock price prediction and credit scoring. Neuro-fuzzy systems were used for a number of sub-domains of marketing and distribution like customer satisfaction, price forecasting, supply chain design and assessment, sales forecasting and demand prediction. The use of the Grey forecasting using ANFIS was analyzed. A system using a combination of Mixed Integer Linear Programming (MILP) and ANFIS was used for the supply chain design. In HRM a neuro-fuzzy system was applied for the ranking of candidates for a job. Neuro-fuzzy technique was mostly used for machine fault identification and monitoring and robot control in productions and operations. A novel neuro-fuzzy system was designed that used the Lyapunov approach for weight tuning to aid in global convergence. Moreover an interval type-2 controller was designed using a weightless neural network strategy. In information systems field few studies applied NFS to problems in this domain for software size estimation and intelligent environment control. Also a neuro-fuzzy approach was applied to a categorical data size estimation and backfiring model
2010	In finance ANFIS was the most popular neuro-fuzzy technique in stock trading. ANFIS was also used for economic crisis prediction. Also a new robust brain-inspired Evolving Mamdani-Takagi-Sugeno based neuro-fuzzy system was developed with performance better than the existing neuro-fuzzy systems of econometric type. In marketing and distribution neuro-fuzzy systems were meagerly used. Neuro-fuzzy systems were popular in production and operations and were used in some new application areas. The performance and reliability of the Evolving extended Takagi-Sugeno neuro-fuzzy algorithm was investigated for tool condition monitoring in a study. A supervised Dynamic Fuzzy Adaptive System was introduced to abrupt Maneuver prediction and also control system using a novel adaptive neuro-fuzzy sliding mode based genetic algorithm was proposed. In information systems a novel approach based on System Evaluation and Estimation Model (SEER) and neuro-fuzzy technique was designed for the software cost estimation. Also a neuro-fuzzy system was used for software quality assessment for the first time. The system also incorporated concepts from human cognitive process into it

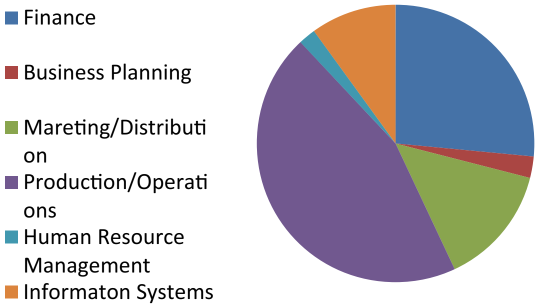
Table 7 continued

2011	Stock trading was the main application area in finance. Reinforcement Learning was used with ANFIS to dynamically find out the periods for momentum and moving averages in stock trading. Moreover, neuro-fuzzy system based on various aspects of Elliot Wave Theory was introduced. A novel learning method based on the PSO, neuro-fuzzy concepts and Recursive Least Square Estimation was also devised. In marketing and distribution neuro-fuzzy approach was introduced to e-commerce, online market research and new product profitability prediction. A new technique based on ANFIS and structural equation modeling was introduced for the new product development. Also a system based on Wavelet Transform and ANFIS was developed where the transform was used for decomposing the input price series into a set of consecutive series to increase the forecasting accuracy. In productions/operations neuro-fuzzy system was introduced for the intelligent landing control of aircrafts and tire reliability detection. A novel prognostic method based on ANFIS and High-order Particle Filtering was designed. A number of studies employing NFS were conducted in machine control as well
2012	In finance this year credit scoring and stock price prediction where the major application areas. A new neuro-fuzzy system based on type-2 fuzzy rules was developed for stock trading. Self-constructing clustering method was used for obtaining type-2 fuzzy rules. In marketing and distribution NFS applications were mainly limited to customer satisfaction models, price forecasting and supply chain assessment. In a study PSO was used with ANFIS to design a prediction system for the sales forecasting. PSO improved the performance of the NFS by refining the membership functions to decrease error. In a study neuro-fuzzy system was used to predict the employee absentees. In this year ANFIS was the dominant fuzzy technique in the field of robot control than the previous years. A novel application area of vehicle control based on neuro-fuzzy and genetic algorithm techniques was introduced. In this model the vehicle current condition as normal or not was found using the fuzzy inference and the genetic algorithm to optimize the fuzzy system. Vehicle control and warning system was the main area researched other than robot control in production and operations. The main application area in information systems was the software effort estimation. The studies done for this purpose mostly integrated neuro-fuzzy systems with several algorithmic software effort estimation models that enhanced the performance of the overall cost estimation process
2013	An interval type-2 fuzzy system was used for foreign exchange rate forecasting. A system based on interval type-2 fuzzy model, type-2 fuzzy c-means clustering and multilayer perceptron was introduced. The trading was the major application of finance in this year. In marketing/distribution the main research area of interest was customer satisfaction modeling. A Fuzzy Data Envelopment Algorithm (FDEA) was used with ANFIS. Also a new co-active neuro-fuzzy inference system was designed for price prediction with results better than the ANFIS. Fewer number of studies were conducted in production and operations field as compared to previous years. A model based on Multiple Regression Analysis (MRA) and neuro-fuzzy approach was introduced for tool wear monitoring. Besides this a system based on MRA, NFS and dynamic programming was used to develop a job shop automated system. In information systems neuro-fuzzy techniques were used for a number of problems like software evaluation, cost estimation and software fault diagnosis. Also ANFIS was introduced for modeling the association between the object-oriented metrics and software change proneness. Another important study was the application of ANFIS in software effort estimation
2014	In finance ANFIS ensemble architecture was also introduced for stock trading. A neuro-fuzzy technique was introduced in marketing decision making process. In another study genetic algorithm and ANFIS were integrated to find out an ordering policy in a supply chain. Also a neuro-fuzzy system based on Fuzzy Linear Regression and neural network was used for house price assessment. In production and operations relatively fewer but significant studies were done. An interval type-2 neuro-fuzzy system was developed for robot control which could perform well in both unstructured and dynamic with high reliability. An intelligent forecasting system based on fuzzy delphi technique and ANFIS was also introduced. Software requirement prioritization was a new sub-domain under information systems explored using NFS. Also a model based on fuzzy C-means clustering and neural network approach was used for software fault estimation. A significant study was the application of ANFIS to a new paradigm of Aspect-Oriented software development

