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Comparative Analysis Of ANFIS And ANN For Evaluating Inter-Agent Dependency Requirements

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Abstract— **The quantification and prediction of inter-agent dependency requirements is one of the main concerns in Agent Oriented Requirements Engineering. To evaluate exertion load of an agent within resource constraints, this work provides a comparative analysis of Adaptive Neuro Fuzzy Inference System (ANFIS) and Artificial Neural Network (ANN). ANN is widely known due to its capability of learning the training data while ANFIS is a hybrid system that combines the potential benefits of both the methods- Fuzzy Inference System (FIS) and ANN. The performance analysis of these methods is accomplished using performance indicators-Coefficient of Correlation (CORR), the Normalized Root Mean Square Error (NRMSE) and Coefficient of Determination. It is observed that ANFIS results in highly correlated data points with least NRMSE over fitted with test data. Moreover decreasing rate of error in hybrid learning algorithm of ANFIS is found higher than back propagation of ANN learning algorithm. Mean execution time for both the methods is computed. Results show that the ANFIS outperforms ANN. Moreover ANFIS is equipped with the capability of generating a FIS with linear relationship in input-output data and hence facilitates analytical inference of fuzzy data, while ANN is limited to forecast the data using its learning potential. Hence employing ANFIS could be a good option to predict and customize dependency requirements in inter-agent communication.**

Keywords-component; Mamdani Fuzzy Inference System (MFIS), Sugeno Fuzzy Inference System (SFIS), Adaptive Neural Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN), Degree of Dependency (DoD), Multi-Agent System (MAS).

I. INTRODUCTION

In software engineering community, there is an ever increasing demand to amend and streamline software projects in terms of Multi-Agent Systems (MAS). MAS involves a large number of agents playing different roles, interacting with each other to achieve personal and common goals [1]. To achieve common goals, tasks are distributed and entrusted to other agents with a purpose to share proficiency and capability; to work in parallel or sequence on common problems. Agent Oriented Requirements analysis necessitates supporting ways for identifying and analyzing dependencies in inter-agent coordination. In literature various Requirements Engineering (RE) frameworks such as Formal Tropos [2], i*[1], REF [3] have been recommended for inter-agent coordination. Tropos [2] is well known methodology that exhibits diverse kinds of dependencies viz. goal, task and resource by employing agent interaction diagrams. i* [1] recommends a modeling framework that focuses on strategic actor relationships. REF [3] adopts graphical notations extensively simulated by i* framework. In this methodology, dependency links are employed to establish dependencies among two or more agents.

All of the above Agent Oriented RE frameworks model inter-agent dependencies using various notations, diagrams and specification languages. However all these frameworks focus more on capturing various kinds of dependencies instead of its degree. Moreover, these frameworks do not support the ways to examine dependency needs of an agent. Degree of Dependency (DoD) is delineated as a metric to quantify an agent's dependency needs for delegating a goal in a distributed environment that would assist the developer in the selection of suitable service provider agents for accomplishing that goal. The evaluation of dependency needs of an agent using Adaptive Neuro Fuzzy Inference System (ANFIS) is obtained in our previous work [4, 5]. ANFIS is a hybrid system that combines the potential benefits of both the methods Artificial Neural Network (ANN) and Fuzzy Inference System (FIS).

ANN is a system of interconnected computational neurons arranged in an organized manner to carry out an extensive computing [9, 10, 21]. It is widely known due to its capability of learning the training data. The most widely used training algorithm for neural networks is the back-propagation algorithm. Though ANFIS can also be trained using the back propagation training algorithm of ANN, but the hybrid approach used in ANFIS involves the least-mean-square and standard delta method as the activation functions in forward and backward passes respectively and hence has the potential to converge faster by reducing the search space dimensions of the original pure back-propagation method used in neural networks.

ANFIS is a class of adaptive networks that is equipped with the capability of generating a Fuzzy Inference System (FIS) with linear relationship in input-output data. FIS is known for its capability of capturing the vagueness and ambiguity inherent in the human mind for decision making, reasoning and exposition of results in an environment of uncertainty and imprecision [8]. In ANFIS during the training process, training time is augmented exponentially with respect to the number of fuzzy sets per input variable used, therefore in order to reduce training time, ANFIS supports subtractive clustering to trim down the input dimensions by accumulating highly densed data points into a number of data clusters [17, 18]. As a result, this technique can be used with a large input-output data set at a very high speed.

This study provides a comparison between ANFIS and ANN for evaluating DoD. The performance analysis of these models is accomplished using performance indicators-Coefficient of Correlation (CORR), the Normalized Root Mean Square Error (NRMSE) and Coefficient of Determination. It is observed that ANFIS results in highly correlated data points with least NRMSE over fitted with test data. Moreover decreasing rate of error in hybrid approach of ANFIS is found higher than back propagation learning algorithm of ANN. Results show that the ANFIS outperforms ANN. Moreover ANFIS is equipped with the capability of generating a FIS with linear relationship in input-output data and hence facilitates analytical inference of fuzzy data, while ANN is limited to forecast the data using its learning capability. Hence ANFIS emerges as a good option to quantify dependency requirements in inter-agent communication.

In order to compare the behavior of both the methods, the quantified values of DoDs using domain knowledge are used as a preprocessing step. As domain knowledge is vague and uncertain, therefore quantification of DoD necessitates a recourse to a method of fuzzy inference. As Mamdani Fuzzy Inference System (MFIS) [6, 7] is capable to devise the fuzzy relationship in the decision rules, therefore this method is employed to mimic the minds of decision makers in order to quantify values of DoDs. The Quantified values of DoD are utilized as the training and test data in order to predict and customize DoD using ANFIS as well as ANN methods.

The organization of the paper is as follows. The Section II introduces MFIS. Section III briefly describes ANN, while section IV presents an introduction to ANFIS. Section V describes the frameworks for evaluating inter-agent dependency requirements. Section VI provides the details of experimental results in order to compare ANFIS and ANN for evaluating DoD and finally section VII concludes the paper.

II. Mamdani Fuzzy Inference System (MFIS)

Mamdani Fuzzy Inference System (MFIS) is widely known due to its ability to represent the vagueness and imprecise information in developing fuzzy models. It consists of the rules of the form "IF x_1 is very less AND x_2 is less THEN y is high,'' where very less, less and high are linguistic terms with functional forms like Gaussian, Sigmoid, etc., also known as membership functions [6, 7, 22, 28, 32, 34].

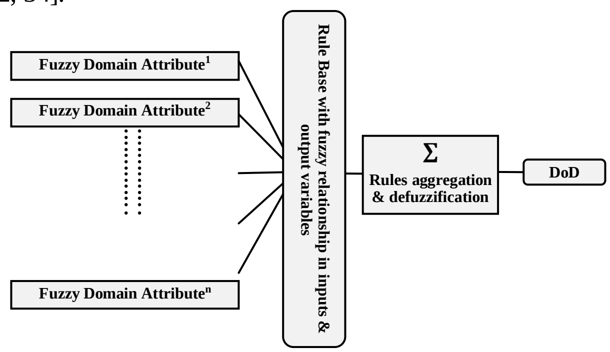

Figure 1. Structure of Mamdani Fuzzy Inference System

It consists of few inputs, output(s), set of predefined rules and a defuzzification method. The framework of MFIS for quantifying the values of DoDs using domain knowledge is shown in figure 1. Implication method is applied to evaluate each rule. Generally min operator representing the AND method is used for implication. Aggregation is employed to unify the outputs of all the rules resulting into a single fuzzy set.

