Comparison of Intelligent Classification Techniques by Practicing a Specific Technology Audit

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***Abstract*--Technology audit activities are carried out for assessment of firms' technological requirements, capacity or management capability . The aim of these assessments is to define the weaknesses of firms and develop actions in order to improve firms' technological capacity and/or technology management capability. Generally these activities are implemented with survey questionnaires. These questionnaires can be filled by managers of firms or can be implemented as an interview by independent experts. However, evaluating surveys and preparing useful comments related to results can consume lots of time and also contain lots of biases/subjectivity. In accordance to ease the decision making process and provide more verified/accurate results, we develop a methodology based on an Artificial Neural Network (ANN) algorithm which is aimed to behave like a decision maker. And in this study, we use a synthetic data set which is prepared for assessment of technology management capability of selected 70 Turkish firms.**

I. MOTIVATION

Technology audit, one of the most important branches of technology management field, covers assessment of firms' technology requirements, technological capacity and also technology management capability [1, 2]. With the assessments, firms' weaknesses can be figured out and according to these weaknesses an action plan can be developed in order to improve firms' technological capacity and/or technology management capability [3]. Hereby, in the long term firms can get better innovation results if they successfully implement these actions and improve their technology management strategies.

In order to define weaknesses or gaps related to technology audit activities, survey questionnaires can be implemented. These surveys can be self-assessment and/or interactive like interviews. Unfortunately, self-assessment questionnaires do not provide well defined answers. On the other hand, when the questionnaires are interactive, time can be wasted with irrelevant conversations during interviews. Also, after getting answers, the process of evaluating surveys and preparing useful comments related to evaluation results is not efficient most of time. Besides these, in consequence of the comments mostly depend on expert opinions, there can be many subjective evaluations and also biases which can affect overall assessment. In accordance to ease the assessment process and provide more verified/accurate comments, Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS) algorithms [4, 5, 6] based methodology were developed.

This paper employs the real data set relating to a former technology management capacity assessment conducted by Sabancı University on 70 Turkish Small and Medium-sized Enterprises (SME) that engaged in maritime, software, manufacturing and defense sectors. The data is used as input to both ANN and ANFIS algorithms in the construction of an artificial decision maker. Within the scope of this study, the most appropriate algorithm was shown with comparing their performance regarding technology audit practice.

Based on this motivation, in the following sections, some useful information about technology management capability, expert systems, ANN and ANFIS are given due to create a general view of the notions. After that, methodology of the study is explained and then practical study with industrial partners are described. At the end of the paper, the results and possible future contributions are examined.

II. TECHNOLOGY MANAGEMENT CAPABILITY

Technology management was defined by Gregory as a process of five activities [7] which are identification, selection, acquisition, exploitation and protection. Related to that, Rush, Bessant and Hobday proposed a new methodology to assess the firm's technology management capability in nine dimensions which consist four activities of Gregory's model except protection [8]. They expand identification as awareness and searching of new technologies. In addition to acquisition, they also consider "external linkages" as a new dimension. They include technology strategy and core competences as new dimensions which have common points with technology selection. In this study we used Rush, Bessant and Hobday's methodology, but we include "protection" as 10^{th} dimension [9]. After all, these dimensions are defined as input parameters for developing the algorithm.

III. EXPERT SYSTEMS

During the past decade, the interest in the results of artificial intelligence research has been growing to an increasing extent. Knowledge based systems are the initial area subject for artificial intelligence. In addition, expert system provides advice derived from its knowledge base, using a reasoning process embedded in its inference engine, the thinking part of the system [10]. As an archaic term, Expert System describes a computer program that simulates the judgment and behavior of a human that has expert knowledge and experience in a particular field. These systems are part of a general category of computer applications known as artificial intelligence (AI). With an expert system, the goal is to specify the rules in a format that is intuitive and easily understood, reviewed, and even edited by domain experts rather than IT experts. The benefits of this explicit knowledge representation are rapid development and ease of maintenance. And most AI study in expert systems involve development of large knowledge based systems in problem areas such as medicine, geological exploration, analysis of oil-well logs, mass spectroscopy interpretation and computer configuration [11]. In this study, ANN and ANFIS stand as a basic expert system in order to support assessment of a real industrial data set regarding a technology management audit practice.

