ISSN: 2321-9653

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

Study of Existing Work on Soft Computing Methodologies and Fusion of Neural Network and Fuzzy Logic for Estimation and Approximation

Nidhi Arora[#1], JatinderKumar R. Saini[*2]

[#] *U.V. Patel College of Engineering, Ganpat University, Kherva, India*

[*] *Narmada College of Computer Application, Bharuch, India*

Abstract*— Estimation and Approximation plays a vital role in planning for future. It is up to the people, especially the business leaders to take its due advantage. Those who understand the significance of estimation, practice it very often. When performed correctly, the act of estimation or approximation of some event can lend a hand in increasing business profitability. These tasks involve analyzing historical data pertaining to domain, current trends and expectations of people connected to it.Exercising estimation is not only complicated due to technological change in the world around, but also due to complexity of the problems. Traditional numerical based techniques for solution of ill-defined non-linear real world problems are not sufficient. Hence, a robust methodology which can deal with dynamic environment, imprecise facts and uncertainty in the available data is required to achieve practical applicability at low cost. The last decade has seen vast improvement in terms of technological advancement. This has given space to methodologies which mimic human behavior and are based on human like capabilities cognition, recognition, understanding, and learning. Soft computing seeks to solve class of problems not suited for traditional algorithmic approaches. A literature study of the most important elements of soft computing relevant to estimation and approximation has been presented.

Keywords- ***Soft computing, Hybrid neuro-fuzzy system, Estimation and approximation, learning, uncertainty***

I. INTRODUCTION

Many real-world problems may not be represented properly using conventional approaches due to the lack of precise knowledge, their non-linear behavior or their high degree of uncertainty. Traditional computing methods work well for problems that can be well characterized like balancing checkbooks, keeping ledgers, and keeping tabs of inventory. Such methods are well defined and do not require any special characteristics of neural networks [Sumathi][1]. Accuracy has become dreamboat for researchers, but in the hunt for accuracy they sometimes ignore important things. According to Fortuna[Fortuna, 2001][2] the basic principle of soft computing is its combined use of new computation techniques that allow it to achieve a higher tolerance level towards imprecision and approximation. The hybrid systems derived from this combination of soft computing techniques are considered to be the new frontier of artificial intelligence.

Zadeh [zadeh, 1998][3] defined Soft computing as an approach for constructing systems which are computationally intelligent, possess human like expertise in particular domain, can adapt to the changing environment and can learn to do better and can explain their decisions [Ajit Abraham, 2004][4]. The applications of soft computing have advantages including solution to non-linear problems, in which mathematical models are not available, and introducing human knowledge such as cognition, recognition, understanding, learning, and others into the fields of computing. If a tendency towards imprecision could be tolerated, then it should be possible to extend the scope of the applications even to those problems where the analytical and mathematical representations are readily available. The

ISSN: 2321-9653

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

motivation for such an extension is the expected decrease in computational load and consequent increase of computation speeds that permit more robust system (Jang et al. 1997) [5]. The focus of our work is to study behaviour and applications of fuzzy logic, neural networks and their combination systems.

With the advent of technology, it has been realized that if fuzzy things are made precise deliberately, it costs not only in terms of complexity in methods, but also in its significance value. There exist methodologies which are more suitable for such kind of problems; a combination of fuzzy sets and neural network techniques are one among the list of techniques (Klir, 1991) [6]. Considering the two approaches separately, each of neural network system and fuzzy inference system has their own characteristics. Neural Networks are suitable structures for function approximation having learning ability. Fuzzy systems are used for enhancing the neural network's explanation capability. One of the best combinations for soft computing technique is hybridization of neural networks and fuzzy logic to get best of the two worlds and to overcome their individual limitations.

Handling uncertainty in such systems is essential because humans do not think in precise terms. The idea behind neuro-fuzzy systems is to mimic human thought and action. Bellman and Zadeh [7] stated that Much of the decision-making in the real world takes place in an environment in which the goals, the constraints and the consequences of possible actions are not known precisely. However, in conventional models, they are represented using crisp models with precision. In an attempt to simplify the complications of the real-world, these models tend to overlook their actual behavior, which make them inefficient to use and sometimes does not give the desired results. In the context of estimation and approximation, a lot of significant work has been carried out in past. Researchers from varied fields have put-in varied creative thoughts and worked on wide-spread models to prove applicability of computational approach for problem solving. Most of these attempts relied on the use of neural network architecture for learning to solve different problems. On the other hand, several researchers investigated the interrelationship between a variety of soft computing techniques to explore their combined benefits.

Soft computing is the fusion of methodologies that were designed to model and enable solutions to real world problems, which are not modeled, or too difficult to model, mathematically. The principle constituents of soft computing are Neural Networks (NN), Fuzzy Logic (FL), Evolutionary Computing (EC) and Probabilistic Computing (PC) further divided into other methodologies as shown in figure 1.

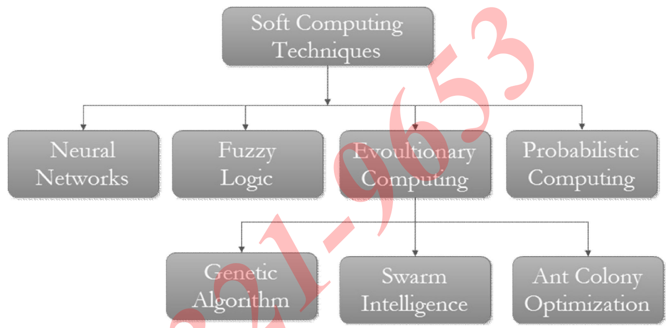

Fig. 1 Soft Computing Techniques

Soft computing is an aggregation of emerging methodologies aims at utilizing the tolerance for imprecision, uncertainty and partial truth towards achieving robustness, flexibility and low cost [5]. As opposed to conventional methods, soft computing methodologies mimic consciousness and cognition in several ways like learning from experience, performing input-output mapping etc. by simulating biological process through parallelization.

A neuro-fuzzy system is essentially a multi-layer neural network and it applies standard learning algorithms developed for neural networks like back-propagation algorithm. In general, a neuro-fuzzy system has input and output layers, and hidden layers representing membership functions and fuzzy rules. When a training example consisting of input-output pair is presented to the network, the back-propagation algorithm computes the network’s actual output and compares it with the target output. The difference, called error, is propagated backwards through the network layer-by-layer from output layer back to the input layer. During error propagation, the neuron activation functions are also modified. The if-then fuzzy rules are supplied by a domain expert for consultation during training. If a poor training data is fed to the network, the expert knowledge can bring the neural network to a solution. Sometimes, the rules used in a neuro-fuzzy system may be false or redundant.