The aggregated output function is defuzzified in a single crisp number using a defuzzification method i.e. Centroid method [6, 7, 8].

III. Artificial Neural Network (ANN)

ANN is a structure of interconnected computational neurons arranged in a systematic manner to carry out substantial computing [9, 10, 21, 31]. It is extensively acknowledged due to its capability of learning the training data. Artificial Neural Network (ANN) architecture usually consists of input layer, hidden layer, and output layer. Each layer is composed of several processing neurons. The neurons in the input layer include the input values obtained from training data. Each neuron in the hidden layer processes the inputs into the neuron outputs. The most extensively used training algorithm for neural networks is the back-propagation algorithm [9, 10].

A. *Back-Propagation Learning Algorithm*

Back-propagation is a feed forward, multilayer network that uses the supervised mode of learning [9, 10]. The number of inputs, outputs, hidden layers and neurons in each layer vary depending on the application. The firing strength of input values known as weights, is propagated to subsequent layer. In addition, biases are also propagated as the input data to the neurons. Biases are the additional weights that contribute in the adjustment of some activation function viz. sigmoid. The main objective of back-propagation method is to adjust the values of weights and biases in such a manner so as to get the same value as the correct output value of network in training data set. The back-propagation cycle is illustrated in figure 2.

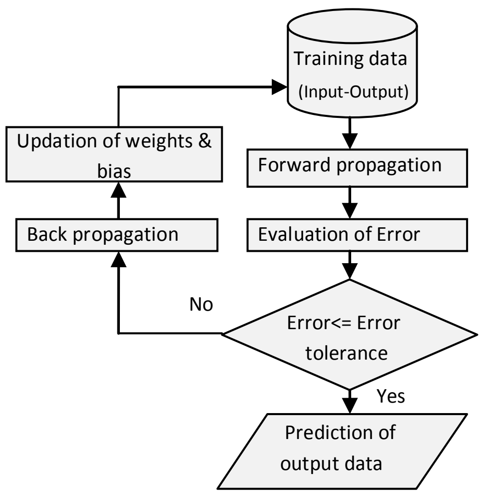

Figure 2. Back propagation cycle

The back-propagation method upgrades the weights and biases in two passes. In forward pass, the inputs, weights and biases are injected to subsequent layer. The activation function is implemented in order to generate the weights for next layer. Finally output layer is ready to generate some output value. The generated and original values of output are utilized to derive the error which further is propagated back till input layer to adjust the weights and biases. This process of multiple forward and backward passes is repeated till error is less than error tolerance and network is ready to result in expected values of output as in training data.

IV. Adaptive Neuro Fuzzy Inference System (ANFIS)

The Adaptive-Neuro Fuzzy Inference System is a hybrid system that combines the potential benefits of both the methods ANN and FL (Fuzzy Logic) [10]. This system has been employed in numerous modeling and forecasting problems [10, 11, 12, 13, 14, 15, 16, 17, 33].

ANFIS starts its functionality with the fuzzification of input parameters defining the membership function parameters and design of fuzzy IF-THEN rules, by effectively employing the learning capability of ANN for automatic fuzzy rule generation and self adjustment of membership functions. The learning capability in ANFIS works in a similar manner as a supervised-learning neural network. The system is trained with a set of data incorporating several inputs and one output. Once trained, the system functions precisely as a fuzzy expert system [16, 18]. The ANFIS architecture is shown in figure 3.

ANFIS is a five-layer network that carries out training in two-passes over a number of epochs. During each epoch, the node outputs are calculated up to layer 4. Finally at layer 5, resulted outputs of various nodes are aggregated to a single consolidated output value and the errors are propagated back through the layers in order to find out the premise parameter.

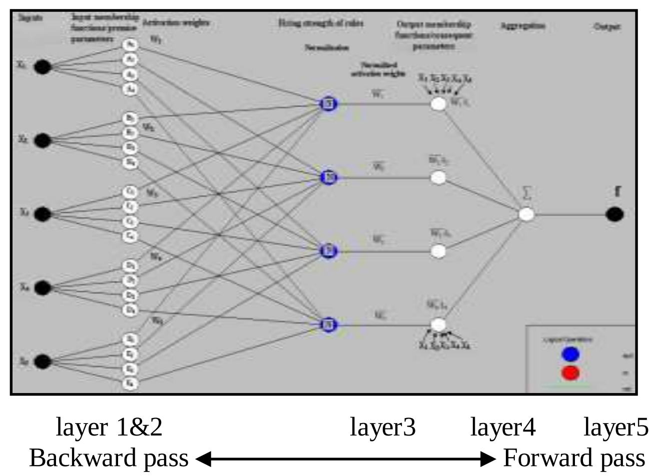

Figure 3. ANFIS Structure

ANFIS employs hybrid learning algorithm to learn from the input-output data [5]. As the training time increases exponentially with the number of fuzzy sets per input variable used, therefore to reduce training time, ANFIS supports subtractive clustering. The brief explanation of training algorithms and subtractive clustering is provided in the subsequent sub-sections.

A. *Hybrid learning algorithm*

The hybrid algorithm is a two-step process First, fixing the premise parameters, the node outputs are disseminated forward and the consequent parameters are evaluated by the least-mean-square method [5, 27]. Then, the consequent parameters are held fixed and the error signals with respect to each node are circulated from the output end to the input end. Thereafter the premise parameters are tuned by the standard back-propagation algorithm [25].

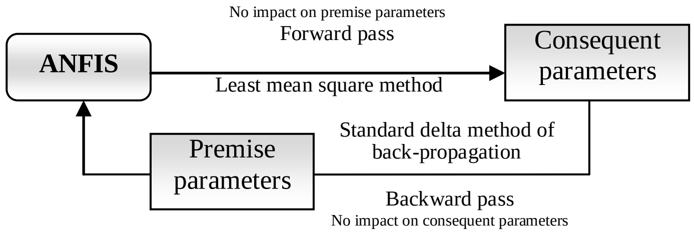

Figure 4. Forward and backward pass in hybrid algorithm

potential to converge faster since it reduces the search space dimensions of the original pure back-propagation method used in neural networks [20].

B. Subtractive Clustering

ANFIS employs hybrid training algorithm to learn from the input-output data. In either case, training time increases exponentially with the number of fuzzy sets per input variable used. Hence to trim down training time, subtractive clustering is employed prior to training process that reduces the input dimensions by accumulating highly dense data points into a number of data clusters [17, 18]. This makes ANFIS amenable to a large data set.