Table 7 continued

2015	A neuro-fuzzy system was applied to movie recommendation on e-commerce sites for the first time. An interval type-2 FCM based interval type-2 neuro-fuzzy system was designed. In production/operations neuro-fuzzy technique was introduced to a novel application area of fabric wrinkle recovery in fabric production industry

Fig. 2 Relative impact of NFS in different business areas



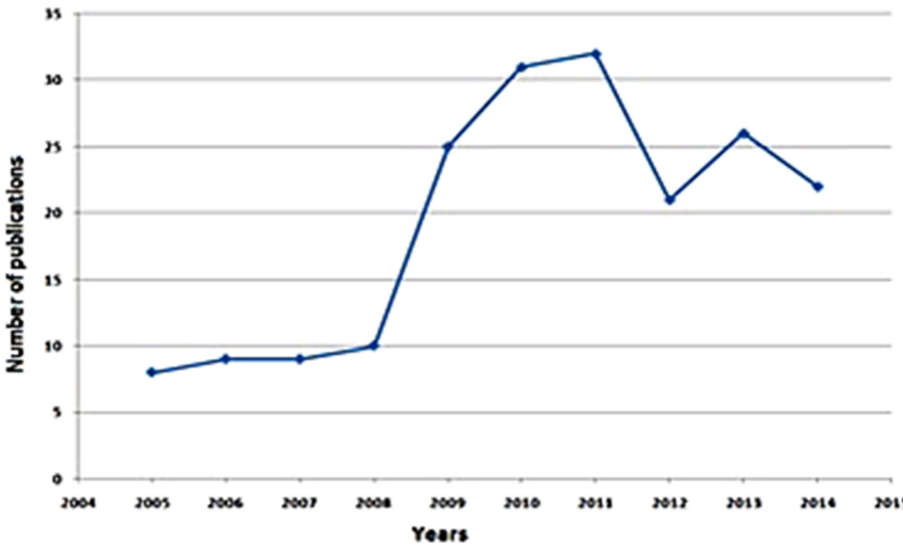


Fig. 3 Yearly distribution of research articles on NFS business application

distribution of research papers on the basis of the application of NFS in different business domains published during 2005–2014. This yearly distribution of the articles shows lesser number of NFS business application based research articles for period 2005–2008 which illustrates lesser popularity of these systems during this period in business altogether. For this period the relevant studies were mostly based on the use of NFS in productions and operations domain and a very few studies used NFS in other business areas like finance, HRM, business planning, marketing and distribution and Information systems. An increase in the article number after this period during 2009–2014 shows the gradual increasing successful application of NFS in all business domains. Since NFS business application based research has grown during recent years and this paper is focused on the articles published in the reputed and well known journals and conference proceedings, articles from various local journals may be missing from this review. Moreover, the relevant articles published in local languages have not been included.

10 Conclusion

In the recent past different hybrid AI techniques obtained by combining two or more AI techniques were developed. The NFS integrate the high explanatory capability of the fuzzy systems with generalization ability of ANNs. The NFS applicability for the real world business problems has been researched extensively since 2005. This paper has presented a survey of the NFS application based research in various business domains using the published research articles in various reputed journals and conferences during 2005–2015 to give an insight into this state-of-art technology in business. An examination of these studies shows that the research on the application of NFS in business is oriented towards continuously increasing the performance of these systems in solving various business problems and also on introducing these systems into newer business problems. During the beginning of the period 2005–2015, NFS were mainly applied for control applications but over years the application areas have extended towards problems like decision making, time prediction, business planning, project cost etc. In most of the research studies it has been demonstrated that NFS perform better than many AI techniques in terms of prediction accuracy, interpretability, convergence time etc.

For improving the performance of NFS various data preprocessing methods were used, higher order neuro-fuzzy methodologies were used and various optimization mechanisms were combined with these systems to improve the overall performance. For addressing business problems different NFS methodologies were applied by the researchers depending on the researchers' expertise, ability and research interest. Altogether the NFS business application research has diversified enormously during this period.

As shown by the number of articles pertaining to various business domains it is also apparent that NFS based systems were extensively used in some business domains but were meagerly used in few areas like business planning, HRM, accounting and auditing. NFS were more prevalent in some of the sub-domains within different business domains. For instance production and operation has been the most popular application area in business in which the equipment control particularly the robot system control was most popular application of NFS. Production and operation was followed by finance and marketing/distribution as the main business domains where stock market prediction and price forecasting sub-domains respectively were the popular application areas of NFS.

In future newer efficient input and output processing techniques and different optimization techniques can be applied with various NFS approaches that have been already developed. Also the use of higher order fuzzy approaches like interval type-2 NFS which have proved to be efficient for addressing various business problems in some studies were limited only to some business applications. There is a lot of scope in introducing these efficient techniques to numerous other real world business problems. Furthermore in finance stock trading was the most focused application area of NFS during 2005–2015 and a number of these studies were focused on applying newer NFS methodologies, combining different preprocessing and optimization techniques with NFS to enhance performance. In future these improvements can be applied to the lesser explored areas of finance like real estate value prediction, bankruptcy prediction, economic crisis prediction etc. In marketing and distribution mainly

ANFIS was used for various prediction problems for which other novel NFS methodologies like type-2 NFS systems and newer fuzzy modeling techniques can be applied. There is a lot of scope in applying the NFS in business planning, HRM and information systems to staff training, motivation, selection etc. where the applicability of NFS has not been yet investigated. Furthermore in the last years the main attention of most of the research on the application of NFS in business was on increasing the accuracy with respect to some error measures like RMSE but the important aspect of interpretability of these neuro-fuzzy models has been overlooked. Therefore the design of interpretable neuro-fuzzy systems with focus on achieving accuracy-interpretability tradeoff can be considered in future. Such systems are indispensible for various decision oriented business applications where model interpretability and transparency is important.