 Vol. 2 Issue V, May 2014

ISSN: 2321-9653

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

II. HISTORICAL BACKGROUND

An easy way to comply with IJRASET paper formatting requirements is to use this document as a template and simply type your text into it.

The work undertaken incorporates fuzzy logic as the intention was to address the typical real-world situations full of uncertainty and vagueness together with the learning capability of neural networks. Fuzzy sets can capture and represent the real world data full of uncertainty. This uncertainty can occur due to many reasons; it can be caused by vagueness in the language or by imprecision in measurement of related factors. In such situations, linguistic variables are used to describe situations, or sometimes to quantify physical objects. It was Lotfi Zadeh [1965][8], who realized that crisp set theory is incapable of representing these situations and objects and do not provide adequate representation for most cases.

Artificial Neural Networks (ANNS) were first introduced by McCulloch and Pitt [9], in 1940s based on the observation that human brain consist of numerous interconnected neurons encapsulating the most rare thing in this world - human intelligence. Zadeh [8] argued that humans do not reason precise numerical values, instead using categories which are not based on numerical values. The advantage of ANNs over conventional computers lies is in its high parallelism. A conventional computer is a sequential machine in which if one of the components fails, then the whole machine goes down. ANN based on human brain is robust than the existing methods based on traditional procedures. The brain function is totally unaffected even if some of the neurons die or misbehave. It is becoming widely accepted that the advent of ANN will open new understanding into how to simplify programming and algorithm design for a given end and for a wide range of ends [Graupe][10]. Although there are some limitations of ANN too, like designing neural networks, long training periods, and possibility of over-fitting, but taking a little care, performing these tasks patiently and in right manner may generate fantastic results. The biggest limitation of numerical procedures is their dependency on fixed set of instructions.

The advantages of ANNs have attracted many researchers to study their behavior and utilizing their architecture in possible real-time solutions. Commonly known as Neural Networks (NN) in short, ANNs are powerful tools in the medical data processing field, and have been used widely [11]. However, NNs are prone to over-fitting, and are hard to understand, so several techniques are proposed to reduce the effect of over-fitting and to extract rules from NNs. Gareta and others (Gareta, Romeo, & Gil, 2006) [12] used an artificial neural network to forecast short-term hourly electricity pool prices. The NN can obtain the structure of a complex system by repeated network training procedure and it does not need to describe its property using mathematical equations. NNs have emerged as a famous solution for tackling pattern recognition and classification tasks. Indeed, NNs are useful for solving pattern classification problems in many different fields, e.g. medical prognosis and diagnosis, industrial fault detection and diagnosis, etc.

ANNs have been used as computational tools for data quality identification because of the belief that they have greater predictive power than signal analysis techniques (Ham & Kostanic, 2001)[13]. However, fuzzy set theory plays an important role in dealing with uncertainty when making decisions in data fusion (Ataei, Aghakouchak, Marefat, & Mohammadzadeh, 2005) [14]. There are numerous applications areas of neural networks and fuzzy logic, where the two techniques have shown acceptable results. Some of the well-known application areas of NN are listed in figure 2 below.

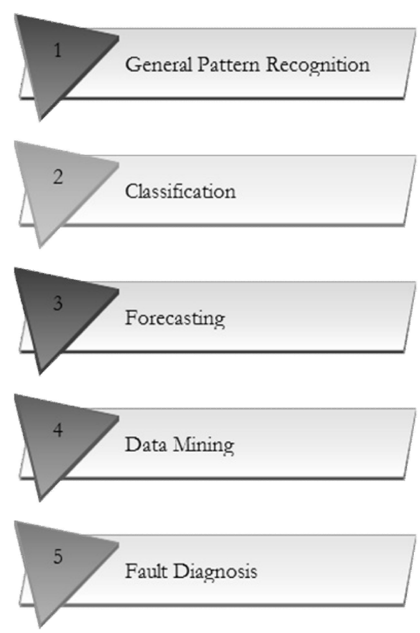

Fig. 2 Applications of Neural Networks

ISSN: 2321-9653

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

Neural networks have been successfully applied to broad spectrum of data-intensive applications, such as pattern recognition and classification [Garcia, Kai, Frate][15,16,17], data mining [Lu, Reyes-Aldasoro][18,19], fault diagnosis [Khomfoi, Zhang & Su][20,21], forecasting [Aburto, Azadeh, Palmer, Xiao, Xu][22,23,24,25,26] etc. Fuzzy systems are used successfully in data analysis & data mining [Chen, Doring, Nasibov, Rokach] [27,28,29,30], image processing [Burillo, Oueslati] [31,32], industrial automation & decision support system [Delgado, Kumara] [33,34], control applications [Kapitanovaa, Kim, Naranjo, Yasunobu] [35,36,37,38] etc. Some of the well-known application areas of FL are listed in figure 3 below.

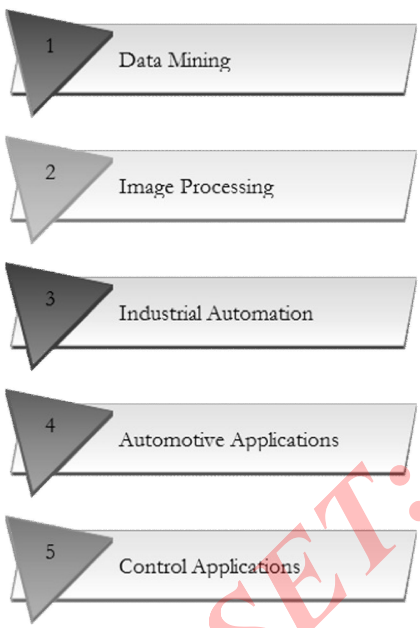

Fig. 3 Applications of Fuzzy Logic

CMAC network has been successfully applied in many fields, such as control applications (Arora, Miller [39,40]), signal processing (Kolcz [41]), pattern recognition (Glanz [42]), image coding (Iiguni [43]), and equalization (Reay [44]) because of its simple structure and fast learning. Some of the advantages of the CMAC network include high convergence rate, good generalization capability, and ease of implementation by hardware, etc. Pelikan et al. [45] proposed combining several feed-forward neural networks to improve time series forecasting accuracy. More literature can be found in the comprehensive review by Clemen [46]. Some of the ensemble techniques for prediction problems with continuous dependent variable include linear ensemble e.g., simple average [47], weighted average [48] and stacked regression [49] and non-linear ensemble e.g., neural network based non-linear ensemble [50]. In [51] it was reported that the generalization ability of a neural network system could be significantly improved by using an ensemble of a number of neural networks. The purpose was to achieve improved overall accuracy on the production data.