The subtractive clustering algorithm generates data clusters with data points having the highest density measures [17]. These cluster centers contribute in ANFIS IF THEN fuzzy rules consisting of the Gaussian premise membership functions and first order Sugeno type consequent membership functions. The four parameters- range of influence, squash factor, accept ratio and reject ratio that contribute towards determining the data points to be chosen as cluster centers [17, 18] are briefly described as follows.

- **Range of influence:** The range of influence specifies the cluster radius. Lesser the value of cluster radius, more the cluster centers and thereby more the identical number of rules. The range of influence should be set in such a manner so as to obtain optimum number of rules.
- **Squash factor:** Squash factor is the ratio of radius defining the neighborhood and the range of influence. To avoid closely spaced clusters, it is advisable to set the value of radius defining the neighborhood higher than the radius of cluster. The resultant value of squash factor would therefore be always greater than 1. As the value of squash factor is increased, the number of rules is monotonically reduced. Therefore in order to keep the optimum size of clusters and corresponding number of rules, the higher values of squash factors are discouraged.
- **Accept ratio:** This ratio determines the potential of the data point to be chosen, as a fraction of the potential of the first cluster center, above which this data point will be accepted as a cluster center.
- **Reject ratio:** Reject ratio is an indicative to reject a data point to be a cluster center, which is obtained from fraction of the potential of the first cluster center, below which a data point would be rejected as a cluster center.

Simulation of ANFIS results in a Sugeno Fuzzy Inference System (SFIS) with a linear relationship in input-output data that finally is utilized in analytical inference of data. The following section describes SFIS.

C. Sugeno Fuzzy Inference System (SFIS)

The Sugeno Fuzzy Inference System (SFIS) is widely employed in establishing a relationship between a series of input and output sets. This relationship is represented by either a linear equation, called ‘‘first-order Sugeno FIS”, or constant coefficient called as ‘‘zero order Sugeno FIS. The structure of the consequent parts of the rule base for the first-order Sugeno model can be expressed by following linear function [5, 28]:

$$y = f_m(X_1, X_2 \ldots\ldots\ldots.. X_k) \quad (1)$$

where m: number of output membership functions and K: number of inputs. For instance, the SFIS having five inputs X_1, X_2, X_3, X_4, X_5 and one output f, for the first-order Sugeno fuzzy model with output membership functions f_1, f_2, f_3, f_4, f_5 and their firing strength W_1,W_2,W_3,W_4,W_5 can be expressed as shown in figure 5.

The rules generated in this model can be defined in the form of premise and consequent parameters. The premise parameters describe the shape of the membership functions, and the consequent parameters describe the output [13]. The rules have the following general structure:

IF (X_1 is A_1) AND (X_2 is B_1) AND (X_3 is C_1) AND (X_4 is D_1) AND (X_5 is E_1) THEN $Y=f_1(X_1,X_2.....X_5)$

where values of input membership functions A_1,B_1,C_1,D_1,E_1 viz. Guassian membership function are determined by their premise values automatically adjusted by ANFIS as shown in figure 3. Similarly parametric values of consequent part viz. a_1,b_1,c_1,d_1,e_1,r_1 as shown in figure 5 are also adjusted automatically by employing ANFIS.

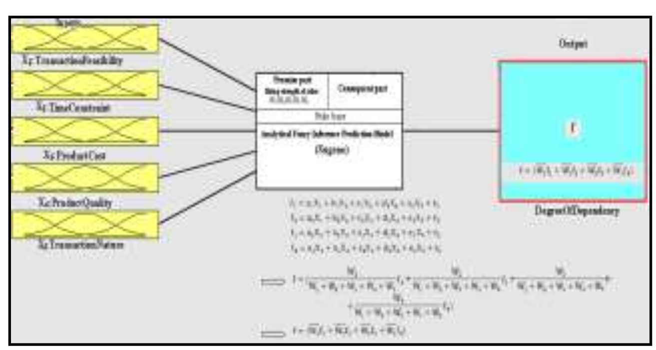

Figure 5. First Order SFIS with five inputs and one output corresponding to ANFIS architecture

The other rules of similar type can be obtained by considering a larger training data set thus rendering the model closer to real-life.

V. Evaluation of Inter-Agent Dependency Requirements

Inter-agent communication is one of the key apprehensions of Agent Oriented requirements engineering. This apprehension is delineated in terms of inter-dependencies and interaction among various agents carrying out collaborative activities. To accomplish cooperative activities, tasks are distributed and delegated to other agents with the intention of sharing mutual proficiency and potential [4, 5]. An agent may be dependent on other agent for carrying out a goal or for craving for a resource to achieve that goal [5]. This requires an agent to quantify the dependency needs entitled as DoD to comprehend whether it should entrust the task to another agent, if yes, then to whom so that overall quality of MAS is not compromised.

To quantify an agent's dependency needs in a distributed environment, this work utilizes ANFIS as well as ANN. The details of the frameworks for evaluating DoD using ANFIS and ANN methods are provided in the following sub-sections.

A. *Framework for evaluating DoD using ANFIS*

The framework for evaluating DoD using ANFIS that characterizes inter-agent dependency requirements is described in three steps and is shown in figure 6.

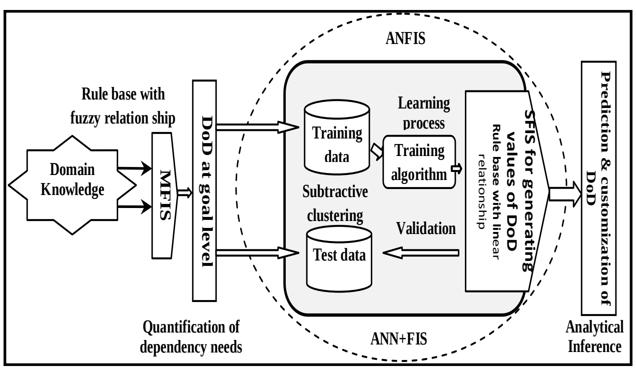

Figure. 6 Framework for evaluating DoD using ANFIS

In step I, domain knowledge of a goal is inferred by domain experts to obtain fuzzy domain attributes and rule base. In step II, the MFIS is applied to quantify DoD. Here the data set consisting of various values of domain attributes and DoD is decomposed in two parts- training and test data. In step III, ANFIS is employed using hybrid training algorithm with a view to developing a model of prediction and customization of DoD. Finally the model is validated against test data in order to ensure a high quality MAS of collaborative endeavours.

The above steps are described in detail in subsequent subsections.

1) *Domain Knowledge*

Domain knowledge is defined as the knowledge about the environment in which the target system functions [19, 20]. Domain knowledge is learned from domain experts in the problem domain. The domain knowledge embraces transactional information viz. credentials, documents, business rules and reports etc. required to specify the requirements. It is an area of expertise or application that needs to be investigated and converted into a set of rules in knowledge base, by knowledge engineers. As an information system is implanted in the domain knowledge of a specific business or activities in an organization, the acquaintance with target business area is indispensable to understand the problem [20].

2) *Quantifying Dependency Requirements*

As domain knowledge is vague and uncertain, quantification of DoD among the agents necessitates a recourse to a method of fuzzy inference. As MFIS is capable to devise the fuzzy relationship in the decision rules, therefore this method is employed to mimic the minds of decision makers [4].