References

Abbasi E, Abouec A (2008) Stock price forecast by using neuro-fuzzy inference system. World Acad Sci Eng Technol 10:10–28
Abbasi A, Asgari MS (2014) Selection using adaptive neuro fuzzy inference system and fuzzy Delphi. Int J Oper Linguist Manag 4:351–371
Abhaya M et al (2014) Intelligent modeling and decision making for the control of industrial robot system based on neuro-fuzzy approach. In: IEEE international conference on control, instrumentation and computation technologies. doi:10.1109/ICCICCT.2014.6993188
Abiyev RH, Kaynak O (2008) Identification and control of dynamic plants using fuzzy wavelet neural networks. In: International symposium on intelligent control. doi:10.1109/ISIC.2008.4635940
Adhyaru DM, Patel J, Gianchandani R (2010) Adaptive neuro-fuzzy inference system based control of robotic manipulators. In: 2nd international conference on mechanical and electrical technology. doi:10.1109/ICARCV.2010.5707354
Ahmad F et al (2015) Forecasting of intellectual capital by measuring innovation using adaptive neuro-fuzzy inference system. Int Rev Appl Sci 1:1–13
Akerkar R, Sajja PS (2010) A neuro-fuzzy decision support system for selection of small scale business. Commun Comput Inf Sci 1:306–331
Akhlaghi P (2008) Complex dynamical system fault diagnosis based on multiple ANFIS using independent component. In: 16th Mediterranean conference on control and automation. doi:10.1109/MED.2008.4602207
Aksoy A et al (2014) Demand forecasting for apparel manufacturers by using neuro-fuzzy techniques. J Model Manag 2:18–35
Alavandar S, Nigam MJ (2008) Adaptive neuro-fuzzy inference system based control of six DOF robot manipulator. J Eng Sci Technol Rev 1:106–111
Alizadeh M et al (2010) An adaptive neuro-fuzzy system for stock portfolio Analysis. Int J Intell Syst 2:99–114
Amjady N (2006) Day-ahead price forecasting of electricity markets by a new fuzzy neural network. IEEE Trans Power Syst 2:887–896
Ang KK, Quek C (2006) Stock trading using RSPOP: a novel rough set-based neuro-fuzzy approach. IEEE Trans Neural Netw 5:1301–1315
Anicic O, Jovic S (2016) Adaptive neuro-fuzzy approach for ducted tidal turbine performance estimation. Renew Sustain Energy Rev 59:1111–1116
Areed FG et al (2010) Adaptive neuro-fuzzy control of an induction motor. Ain Shams Eng J 1:71–78
Atsalakis G, Dimitrakakis E (2011) Elliott wave theory and neuro-fuzzy systems, in stock market prediction: the WASP system. Expert Syst Appl 8:9178–9196
Atsalakis GS et al (2007) Probability of trend prediction of exchange rate by ANFIS. doi:10.1142/9789812709691_0050
Avasilcai S, Pislaru M (2013) Neuro-fuzzy model related to job assignation. In: Emerging trends in computing, informatics, systems sciences engineering, vol 1, pp 927–935
Azadeh SM et al (2011) A neuro-fuzzy-stochastic frontier analysis approach for long-term natural gas consumption forecasting and behavior analysis: the cases of Bahrain, Saudi Arabia, Syria, and UAE. Appl Energy 11:3850–3859
Azadeh A et al (2013) Neuro-fuzzy-multivariate algorithm for accurate gas consumption estimation in South America with noisy inputs. Int J Electr Power Energy Syst 1:315–325

Azadeh A et al (2014) A flexible neuro-fuzzy approach for improvement of seasonal housing price estimation in uncertain and non-linear environments. S Afr J Econ 4:567–582
Azadeh A et al (2015) Improved trust prediction in business environments by adaptive neuro fuzzy inference systems. Int J Emerg Technol Adv Eng 6:19–26
Azmi AI, Lin RJT, Bhattacharyya D (2013) Tool wear prediction models during end milling of glass fibre-reinforced polymer composites. Int J Adv Manuf Technol 1:701–718
Bagheri A et al (2014) Financial forecasting using ANFIS networks with quantum-behaved particle Swarm optimization. Expert Syst Appl 14:6235–6250
Banik S, Khan K (2012) Modeling chaotic behavior of Dhaka stock market index values using the neuro-fuzzy model. Recent Pat Comput Sci 5:72–77
Banik S et al. (2007) Modeling chaotic behavior of Dhaka stock market index values using the neuro-fuzzy model. In: 10th international conference on computer and information technology. doi:10.1109/ICCITECHN.2007.4579362
Behrouznia A et al (2011) Prediction of manufacturing lead time based on adaptive neuro-fuzzy inference system (ANFIS). In: International symposium on innovations in intelligent systems and application. doi:10.1109/INISTA.2011.5946049
Beldjehem M (2010) A unified granular fuzzy-neuro framework for predicting and understanding software quality. Int J Softw Eng Appl 4:17–35
Bellon C et al (1992) Fuzzy boom in Japan. Int J Intell Syst 4:293–316
Boyacioglu MA, Avci D (2010) An adaptive network-based fuzzy inference system (ANFIS) for the prediction of stock market return: the case of the Istanbul stock exchange. Expert Syst Appl 12:7908–7912
Braik M et al (2013) Design and automation for manufacturing processes: an intelligent business modeling using adaptive neuro-fuzzy inference systems. Bus Intell Perform Manag 1:91–208
Budiharto W et al (2010) Indoor navigation using adaptive neuro fuzzy controller for servant robot. In: Second international conference on computer engineering and applications, vol 1, pp 582–586
Catalão JPS, Pousinho MI, Mende VM (2011) Short-term electricity prices forecasting in a competitive market by a hybrid intelligent approach. Energy Convers Manag 52:1061–1065
Chai SH, Lim JS (2007a) Economic turning point forecasting using fuzzy neural network and non-overlap area distribution measurement method. Korean Econ J 1:111–130
Chai SH, Lim JS (2007b) Economic turning point forecasting using neural network with weighted fuzzy membership functions. New Trends Appl Artif Intell 1:145–154
Chakrabarti P, Basu JK (2010) Business planning in the light of neuro-fuzzy and predictive forecasting. In: Signal proceedings of conference held as part of the future generation information technology international conference (FGIT 2010), Jeju Island, Korea, pp 283–290
Chan KY, Kwong CK, Dillon T (2012) An enhanced neuro-fuzzy approach for generating customer satisfaction models. Studies in computational intelligence. Springer, Berlin
Chang Z et al (2007a) Prediction of amount of imports based on adaptive neuro-fuzzy inference system. In: The international conference on intelligent pervasive computing. doi:10.1109/IPC.2007.36
Chang PC et al (2007b) The development of a weighted evolving fuzzy neural network for PCB sales forecasting. Expert Syst Appl 1:86–96
Chatterjee A et al (2005) A particle-swarm-optimized fuzzy-neural network for voice-controlled robot systems. IEEE Trans Ind Electron 6:1478–1489
Chen C et al (2011) Machine condition prediction based on adaptive neuro-fuzzy and high-order particle filtering. IEEE Trans Ind Electron 9:4353–4364
Chen C et al (2012) Machine remaining useful life prediction: an integrated adaptive neuro-fuzzy and high-order particle filtering approach. Mech Syst Signal Process 1:597–607
Chen M-Y, Chen D-R, Fan M-H, Huang T-Y (2013) International transmission of stock market movements: an adaptive neuro-fuzzy inference system for analysis of TAIEX forecasting. Neural Comput Appl 1:369–378
Cherroun L et al (2014) Neuro-fuzzy controller for the path following behavior and moving target pursing by a mobile robot. In: International journal of system assurance engineering and management. doi:10.1007/s13198-013-0174-5
Ching LS, Chen CJ, Yang SM (2010) A self-organized neuro-fuzzy system for stock market dynamics modeling and forecasting. In: Proceedings of the 14th WSEAS international conference on computers, vol 2, pp 733–745
Chiroma H, Abdulkareem S, Abubakar A, Zeki A (2013) Co-active neuro-fuzzy inference systems model for predicting crude oil price based on OECD inventories. Res Innov Inf Syst 1:232–235
Christina C, Umbara RF (2015) Gold price prediction using type-2 neuro-fuzzy modeling and ARIMA. In: 3rd international conference on information and communication technology (ICoICT). doi:10.1109/ICoICT.2015.7231435