In early 60s, it was felt that all real-time systems have one thing in common and that is the existence of uncertainty. When studied keenly for years, it was gradually found that this presence of vagueness formed a restriction in getting right outcome from ANN based systems. To fulfill the need of handling underlying uncertainty, Zadeh [1965] [8] gave fuzzy set theory to the world of research. Fuzzy set theory gave a direction to support large number of applications for dealing with complexity, uncertainty and imprecision in various systems. This started an era of hybrid computing; with a new branch of computation in effect. The trainability of ANNs was pooled with Fuzzy Logic (FL) for handling uncertainty. When the input and output variables as well as the fuzzy partition of the variables become too much, fuzzy rules extracted by neural networks will be obtained and at the same time the rules will be exponentially growing (Benitez & Castro, 1996) [51]. On the one hand, genetic algorithms can be used to extract fuzzy rules to achieve the global optimization search (Lim, Rahardja, & Gwee, 1996) [52] while on the other hand; it is hard to get the expression of chromosome and conformation of fitness function.

Many researchers have presented the applications of statistical and intelligent techniques to bankruptcy prediction problem in banks, but the hybridization then combined techniques other that just ANNs and FL. Ahn et al. [53] proposed hybrid models combining rough sets and back propagation for bankruptcy prediction in Korean firms. They observed that the hybrid models with feature selection and sample size reduction aspects yielded better solutions compared to back propagation and discriminant analysis. Cheng, Chen, & Fu, 2006 [54] combined RBF network with logit analysis learning to predict financial distress. They compared the proposed technique with logit analysis and a back propagation neural network and found that their method is superior to both the techniques. Besides these generic advantages, the neuro-fuzzy approach also provides the corresponding application specific merits [55-57].

ISSN: 2321-9653

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

Soft computing is a new paradigm that blends different and unrelated intelligent technologies effortlessly in various ways to exploit their strengths (Kumar & Ravi, 2007 [58]; Kurt, Ture, & Kurum, 2008[59]). Soft computing methodologies span vast application areas including Banking and finance [Atiya, Purvinis, Shaw, Shin] [60,61,62,63], Telecommunication [Toosi, Yun] [64,65], Robotics [Hui 2002, Sadati, Subudhi] [66,67,68], Medicine [Miller 2007, Uzoka 2011] [69,70], Engineering [Chen, Fadare, Oh] [71,72,73], Security [Baskar, Kucuktezcan] [74,75], Image processing [Doulamis, Parisi, Yu][76,77,78] etc. A common fact in all these problems is that the world around is full of uncertainties and imprecision and hence is difficult to characterize. Consequently, the uncertainty in the result is due to the combined and accumulated effects of the uncertainties used in the calculation of these results [Kirkpatrick, 1992] [79].

Neuro-fuzzy systems either belong to Takagi–Sugeno or Mamdani type. Sugeno type neuro-fuzzy models (Sugeno & Tanaka, 1991; Sugeno & Yasukawa, 1993) [80,81] are commonly used in model-based applications whereas Mamdani type neuro-fuzzy systems make use of heuristics (Thiesing & Vornberger, 1997) [82]. On the positive side, Sugeno models are general approximators, provide high accuracy and are easy to interpret, while on the negative side they usually need complex learning procedures and are computational expensive.

In a hybrid model, neural network learning algorithms are fused with fuzzy reasoning of fuzzy logic. By integrating the two techniques their shortcomings can be overcome leaving out their individual drawbacks. In a neuro-fuzzy model, each of the components plays its own role; neural network determine the parameters of fuzzy inference systems while membership function and if-then rules are handled by fuzzy logic. A fuzzy inference system uses human expertise by storing required knowledge in its rule-base, and then performs fuzzy reasoning on the input to infer the overall output value. With the proving capability of the ANFIS as a powerful approximation method that has the both ability of the learning parameter in the neural networks and the localized approximation of the TSK fuzzy model [83], different types of networks based on neuro-fuzzy model has been proposed. In TSK fuzzy model the consequent part of each rule is approximated by a linear function of the inputs [84]. Essentially, neuro-fuzzy models based on TSK model are nonlinear, but conceptually, it is an aggregation of the linear models. SFAM and FAM have been used in numerous classification problems [85,86].

Wang et al. (2008) [87] proposed an Adaptive Neuro-Fuzzy Inference System (ANFIS) and a Kernel system to solve the problem of predicting rush orders for regulating the capacity reservation mechanism in advance. This demonstrates that forecasting rush orders holds high difficulty and the suitability of neuro-fuzzy system approach proposed in this paper is much better than the traditional regression analysis. Daoming (2006) [88] proposed a method of using ANFIS for the modeling and predicting of high pressure cleaning process. ANFIS is better than Fuzzy logic for the prediction of high-pressure waterjet epoxy paint cleaning. Aboozar Khajeh (2010) [89] developed ANFIS and Radial Basis Function Neural Network (RBF NN) models have been developed for prediction of solubility of various gases in polystyrene. They indicated that ANFIS and RBF NN are effective methods for prediction of solubility of gases in polystyrene and have better accuracy and simplicity compared with the classical methods. Chang (2006) [90] investigated the accuracy of neuro-fuzzy model in reservoir operation using two ANFIS models: one with human decision as input, another without. The results demonstrated ANFIS to be successful and highly accurate and reliable for reservoir water level forecasting in the next three hours.

Prediction is one the most studied functionality of ANN where they are found to be capable of giving satisfactory outcome. Wua (2009) [91] introduced a new price forecasting technique for used cars using the BP network and ANFIS model. The research successfully verifies the effectiveness of the BP network and ANFIS model to forecast the price of used cars. The ANFIS mode can provide better forecasting performance than the BP network. The presented ANFIS model combined the neural network adaptive capability and the fuzzy logic qualitative approximation. Ying-Ming Wang [92] developed an adaptive neuro-fuzzy inference system for bridge risk assessment. The developed ANFIS learns the if–then rules between bridge risk scores and risk ratings from the past bridge maintenance projects and memorizes them for generalization and prediction. It has been observed that ANFIS outperforms artificial neural networks. Arora et al. [93] studied the risk of not taking health insurance and developed ANFIS model for determining the degree to which an insurance seeker is exposed to risk if he fails to take insurance.