For designating a goal to other agents, an agent requires to assess its own dependency needs based on domain knowledge. The quantification of dependency requirements involves the fuzzification of domain attributes, formulation of knowledge rule base and finally application of a defuzzification method viz. centroid in order to obtain the crisp value of DoD. The details of quantification of DoD characterized by domain knowledge using MFIS have been exemplified in our previous work [4, 5].

MFIS is simulated a number of times to obtain training and test data.

- ***Training data:*** Training data is the data employed to train the system. One set of various values of DoDs obtained from MFIS is treated as training data.
- ***Test Data:*** Test data is the data which is employed to check the validity of the system. MFIS is simulated a number of times to generate the values to be treated as test data.

3) *Analytical Inferencing using ANFIS*

Inference of the relationship between domain attributes and DoD predicated by the ANFIS is critical for planning the optimum number of agents as well as determining the effectiveness of the MAS. Simulation of ANFIS results in a Sugeno Fuzzy Inference System (SFIS) with a linear relationship in input-output data that finally is utilized in analytical inference of data. The simulation of ANFIS with the optimized combination of reject ratio, range of influence, accept ratio and squash factor for subtractive clustering is illustrated in figure 7.

Figure 7. Simulation of ANFIS

The SFIS obtained as the resultant of the simulation of ANFIS with a linear relationship in input output data works as the analytical inference model and is utilized to predict and customize the values of DoDs. The screen shot of SFIS developed in MatLab is illustrated in figure 8.

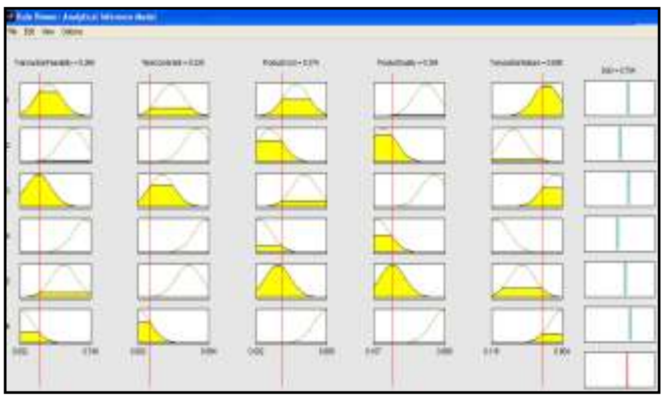

Figure 8. Prediction of DoD using SFIS

B. Framework for evaluating DoD using ANN

The framework for evaluating DoD using ANN involves quantification of values of DoDs as the pre-processing step, training the system using the learning algorithm and finally validating the system using test data. The frame work for evaluating DoD using ANN is illustrated in figure 9.

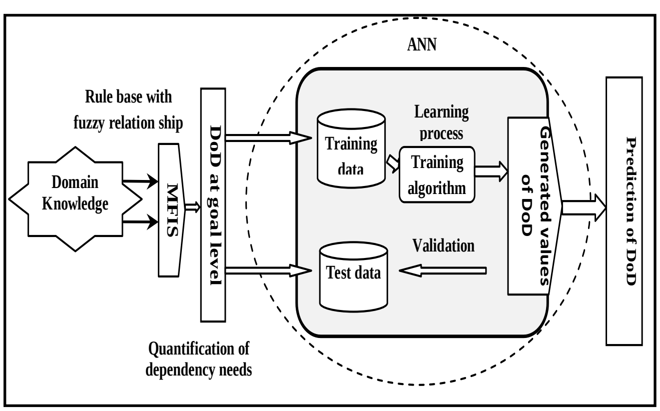

Figure 9. Framework for evaluating DoD using ANN

The architecture of ANN for predicting DoD involves input, output and a number of hidden layers. The input layer takes the input-output values from the training data and output layer results in the predicted values of DoD. In order to keep the similarity in the architecture of both the methods ANFIS and ANN, the number of hidden layers is taken as 3. As the excessive number of neurons would increase the complexity of the system and hence the training time, therefore number of neurons in each hidden layer is taken as approximately 2/3rd of the input parameters in the training ta. The architecture of ANN involving weights and biases illustrated in figure10.

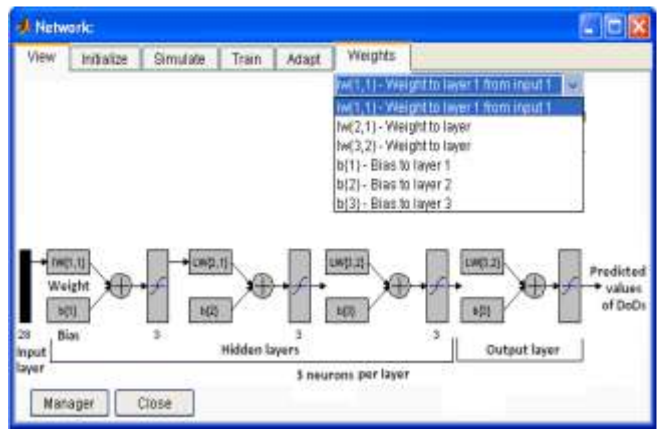

Figure 10. Architecture of ANN for evaluating DoD

The framework for evaluating DoD using ANN is similar in many respects to the frame work of ANFIS. The quantification of DoD from domain knowledge using MFIS as a preprocessing step is similar in both the frame works. The difference lies in the training algorithms used by these methods. The most popular back propagation method is utilized as the training algorithm in ANN. Though ANFIS can also be trained using the back propagation training algorithm, but the hybrid approach used in ANFIS involves the least-mean-square and standard delta method as the activation functions in forward and backward passes respectively and hence has the potential to converge faster by reducing the search space dimensions of the original pure back-propagation method used in ANN [5]. Moreover ANFIS utilizes subtractive clustering as the part of its framework and trims down the input dimensions by accumulating highly densed data points into a number of data clusters [17, 18]. As a result, this technique can be used with a large input-output data set at a very high speed. Another difference lies in the output values generated in both the frame works. ANFIS results in a SFIS with a linear relationship in input-output data with a capability to predict as well as customize DoDs, while ANN is limited with the potential of forecasting the values of DoDs.

VI. EXPERIMENT AND RESULTS

In order to exhibit the behavior of ANFIS and ANN methods, an experiment was carried out for evaluating inter-agent dependency requirements entitled as DoD in materials e-procurement MAS. Materials e-procurement MAS is composed of Purchase Head Agent, Raw Material Agents, Spares Agents, Packaging Agents, Consumable Agents and Miscellaneous Items Agents involved with procuring diverse items viz. raw materials, spares, packaging, consumable and miscellaneous for various projects distributed over various locations.

The experiment was done on Intel CPU having 1.99 GB of RAM and speed 1.86 GHz. The Matlab software was employed to implement the frame works for evaluating DoD using ANFIS and ANN. The training and test data using domain knowledge was obtained as a preprocessing step of the frameworks that is described in the following sub-section.