Chung HT, Jang JO (2009) Neuro-fuzzy network control for a mobile robot. In: American control conference. doi:10.1109/ACC.2009.5159871
Constantinescu A, Badea L, Cucui I, Ceaus G (2010) Neuro-fuzzy classifiers for credit scoring. Recent Adv Manag Mark Finances 1:132–136
Cui BD (2011) Adaptive neuro-fuzzy inference system modelling of surface roughness in high speed turning of AISI P 20 tool steel. Adv Mater Res 314:341–345
Cuong BC, Chien PV (2011) An experiment result based on adaptive neuro-fuzzy inference system for stock PricE. J Comput Sci Cybern l27:51–60
de Carvalho Alves M et al (2009) Neuro-fuzzy operational performance of a coffee harvester machine. J Converg Inf Technol 2:52–59
Demirli K, Khoshnejad M (2009) Autonomous parallel parking of a car-like mobile robot by a neuro-fuzzy sensor-based controller. Fuzzy Sets Syst 19:2876–2891
Didehkhani H et al (2009) Assessing flexibility in supply chain using adaptive neuro fuzzy inference system. In: IEEE international conference on industrial engineering and engineering management. doi:10.1109/IEEM.2009.5373292
Dimitrios EK, Mantas G (2012) Health products sales forecasting using computational intelligence and adaptive neuro fuzzy inference systems. Oper Res 1:29–43
Dimitrios C et al (2011) New adaptive neuro-fuzzy controller for trajectory tracking of robot manipulators. Int J Robot Autom 1:64–75
Dimitrov KD (2011) Neuro-fuzzy system for enhanced fault diagnosis in industrial facility. Recent 2:112–118
Doctor F et al (2009) A neuro-fuzzy based agent for group decision support in applicant ranking within human resources system. In: IEEE international conference on fuzzy systems. doi:10.1109/FUZZY.2009.5277379
Douiri R, Cherkaoui M, Nasser T, Essadki A (2011) A neuro fuzzy PI controller used for speed control of a direct torque to twelve sectors controlled induction machine drive. In: International conference on multimedia computing and systems. doi:10.1109/ICMCS.2011.5945686
Du WL, Capretz LF (2010) Improving software effort estimation using neuro-fuzzy model with SEER-SEM. Glob J Comput Sci Technol 12:52–64
Du WL, Capretz LF, Nassif AB, Ho D (2013) A hybrid intelligent model for software cost estimation. J Comput Sci 9:1506–1513
Dybkowski O-K, Szabat M (2010) Adaptive sliding-model neuro-fuzzy control of the two-mass induction motor drive without mechanical sensors. IEEE Trans Ind Electron 57:553–564
Erdem H (2011) Application of neuro-fuzzy controller for sumo robot control. Expert Syst Appl 8:9752–9760
Fallahzadeh E, Montazeri MA (2013) Forecasting foreign exchange rates using an IT2 FCM based IT2 neuro-fuzzy System. In: 21st Iranian conference on electrical engineering. doi:10.1109/IranianCEE.2013.6599870
Fazlollahtabar H, Mahdavi-Amiri N (2013) Design of a neuro-fuzzy-regression expert system to estimate cost in a flexible jobshop automated manufacturing system. Int J Adv Manuf Technol 5:1809–1823
Ferreira JP et al (2009) Rejection of an external force in the sagittal plane applied on a biped robot using a neuro-fuzzy controller. Int Conf Adv Robot 1:1–6
Gajate A et al (2010) Transductive-weighted neuro-fuzzy inference system for tool wear prediction in a turning process. Hybrid Artif Intell Syst 1:13–120
Gajate A et al (2012) Tool wear monitoring using neuro-fuzzy techniques: a comparative study in a turning process. J Intell Manuf 3:869–882
Garcia-Diaz N et al (2015) Software development time estimation based on a new neuro-fuzzy approach. In: 10th Iberian conference on information systems and technologies (CISTI). doi:10.1109/CISTI.2015.7170378
Gerek IH (2014) House selling price assessment using two different adaptive neuro-fuzzy techniques. Autom Constr 1:33–39
Guan J et al (2014) Analyzing massive data sets: an adaptive fuzzy neural approach for prediction, with a real estate illustration. J Organ Comput Electron Commer 1:94–112
Gumus AT, Guneri AF, Keles S (2009) Supply chain network design using an integrated neuro-fuzzy and MILP approach: a comparative design study. Expert Syst Appl 10:12570–12577
Gunasekaran M, Ramaswam KS (2014) A hybrid intelligent system of ANFIS and CAPM for stock portfolio optimization. J Intell Fuzzy Syst 26:277–286
GüNeri AF, Ertay T, YüCel A (2011) An approach based on ANFIS input selection and modeling for supplier selection problem. Expert Syst Appl 38:14907–14917
Gupta R, Naqvi SK (2015) A framework for applying critical success factors to ERP implementation projects. Int J Bus Inf Syst. doi:10.1504/IJBIS.2014.065565

