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Forecasting of Intellectual Capital by Measuring Innovation Using Adaptive Neuro-Fuzzy Inference System

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Abstract

Purpose – The aim of every organization is to achieve its set goals and objectives as well as secure competitive advantage over its competitors. However, these cannot be achieved or actualized if staff or workers act independently and do not share ideas. Today prominent businesses are becoming more aware that the knowledge of their employees is one of their primary assets. Sometimes organizational decisions cannot be effectively made with information alone; there is need for knowledge application. An effective Knowledge Management System can give a company the competitive edge it needs to be successful, and, for that reason, knowledge Management projects should be high priority. This means that for any organization to be competitive in today's global world there is need for combination or pooling together of ideas by employees in order to achieve teamwork; this is in support of the saying that 'two good heads are better than one'. Due to the advent of the knowledge-based economy and the developments in activity nature of the companies at international level, intellectual capital is taken to be one of the fundamental pillars of the companies for achieving efficiency. The aim of this study is to predict the amount and effectiveness of intellectual capital or intangible assets on the basis of innovation ability of the companies using an integrated artificial neural networks fuzzy logic analysis approach in order to cope with future challenges of strategic management. Design/methodology/approach – This paper suggests some guidelines for setting up the development of valuation approach based on application and adaption of selected financial and non-financial indicators by means of artificial neural networks and fuzzy logic. The artificial neural network model is highly accurate in predicting intellectual capital of the companies. This research paper presents the construction and design of Hybrid Application using Neural Network and Fuzzy Logic. This proposed system uses a simplified algorithmic design approach with wide range of input and output membership functions. In this research a hybrid Neuro-Fuzzy systems modelling methodology is developed and applied to an empirical data set in order to determine the hidden fuzzy if-then rules. Furthermore, the proposed methodology is a valuable tool for successful knowledge management. Findings – The findings show the opinion of that the complexity of development has been improved by expansion in the amount of knowledge available to organizations. Future research should contain of high degree of study to analytically examine the successful project knowledge management in different types of plans, companies and commences. Learning comes through creating and applying knowledge, whilst learning increases an individual's and organization's knowledge asset. Both learning and knowledge management feed off the same root: learning, improved capacity to perform work tasks, ability to make effective decisions, predict future parameters on the basis of some certain parameters and positively impact the world around us. Challenges – Identification and evaluation of the significant factors that create and determine enterprise value in industry is based on complex calculations involving many variables. Regardless of this reason, existing business valuation methods for such companies have to be improved with taking into account a numerous qualitative and even additional quantitative factors.

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Therefore, economic experts and scientists in the field of business valuation are confronted with new challenges in determination of appropriate approaches that should be able to eliminate the disadvantages of existing valuation methods. The environment in which businesses operate is ever changing. The market has become global and the technological advancement has changed the way business is done. The resulting impact of globalization is fierce competition that has altered the business landscape. Firms are increasingly employing various techniques in order to remain relevant and competitive. Since decision making is considered as the management main elements and sometimes equivalent to management itself, it is essential that researchers pay a specific attention to this field because if decisions are made in an optimized and effective form in an organization. This work is motivated by the need for a model that addresses the study of Knowledge in specific environments such as Business and Management, where several situations are very difficult to be analyze in conventional ways and therefore is insufficient in describing the complications of represent a realistic social phenomena and their social actors. Distributed Agency methodology will be used that requires the use of all available computational techniques and interdisciplinary theories as an approach to describe the interactions between agents in the development of social phenomena. Data Mining and Neuro-Fuzzy System are also used as part of the methodology to discover and assign rules on agents that represent real-world companies and employees. Practical implications – Today most organizations have discovered that advanced trainings can be considered as the key asset for modern organizations. This study presents a forecasting model that predicts intangible assets on the basis of innovation performance in organizational training using widely applied innovation criteria. The research focused on criteria, such as organization culture, ability to respond to organizational technology changes, relationship with other organizations in the training process and the use of high technology in education. The adaptive neuro-fuzzy inference systems (ANFIS) approach has been used to verify the proposed model. It is possible to predict innovation performance and it can also adjust allocated resources to organizational training system for its innovation objectives with this method. Originality/value – A great deal of work has been published over the past decade on the application of neural networks in diverse fields. This paper presents a model that measure and forecasts the intangible assets by the development of an Adaptive Neural Network with Fuzzy Inference system (ANFIS), using data that concern human capital, organizational support and innovativeness. The results indicate that fuzzy neural networks could be an efficient system that is easy to apply in order to accurately measure and forecast the intangible assets by measuring innovation capabilities of an organization or firm.

Keywords: Intellectual capital, Human capital, Innovation, Artificial neural network, Fuzzy logic, Organizations, Intangible assets, Inference system.

Contents

1. Introduction

The modern-day technologies in the areas of information storage and retrieval, web search, image processing, control, pattern recognition, bio-information and computational biology, e-markets, autonomous navigation, and guidance are benefited using fuzzy sets. The current trends of information technology have proved that the increasing level of intelligence, autonomy and required flexibility comes true with the increased human centricity of resulting results. The holistic view covers concepts, design methodologies, and algorithms with interpretation, analysis, and engineering knowledge. In order to communicate between these two words we need to develop an interface. This is the key motivation behind the emergence of human-centric systems and human centric computing.

