

## **A Review of Training Methods of ANFIS for Applications in Business and Economics**

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### **Abstract**

*Fuzzy Neural Networks (FNNs) techniques have been effectively used in applications that range from medical to mechanical engineering, to business and economics. Despite of attracting researchers in recent years and outperforming other fuzzy systems, Adaptive Neuro-Fuzzy Inference System (ANFIS) still needs effective parameter training and rule-base optimization methods to perform efficiently when the number of inputs increase. Moreover, the standard gradient based learning via two pass learning algorithm is prone slow and prone to get stuck in local minima. Therefore many researchers have trained ANFIS parameters using metaheuristic algorithms however very few have considered optimizing the ANFIS rule-base. Mostly Particle Swarm Optimization (PSO) and its variants have been applied for training approaches used. Other than that, Genetic Algorithm (GA), Firefly Algorithm (FA), Ant Bee Colony (ABC) optimization methods have been employed for effective training of ANFIS networks when solving various problems in the field of business and finance.*

**Keywords:** ANFIS; fuzzy; metaheuristic; optimization; training

### **1. Introduction**

Fuzzy Neural Networks (FNNs) based models have been designed to solve problems in business and economics. The applications are found in stock market prediction, supply chain management, profit maximization, bankruptcy prediction of firms, electric load forecasting *etc.* [1-2]. Among other fuzzy systems, Adaptive Neuro-Fuzzy Inference System (ANFIS) is more frequently used technique since it is computationally less expensive, transparent, and produces results as robust as statistical models [3-4]. These systems have even evolved in their characteristics like flexibility, speed, and adaptability [5]. After designing and testing ANFIS systems, Neshat *et al.* [6] found that the results were better than other fuzzy expert systems. Moreover, ANFIS can be interpreted as local linearization model for model estimation, thus it has a good applicability in system modeling. The efficient design of ANFIS based models requires effective parameter training for enhanced accuracy. The standard parameter learning process of ANFIS, which uses derivative based learning, has high probability of falling in local minima. The derivative-free techniques, using metaheuristic algorithms, are more powerful in this case [7].

This paper surveys various ANFIS training and optimization methods used while solving problems in business and economics. The rest of this study is organized as follows. In Section 2, the concept of ANFIS and its training mechanism is explained. Section 3 provides an overview of the training approaches applied on ANFIS. Applications of ANFIS in business and finance are reviewed in Section 4. Section 5 duly concludes this study.

## 2. The Concept of ANFIS

Jang introduced ANFIS in 1993 [8], which can approximate every plant with the help of effective parameter training and the adequate number of rules [9, 10]. Because, the number of parameters determine the cost of training, therefore, Gaussian type of membership function (MF) is used more often than other types of MFs; as it uses only two parameters [3].

### 2.1. ANFIS Structure

ANFIS is a framework of neuro-fuzzy model which adapts itself through learning. Its architecture consists of two types of nodes: fixed and adaptable as shown in Figure 1. To better understand ANFIS, the two fuzzy if-then rules are considered here.

$$\text{Rule 1: If } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f = p_1x + q_1y + r_1$$

$$\text{Rule 2: If } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f = p_2x + q_2y + r_2$$

The above mentioned rules can also be rewritten in terms of membership degrees as:

$$\text{Rule 1: If } \mu_{A_1}(x) \text{ and } \mu_{B_1}(y) \text{ then } f = p_1x + q_1y + r_1$$

$$\text{Rule 2: If } \mu_{A_2}(x) \text{ and } \mu_{B_2}(y) \text{ then } f = p_2x + q_2y + r_2$$

where  $A_i$  and  $B_i$  are MFs; and  $p_i, q_i, r_i$  are the parameters of the consequent part of fuzzy rules. The nodes of layer 1 (MFs layer) and layer 4 (consequent layer) are adaptable, whereas the nodes of layer 2 (product layer) and layer 3 (normalization layer) are fixed. The five layer architecture of ANFIS is explained as following:

Layer 1: Each node  $i$  of this layer is a parameterized MF *i.e.*, Triangle, Trapezoidal, Gaussian, or generalized Bell function. The parameters of MFs are referred to as premised parameters.

$$\begin{aligned} O_{1,i} &= \mu_{A_i}(x), & i &= 1,2 \\ O_{1,i} &= \mu_{B_{i-2}}(y), & i &= 3,4 \end{aligned} \quad (1)$$

In case Gaussian shape of MFs (Eq. 2), the two parameters  $\{c, \sigma\}$  are premise parameters, which are trained during the process of learning.

$$\text{gaussian}(x; c, \sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \quad (2)$$

Layer 2: The nodes of this layer are product  $\prod$  which calculate the firing strength of a rule.

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1,2 \quad (3)$$

The auto-generated rules, using grid partitioning, are  $m^n$  where  $m$  is the number of MFs in each input and  $n$  is the total number of inputs.

Layer 3: Each node, represented as  $N$ , normalizes the firing strength of a rule by calculating the ratio of the  $i$ th rule's firing strength to the sum of all rules' firing strength.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \quad (4)$$

where  $w_i$ ,  $w_1$ ,  $w_2$ , and  $\bar{w}$  are  $i$ th rule's firing strength, firing strength of first rule, firing strength of second rule, and the normalized firing strength of  $i$ th rule, respectively.

Layer 4: These nodes of this layer represent consequent part of a fuzzy rule with node function  $f_i = p_i x + q_i y + r_i$

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i), \quad i = 1, 2. \quad (5)$$

where  $\bar{w}$  is the normalized firing strength of  $i$ th rule, and  $\{p_i, q_i, r_i\}$  is a first order polynomial of  $i$ th rule's consequent part. The parameters  $\{p_i, q_i, r_i\}$  are identified during the training process of ANFIS.

Layer 5: This node only does the summation of outputs of all the rules from previous layer.

$$O_{5,i} = \sum_{i=1}^2 \bar{w}_i f_i = \frac{\sum_{i=1}^2 \bar{w}_i f_i}{w_1 + w_2} \quad (6)$$

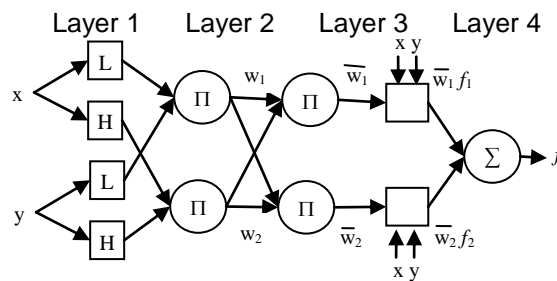


Figure 1. ANFIS Architecture [11]

## 2.2. ANFIS Learning

ANFIS learns by identifying its adaptable parameters, such as  $c$ ,  $\sigma$  and  $\{p_i, q_i, r_i\}$  in order to minimize the error between actual and the desired output. The standard two pass learning process of ANFIS uses a hybrid of gradient descent (GD) and least squares estimator (LSE) (Table 1).

Table 1. Two Pass Hybrid Learning Algorithm for ANFIS [17]

|                       | Forward Pass | Backward Pass |
|-----------------------|--------------|---------------|
| Antecedent Parameters | Fixed        | GD            |
| Consequent Parameters | LSE          | Fixed         |
| Signals               | Node Outputs | Error Signals |

As shown in the above table, the consequent parameters are updated by LSE in forward pass. Whereas, the premise parameters are trained using GD, in backward pass, using back-propagation (BP) method. The identification of the premise parameters is influenced by BP algorithm of ANN, which has drawback to be likely trapped in local minima [9].

In order to minimize error and increase performance, there is a need of effective training method of ANFIS [10]. Therefore, many researchers have proposed various approaches of training the ANFIS network using metaheuristic algorithms alone, and also in the hybrid of gradient methods.