Guresen E, Kayakutlu G, Daim TU (2011) Using artificial neural network models in stock market index prediction. Expert Syst Appl 38:10389–10397
Hajialiakbari F et al (2013) Assessment of the effect on technical efficiency of bad loans in banking industry: a principal component analysis and neuro-fuzzy system. Neural Comput Appl 23:315–322
Havangi R et al (2010) Adaptive neuro-fuzzy extended Kaiman filtering for robot localization. Int J Comput Sci Issues 7:15–23
Hiziroglu A (2013) A neuro-fuzzy two-stage clustering approach to customer segmentation. J Mark Anal 1:202–221
Ho WL, Tung WL, Quek C (2010) Brain-inspired evolving neuro-fuzzy system for financial forecasting and trading of the s&p500 index, vol 6230. Springer, Berlin, pp 60–607
Ho D et al (2015) Neuro-fuzzy algorithmic (NFA) models and tools for estimation. In: 20th international forum on COCOMO and software cost modeling, vol 1, pp 1–5
Holimchayachotikul P, Leksakul K, Montella DR (2010) Predictive collaborative performance system in B2B supply chain using neuro-fuzzy approach. In: Proceedings of the 9th WSEAS international conference on system science and simulation in engineering, vol 1, pp 348–353
Huang X et al (2006) A soft computing framework for software effort estimation. Soft Comput 10:170–177
Hussain T et al (2015) Comparison of artificial neural network and adaptive neuro-fuzzy inference system for predicting the wrinkle recovery of woven fabrics. J Text Inst. doi:10.1080/00405000.2014.953790
Jang J-SR (1993) ANFIS: adaptive-network-based fuzzy inference system. IEEE Trans Syst Man Cybern 1:665–685
Jang JO (2011) Adaptive neuro-fuzzy network control for a mobile robot. J Intell Robot Syst 62:567–586
Javadi-Moghaddam J, Bagheri A (2010) An adaptive neuro-fuzzy sliding mode based genetic algorithm control system for under water remotely operated vehicle. Expert Syst Appl 37:647–660
Jin X-H (2011) Model for efficient risk allocation in privately financed public infrastructure projects using neuro-fuzzy techniques. J Const Eng Manag 137:1003–1014
Jovic S, Anicic O, Pejovic B (2016a) Management of the wind speed data using adaptive neuro-fuzzy methodology. Flow Meas Instrum 50:201–208
Jovic S, Aničić O, Marsenić M, Nedić B (2016b) Solar radiation analyzing by neuro-fuzzy approach. Energy Build 129:261–263
Kaiser C, Schlick S, Bodendorf F (2011) Warning system for online market research—identifying critical situations in online opinion formation. Knowl Based Syst 24:824–836
Kablan A (2009) Adaptive neuro fuzzy inference systems for high frequency financial trading and forecasting. In: Third international conference on advanced engineering computing and applications in sciences. doi:10.1109/ADVCOMP.2009.23
Karunarathne L, Knowles K (2010) Adaptive neuro fuzzy inference system-based intelligent power management strategies for fuel cell/battery driven unmanned electric aerial vehicle. J Aerosp Eng 224:77–88
Kayacan E, Ramon H, Saeys W (2012) Adaptive neuro-fuzzy control of a spherical rolling robot using sliding-mode-control-theory-based onlin learning algorithm. IEEE Trans Man Cybern 43:170–179
Kaynar O, Yilmaz I, Demirkoparan F (2010) Forecasting of natural gas consumption with neural network and neuro fuzzy system. Geophys Res Abstr 12:221–238
Khaldoun T, Al-Din MSN (2009) A neuro-fuzzy reasoning system for mobile robot navigation. Jordan J Mech Ind Eng 3:77–88
Kharmandar N, Khayyat A (2011) Force impedance control of a robot manipulator using a neuro-fuzzy controller. In: International conference on mechatronic science, electric engineering and computer. doi:10.1109/MEC.2011.6025526
Khashei M, Bijari M (2014) Fuzzy artificial neural network (p, d, q) model for incomplete financial time series forecasting. J Intell Fuzzy Syst 26:831–845
Khashei M, Rezvan MT, Hamadani AZ, Bijari M (2013) A bi-level neural-based fuzzy classification approach for credit scoring problem. Complexity 18:46–57
Khatibi V et al (2011) An RBF-based neuro-fuzzy system for scenario planning in project management. In: International conference on financial management and economics, vol 11, pp 77–82
Kotaiah B et al (2015) An analysis of software reliability assessment with neuro-fuzzy based expert systems. In: Proceedings of 2015 international conference on soft computing and software engineering, vol 62, pp 92–98
Kothandaraman R, Ponnusamy L (2012) PSO tuned adaptive neuro-fuzzy controller for vehicle suspension systems. J Adv Inf Technol 3:57–63
Kumar D, Dhama K (2012) Neuro-fuzzy control of an intelligent mobile robot. In: Second international conference on advanced computing & communication technologies, vol 1, pp 106–111
Kumar R, Sudha KR, Pushpalatha DV (2012) Modelling and control of 5DOF robot arm using neuro-fuzzy controller. Int J Eng Res Technol 1:1–8