IV. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANN) is a computational system inspired by the structure, processing method, learning ability of a biological brain. The basic architecture consists of three types of neuron layers which are called input, hidden, and output layers. ANN is the most common technique for classification, clustering and anomaly detection. ANN can be seen as a black box which takes the input(s) and gives the output(s) like imitating the behavior of interconnected electro-chemical neurons. For its applications, Feed Forward Neural Network is the most used structure.

The basic structure of ANN is given in Figure 1.

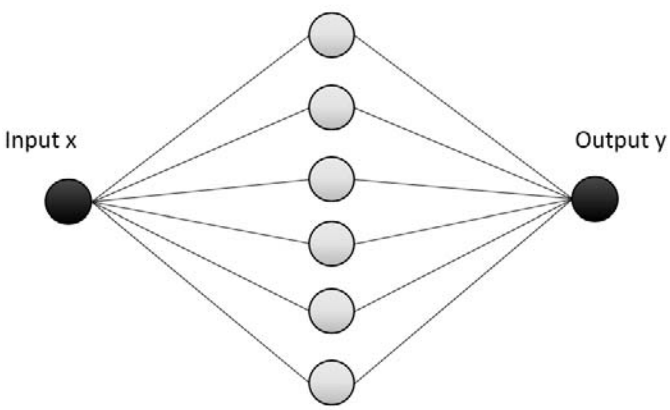

Figure 1 Single Input – Single Output ANN System

The weights in a neural network are the most important factors while determining its functionality. Training is the act of presenting the network with some sample data and modifying the weights to better approximate the desired function.

There are two prevalent types of learning for ANN which are supervised and unsupervised learning. In supervised learning, weights are modified in order to reduce the difference between the actual and desired outputs. On the other hand, in unsupervised learning, the network identifies the patterns and differences in the inputs without any external assistance. The number of neurons is very important. If the neuron number is too little, the system under fits the data, other words it cannot learn the details. Contrarily, if the neuron number is too many, the system can learn insignificant details which also called as "memorize". ANN has proven its ability in the estimation of continuous nonlinear function at any demanded level of preciseness [12].

Multilayer Perceptron (MLP) with backpropagation algorithm is one of the most popular ANN technique that theoretically enables modelling and simulation of any nonlinear system under selection of an appropriate internal structure for ANN. Backpropagation, as a supervised learning algorithm, prevails in a network environment with inputs and desired outputs in an aim to minimize the difference between network output and the desired output. The activation function of backpropagation algorithm is used to activate neurons as seen Equation (1) [13].

$$A_j(\overline{p}, \overline{w}) = \sum_{i=0}^{n} p_i w_{ji} \quad (1)$$

Given inputs and neuron weights are determinatives of activation function. The state of which the output function and activation function are identical is designated as linear network that has a lot of limitations.

In this paper we have used backpropagation algorithm within the layers of the Feed Forward Network.

V. ANFIS

ANFIS is a class of adaptive network that is functionally equivalent to fuzzy inference system. ANFIS system is a hybrid method which uses neural network and fuzzy logic algorithms. With this way, it can avoid some disadvantages of both neural network and fuzzy logic. Referred to ANFIS, adaptive neuro fuzzy inference system or adaptive network-based fuzzy inference system represents a class of adaptive networks based on Takagi-Sugano type fuzzy model. ANFIS also uses a hybrid learning algorithm. In this process, at first an initial fuzzy model along with its input variables are derived with the help of the rules extracted from the input-output data which is modeled. Next, the neural network is used to fine tune the rules of the initial fuzzy model to produce the final ANFIS model of the system. In the forward pass, the algorithm uses least-squares method to identify the consequent parameters. And in the backward pass, the errors are propagated backward and the premise parameters are updated by gradient descent. In this study, we used forward pass system as shown with a basic structure in Figure 2 [6].

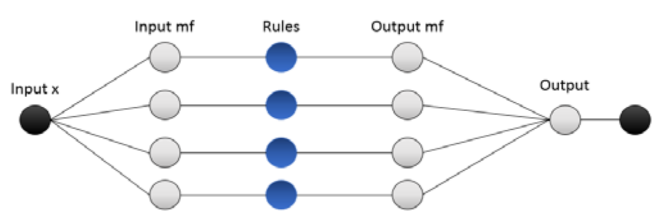

Figure 2 Single Input – Single Output ANFIS System

ANFIS stands for ANN Based Fuzzy Inference Systems or equivalently Artificial Neuro-Fuzzy Inference System is a Multilayer Feed Forward Network, uses hybrid learning algorithm and Takagi-Sugeno fuzzy models. Suppose that the rule base contains the following two Sugeno-type fuzzy if-then rules:

Rule1: if x is A1 and y is B1 then f1=p1x+q1y+r1
Rule2: if x is A2 and y is B2 then f2=p2x+q2y+r2

Where x and y are the inputs, Ai and Bi are the fuzzy sets, fi is the output, and {pi, qi, ri} are the parameters that are determined during the training process [12].