ISSN: 2321-9653

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

The prediction of bankruptcy for financial firms especially banks has been the extensively researched area since late 1960s [94]. Creditors, auditors, stockholders and senior management are all interested in bankruptcy prediction because it affects all of them alike [95]. Lensberg et al. (2006) [96] choose six variables from twenty-eight variables by using genetic programming for bankruptcy prediction and find that GP is better than the traditional probit model. The performance of bankruptcy prediction fully depends on the input variables. In literature [97,98,] (Jo & Han, 1996; Mina, 2005, Park & Han, 2002), there are many cases which have difficulties in economic interpretation, but are significant to classify business units into bankruptcy or non-bankruptcy group.

Kusan [99] developed a new grading model for predicting selling price of house-building. Fuzzy logic systems, considering the city plans, the nearness to cultural, medical, training and educational buildings, the public transportations systems, the other environmental factors and the increased technological upgrading deals with information about construction, have been employed in order to construct the model and achieve the aim. In the evaluation of real estate price, the applicability of ANN and FL has been proved and determined that appropriate results obtained by using artificial intelligence methods. Moreover, it is concluded that the performance of the multi regression application for house prices is quite well (Lokshina, Hammerslag, & Insinga, 2003) [100]. In one of the interesting control applications of neuro-fuzzy networks by Arora and Mehta [101] the Air-Fuel Ratio was determined for Combustion Engines and if it is not found to be adequate for combustion, surplus or deficit amount of air is calculated to be passed to combustion chamber to avoid emission of harmful gases.

Kangji [102] presented a hybrid genetic algorithm, adaptive network-based fuzzy inference system (GA-ANFIS) in building energy prediction. They suggested a hierarchical structure of ANFIS to solve the curse-of-dimensionality and found better performance of proposed technique as compared to Artificial Neural Networks using two different kinds of data sets. In another work, Biu et al. [103] carried out Landslide susceptibility mapping using ANFIS and found ANFIS models with the Sigmf and Gaussmf to have good prediction capability. Mohandes et al. [104] modeled wind profile up to a height of 100 m using ANFIS to compare estimated values with 1/7th law and experimental wind shear method.

Hosoz [105] predicted the performance of a vapor-compression refrigeration system with a cooling tower using an ANFIS model including the evaporating temperature, compressor power and coefficient of performance. The predictions agreed well with the experimental data.

Method of classification and prediction usually involve a number of parameters. However, not all of these features are equally important to achieve the required result. There can be many reasons for that; some of the parameters may be redundant, while some others may follow the same behavior. To experience good performance from the built model, it is better to identify and discard such parameters. Another benefit of feature selection is reduction in dimensionality of input data which relaxes the complexity of the problems and hence needs less computation effort. Parameter selection have been studied and applied by (Chen, Somol) [106,107] using methods like Branch and Bound, (Estevez, Fleuret) [108,109] using mutual information, (Lindenbaum, Tahir) [110,111] using nearest neighborhood method, (Huang, Raymer) [112,113] using genetic algorithm and many more.

The performance of ANNs hybridized with other techniques can be improved in the light of right choice of input parameters. Additionally, smallest number of parameters increases the response time of the system. Feature selection has been studied and used to explore the effect of irrelevant attributes on the performance of systems (Acir et al., 2006, Valentini et al., 2004) [114,115]. Among the commonly used methods for dimensionality reduction and parameter selection are Linear Discriminant Analysis (Lotlikar, Lu) [116,117], MDA (Song, Yan) [118,119], ICA and PCA (Capar, Kim) [120,121], etc. Statistical techniques such as regression analysis [122], logistic regression [123] are employed in the past which typically make use of the company's financial data to predict the financial state of the company. The usage of MDA or statistical techniques, in general, relies on the restrictive assumption on linear seperability, multivariate normality and independence of the predictive variables [124,125]. McKee [126] employed rough set theory to predict corporate bankruptcy and concluded that it significantly outperformed a recursive partitioning model.

A lot of research has been carried out to study the strengths of neuro-fuzzy networks. The scope of integration of these two techniques cannot be limited to specific type of applications or to certain domain. There are lot of neural networks which can be possibly combined with fuzzy logic to

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

take the advantage of the two extremes. These models may result into fruitful applications in their respective areas.

III. CONCLUSIONS

Neuro-fuzzy networks have shown a great deal of success in their applications in wide range of problem areas. The common problems faced in the models studied are long training periods and sometimes over-fitting. A neuro-fuzzy network is in a way a neural network with multiple layers and with the size of network and complexity of the problem, the limitation of neural networks may increase. The Integration of neural network with fuzzy logic comes up with solution of their individual limitations but the problem of local minima remains the same. Some data pre-processing techniques can be applied on the training data before it is used to train the network. This may possibly reduce the training time and hence the convergence time of the neuro-fuzzy network. Secondly, choosing the right parameter values can play an important role during training. Although this may take some trials, but once the values of these parameters are fixed, the network can give expected performance.

From the view point of business, there are lots of real world problems full of vagueness and uncertainty which need good attention these days. To deal with these problems where decision-making using classical methods fail some hybrid soft computing models can come up. In this view, it is not suggested to abandon all these classical methods at once. Instead, business people can think of giving due attentions to fuzziness in their business by proper utilization of these models.

REFERENCES

[1] S. M. Metev and V. P. Veiko, *Laser Assisted Microtechnology*, 2nd ed., R. M. Osgood, Jr., Ed. Berlin, Germany: Springer-Verlag, 1998.

[2] Sumathi, S., Paneerselvam, S., (2010), Computational Intelligence Paradigms: Theory & Applications using MATLAB.

[3] Fortuna, L., Rizzotto, G., Lavorgna, M., Nunnari, G., Xibilia, G.M., Caponetto, R., (2001), Soft Computing: New Trends and Applications, Springer-Verlag London Berlin Heidelberg.

[4] Zadeh, L.A., (1998), Forward in: E. Orlowska (Ed.), Incomplete Information: Rough Set Analysis, Physica-Verlag, Heidelberg, pp. 5-6.