A. Obtaining Training and Test Data

Fifteen domain experts from materials management were involved to provide the assistance in formulating a knowledge rule base over five domain attributes namely Product Cost, Transaction Feasibility, Time Constraint, Product Quality and Transaction Nature [6]. The decision rules in rule base pertaining to raw materials were framed in the following manner [6]:

"If (TransactionFeasibility is less) and (TimeConstraint is tight) and (ProductCost is high) and (ProductQuality is high) and (TransactionNature is highlycritical) then (DoD is high)"

The other rules were formulated in the rule base in a similar manner. MFIS was employed in order to quantify dependency needs using knowledge rule base. It was simulated a number of times and results were recorded in an input-output data set. This data set was divided in two parts-one as training data as shown in table 1 and another as test data. The training data was employed to train the system while the test data was utilized for its validation.

TABLE 1. QUANTIFICATION OF DOD W.R.T. VARIOUS DOMAIN ATTRIBUTES (TRAINING DATA SET)

Domain Attributes (Inputs)					Output
TransactionFeasibility	TimeConstraint	ProductCost	ProductQuality	TransactionNature	DoD
0.092	0.092	0.868	0.869	0.804	0.701
0.220	0.252	0.692	0.774	0.764	0.698
0.228	0.260	0.676	0.766	0.756	0.697
0.260	0.356	0.628	0.758	0.740	0.690
0.276	0.372	0.620	0.750	0.732	0.682
0.300	0.388	0.604	0.734	0.716	0.656
0.324	0.404	0.580	0.726	0.700	0.603
0.332	0.420	0.564	0.710	0.692	0.565
0.340	0.436	0.548	0.694	0.676	0.540
0.356	0.460	0.532	0.671	0.652	0.515
0.372	0.468	0.516	0.655	0.620	0.506
0.388	0.484	0.508	0.647	0.596	0.503
0.396	0.492	0.484	0.631	0.580	0.501
0.420	0.508	0.460	0.607	0.556	0.500
0.460	0.636	0.340	0.337	0.468	0.492
0.500	0.660	0.332	0.313	0.414	0.463
0.516	0.684	0.324	0.274	0.412	0.393
0.532	0.692	0.300	0.266	0.388	0.340
0.540	0.700	0.276	0.242	0.372	0.324
0.556	0.732	0.260	0.234	0.340	0.309
0.580	0.748	0.244	0.218	0.324	0.302
0.612	0.780	0.220	0.210	0.300	0.295
0.636	0.812	0.204	0.202	0.252	0.278
0.620	0.828	0.180	0.187	0.212	0.248
0.668	0.844	0.148	0.155	0.204	0.175
0.700	0.860	0.124	0.147	0.164	0.173
0.724	0.876	0.108	0.131	0.140	0.170
0.748	0.884	0.092	0.107	0.116	0.162

The fuzzy surface plots were obtained in order to depict the relationship between input and output variables. Figure 11 exhibits the relationship between the input variables-Transaction Nature and Time Constraint and the output variable-DoD.

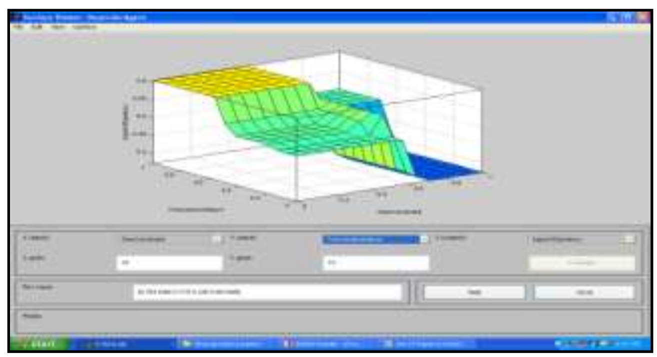

Figure 11. DoD w.r.t. Transaction Nature, Time Constraint

DoD is found inversely proportional to Time Constraint and directly proportional to Transaction Nature. It signifies that highly critical items viz. raw materials used in producing the goods with tight time constraint require high DoD.

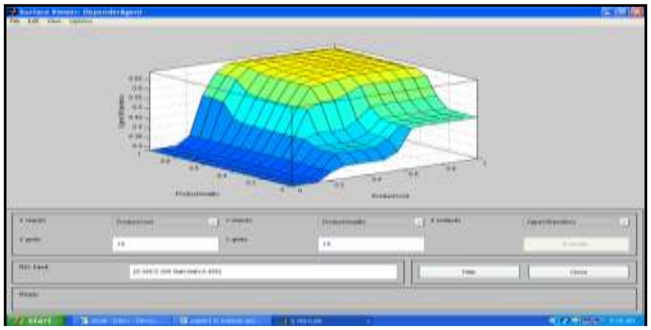

Figure 12. DoD w.r.t. Product Cost, Product Quality

Figure 12 exhibits that DoD is directly proportional to Product Cost as well as Product Quality. It signifies that high product cost and quality required in obtaining a goal necessitate high dependency requirements in the form of DoD.

Factors	**ANFIS**	**ANN**
Analytical Inference	Prediction & Customization	Prediction
Execution time	Less	Comparatively high
Capability of capturing fuzziness	Using FIS	Not available
Error rate	less	high
Correlation in test and generated data	High	Less
Coefficient of Determination	High	Less
Speed	High	Less
Outputs generated	SFIS having a knowledge rule base with the capability of prediction and customization of DoDs	Predicted value of DoD

A comparative analysis of ANFIS and ANN methods for evaluating DoD is provided in the following sub-section.

B. Comparative Analysis

The comparative analysis of the frameworks ANFIS and ANN for evaluating DoDs incorporates a number of assessment parameters viz. trend of generated data, best-fitness of the test and predicted data, trend of error, capability of analytical inference and finally time analysis.

The Normalized Root Mean Square Error (NRMSE) and Coefficient of Correlation (CORR) are used as the performance indicators to examine the fitness of predicted data against test data.

RMSE is defined as the square root of the mean squared error and NRMSE is to normalize RMSE to the mean of the predicted values.

$$\mathrm{RMSE} = \left[\frac{\sum_1^N \sqrt{(\mathrm{Predicted}_{\ \mathrm{data}} - \mathrm{Test}_{\ \mathrm{data}})^2}}{\mathrm{N}}\right] \tag{2}$$

$$\mathrm{NRMSE} = \left[\frac{\mathrm{RMSE}}{\left(\frac{1}{\mathrm{N}}\right)\left(\sum_1^N \mathrm{Predicted}_{\ \mathrm{data}}\right)}\right] \tag{3}$$

where N is the number of data points in the training and test data.

The statistical measure Coefficient of Correlation (CORR) is utilized to check how well the predicted values "fit" with the test data. In order to infer additional information regarding the predicted data, the square of Coefficient of Correlation entitled as Coefficient of Determination is employed [29]. It provides a measure of how well future outcomes are likely to be predicted by the framework. It is denoted as R^2 and can be obtained using the following equation.

$$\mathrm{R}^2 = 1 - \frac{\sum_1^N (\mathrm{Test}_{\ \mathrm{data}} - \mathrm{Predicted}_{\ \mathrm{data}})^2}{\sum_1^N (\mathrm{Test}_{\ \mathrm{data}} - \mathrm{MeanofTest}_{\ \mathrm{data}})^2} \tag{4}$$

The value of R^2 lies in between 0 and 1.0. It is used to describe how well a regression line fits a set of predicted data. The value of R^2 near 1.0 indicates that a regression line fits the predicted data well, while value of R^2 closer to 0 indicates a regression line does not fit the predicted data very well.