Kumar S et al (2015) Application of adaptive neuro-fuzzy inference system and artificial neural network in inventory level forecasting. Int J Bus Intell Syst. doi:10.1504/IJBIS.2015.068164
Kurnaz S et al (2007) Adaptive neuro-fuzzy inference system based autonomous flight control of unmanned air vehicles. Adv Neural Netw 1:14–21
Kurnaz S, Cetin O, Kaynak O (2010) Adaptive neuro-fuzzy nference system based autonomous flight control of unmanned air vehicle. Expert Syst Appl 37:1229–1234
Kwong CK, Wong TC, Chan KY (2009) A methodology of generating customer satisfaction models for new product development using a neuro-fuzzy approach. Expert Syst Appl 36:11262–11270
Lakshmi KV, Mashuq-un-Nabi (2012) An adaptive neuro-fuzzy control approach for motion control of a robot arm. In: International conference on informatics, electronics & vision. doi:10.1109/ICIEV.2012.6317522
Latif HH, Paul SK, Azeem A (2014) Ordering policy in a supply chain with adaptive neuro-fuzzy inference system demand forecasting. Int J Manag Sci Eng Manag 9:114–124
Lee CH et al (2006) A brain inspired fuzzy neuro-predictor for bank failure analysis. In: Congress on evolutionary computation. doi:10.1109/CEC.2006.1688574
Lei Y et al (2007) Diagnosis of rotating machinery based on multiple ANFIS combinations with GAs. Mech Syst Signal Process 2:2280–2294
Lei Y et al (2008) A new approach to intelligent fault diagnosis of rotating machinery. Expert Syst Appl 35:1593–1600
Li S et al (2005) Job shop scheduling in real-time cases. Int J Adv Manuf Technol 26:870–875
Li C, Lin CW, Huang H (2011) Neural fuzzy forecasting of the china yuan to US dollar exchange rate: a swarm intelligence approach. Adv Swarm Intell 6728:616–625
Liu I-G et al (2006) Application of fuzzy neural network for real estate prediction. Adv Neural Netw 3973:1187–1191
Liu G, Liu M, Liu Y (2012a) Application of neuro-fuzzy inference in longitudinal vehicle control and warning systems. Adv Mech Electron Eng 176:611–616
Liu C-F, Yeh C-Y, Lee S-J (2012b) Application of type-2 neuro-fuzzy modeling in stock price prediction. Appl Soft Comput 12:1348–1350
Liu T-I et al (2013) Monitoring and diagnosis of the tapping process for product quality and automated manufacturing. Int J Adv Manuf Technol 64:1169–1175
Li R, Xiong Z-B (2005) Forecasting stock market with fuzzy neural networks. In: IEEE proceedings of international conference on machine learning and cybernatics. doi:10.1109/ICMLC.2005.1527543
Macwan N, Sajja PS (2013) Retention of efficient human resources—a neuro-fuzzy way. In: International magazine on advances on advances in computer science and telecommunications, vol 3, pp 187–191
Mahdaoui R et al (2011) A temporal neuro-fuzzy monitoring system to manufacturing systems. Int J Comput Sci Issues 8:237–246
Mahmud MS, Meesad P (2015) An innovative recurrent error-based neuro-fuzzy system with momentum for stock price prediction. Soft Comput 1–19
Maksimovic G, Jovic S, Jovanovic R (2016) Economic growth rate management by soft computing approach. Stat Mech Appl Phys A. doi:10.1016/j.physa.2016.08.063
Martin P, Emami MR (2010) Neuro-fuzzy compliance control for rehabilitation robotics. In: 3rd IEEE RAS and EMBS international conference on biomedical robotics and biomechatronics. doi:10.1109/BIOROB.2010.5626050
Martiniano A, Ferreira RP, Sassi RJ, Affonso C (2012) Application of a neuro fuzzy network in prediction of absenteeism at work. In: 7th Iberian conference on information systems and technologies, vol 1, pp 1–14
Marwala L, Twala B (2014) Forecasting electricity consumption in South Africa: ARMA, neural networks and neuro-fuzzy systems. In: International joint conference on neural networks. doi:10.1109/IJCNN.2014.6889898
Marza V et al (2008) Estimating development time of software projects using a neuro fuzzy approach. World Acad Sci Eng Technol 1:10–27
Meesad P, Srikhacha T (2008) stock price time series prediction using neuro-fuzzy with support vector guideline system. In: Ninth ACIS international conference on software engineering, artificial intelligence, networking, and parallel/distributed computing. doi:10.1109/SNPD.2008.55
Melingui A et al (2014) fuzzy controller for autonomous navigation of mobile robots. In: IEEE conference on control applications (CCA). doi:10.1109/CCA.2014.6981474
Mewada KM, Sinhal A, Verma B (2013) Adaptive neuro-fuzzy inference system (ANFIS) based software evaluation. Int J Comput Sci Issues 10:244–250
Misra AK et al (2012) Software development effort and cost estimation: neuro-fuzzy model. J Comput Eng 2:12–14
Moayer S, Bahri PA (2009) Hybrid intelligent scenario generator for business strategic planning by using ANFIS. Expert Syst Appl 36:7729–7737

Mohanty PK, Parhi DR (2014) Navigation of autonomous mobile robot using adaptive neuro-fuzzy controller. Adv Intell Syst Comput 243:521–530

Momeni H, Yavari A (2014) Complexity evaluation of aspect-oriented software with adaptive neuro-fuzzy inference system. Int J Basic Sci Appl Res 3:22–30

Momeni H, Motameni H, Larimi M (2014) A neuro-fuzzy based approach to software quality requirement prioritization. Int J Appl Inf Syst 7:15–20

Nair BB, Minuvarthini M, Sujithra B, Mohandas VP (2010) Stock market prediction using a hybrid neuro-fuzzy system. In: International conference on advances in recent technologies in communication and computing (ARTCom). doi:10.1109/ARTCom.76

Nauck D, Klawon F, Kruse R (1997) Foundations of neuro-fuzzy systems. Wiley, New York

Nawaz A, Khanum A (2011) Ranked neuro fuzzy inference system (RNFIS) for information retrieval. Adv Neural Netw 6675:578–586