### 3. Training Methods of ANFIS

Structure learning and parameters identification are the two dimensions of ANFIS training. Some have focused on either of the two dimensions, while others have tried to work on both of the issues. But, keeping balance, between reducing the complexity of the ANFIS structure and increasing its accuracy by parameter tuning, is often a challenge.

The original ANFIS proposed by Jang [8] uses hybrid learning, which uses GD for tuning antecedent parameters and LSE for identifying the consequent parameters. However, the drawbacks of GD (complexity and tendency to trap in local minima) have opted the researchers to different alternatives. These alternatives comprise of metaheuristic algorithms. The basic idea of population based optimization algorithms is to create a population of solution candidates. The solution candidates iteratively explore the search space and exchange information, thus chances of converging on the global minima are significantly increased.

Extensive literature review shows that a variety of metaheuristic algorithms have been integrated with ANFIS, such as PSO, GA, ABC, and their variants, for a range of problems of prediction, classification, and control. Mostly, PSO and its variants have been applied on ANFIS training and optimization. As literature shows, [12-15] have used PSO in combination with LSE to modify the antecedent and the consequent parameters of ANFIS models, respectively. They just focused on parameter learning, and did not optimize fuzzy rule-set. They developed ANFIS based prediction models for predicting electricity prices, wind power and customer satisfaction for a new product. Turki *et al.* [16] and Rini *et al.* [17] applied PSO alone for training both the premise and consequent parameters of ANFIS based models. Rini, Shamsuddin [17] also used PSO for ANFIS training. In addition to parameter identification, they also optimized fuzzy rule-base by applying threshold value on the rules' firing strength.

Other than the standard PSO, its variants have also been employed to ANFIS learning. Bagheri *et al.* [18] proposed Foreign Exchange Market trend forecasting system using ANFIS tuned by Quantum-behaved PSO (QPSO). Whereas, Liu, Leng [10] improved QPSO for tuning MFs, and identified consequent parameters by LSE. Another variant of PSO, Adaptive Weighted PSO (AWPSO) with Forgetting Factor Recursive Least Square (FFRLS) which one of least square methods, was proposed by Shoorehdeli, Teshnehlab [7] to identify the premise and consequent parameters, respectively. The same authors Shoorehdeli *et al.* [19] improved their previous research by employing Extended Kalman Filter (EKF), another form of least square methods, with AWPSO.

Apart from PSO, as empirical study suggests, GA is the second most common approach to ANFIS identification. Soleimani and Salmalian [20] deployed GA and Singular Value Decomposition (SVD) for the optimum design of both Gaussian MFs and linear coefficients of the network, respectively. GA in combination with least square methods is implemented by Soto *et al.* [21] and Malleswaran *et al.* [22] to acquire optimum ANFIS network. The prior research used ANFIS for solving classification problem, while the later one chose ANFIS to predict the values of Longitude and Altitude. Cardenas *et al.* [23] trained the parameters of ANFIS using GA alone for energy load forecast.

In the search of more effective training and optimization of ANFIS models, the researchers have explored the use of Firefly Algorithm (FA), Artificial Bee Colony (ABC), and Differential Evolution with Ant Colony Search (DEACS) algorithms [2], [24-25]. All of them were employed for both antecedent and consequent parameters learning. Wang, Zhang [25] were among others who, together with parameter identification, also optimized the rule-base by pruning redundant rules through threshold value on rules' firing strength. Cat Swarm Optimization (CSO) algorithm has also been proposed by Orouskhani *et al.* [26] in conjunction with GD to train MFs and linear

coefficients, respectively. Table 2 lists ANFIS training and optimization approaches discussed above.