A comprehensive difference of ANFIS and ANN is provided in table2. It is observed that ANFIS results in highly correlated data points with least NRMSE over fitted with test data. Moreover decreasing rate of error in hybrid learning algorithm of ANFIS is found higher than back propagation of ANN learning algorithm. Mean execution time for both the methods is computed. Results show that the ANFIS outperforms ANN. Moreover ANFIS is equipped with the capability of generating a linear relationship in input-output data and hence facilitates analytical inference of data, while ANN is limited to predict the data using its learning capability.

TABLE 2. COMPARATIVE ANALYSIS OF MFIS AND SFIS FOR EVALUATING DOD

Hence ANFIS emerges as a good option to quantify dependency requirements in inter-agent communication. The exhibition of the behavior of both the methods against a number of parameters viz. trend of data, best-fitness of test and generated data etc. are illustrated in the following sub-sections.

B.(i) Trend of Predicted data

The trend of predicted data using ANFIS and ANN is illustrated in figures 13 and 14 respectively. Figure 13 illustrates that predicted data using ANFIS is converging more to the regression line. Approximately 99.9% of the predicted data fits along the regression line, while in case of figure 14, 98.5% predicted data is converging to the regression line. Hence ANFIS appears as a better choice in predicting the values of DoDs more accurately.

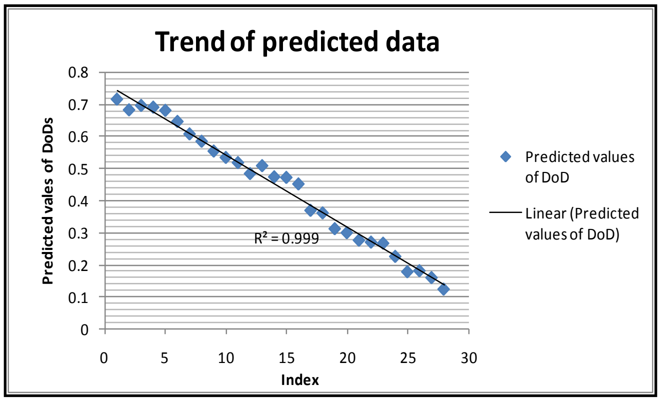

Figure 13. Trend of predicted data using ANFIS

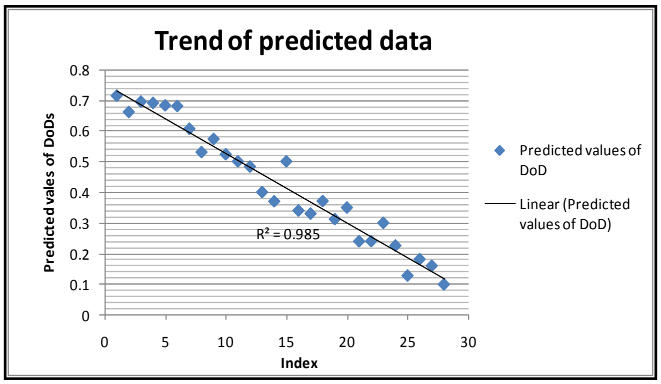

Figure 14. Trend of predicted data using ANN

B.(ii) Best-fitness of Test and Predicted Data

Figures 15 and 16 illustrate the fitness of generated data over test data using back propagation of ANN and hybrid algorithm of ANFIS respectively. The CORR and NRMSE between predicted and test data using both learning algorithms, are shown in table 3.

TABLE 3 COMPARATIVE ANALYSIS OF HYBRID AND BACK PROPAGATION LEARNING ALGORITHMS

Hybrid		Back propagation	
CORR	**NRMSE**	**CORR**	**NRMSE**
0.999996	**0.001163**	**0.992779**	**0.068694**

It was observed that hybrid algorithm resulted in highly correlated data points with least value of NRMSE over fitted with test data as illustrated in figure 16.

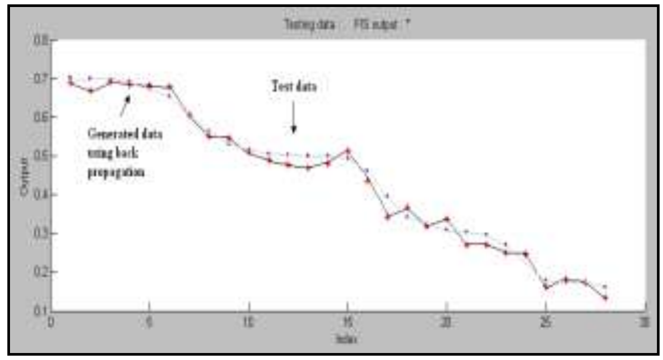

Figure 15. Trend of predicted over test data using ANN (back propagation learning algorithm)

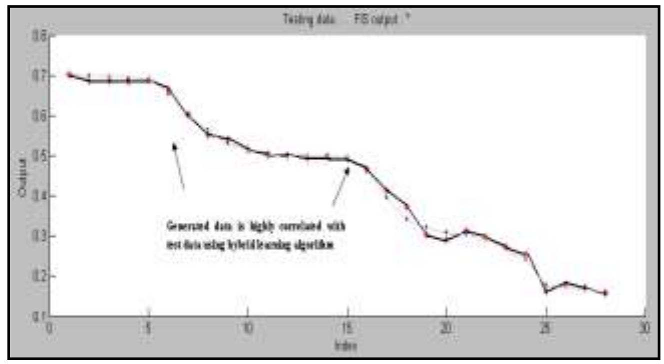

Figure 16. Trend of predicted over test data using ANFIS (hybrid learning algorithm)

B.(iii) Trend of Error

Figures 17 and 18 illustrate the trend of errors using back propagation and hybrid learning algorithms of ANN and ANFIS respectively. These depict that error monotonically decreases with an increase in number of echoes.