VI. METHODOLOGY AND STUDY

Developed methodology falls under 5 basic steps within the technology management capability audit practice. In the first step, the influential parameters that may lead to accuracy of audit results were identified. These parameters are transferred from specific survey questions [9] and then defined as input parameters as given in Table 1.

TABLE 1 INPUT PARAMETERS

Input Parameters	
1	Awareness of new technologies
2	Searching of new technologies
3	Core competences
4	Technology strategy
5	Assessing and selecting technology
6	Technology acquisition
7	Implementing and absorbing technology
8	Learning
9	Building external linkages
10	IP Protection

Each input parameter contains a set of questions which are asked during the interviews in order to determine the firm's current capability and actions regarding these capabilities. Then, the technology audit results were defined based on the selected 70 companies' answers. These results are called as output parameters, which can be seen in Table 2 with their brief explanations [8].

TABLE 2 OUTPUT PARAMETERS

Output Parameters		
Type 1 (A)	Unaware / Passive	Firm has no information about technology management capabilities
Type 2 (B)	Reactive	Firm has limited information about technology management capabilities, but has no actions to improve firm's competitiveness
Type 3 (C)	Strategic	Firm has information about technology management capabilities but has limited actions to improve firm's competitiveness
Type 4 (D)	Creative	Firm has comprehensive information about technology management capabilities and has several actions to become more competitive

In the second step, expert opinions were applied in order to give some weights to input parameters for training process of ANN and ANFIS. In this process, up most known multi criteria decision making method, Analytic Hierarchy Process (AHP), was used.

Regarding this step, the most influential parameter was found as "technology strategy". From that point of view, it can be said that companies' who has well defined technology strategies are well aware their technological capabilities and are capable of assessing and developing technology management capability than other companies.

In the third step, the links between input parameters and output parameters were created. Each input and output relation is defined as a "case" for the analysis. Regarding that, totally 50 cases for training and 20 cases for testing were identified. The sample input and output table is depicted by Table 3.

Later on, the fourth step is the preparation of ANN and ANFIS algorithms by utilizing the defined cases. As mentioned before, ANN, ANFIS and Fuzzy Logic are foremost of intelligent classification methods. Although ANN and Fuzzy Logic gain wide areas of implementation due to their pre-existence, ANFIS presents an advanced product that minimizes the conditional complications of ANN and Fuzzy Logic. ANN and ANFIS are selected as solution algorithms to our case since the enormous work load arising from entire input-output structure would not suit the implementation of fuzzy rules [14]. Besides, ANFIS based rules facilitate the corroboration of Neural Network formation within ANFIS and shorten learning period. In that respect, we regard ANFIS more effective than ANN and Fuzzy Logic during system

TABLE 3 EXAMPLE INPUT AND OUTPUT TABLE

	INPUT										OUTPUT			
CASES	Awareness of new technologies	Searching of new technologies	Core competences	Technology strategy	Assessing and selecting technology	Technology acquisition	Building External Linkages	Implementing and absorbing technology	Learning	Protection	A	B	C	D
F-1	0,017	0,021	0,017	0,016	0,021	0,016	0,018	0,020	0,018	0,020	0	0	1	0
F-2	0,021	0,018	0,023	0,025	0,023	0,023	0,023	0,020	0,020	0,018	1	0	0	0
F-3	0,017	0,017	0,021	0,021	0,023	0,021	0,023	0,022	0,018	0,021	0	1	0	0
F-4	0,021	0,017	0,023	0,023	0,023	0,022	0,025	0,022	0,022	0,020	1	0	0	0
F-5	0,021	0,018	0,021	0,020	0,023	0,019	0,019	0,012	0,018	0,017	0	0	1	0
F-6	0,021	0,021	0,020	0,022	0,023	0,022	0,020	0,022	0,022	0,023	0	1	0	0
F-7	0,017	0,021	0,018	0,017	0,014	0,018	0,020	0,014	0,020	0,015	0	0	1	0

construction as well as system run for accomplishment of current and similar studies. Moreover, ANFIS and ANN take precedence over Fuzzy Logic which hardly satisfies the generation of implementation based oral cases.