**Table 2. ANFIS Optimization and Training Approaches**

| Research                        | ANFIS Training |            | ANFIS rule-base optimized |
|---------------------------------|----------------|------------|---------------------------|
|                                 | MF             | Consequent |                           |
| Pousinho, Mendes [14]           | PSO            | LSE        | No                        |
| Catalao, Pousinho [12]          | PSO            | LSE        | No                        |
| Pousinho, Mendes [15]           | PSO            | LSE        | No                        |
| Jiang, Kwong [13]               | PSO            | LSE        | No                        |
| Sargolzaei <i>et al.</i> [27]   | PSO            | PSO        | No                        |
| Turki, Bouzaida [16]            | PSO            | PSO        | No                        |
| Rini, Shamsuddin [17]           | PSO            | PSO        | Yes                       |
| Liu, Leng [10]                  | IQPSO          | LSE        | No                        |
| Bagheri, Mohammadi Peyhani [18] | QPSO           | LSE        | No                        |
| Shoorehdeli, Teshnehlab [7]     | AWPSO          | FFRLS      | No                        |
| Shoorehdeli, Teshnehlab [19]    | AWPSO          | EKF        | No                        |
| Soto, Melin [21]                | GA             | LSE        | No                        |
| Malleswaran, Vaidehi [22]       | GA             | LMS        | No                        |
| Cardenas, Garcia [23]           | GA             | GA         | No                        |
| Karaboga and Kaya [24]          | ABC            | ABC        | No                        |
| Nhu, Nitsuwat [2]               | FA             | FA         | No                        |
| Wang, Zhang [25]                | DEACS          | DEACS      | Yes                       |
| Orouskhani, Mansouri [26]       | CSO            | GD         | No                        |

The number of inputs in the models mentioned above had minimum two and maximum five inputs. On the other hand, minimum MFs for each input were two and maximum six. Mostly, Gaussian shape of MFs was defined, and in addition to it, Triangular and Generalized Bell shape membership functions were also tried. Due to less number of inputs, mostly researchers preferred grid partitioning method of input space partitioning. But, the wider usage of grid partitioning has been blocked due to curse of dimensionality. This means the total number of rules and their linear coefficients increase as the number of inputs and MFs increase. This raises the need of optimizing the rule-base. There is a little evidence of this matter as only Rini, Shamsuddin [17] and Wang, Zhang [25] are among the other researchers, mentioned in Table 2, have tried obtaining useful rule-set by pruning less-important rules. They tried to perform accuracy maximization and complexity minimization simultaneously in order to achieve ANFIS systems with high accuracy and interpretability. Moreover, Rini *et al.* [28] also observed that optimizing the network with respect to one criterion, may poorly satisfy the other.

#### 4. ANFIS Applications in Business and Economics

The training methods of ANFIS, found in the previous section, have been implemented for solving problems in the field of business and economics. Many have contributed to research in the financial areas such as predicting financial crisis, bankruptcy and credit risk. Additionally, soft computing techniques have also been employed for currency, stock, and gold price forecast. But, no significant research is found on modeling small and medium enterprises (SMEs) strength/failure/distress or credit rating prediction using fuzzy neural networks – ANFIS specifically. Artificial Neural Networks (ANNs) have been implemented in business and finance because they have outperformed traditional

statistical models in terms of accuracy [29]. FNN, particularly ANFIS, has not only solved the “Black Box” issue of ANN but also achieved more accuracy than ANN models. Moreover, ANFIS models have gained more popularity than FNNs due to the advantage of efficiency in computing, effectively adaptable with optimization techniques [30].

## 5. Conclusion

ANFIS has not only outperformed Artificial Neural Networks (ANNs) and other types of Fuzzy Inference Systems (FISs), but it has been widely applied in business and finance. ANFIS is popular in other types of FISs, because it is easy to understand, flexible, and adaptable. However, when the number of inputs enlarges, exponential surge in the number of rules increases its complexity and computational cost. Moreover, the original two-pass learning algorithm uses gradient search method which is computationally expensive and less efficient. To avoid the drawbacks of original hybrid learning algorithm of ANFIS, many researchers have trained ANFIS using metaheuristic algorithms like GA, PSO, ABC, CSO, and their variants. However, very few have considered reducing the number of rules in ANFIS rule-base. Moreover, the applications of FNNs including ANFIS have been trended towards large firms employing non-financial factors as their inputs. Since, the small medium enterprises (SMEs) have different operational style as compared to their larger counterparts, non-financial factors play pivotal role in the operations of an SME. No significant research has been found in context with ANFIS which has targeted SMEs using non-financial factors.