Nazari-Shirkouhi S, Keramati A, Rezaie K (2013) Improvement of customers' satisfaction with new product design using an adaptive neuro-fuzzy inference systems approach. Neural Comput Appl 23:333–343

Nhu HN et al (2013) Prediction of stock price using an adaptive neuro fuzzy inference system trained by firefly algorithm. In: International conference on computer science and engineering conference vol 1, pp 302–307

Nilashi M et al (2011) A comparative study of adaptive neuro fuzzy inferences system (ANFIS) and fuzzy inference system (FIS) approach for trust in B2C electronic commerce websites. J Converg Inf Technol 6:25–43

Nurmaini S, Zaiton S, Norhayati D (2009) An embedded interval type-2 neuro fuzzy controller for mobile robot navigation. In: International conference on systems, man and cybernetics. doi:10.1109/ICSMC.2009.5346800

Obe O, Dumitrache I (2012) Adaptive neuro-fuzzy controler with genetic training for mobile robot control. Int J Comput Sci 6:135–146

Oğuz Y, Üstün SV, Yabanova İ, Yumurtaci M, Güney İ (2012) Adaptive neuro-fuzzy inference system to improve the power quality of a split shaft microturbine power generation system. J Power Sources 97:196–209

Özkana G, İnalb M (2014) Comparison of neural network application for fuzzy and ANFIS approaches for multi-criteria decision making problems. Appl Soft Comput 24:232–238

Palluat N et al (2006) A neuro-fuzzy monitoring system: application to flexible production systems. Comput Ind 57:528–538

Patel P, Marwala T (2006) Neural networks, fuzzy inference systems and adaptive-neuro fuzzy inference systems for financial decision making. In: International Conference on Neural Information Processing, vol 1, pp 430–439

Peer A, Malhotra R (2013) Application of adaptive neuro-fuzzy inference system for predicting software change proneness. In: International conference on advances in computing, communication and informatics, vol 1, pp 2026–2031

Pham DT, Fahmy AA (2005) Neuro-fuzzy modelling and control of robot manipulators for trajectory tracking. In: Proceedings of the 16th IFAC world congress, vol 16, pp 1452–1452

Pousinho HMI, Mendes VMF, Catalão JPS (2012) Short-term electricity prices forecasting in a competitive market by a hybrid PSO-ANFIS approach. Int J Electr Power Energy Syst 1:29–35

Quintero M, Christian G, Jorhabib Eljaik (2009) Control architecture for intelligent offices: an approach based on neuro-fuzzy systems. In: Proceedings of the WSEAES 13th international conference on computers, vol 1, pp 380–385

Radeerom M, Kulthon ML (2013) A rule-based neuro-fuzzy stock trading decision support system using technical analysis. Adv Sci Lett 19:534–538

Radeerom M, Wongsuwarn H, Kasemsan K (2012) Intelligence decision trading systems for stock index. Intell Inf Database Syst 7:366–375

Rafik M, Mouss LH, Mouss MD, Chouhal O (2011) Temporal neuro-fuzzy systems in fault diagnosis and prognosis. Int Rev Model Simul 4:436–440

Rajab S, Sharma V (2015) Performance evaluation of ANN and neuro-fuzzy system in business forecasting. In: 2nd international conference on computing for sustainable global development (INDIACom), vol 1, pp 749–754

Rani P, Salaria DS (2013) Neuro-fuzzy based software risk estimation tool. Glob J Comput Sci Technol 13:13–18

Rao P, Seetha Ramaih P (2013) A novel approach to design neuro-fuzzy expert system for software estimation. Bus Intell Perform Manag 2:3012–3017

Rigatos GG (2009) Adaptive fuzzy control of DC motors using state and output feedback. Electr Power Syst Res 79:1579–1592