Here, MLP network sends forward inputs as signals and receives outputs as error feed backs by the act of backpropagation algorithm. Then gradient descent method is applied to minimize the mean squared error between network output and desired output. Progressively, Gradient Descent Algorithm may trap in local minimum causing the increase in problem momentum. For avoidance of such a situation, Gradient Descent Momentum Algorithm was chosen and employed among other learning algorithms such as Levenberg-Marquardt, Gradient Descent, etc.

Furthermore, 2-layer system was considered to be adequate for existing input/output structure and yet our trials resulted in the reach of desired error rate sufficiently by 7 hidden layer neuron. Any effort to increase this number no longer counts as significant achievement but would bring in run time burden.

Sugeno type structure is the most widely used type within ANFIS and owing our familiarity and past experiences, we proceeded with that type in conduction of this study. The rule number was set as 4 purposely in an aim to distinguish top 4 high-impact item on input/output table so that high accuracy and run time optimization were enabled for NN construction.

Regarding ANN part, feed-forward back propagation neural network was chosen as network type of the training algorithm. In order to get better results in the analysis part, the parameters shown in Table 4 were preferred. Here, as a training function, Levenberg Marquart was chosen, owing to LM algorithm is more robust than other algorithms such as Gauss-Newton Algorithm. In the analysis, number of layers are 2 and hidden layers are 7 in order to made an optimization between the best running time and best accuracy. Minimum gradient value was taken as 1e-020, this value must be chosen very small related to number of inputs/outputs. Also, linear transfer function was chosen in order to provide high quality in classification. Lastly, for training and testing, each case was chosen randomly by both systems. Through the nature of ANN, our system can "learn" instead "memorize".

For the classifications and simulation steps, MATLAB software was used. A basic figure which depicted MATLAB software interface can be seen in Figure 3.

TABLE 4 PARAMETERS FOR ANALYSIS

Parameter	Type
Training Function	Levenberg-Marquardt
Adaptation Learning Function	Gradient descent with momentum weight and bias learning function
Performance Function	Mean squared normalized error performance function
Number of Layers	2
Number of Hidden Layer Neurons	7
Minimum Gradient Value	1e-020
Transfer Function	Linear transfer function (purelin)
Data Division for Train/Test	Random

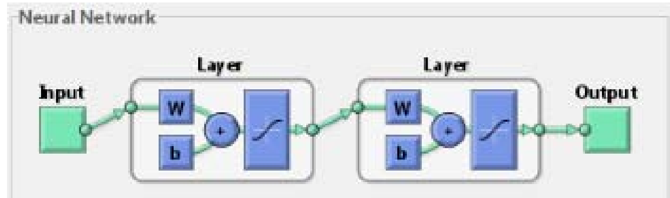

Figure 3 ANN structure

Unlike ANN practice, ANFIS requires some definition of particular rules in order to denote fuzzification layer and fuzzy rule layer. Choosing a rule, however, is another optimization problem owing the complexity occurred. Corresponding ANFIS rule structure formation can be seen in Figure 4. Here, input parameters are functions and they are analyzed in selected rules and then give a result as function result.

The ANFIS rules that were used in the algorithm are similar to followings [6]:

- If (Technology_Strategy is Very High) then (output is A)
- If (Learning is Low) and If (Technology_Strategy is Low) then (output is D)
- If (Learning is High) and If (Technology_Strategy is High) then (output is A)
- If (Core_Competences is High) and If (Technology_Acquisition is High) then (output is A)

ANFIS format is quite difficult to prepare when it is compared with ANN. In ANFIS, the expert/decision maker should prepare each case statement himself, however in ANN model, current collected data is enough to create such an input-output table and run to figure out the results.

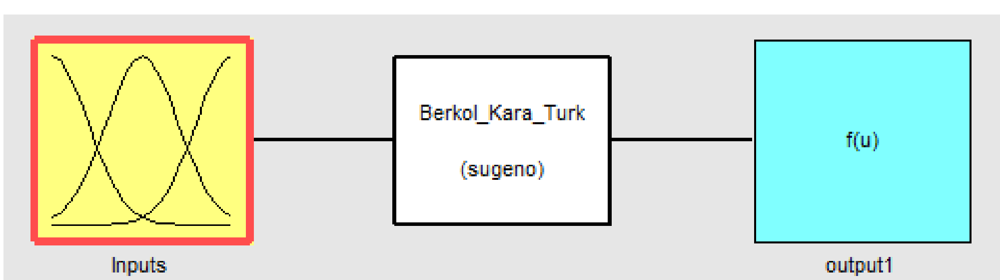

Figure 4 ANFIS rule structure

Finally, at the fifth (last) step, the results of ANN and ANFIS analysis were compared in order to see the most appropriate algorithm that can behave like an expert/decision maker for the specific technology audit practice. Figure 5 gives the overall methodology picture as reference to all these progressive/subsequent steps.