[5] Abraham, A., Philip, S., Mahanti, P.K., (2004), Soft Computing Models for Weather Forecasting, International Journal of Applied Science and Computations, USA, 11(3), pp. 106-117.

[6] Jang, R., Sun, C.T., Mizutani, E., (1997), Neuro-Fuzzy and soft Computing: A Computational Approach to Learning and Machine Intelligence.

[7] Klir, G., (1989), Is There More to Uncertainty than Some Probability Theorists Would Have Us Believe? International Journal of General Systems, 15(4), pp. 347-378.

[8] Bellman, R. and Zadeh, L.A., (1970), Decision making in a fuzzy environment, Management Science, Vol. 17, pp. 141–164.

[9] Zadeh, L.A. (1965), Fuzzy sets, Information and Control, Vol. 8 (3), pp. 338–353.

[10] McCulloch, W. and Pitt, W., (1943), A logical calculus of the idea immanent in nervous activity, Bulletin of Mathematical Biophysics, Vol. 5, pp. 115-133.

[11] Graupe, D., (2007), Principles of Artificial Neural Networks, Second Edition, Advanced Series on Circuits and Systems, Vol. 6, World Scientific.

[12] Paulo, J.G., Lisboa, E.C.I., Piotr, S.S. (2000), Artificial Neural Networks in Biomedicine, Springer, London.

[13] Gareta, R., Romeo, L. M., & Gil, A. (2006), Forecasting of electricity prices with neural networks. Energy Conversion and Management, 47, pp. 1770–1778.

[14] Ham, F., & Kostanic, I. (2001), Principles of neurocomputing for science & engineering, McGraw-Hill.

[15] Ataei, Sh., Aghakouchak, A.A., Marefat, M.S., Mohammadzadeh, S. (2005), Sensor fusion of a railway bridge load test using neural networks, Expert Systems with Application, Vol. 29, pp. 678-683.

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

[16] Garcia, C., Delakis, M., (2004), Convolutional face finder: A neural architecture for fast and robust face detection, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.26(11), pp. 1408–1423.

[17] Kai, Z., Jianchun, P., Feng, S., (2000), Short-term load forecast based pattern recognition, Human Power system, Vol. 20(6), pp.1-12.

[18] Frate, F.D., Pacifici, F., Schiavon, G., and Solimini, C., (2007), Use of Neural Networks for Automatic Classification From High-Resolution Images, IEEE Transactions on Geoscience and Remote Sensing, Vol. 45(4), pp. 800-809.

[19] Lu, H., Setiono, R., and Liu, H. (1996), Effective Data Mining Using Neural Networks, IEEE Transactions on Knowledge and Data Engineering, Vol. 8(6), pp. 957-961.

[20] Reyes-Aldasoro, C.C., Ganguly, A.R., Lemus, G., Gupta, A. (1999), A hybrid model based on dynamic programming, neural networks, and surrogate value for inventory optimization applications, Journal of the Operational Research Society, Vol. 50, pp. 85-94.

[21] Khomfoi, S., Tolbert, L.M. (2007), Fault Diagnostic System for a Multilevel Inverter Using a Neural Network, IEEE Transactions on Power Electronics, Vol. 22(3), pp.1062-1069.

[22] Zhang, Y., Su, H. (2010), Turbo-generator vibration fault diagnosis based on PSO-BP neural networks, WSEAS Transactions on Systems and Control archive, Vol. 5(1), pp. 37-47.

[23] Aburto, L., Weber, R. (2007), Improved supply chain management based on hybrid demand forecasts, Applied Soft Computing, Vol. 7(1), pp.136–144.

[24] Azadeh, A., Ghaderi, S.F., Sohrabkhani, S. (2007), Forecasting electrical consumption by integration of neural network, time series and ANOVA, Applied Mathematics and Computation, Vol.186, pp. 1753–1761.

[25] Palmer, A., Montano, J.J., Sese, A. (2006), Designing an artificial neural network for forecasting tourism time series, Tourism Management, Vol.27, pp. 781–790.

[26] Xiao, Z., Ye, S.J., Zhong, B., Sun, C.X. (2009), BP neural network with rough set for short term load forecasting, Expert Systems and Applications, Vol. 36(1), pp. 273–279

[27] Xu, K., Xie, M., Tang, L.C., Ho, S.L. (2003), Application of neural networks in forecasting engine systems reliability, Applied Soft Computing, Vol. 2(4), pp. 255-268.

[28] Chen, Q., Mynett, A.E. (2003), Integration of data mining techniques and heuristic knowledge in fuzzy logic modelling of eutrophication in Taihu Lake, Ecological Modelling, Vol. 162(1–2), pp. 55–67.

[29] Doring, C., Lesot, M. J., Kruse, R. (2006), Data analysis with fuzzy clustering methods, Computational Statistics & Data Analysis, Vol. 51(1), pp. 192-214.

[30] Nasibov, E.N. (2011), Fuzzy Logic in Statistical Data Analysis, International Encyclopedia of Statistical Science, pp. 558-563.

[31] Rokach, L. (2010), Using Fuzzy Logic in Data Mining, Data Mining and Knowledge Discovery Handbook, pp. 505-520.

[32] Burillo, P., Frago, N., Fuentes, R. (2003), Fuzzy Morphological Operators in Image Processing, Mathware & Soft Computing, Vol. 10, pp. 85-100.

[33] Oueslati, S., Cherif, A., Solaiman, B. (2010), Maximizing Strength of Digital Watermarks using Fuzzy Logic, Signal & Image Processing: An International Journal, Vol. 1(2), pp.112-124.

[34] Delgado, G., Aranda, V., Calero, J., Sanchez, M.M., Serrano, J.M., Sanchez, D., Vila, M.A. (2008), Building a fuzzy logic information network and a decision-support system for olive cultivation in Andalusia, Spanish Journal of Agricultural Research, Vol. 6(2), pp. 252-263.

[35] Kumara, D., Singha, J., Singha, O.P., Seema, (2013), A fuzzy logic based decision support system for evaluation of suppliers in supply chain management practices, Mathematical and Computer Modelling, Vol. 57(11–12), pp. 2945–2960.

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

[36] Kapitanovaa, K., Sona, S.H., Kangb, K.D. (2012), Using fuzzy logic for robust event detection in wireless sensor networks, Ad Hoc Networks, Vol. 10(4), pp. 709–722.