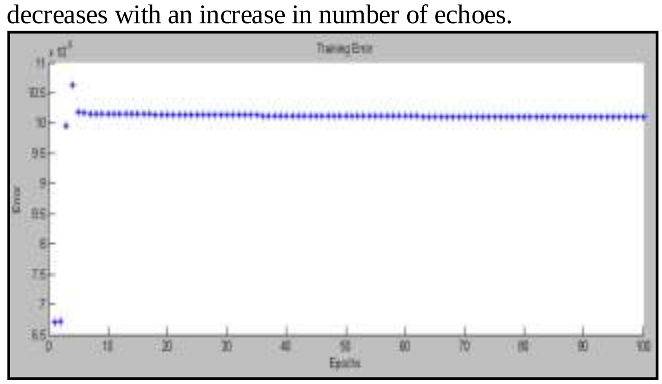

Figure 17. Trend of errors with ANN (back propagation learning algorithm)

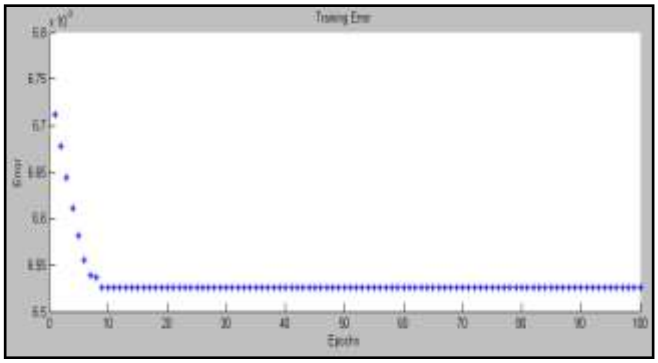

Figure 18. Trend of errors with ANFIS (hybrid learning algorithm)

Hence hybrid learning algorithm was found to be a better option used in ANFIS.

B.(iv) Capability of Analytical Inference

Inference of the relationship between domain attributes and DoD is critical for planning the optimum number of agents as well as determining the effectiveness of the MAS. Simulation of ANFIS results in SFIS with a linear relationship in input-output data that finally is utilized in analytical inference of data. This potential of SFIS would assist the developer to tailor inputs as per required level of DoD and facilitate analytical decision making for estimating the exertion load of an agent in a distributed paradigm. The rules in SFIS rule base are of the following type:

IF (TransactionFeasibility is Mf1) and (TimeCostraint is Mf2) and (ProductCost is Mf3) and (ProductQuality is Mf4) and (TransactionNature is Mf5) Then DegreeOfDependency=-1.195TransactionFeasibility+ 0.5636TimeCostraint+0.2609ProductCost- 0.78ProductQuality - 1.093TransactionNature +1.648

where input membership functions viz. Mf1, Mf2 etc. are Gaussian functions that are automatically adjusted by learning the training data. The consequent part of the rule base discovered by ANFIS, specifies a linear relationship between input domain attributes and DoD that is utilized in the prediction and customization of DoDs within the resource constraints. The implication of subtractive clustering algorithm in ANFIS reduces number of rules in Sugeno rule base by accumulating highly densed data points into a number of clusters. Consequently the compact rule base enhances the analytical potential of the model within the resource constraints.

On the contrary, ANN does not infer the data analytically and is only equipped with the potential to forecast the values of DoDs using the training data.

B.(v) Time Analysis

A data of 128 input values against the domain attributes Transaction Feasibility, Time Constraint, Product Cost, Product Quality and Transaction Nature, was employed to check the behavior of ANN and ANFIS in predicting various values of DoD.

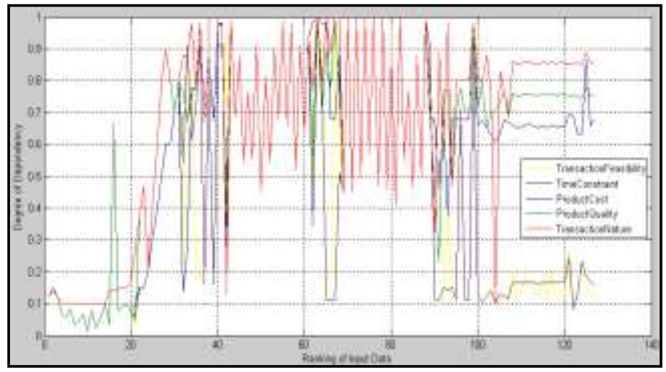

Figure 19. Variations in input data viz. Transaction Feasibility, Time Constraint, Product Cost, Product Quality, Transaction Nature

The input data for various domain attributes was framed to incorporate frequent variations as illustrated in figure 19. Both the techniques ANN and ANFIS were executed for the same set of input data.

In order to analyze execution time in predicting the values of DoDs, an experiment was done in MatLab. The simulation was done 2000 number of times for various input vectors leading to an upper limit of 128.

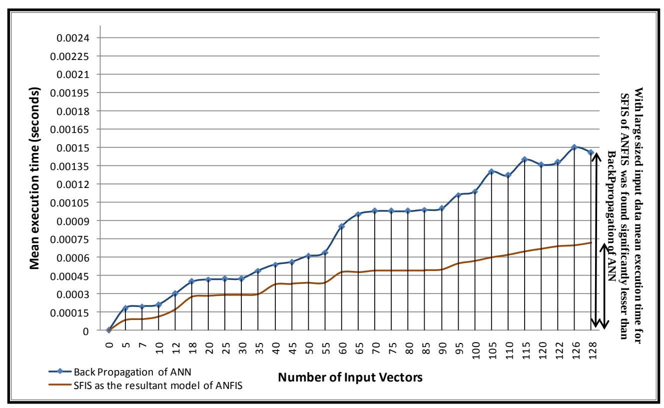

Figure 20. Execution time analysis for ANN and ANFIS

The mean execution time was collected for both the methods. It was observed that with a rise in input vectors, the execution time in back propagation of ANN was drastically increasing in comparison to SFIS, a resultant model of ANFIS as illustrated in figure 20. With large sized input vectors, the execution time in SFIS was found to be approximately half of the execution time using back propagation of ANN.

Hence ANFIS with exclusive characteristics appears as a better choice for the prediction and customization of DoD.

VII. Conclusion

This work provides a comparative analysis of ANFIS and ANN methods for evaluating DoD. ANN is extensively known due to its capability of learning the training data while ANFIS is a hybrid system that combines the potential benefits of both the methods FIS and ANN. The performance analysis of these methods is accomplished using performance indicators-CORR, R^2 and NRMSE. It is observed that ANFIS results in highly correlated data points with least NRMSE over fitted with test data. Moreover decreasing rate of error in hybrid learning algorithm of ANFIS is found higher than back propagation of ANN learning algorithm. Mean execution time for both the methods is computed. Results show that the ANFIS outperforms ANN. ANFIS trims down the input dimensions by accumulating highly densed data points into a number of data clusters and hence can be used with a large input-output data set at a very high speed. In addition, ANFIS is equipped with the capability of generating a FIS with linear relationship in input-output data and hence facilitates analytical inference of fuzzy data, while ANN is limited to forecast the data using its learning potential. Hence ANFIS with exclusive characteristics appears as a better choice for the prediction and customization of DoD.