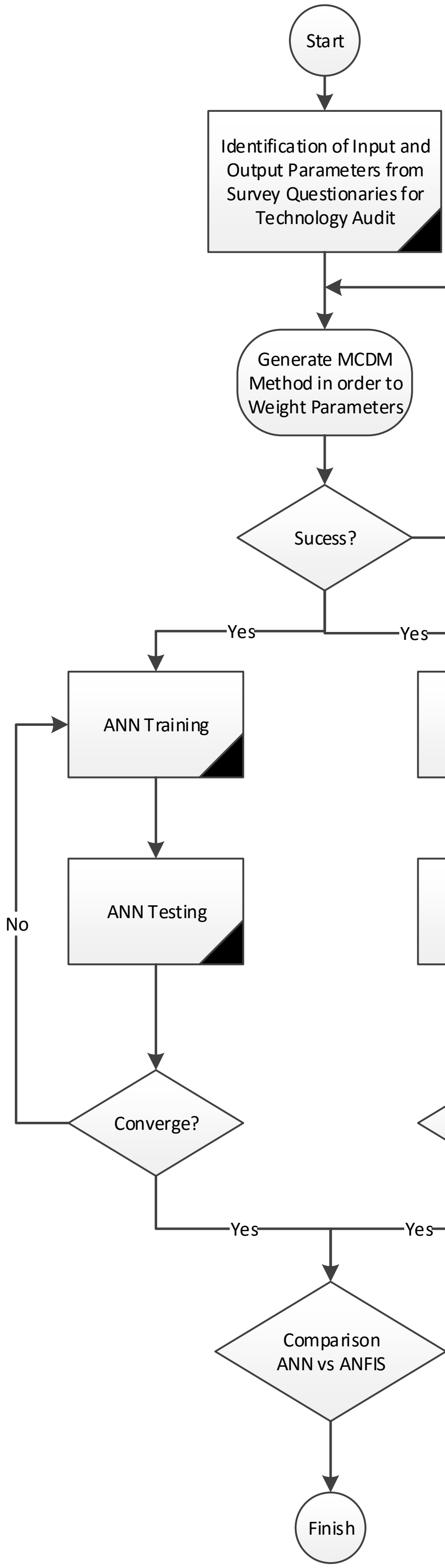

Figure 5 Flow chart of technology management capability audit methodology with ANN and ANFIS

VII. RESULTS

In this study, we use real industrial based data set for developing a decision making methodology for technology management capacity auditing. Throughout our analyses, we used both ANN and ANFIS algorithms and showed that both algorithms completed the learning stage with the minimum desired error value. Also, we compared ANN and ANFIS algorithms in order to find the best decision maker for given practice. According to the analyses, ANN results can be seen in Table 5.

TABLE 5 ANN RESULTS

Parameter	Result
Total Epochs	30
Gradient (desired)	1.00e-20
Gradient (actual)	5.19e-21
Run Time	8 Seconds
Total RMS Error	0.028
Program Size	327 Bytes

Evidently, ANN algorithm reached a lower error value in 30 epochs. The system completed the simulation in 8 seconds, mainly due to system complexity. Also remarkable is that, total (Root Mean Square) RMS Error value remains very low for such kind of complex system.