[37] Kim, J., Park, S., Han, Y., Chung, T. (2008), CHEF: cluster head election mechanism using fuzzy logic in wireless sensor networks, ICACT, pp. 654–659.

[38] Naranjo, J.E. Gonzalez, C., García, R. and Pedro, T.D. (2007), Using Fuzzy Logic in Automated Vehicle Control, IEEE Intelligent Systems, pp. 36-45.

[39] Yasunobu, S., Miyamoto, S., Ihara, H. (2002), A Fuzzy Control for Train Automatic Stop Control, Transaction of the Society of Instrument and Control Engineers, Vol.E-2(1).

[40] Arora, N. (2009), Regulating air-fuel balance in combustion engines using adaptive learning in neural network, Proceeding of International Conference on Methods and Models in Computer Science, ICM2CS 2009, pp.1-6.

[41] Miller, W. T., Hewes, R. P., Glanz, F. H., Graft, L. G. (1990), Real time dynamic control of an industrial manipulator using a neural network-based learning controller. IEEE Transactions on Robotic and Automation, Vol. 6, pp. 1–6.

[42] Kolcz, A., & Allinson, N. M. (1994), Application of the CMAC input encoding scheme in the N-tuple approximation network. IEE Proceedings – Computer and Digital Techniques, Vol. 141, pp. 177–183.

[43] Glanz, F. H., Miller, W. T., Graft, L.G. (1991), An overview of the CMAC neural network. Proceedings of IEEE on Neural Networks and Ocean Engineering, pp. 301–308.

[44] Iiguni, Y. (1996), Hierarchical image coding via cerebellar model arithmetic computers. IEEE Transactions on Image Processing, Vol. 5, pp. 1393–1401.

[45] Reay, D. (1995), Nonlinear channel equalization using associative memory neural networks. In Proceedings of international workshop on applied neural networks and telecommunications, pp. 17–24.

[46] Pelikan, E., Groot, C.D., Wurtz, D. (1992), Power consumption in West-Bohemia: improved forecasts decorrelating connectionist networks, Neural Network World, 2, pp. 701–712.

[47] Clemen, R. (1989), Combining forecasts: a review and annotated bibliography with discussion, International Journal of Forecasting, Vol. 5, pp. 559–608.

[48] Baek, J., Cho, S. (2003), Bankruptcy prediction for credit risk using an auto associative neural networks in Korean firms, in: IEEE International Conference on Computational Intelligence for Financial Engineering, Hong-Kong.

[49] Perrone, M.P., Cooper, L.N. (1993), When networks disagree: ensemble methods for hybrid neural networks, in: R.J. Mammone (Ed.), Neural Networks For Speech and Image Processing, Chapman Hall, pp. 126–142.

[50] Breiman, L. (1996), Bagging predictors, Machine Learning, Vol. 24, pp. 123–140.

[51] Yu, L., Wang, S.Y., Lai, K.K. (2005), A novel non-linear ensemble forecasting model incorporating GLAR and ANN for foreign exchange rates, Comput. Oper. Res, Vol. 32(10), pp. 2523–2541.

[52] Benitez, J.M., Castro, J.L., Requena, I. (1996), Translation of artificial neural networks into fuzzy additive systems, In Proceedings of IPMU96-information processing and management of uncertainty in knowledge-based systems, pp. 156–168.

[53] Lim, M.H., Rahardja, S., Gwee, B.H. (1996). A GA paradigm for learning fuzzy rules. Fuzzy Sets and Systems, Vol. 82, pp. 177–186.

[54] Ahn, B.A., Cho, S.S., Kim, C.Y. (2000), The integrated methodology of rough set theory and artificial neural network for business failure prediction, Expert Systems and Applications, Vol. 18, pp. 65–74.

[55] Cheng, C. B., Chen, C. L., & Fu, C. J. (2006), Financial distress prediction by a radial basis function network with logit analysis learning, Computers and Mathematics with Applications, Vol. 51, pp. 579–588.

[56] Abraham, A., Nath, B. (2001), A Neuro-fuzzy approach for modelling electricity demand in Victoria, Applied Soft Computing, Vol. 1, pp. 127–138.

[57] Kukolj, D. (2002), Design of adaptive Takagi–Sugeno–Kang fuzzy models, Applied Soft Computing, Vol. 2, pp. 89–103.

[58] Mitra, S., Hayashi, Y. (2000), Neuro-fuzzy rule generation: survey in soft computing framework, IEEE Transactions on Neural Networks, Vol. 11, pp. 748–768.

[59] Kumar, P.R., Ravi, V. (2007), Bankruptcy prediction in banks and firms via statistical and intelligent techniques-A review, European journal of Operational Research, Vol. 180, pp. 1–28.

[60] Kurt, I., Ture, M., Kurum, A.T. (2008), Comparing performances of logistic regression, classification and regression tree, and neural networks for predicting coronary artery disease. Expert Systems with Applications, Vol. 34(1), pp. 366–374.

[61] Atiya, A.F. (2001), Bankruptcy Prediction for Credit Risk Using Neural Networks: A Survey and New Results, IEEE Transactions on Neural Networks, Vol. 12(4).

[62] Purvinis, O., Virbickaite, R., Sukys, P. (2008), Interpretable Nonlinear Model for Enterprise Bankruptcy Prediction, Nonlinear Analysis: Modeling and Control, Vol. 13(1), pp. 61–70.

[63] Shaw, M. J. and Gentry, J., (1988), Using an expert system with inductive learning to evaluate business loans, Financial Management, Vol. 17(3), pp. 45-56.

[64] Shin, K.S., Lee, T.S. and Kim, H.J. (2005), An application of support vector machines in bankruptcy prediction model, Expert Systems with Applications, Vol. 28, pp. 127-135.

[65] Toosi, A.N., Kahani, M. (2007), A new approach to intrusion detection based on an evolutionary soft computing model using neuro-fuzzy classifiers, Computer Communications, Vol. 30(10), pp. 2201-2212.

[66] Yun, S., Lee, J., Chung, W., Kim, E., Kim, S. (2009), A soft computing approach to localization in wireless sensor networks, Expert Systems with Applications, Vol. 36(4), pp. 7552-7561.