REFERENCES

[1] Singh, Evaluation of Agent Oriented Requirements Engineering Frameworks, ISBN: 978-0-7695-3336-0,2008,IEEEVol:2, pp: 33-38

[2] Jaelson Castro, Manuel Kolp, Towards requirements-driven information systems engineering: the Tropos project, Elsevier Information Systems 27 (2002) 365–389 9

[3] Paolo Donzelli, A goal-driven and agent-based RE framework*, Springer-Verlag London Limited 2003, Requirements Eng (2004) 9: 16–39 DOI 10.1007/s00766-003-0170-4

[4] Vibha Gaur, Anuja Soni, Evaluating Degree of Dependency from Domain Knowledge using Fuzzy Inference System, Springer in CCIS Series, 204, pp. 101–111, 2011 CCSEIT-2011

[5] Vibha Gaur, Anuja Soni, Analytical inference model for prediction and customization of inter-agent dependency requirements, ACM SIGSOFT Software Engineering Notes, Volume 37 Issue 2, March 2012, pp. 1-11

[6] Sivarao, Peter Brevern, GUI Based Mamdani Fuzzy Inference System Modeling To Predict Surface Roughness in Laser Machining,2009, International Journal of Electrical & Computer Sciences IJECS Vol: 9 No: 9

[7] Sivarao, Peter Brevern, GUI Based Mamdani Fuzzy Inference System Modeling To Predict Surface Roughness in Laser Machining, International Journal of Electrical & Computer Sciences IJECS Vol: 9

[8] George J. Klir, Fuzzy Sets and Fuzzy Logic, PHI publications, 1995,ISBN:81-203-1136-1

[9] Mohammed A. Mashrei, Neural Network and Adaptive Neuro-Fuzzy Inference System Applied to Civil Engineering Problems, Book:Fuzzy Inference System - Theory and Applications, ISBN 978-953-51-0525-1, Hard cover, 504 pages, Publisher: InTech, 2012

[10] S. Areerachakul, Comparison of ANFIS and ANN for Estimation of Biochemical Oxygen Demand Parameter in Surface Water, International Journal of Chemical and Biological Engineering, vol. 6, 2012

[11] Adel Mellit, ANFIS-based modelling for photovoltaic power supply system: A case study, Renewable Energy 36, 2011, 250e258, Elsevier

[12] Julián Moreno, Hydraulic plant generation forecasting in Colombian power market using ANFIS, Energy Economics 31, 2009, 450–455,Elsevier

[13] Melek Acar Boyacioglu , Derya Avci, An Adaptive Network-Based Fuzzy Inference System (ANFIS) for the prediction of stock market return: The case of the Istanbul Stock Exchange, Expert Systems with Applications 37,2010, 7908‑7912,Elsevier

[14] Adel Mellit, Soteris A. Kalogirou, ANFIS-based modelling for photovoltaic power supply system: A case study, Renewable Energy 36, 2011, 250e258,Elsevier

[15] C. Kezi Selva Vijila, C.Ebbie Selva Kumar, Interference cancellation in EMG signal Using ANFIS, International Journal of Recent Trends in Engineering, Vol 2, No. 5, November 2009,ACEEE

[16] Mohammad Zounemat-Kermani, Mohammad Teshnehlab, Using adaptive neuro-fuzzy inference system for hydrological time series prediction, Applied Soft Computing 8, 2008, 928–936,Elsevier

[17] A. M. Elwakdy, B. E. Elsehely Speech recognition using a wavelet transform to establish fuzzy inference system through subtractive clustering and neural network (ANFIS), International Journal of Circuits, Systems and Signal Processing, Issue 4, Volume 2, 2008

[18] C. D. Doan, S. Y. Liong and Dulakshi S. K. Karunasinghe, Derivation of effective and efficient data set with subtractive clustering method and genetic algorithm, Journal of Hydroinformatics,2005

[19] Akira Osada, The Role of Domain Knowledge Representation in Requirements Elicitation, 25th conference on IASTED International Multi-Conference: Software Engineering, 2007

[20] Preethu Rose, A Method and Framework for Domain Knowledge Assisted Requirements Evolution, International Conference on Software Engineering, 2009

[21] S.N. Sivanandam , S.N. Deepa, Principles of Soft Computing, Second edition, ISBN:978-81-265-2741-0, Wiley India, 2011

[22] Sivarao, Peter Brevern, GUI Based Mamdani Fuzzy Inference System Modeling To Predict Surface Roughness in Laser Machining, International Journal of Electrical & Computer Sciences IJECS Vol: 9 No: 9

[23] Cameron Potter, Michael, ANFIS Application to Competition on Artificial Time Series (CATS), Fuzzy Systems 2004, Proceedings, IEEE International Conference, vol.1, pp. 469 - 474

[24] Tahir Ayata, Ertugrul Cam, Osman Yildiz, Adaptive neuro-fuzzy inference systems (ANFIS) application to investigate potential use of natural ventilation in new building designs in Turkey, Elsevier, Energy Conversion and Management 48 (2007) 1472‑1479

[25] Luis G. Martínez, Antonio Rodríguez-Díaz, Guillermo Licea, Juan R. Castro, Big Five Patterns for Software Engineering Roles Using an ANFIS Learning Approach with RAMSET, Springer, MICAI 2010, Part II, LNAI 6438, pp. 428–439

[26] Sezer Gören, Adem Karahoca, Filiz Y. Onat, M. Zafer Gören, Prediction of cyclosporine A blood levels: an application of the adaptive-network-based fuzzy inference system (ANFIS) in assisting drug therapy, Springer, Eur J Clin Pharmacol (2008) 64:807–814, DOI 10.1007/s00228-008-0490-x

[27] Chun-Tian Cheng, Jian-Yi Lin, Long-Term Prediction of Discharges in Manwan Hydropower Using Adaptive-Network-Based Fuzzy Inference Systems Models, LNCS 3612, pp. 1152 – 1161, 2005., Springer-Verlag Berlin Heidelberg

[28] Vibha Gaur, Anuja Soni, S.K.Muttoo, Neeraj Jain, Comparative Analysis of Mamdani and Sugeno Inference Systems for Evaluating Inter-Agent Dependency Requirements, 12th International Conference on Hybrid Intelligent Systems, Pune India, 2012 IEEE explore

[29] Ozgur Kisi and Murat Ay, Comparison OF ANN and ANFIS Techniqes in Modeling Dissolved Oxygen, Sixteenth International Water Technology Conference, IWTC-16 2012, Istanbul, Turkey

[30] Indrajit De, Jaya Sil, ANFIS Tuned No-Reference Quality Prediction of Distorted/Decompressed Images featuring Wavelet Entropy, International Journal of Computer Information Systems and Industrial Management Applications, Volume 3 (2011) pp. 298-305

[31] Uwe Jaenen, Carsten Grenz, Christian Paul and Joerg Haehner, Using Feed-Forward Neural Networks for Data Association on Multi-Object

Tracking Tasks, International Journal of Computer Information Systems and Industrial Management Applications, Volume 4 (2012) pp. 383–391

[32] Rim Rekik and Ilhem Kallel, Fuzz-Web: A Methodology Based on Fuzzy Logic for Assessing Web Sites, International Journal of Computer Information Systems and Industrial Management Applications, Volume 5 (2012) pp. 126-136

[33] Fatai A. Anifowose, Jane Labadin and Abdulazeez Abdulraheem, Prediction of Petroleum Reservoir Properties using Different Versions of Adaptive Neuro-Fuzzy Inference System Hybrid Models, International Journal of Computer Information Systems and Industrial Management Applications, Volume 5 (2013) pp. 413-426

[34] Tanish Zaveri, Ishit Makwana, Novel Hybrid Multispectral Image Fusion Method using Fuzzy Logic, International Journal of Computer Information Systems and Industrial Management Applications, Vol.2 (2010), pp.096-103

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