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## References

- [1] S. Kar, S. Das and P. K. Ghosh, "Applications of neuro fuzzy systems: A brief review and future outline", *Applied Soft Computing*, (2014), vol. 15, pp. 243-259.
- [2] H. N. Nhu, S. Nitsuwat and M. Sodanil, "Prediction of stock price using an adaptive Neuro-Fuzzy Inference System trained by Firefly Algorithm. in *Computer Science and Engineering Conference (ICSEC)*, 2013 International, IEEE, (2013).
- [3] M. A. Awadallah, E. H. E. Bayoumi and H. M. Soliman, "Adaptive deadbeat controllers for brushless DC drives using PSO and ANFIS techniques", *Journal of Electrical Engineering*, (2009), vol. 60, no. 1, pp. 3-11.
- [4] O. Taylan and B. Karagözoğlu, "An adaptive neuro-fuzzy model for prediction of student's academic performance. *Computers & Industrial Engineering*, (2009), vol. 57, no. 3, pp. 732-741.
- [5] P. Liu, and H. X. Li, *Fuzzy neural network theory and application*, World Scientific, vol. 59. (2004).
- [6] M. Neshat, A. Adeli, A. Masoumi and M. Sargolzae, "A Comparative Study on ANFIS and Fuzzy Expert System Models for Concrete Mix Design", (2011).
- [7] M. A. Shoorehdeli, M. Teshnehlab, A. K. Sedigh and M. A. Khanesar, Identification using ANFIS with intelligent hybrid stable learning algorithm approaches and stability analysis of training methods. *Applied Soft Computing*, vol. 9, no. 2, (2009), pp. 833-850.
- [8] J. S. R. Jang, "ANFIS: adaptive-network-based fuzzy inference system. *Systems, Man and Cybernetics, IEEE Transactions on*, vol. 23, no. 3, (1993), pp. 665-685.
- [9] K. Ananda and M. Punithavalli, "Efficient cancer classification using fast adaptive neuro-fuzzy inference system (FANFIS) based on statistical techniques", (*IJACSA*) *International Journal of Advanced Computer Science and Applications*, Special Issue on Artificial Intelligence, (2011), pp. 132-137.
- [10] P. Liu, W. Leng and W. Fang, "Training anfis model with an improved quantum-behaved particle swarm optimization algorithm. *Mathematical Problems in Engineering*, 2013. 2013.
- [11] H. Ishibuchi, and Y. Nojima, "Multiobjective genetic fuzzy systems", in *Computational Intelligence*, Springer, (2009), pp. 131-173.