[67] Hui, D., Fuchun, S., Zengqi, S. (2002), Observer-based adaptive controller design of flexible manipulators using time-delay neuro-fuzzy networks, Journal of Intelligent Robotic System, Vol.34(4), pp. 453–466.

[68] Sadati,N., Ghadami, R. (2008), Adaptive multi-model sliding mode control of robotic manipulators using soft computing, Neurocomputing, Vol. 71(13–15), pp. 2702-2710.

[69] Subudhi, B., Morris, A.S. (2009), Soft computing methods applied to the control of a flexible robot manipulator, Applied Soft Computing, Vol. 9(1), pp.149-158.

[70] Miller, K., Joldes, G., Lance, D. and Wittek, A. (2007), Total Lagrangian explicit dynamics finite element algorithm for computing soft tissue deformation. Communications in Numerical Methods in Biomedical Engineering, Vol. 23, pp. 121–134.

[71] Uzoka, F.M.E., Osuji, J., Obot, O. (2011), Clinical decision support system (DSS) in the diagnosis of malaria: A case comparison of two soft computing methodologies, Expert Systems with Applications, Vol. 38(3), pp. 1537-1553.

[72] Chen, C.W., Chen, P.C., Chiang, W.L. (2013), Modified intelligent genetic algorithm-based adaptive neural network control for uncertain structural systems, Journal of Vibration and Control, Vol. 19(9), pp. 1333-1347.

[73] Fadare, D.A. (2010), The application of artificial neural networks to mapping of wind speed profile for energy application in Nigeria, Applied Energy, Vol. 87(3), pp. 934-942.

[74] Oh, H.J., Pradhan, B. (2011), Application of a neuro-fuzzy model to landslide-susceptibility mapping for shallow landslides in a tropical hilly area, Computers & Geosciences, Vol. 37(9), pp. 1264-1276.

[75] Baskar, G., Mohan, M.R. (2009), Contingency constrained economic load dispatch using improved particle swarm optimization for security enhancement,

ISSN: 2321-9653

Electrical Power System Research, Vol. 79 (4), pp. 615–621.

[76] Kucuktezcan, C.F., Istemihan G.V.M. (2012), A new dynamic security enhancement method via genetic algorithms integrated with neural network based tools, Electric Power Systems Research, Vol. 83(1), pp. 1-8.

[77] Doulamis, A.; Doulamis, N.; Kollias, S.D. (2000), On-line retrainable neural networks: improving the performance of neural networks in image analysis problems, IEEE Transactions on Neural Networks, Vol. 11(1), pp. 137-155.

[78] Parisi, R., Di Claudio, E.D., Lucarelli, G., Orlandi, G. (1998), Car plate recognition by neural networks and image processing, Proceedings of the IEEE International Symposium on Circuits and Systems, Vol. 3, pp. 195-198.

[79] Yu, P.T., Tsai, H.H., Lin, J.S. (2001), Digital watermarking based on neural networks for color images, Signal Processing, Vol. 81(3), pp. 663-671.

[80] Kirkpatrick, L.D., Wheeler, G.F. (1992), Physics: A World View, Saunders College Publishing.

[81] Sugeno, M., Tanaka, K. (1991), Successive identification of a fuzzy model and its applications to predictions of complex systems, Fuzzy Sets and Systems, Vol. 42(3), pp. 315–334.

[82] Sugeno, M., Yasukawa, T. (1993), A fuzzy-logic-based approach to qualitative modeling, IEEE Transactions on Fuzzy System, Vol. 1(1), pp. 7–31.

[83] Thiesing, F.M., Vornberger, O. (1997), Sales forecasting using neural networks, International Conference on Neural Networks, Vol. 4, pp. 2125–2128.

[84] Jang, J.S.R., (1993), ANFIS: adaptive-network-based fuzzy inference system, IEEE Transactions on Systems, Man, and Cybernetics, Vol. 23(3), pp. 665–685.

[85] Takagi, T. and Sugeno, M. (1985), Fuzzy identification of systems and its applications to modeling and control, IEEE Transactions on Systems, Man, and Cybernetics, Vol .15, pp. 116–132.

[86] Carpenter, G.A., Grossberg, S., Markuzon, N., Reynolds, J.H., Rosen, D.B., (1992), Fuzzy ARTMAP: a neural network architecture for incremental supervised learning of analog multidimensional maps, IEEE Transactions on Neural Networks Vol. 3(5), pp. 698–713.

[87] Kasuba, T., (1993), Simplified fuzzy ARTMAP, AI Expert, Vol. 8(11), pp. 19–25.

[88] Wang, W.P., Chen, Z. (2008), A neuro-fuzzy based forecasting approach for rush order control applications, Expert Systems with Applications, Vol. 35, pp. 223–234.

[89] Daoming, G., Jie, C. (2006), ANFIS for high-pressure waterjet cleaning prediction, Surface & Coatings Technology, Vol. 201, pp. 1629-1634.

[90] Khajeh, A., Modarress, H. (2010), Prediction of solubility of gases in polystyrene by Adaptive Neuro-Fuzzy Inference System and Radial Basis Function Neural Network, Expert Systems with Applications, Vol. 37, pp. 3070–3074.

[91] Chang, F.J., Chang, Y.T. (2006), Adaptive neuro-fuzzy inference system for prediction of water level in reservoir, Advances in Water Resources, Vol. 29, pp. 1–10.

[92] Wua, J.D., Hsu, C.C., Chen, H.C. (2009), An expert system of price forecasting for used cars using adaptive neuro-fuzzy inference, Expert Systems with Applications, Vol. 36, pp. 7809–7817.

[93] Wang, Y.M., Taha, M.S., Elhag (2008), An adaptive neuro-fuzzy inference system for bridge risk assessment, Expert Systems with Applications, Vol. 34, pp. 3099–3106.

[94] Arora N., Vij, S. (2013), Reckoner for health risk and insurance premium using adaptive neuro-fuzzy inference system, Journal of Neural Computing and Applications, Springer London, Vol. 23(7-8), pp. 2121-2128.

[95] Altman, E. (1968), Financial ratios, discriminant analysis, and the prediction of corporate bankruptcy, Journal of Finance, Vol. 23, pp. 589–609.

[96] Swicegood, P.G. (1998), Predicting poor bank profitability: a comparison of neural network,

discriminant analysis and professional human judgement, Ph.D. Thesis, Department of Finance, Florida State University.