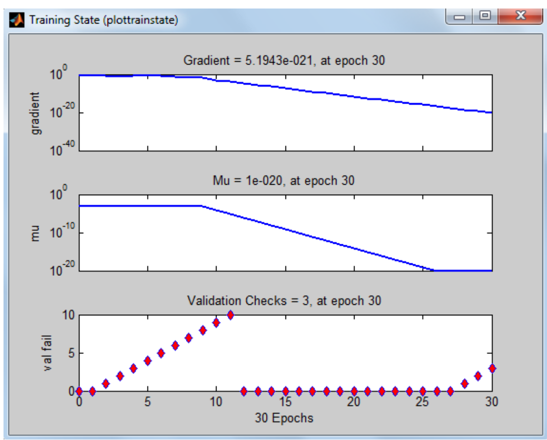

Figure 6 Training State Graphs for ANN

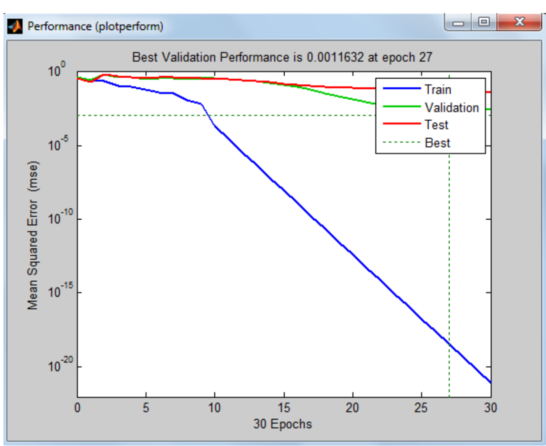

Figure 7 Performance Graph of ANN

In addition, Figure 6 and Figure 7 give training-testing-validation graphs. As seen below, system trained effectually, and reached the desired gradient value. As seen from Figure 7, the best validation performance is at epoch 27.

Furthermore, the details of ANFIS algorithm and analysis results can be seen in Table 6. Again, the training and testing processes are accomplished. As a matter, for ANFIS implication, fuzzyfication and defuzzyfication parameters, and also membership function should be defined as given in the table. These parameters were taken from previous experiences [4, 6].

TABLE 6 ANFIS ANALYSIS DETAILS

Parameter	Type
FIS Type	Sugeno
Deffuzification Type	Wtaver (Open Fuzzy Logic Designer)
Membership Function	Gbellmf (Generalized bell-shaped membership function)
Number of nodes	18
Linear and nonlinear parameters	11
Rules	4
Training Samples	52

Parameters like fitting error, program size and program run time results are taken into account in the comparison of ANN and ANFIS algorithms as shown by Table 7.

TABLE 7 COMPARISON TABLE

	ANN	ANFIS
Total RMS Error	0.028	0.016
Program Size	327 Bytes	578 Bytes
Run Time	8 Seconds	0.387 Seconds

As it can be concluded from the tables, ANFIS is superior to ANN regarding total RMS error and run time outcomes. Notably, ANN has a lower program size than ANFIS. Such a feature could make ANN proficient especially for implications involving big data.

Except those, this study is conducted without the consideration of Central Processing Unit (CPU) time since it did not aim to obtain real time data and results.

VIII. COMMENTS AND FUTURE STUDIES

In the sense of technology management, this methodology showed that classification algorithms can be used as experts/decision makers in high amount of questionnaire implications in order to get quick and mostly unbiased results. As we indicated in introduction, there are two ways of carrying out of technology audit studies that are self-assessment and interview. Development of such kind of experts systems will make beneficial especially the self-assessment method. Companies can fill the questionnaire online and can get their results right away. Most online tool provides such generic reports, however our tool will provide more concrete and customized results with the help of ANFIS system. The idea behind these online tools is to increase the number of sample that can be benchmarked, so that such expert systems will attract more companies' attention.

In this study, sectorial differences and organization size were neglected while carrying out technology audit because of the limited number of sample. Future studies can be diversified by focusing sector wise and organization size wise. In this sense, the input parameters shall be weighted according to different sectorial dynamics and organization size.

In the algorithm side, inherently, these types of optimization problems are very complicated, because of their input/output complexities. The idea of implementing an artificial intelligent classification or clustering technique should be considered prior to start of the work at the beginning of the work. Regarding that, the biggest problem of ANN is structure of hidden layer neurons. For higher degree of performances, hidden layer neurons should be increased. Nevertheless, this will be another trade off, as it is a matter of program size and run time. Online systems or toolboxes would perform faster than the offline. In terms of ANFIS, its performance can also be improved by using more number of rules. However, it may slows down ANFIS total analysis process. Nonetheless, identifiability of the rules for systems, which have extortionate input parameters, is very difficult.

Furthermore, in the future studies, most influential parameters which affect technology management capability audit practices will be identified and embedded in the methodology in order to improve the algorithm's decision accuracy.

Once and for all, classification methods can be used in any type of technology management relevant decision making practices as given in the study. Companies that embrace these implementations could reach an awareness state reliably in their endeavor of technology acquisition (searching, selecting, developing, transferring) and management activities. Hence, they can develop and sustain well-suited technology strategies to keep up with or exceed the evolving emerging needs of the market.

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