- [12] J. P. S. Catalao, H. M. I. Pousinho and V. M. F. Mendes, "Hybrid wavelet-PSO-ANFIS approach for short-term electricity prices forecasting", *IEEE Transactions on Power Systems*, vol. 26, no. 1, (2011), pp. 137-144.
- [13] H. Jiang, C. K. Kwong, W. H. Ip and T. C. Wong, "Modeling customer satisfaction for new product development using a PSO-based ANFIS approach", *Applied Soft Computing*, vol. 12, no. 2, (2012), pp. 726-734.
- [14] H. M. I. Pousinho, V. M. F. Mendes and J. P. S. Catalão, "A hybrid PSO-ANFIS approach for short-term wind power prediction in Portugal", *Energy Conversion and Management*, vol. 52, no. 1, (2011), pp. 397-402.
- [15] H. M. I. Pousinho, V. M. F. Mendes and J. P. S. Catalão, "Short-term electricity prices forecasting in a competitive market by a hybrid PSO-ANFIS approach", *International Journal of Electrical Power & Energy Systems*, vol. 39, no. 1, (2012), pp. 29-35.
- [16] M. Turki, S. Bouzaida, A. Sakly and F. M'Sahli, "Adaptive control of nonlinear system using neuro-fuzzy learning by PSO algorithm. in *Electrotechnical Conference (MELECON)*", 2012 16th IEEE Mediterranean, (2012).
- [17] D. P. Rini, S. M. Shamsuddin and S. S. Yuhaniz, "Balanced the Trade-offs problem of ANFIS Using Particle Swarm Optimisation", *TELKOMNIKA Telecommunication, Computing, Electronics and Control*, vol. 11, no. 3, (2013), pp. 611-616.
- [18] A. Bagheri, H. Mohammadi Peyhani and M. Akbari, "Financial forecasting using ANFIS networks with Quantum-behaved Particle Swarm Optimization", *Expert Systems with Applications*, vol. 41, no. 4, (2014), pp. 6235-6250.
- [19] M. A. Shoorehdeli, M. Teshnehlab and A. K. Sedigh, "Training ANFIS as an identifier with intelligent hybrid stable learning algorithm based on particle swarm optimization and extended Kalman filter", *Fuzzy Sets and Systems*, vol. 160, no. 7, (2009), pp. 922-948.
- [20] M. Soleimani and K. Salmalian, "Genetic algorithm optimized ANFIS networks for modeling and reduction of energy absorption rate of brass energy absorbers", *Appl Math Is Az Un La*, vol. 8, (2012), pp. 29-45.
- [21] J. Soto, P. Melin and O. Castillo, "Optimization of interval type-2 fuzzy integrators in ensembles of ANFIS models for prediction of the Mackey-Glass time series. in *Norbert Wiener in the 21st Century (21CW)*", 2014 IEEE Conference on, (2014).
- [22] M. Malleswaran, V. Vaidehi and R. A. Joseph, "Genetically optimized ANFIS based Intelligent Navigation System", in *Advanced Computing (ICoAC)*, 2011 IEEE, Third International Conference on, (2011).
- [23] J. J. Cardenas, A. Garcia, J. L. Romeral and K. Kampouropoulos, "Evolutive ANFIS training for energy load profile forecast for an IEMS", in an automated factory. in *Emerging Technologies & Factory Automation (ETFA)*, 2011 IEEE 16th Conference, (2011).
- [24] D. Karaboga and E. Kaya, "Training ANFIS using artificial bee colony algorithm in Innovations in Intelligent Systems and Applications (INISTA)", 2013 IEEE International Symposium on. IEEE, (2013).
- [25] R. Wang, J. Zhang, Y. Zhang and X. Wang, "Assessment of human operator functional state using a novel differential evolution optimization based adaptive fuzzy model", *Biomedical Signal Processing and Control*, vol. 7, no. 5, (2012), pp. 490-498.
- [26] M. Orouskhani, M. Mansouri, Y. Orouskhani and M. Teshnehlab, "A Hybrid Method of Modified Cat Swarm Optimization and Gradient Descent Algorithm for Training ANFIS", *International Journal of Computational Intelligence and Applications*, vol. 12, no. 02, (2013).
- [27] A. Sargolzaei, K. Faez and S. Sargolzaei, "A new method for Foetal Electrocardiogram extraction using Adaptive Neuro-Fuzzy Interference System trained with PSO algorithm", in *Electro/Information Technology (EIT)*, 2011 IEEE International Conference on, (2011).
- [28] D. P. Rini, S. M. Shamsuddin and S. S. Yuhaniz, "Particle swarm optimization for ANFIS interpretability and accuracy", *Soft Computing*, (2014).
- [29] M. Y. Chen, "A hybrid ANFIS model for business failure prediction utilizing particle swarm optimization and subtractive clustering", *Information Sciences*, vol. 220, (2013), pp. 180-195.
- [30] R. Pradhan, K. K. Pathak and V. P. Singh, "Application of neural network in prediction financial viability", *International Journal of Soft Computing and Engineering (IJSCE) ISSN*, (2011), pp. 2231-2307.

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