[97] Lensberg, T., Eilifsen, A., McKee, T.E. (2006). Bankruptcy theory development and classification via genetic programming, European Journal of Operational Research, Vol. 169, pp. 677–697.

[98] Jo, H., Han, I. (1996), Integration of case-based forecasting, neural network, and discriminant analysis for bankruptcy prediction, Expert Systems with Applications, Vol. 11, pp. 415–422.

[99] Mina, J.H., Lee, Y.C. (2005), Bankruptcy prediction using support vector machine, Expert Systems with Applications, Vol. 28, pp. 603–614.

[100] Kusan, H., Aytekin, O., Ozdemir, I., (2010), The use of fuzzy logic in predicting house selling price, Expert Systems with Applications, Vol. 37, pp. 1808–1813.

[101] Lokshina, I.V., Hammerslag, M.D., Insinga, R.C. (2003), Applications of artificial intelligence methods for real estate valuation and decision support, In Hawaii international conference on business, Honolulu.

[102] Arora, N., Mehta, S. (2013), Air fuel ratio detector corrector for combustion engines using adaptive neuro-fuzzy networks, An International Journal of Optimization and Control: Theories & Applications, Vol. 3(2), pp. 85–97.

[103] Kangji Li, Hongye Su, Jian Chu, (2011), Forecasting building energy consumption using neural networks and hybrid neuro-fuzzy system: A comparative study, Energy and Buildings, Vol. 43(10), pp. 2893-2899,

[104] Bui, D.T., Pradhan, B., Lofman, O., Revhaug, I., Dick, O.B. (2012), Landslide susceptibility mapping at Hoa Binh province (Vietnam) using an adaptive neuro-fuzzy inference system and GIS, Computers & Geosciences, Vol. 45, pp. 199-211.

[105] Mohandes, M., Rehman, S., Rahman, S.M. (2011), Estimation of wind speed profile using adaptive neuro-fuzzy inference system, Applied Energy, Vol. 88(11), pp. 4024-4032,

[106] Hosoz, M. Ertunc, H.M., Bulgurcu, H., (2011), An adaptive neuro-fuzzy inference system model for predicting the performance of a refrigeration system with a cooling tower, Expert Systems with Applications, Vol. 38(11), pp. 14148-14155.

[107] Chen, X.W. (2003), An improved branch and bound algorithm for feature selection, Pattern Recognition Letters, Vol. 24(12), pp. 1925–1933.

[108] Somol, P., Pudil, P., Kittler, J. (2004), Fast branch & bound algorithms for optimal feature selection, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 26(7), pp. 900-912.

[109] Estevez, P.A., Tesmer, M., Perez, C.A., Zurada, J.M. (2009), Normalized Mutual Information Feature Selection, IEEE Transactions on Neural Networks, Vol. 20(2), pp. 189-201.

[110] Fleuret, F. (2004), Fast Binary Feature Selection with Conditional Mutual Information, The Journal of Machine Learning Research archive, Vol. 5, pp. 1531-1555.

[111] Lindenbaum, M., Markovitch, S., Rusakov, D. (2004), Selective Sampling for Nearest Neighbor Classifiers, Machine Learning, Vol. 54(2), pp. 125-152.

[112] Tahir, M.A., Bouridane, A., Kurugollu, F. (2007), Simultaneous feature selection and feature weighting using Hybrid Tabu Search/K-nearest neighbor classifier, Pattern Recognition Letters, vol. 28, pp. 438–446.

[113] Huang, C.L., Wang, C.J. (2006), A GA-based feature selection and parameters optimization for support vector machines, Expert Systems with Applications, Vol. 31(2), pp. 231-240.

[114] Raymer, M.L., Punch, W.F., Goodman, E.D., Kuhn, L.A., Jain, A.K. (2000), Dimensionality reduction using genetic algorithms, IEEE Transactions on Evolutionary Computation, Vol. 4(2), pp. 164-171.

[115] Acir, N., Ozdamar, O, Guzelis, C. (2006), Automatic classification of auditory brainstem responses using SVM-based feature selection algorithm for threshold detection Engineering Applications of Artificial Intelligence, Vol. 19, pp. 209–218.

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

[116] Valentini, G. Muselli, M., Ruffino, F. (2004), Cancer recognition with bagged ensembles of support vector machines Neurocomputing, Vol. 56, pp. 461–466.

[117] Lotlikar, R., Kothari, R. (2000), Fractional-step dimensionality reduction, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 22(6), pp. 623-627.

[118] Lu, J., Plataniotis, K.N., Venetsanopoulos, A.N. (2003), Face recognition using LDA-based algorithms, IEEE Transactions on Neural Networks, Vol. 14(1), pp.195-200.

[119] Song, Y., Nie, F., Zhang, C., Xiang, S. (2008), A unified framework for semi-supervised dimensionality reduction, Pattern Recognition, Vol. 41(9), pp. 2789-2799.

[120] Yan, S., Xu, D., Yang, Q., Zhang, L., Tang, X., Zhang, H.J. (2007), Multilinear Discriminant Analysis for Face Recognition, IEEE Transactions on Image Processing, Vol. 16(1), pp. 212-220.

[121] Capar, A., Ayvaci, A., Kahraman, F., Demirel, H., Gokmen, M. (2004), Linear dimension reduction methods in character recognition systems, Proceedings of the IEEE 12th Conference on Signal Processing and Communications Applications, pp. 611-614.

[122] Kim, H.C., Kim, D., Bang, S.Y. (2003), Extensions of LDA by PCA mixture model and class-wise features, Pattern Recognition, Vol. 36(5), pp. 1095-1105.

[123] Korobow, L., Stuhr, D., Martin, D. (1976), A probabilistic approach to early warning changes, in: Bank Financial Condition, Federal Reserve Bank of New York, pp. 187–194.

[124] Pantalone, C.C., Platt, M.B. (1987), Predicting commercial bank failure since deregulation, New England Economic Review, pp. 37–47.

[125] Karels, G.V., Prakash, A.J. (1987), Multivariate normality and forecasting of business bankruptcy, Journal of Business, Finance & Accounting, Vol. 14, pp. 573–593.

[126] Odom, M., Sharda, R. (1990), A neural network for bankruptcy prediction, in: IJCNN International Conference on Neural Networks, San Diego, CA.

[127] McKee, T.E. (2000), Developing a bankruptcy prediction model via rough set theory, International Journal of Intelligent Systems in Accounting Finance and Management, Vol. 9, pp. 159–173.