Sadeghian M, Fatehi A (2011) Identification, prediction and detection of the process fault in a cement rotary kiln by locally linear neuro- fuzzy technique. J Process Control 21:302–308
Sadighi A, Kim W (2011) Adaptive-neuro-fuzzy-based sensorless control of a smart-material actuator. IEEE/ASME Trans Mechatron 16:371–379
SahIn Y, Tinkir M (2010) Neuro-fuzzy trajectory control of a scara robot. In: International conference on computer and automation engineering, vol 2, pp 298–302
Sainz GI et al (2005) Fault detection and fuzzy rule extraction in AC motors by a neuro-fuzzy ART-based system. Eng Appl Artif Intell 18:867–874
Samhouri M et al (2009) An Intelligent Machine condition monitoring system using time-based analysis: neuro-fuzzy versus neural network. Jordan J Mech Ind Eng 3:294–305
Sandhu PS, Singh H (2005) Neuro-fuzzy based approach for the prediction of quality of reusable software components. In: Proceedings of the 2005 conference on new trends in software methodologies, tools and techniques, vol 1, pp 156–169
Sathiyasekar K, Thyagarajah K, Krishnan A (2011) Neuro fuzzy based predict the insulation quality of high voltage rotating machine. Expert Syst Appl 38:1066–1072
Saxena UR, Singh SP (2012) Software effort estimation using neuro-fuzzy approach. In: Sixth international conference of software engineering. doi:10.1109/CONSEG.2012.6349465
Seising R (2012) Fuzzy sets and systems before the fuzzy boom. Adv Comput Intell Commun Comput Inf Sci 297:541–551
Sekar G (2011) Portfolio optimization using neuro fuzzy system in Indian stock market. J Glob Res Comput Sci 3:44–47
Seker A, Erol S, Botsali R (2013) A neuro-fuzzy model for a new hybrid integrated process planning and scheduling system. Expert Syst Appl 40:5341–5351
Setlak G (2008) The fuzzy-neuro classifier for decision support. Int J Inf Theor Appl 15:21–26
Shi J et al (2009) A novel neuro-fuzzy model- based run-to-run control for batch processes with uncertainties. In: Proceedings of the 21st annual international conference on Chinese control and decision conference doi:10.1109/CCDC.2009.5195238
Sithu M, Thein NL (2011) A resource provisioning model for virtual machine controller based on neuro-fuzzy system. In: 2nd international conference on next generation information technology, vol 1, pp 109–114
Sree R (2012) Hybrid neuro-fuzzy systems for software development effort estimation. Int J Comput Sci Eng 4:1924–1932
Sreekantha DK, Kulkarni RV (2012) Expert system design for credit risk evaluation using neuro-fuzzy logic. Expert Syst 29:56–69
Svalina I, Galzina V, Lujić R, ŠImunović G (2013) An adaptive network-based fuzzy inference system (ANFIS) for the forecasting: the case of close price indices. Expert Syst Appl 40:6055–6063
Tan A et al (2008) Maximizing winning trades using a novel RSPOP fuzzy neural network intelligent stock trading system. Appl Intell 1:116–128
Tan Z, Quek C, Cheng PYK (2011) Stock trading with cycles: a financial application of ANFIS and reinforcement Learning. Expert Syst Appl 9:4741–4755
Tarjoman M, Zarei S (2009) The chaotic robot prediction by neuro fuzzy algorithm. In: Conference of the international journal of arts and sciences vol 1, pp 43–52
Toledo-Moreo R et al (2010) Maneuver prediction for road vehicles based on a neuro-fuzzy architecture with a low-cost navigation unit. IEEE Trans Intell Transp Syst 11:498–504
Toloie-Eshlaghy A, Sadat P, Kooshki T (2011) Prediction of reliability of vehicle tire with use of neuro-fuzzy networks. Elixir Manag Arts 1:5877–5881
Tozan H, Vayvay O (2009) A combined grey & ANFIS approach to demand variability in supply chain networks. In: Proceedings of the 10th WSEAS international conference on fuzzy systems, vol 1, pp 22–27
Tran VT, Yang BS (2010) Machine fault diagnosis and condition prognosis using classification and regression trees and neuro-fuzzy inference systems. Control Cybern 39:25–55
Trinkle BS (2005) Forecasting annual excess stock returns via an adaptive network-based fuzzy inference system. Intell Syst Account Finance Manag 13:165–177
Vella V, Ng WL (2014) Enhancing risk-adjusted performance of stock market intraday trading with neuro-fuzzy systems. Neurocomputing 141:170–187
Vieira J, Dias FM, Mota A (2004) Neuro-fuzzy systems: a survey. In: 5th WSEAS NNA international conference on neural networks and applications
Wang WP, Chiu C-C (2010) Towards managing demand variability by neuro-fuzzy approach. In: IEEE international conference industrial engineering and engineering management, vol 1, pp 1688–1692
Wang Z-L, Yang C-H, Guo T-Y (2010) The design of anautonomous parallel parking neuro-fuzzy controller for a car-like mobile robot. In: Proceedings of SICE annual conference, vol 1, pp 2593–2599

Wong J, Ho D, Capret LF (2009) An investigation of using neuro-fuzzy with software size estimation. In: Proceedings of the seventh ICSE conference on software quality, vol 1, pp 51–58
Wu J-D, Hsu C-C, Chen H-C (2009) An expert system of price forecasting for used cars using adaptive neuro-fuzzy inference. Expert Syst Appl 36:7809–7817
Xiao Y et al (2014) A neuro-fuzzy combination model based on singular spectrum analysis for air transport demand forecasting. J Air Transp Manag 39:1–11
Xiong Z-B, Li R-J (2005) Credit risk evaluation with fuzzy neural networks on listed corporations of China. In: Proceedings of 2005 IEEE international workshop on VLSI design and video technology. doi:10.1109/IWVDVT.2005.1504634
Xiong ZB (2010) Credit risk prediction study based on modified particle Swarm optimized fuzzy neural networks. Adv Mater Res 108:1326–1331
Xu B et al (2012) Neuro-fuzzy control of underwater vehicle-manipulator system. J Frankl Inst 349:1125–1138
Xu K, Zhang G (2011) Dynamic neuro-fuzzy control design for civil aviation aircraft in intelligent landing system. In: International conference on mechatronics and automation. doi:10.1109/ICMA.2011.5986355
Yang B et al (2007) Early software quality prediction based on a fuzzy neural network model. In: Third international conference on natural computation. doi:10.1109/ICNC.2007.347
Yang Y, Liu Y, Tang F, Liu Y (2011) Fuzzy neural network model for assessing credit risk in commercial banks. In: International conference on business management and electronic information (BMEI). doi:10.1109/ICBMEI.2011.5917027
Yao S et al (2007) A foreign exchange portfolio management mechanism based on fuzzy neural networks. In: IEEE congress on evolutionary computation. doi:10.1109/CEC.2007.4424795
Yao P, Wu C, Yao M (2009) Credit risk assessment model of commercial banks based on fuzzy neural network. Adv Neural Netw 5551:976–985
Ye Z, Sadeghian A, Wu B (2006) Mechanical fault diagnostics for induction motor with variable speed drives using adaptive neuro-fuzzy inference system. Electr Power Syst Res 176:742–752
Zahedia G et al (2012) Electricity demand estimation using an adaptive neuro-fuzzy network: a case study from the Ontario province, Canada. Energy 49:323–328
Zahin S et al (2013) A comparative analysis of power demand forecasting with artificial intelligence and traditional approach. Int J Bus Intell Syst. doi:10.1504/IJBIS.2013.054469
Zarandi F, Ahmadpour P (2009) Fuzzy agent-based expert system for steel making process. Expert Syst Appl 36:9539–9547
Zerfa H, Nouibat W (2013) Fuzzy reactive navigation for autonomous mobile robot with an offline adaptive neuro fuzzy system. In: 3rd international conference on systems and control, vol 1, pp 950–955
Zhang W et al (2015) A neuro-fuzzy decoupling approach for real-time drying room control in meat manufacturing. Expert Syst Appl 42:1039–1049
Zheng W, Gai X, Chen H (2010) Neuro-fuzzy control of underwater robot based on disturbance compensation. In: 8th world congress on intelligent control and automation. doi:10.1109/WCICA.2010.5553950
Zhu A et al. (2009) An adaptive neuro-fuzzy controller for robot navigation. Recent advances in intelligent control systems, vol 1. Springer, London, pp 277–307
Zio E, Gola G (2006) Neuro-fuzzy pattern classification for fault diagnosis in nuclear components. Ann Nucl Energy 33:415–426