The environment in which businesses operate is ever changing. The market has become global and the technological advancement has changed the way business is done. The resulting impact of globalization is fierce competition that has altered the business landscape. Firms are increasingly employing various techniques in order to remain relevant and competitive. The strategies include product differentiation, cost reduction, pricing among others [1]. Knowledge and Knowledge Management are concepts, which are debated extensively by managers, analyst and academicians. Managers ask for more information to support decisions. This led to the use of information technology to build transaction support systems, Management information systems and data warehouses resulting in too much information, which has neither helped the managers nor provided any value to the organizations. Data leads to information, but what organizations were really looking for was knowledge. When we refer to knowledge, most of us mainly tend to think of codified and documented knowledge like patents, databases, manuals, white papers etc. With this “explicit knowledge” is important, what is even more important and value adding from the perspective of competitive advantage is the “tacit knowledge” which is embedded in the minds of the people [2]. The tacit knowledge is intuitive, contextual, linked to experience, past memories and difficult to codify, document and communicate. Since organizational knowledge is one of the important assets of the organization, it needs to be managed like other assets, Knowledge here could be referred to as the understanding that a person has gained through education, experience, discovery, intuition and insight or a combination of instincts, ideas, rules and procedures that guide actions and decisions [3]. It is an intangible asset that is unique and can be used to achieve long-term strategic benefits or advantage. This is because knowledge has more competitive significance than physical assets in a multinational organization that relies on unique competencies and methods; also, unlike other physical assets of an organization, knowledge is not subject to the law of diminishing returns as the physical assets, but increases in value as people share it. Knowledge can be in a form that can be stated, codified or written and understandable by everyone(explicit)or in a form that cannot be expressed easily and unconsciously applied but understood by individuals(implicit or tacit) [4].

Periods of rapid change create a premium on learning – for both individuals and organizations. Prosperity and growth are the rewards of those who are the fastest at learning and putting their learning in action; stagnation and decline are the penalties for delay. Because intellectual capital resides both in tacit form (human education, experience and expertise) and explicit form (documents and data), KM depends on both cultural and technological processes of creation, collection, sharing, recombination and reuse. The goal is to create new value by improving the efficiency and effectiveness of individual and collaborative knowledge work while increasing innovation and sharpening decision-making.

Work discretion, that is to say the ability to take initiative in decision making is demonstrated to enhance the innovativeness and overall performance of the companies. On the other hand, high level of trust among the employees in the reward system of their company also positively influences their commitment to innovativeness [5]. Management support, i.e., the encouragement of new idea generation and development, positively influence a firms’ entrepreneurial behavior and enhance potential entrepreneurs’ willingness to innovate. Besides, if the employees feel free from any punishment, adverse criticism, or loss of support in case of failure of their projects or ideas, then their commitment to innovative attempts will be increased.

Innovation is a multidimensional concept, which appears in different. Innovation concepts were discussed, defined and developed from the perspective of several disciplines: sociology, psychology, economics, linguistics, management, cognitive science, philosophy [6].

Enterprise innovation is a popular topic among researchers. Business organizations have an inherent tendency toward conservatism and preference for certainty instead of risky ventures and innovations. Several researchers assume that it is possible to innovate and innovations are occurring in Business organizations.

Innovation in organizations involves creating something new and having this ‘new’ implemented and adopted by others. It is claimed that the main concept of innovation depends on the newness. Some researcher describe this ‘new’ as a concept, idea, service, product, policy, process, procedure, system, structure, and much more.

Intellectual capital is the total stocks of all kinds of intangible assets, knowledge, capabilities, and relationships, etc, at employee level and organization level within a company. It is examined in the literature under three subgroups; namely, human, social and organizational capital. The human capital is the sum of knowledge and skills that can be improved especially by education and work experience of the employees of an organization. It is suggested that the human capital of a firm is crucial in terms of the innovativeness, due to its ability to obtain and make use of the outcomes of other firms’ R&D activities. Human capital also enhances the organizational competencies of the firms by increasing the returns from the innovations and reducing the risks. Hence, the human capital not only has direct effect on innovativeness but is also a precious resource that may act as a moderator in the relationship of organizational support and innovativeness.

The information technology is one of these dynamic sectors that present a number of distinctive features which need to improve the knowledge to increase their competitiveness, one of the main characteristics is that the staff working in this industry must have technical and scientific capabilities that require training in the area of mathematics, logics and in several cases also in computer science.

Fuzzy logic, instead, handles with imprecise information and linguistic concepts, develops the approximate reasoning in order to perform non-linear mappings between inputs and outputs, but it is not capable of self-learning.

This study proposes the use of a hybrid intelligent system called ANFIS for predicting the intellectual capital on the basis of innovation measurement, which combines the learning capabilities of a neural network and the reasoning capabilities of fuzzy logic in order to achieve improved prediction capabilities, avoiding rule matching time of an inference engine in the traditional fuzzy logic system [7].

In addition, the majorities of time series models are linear, and so are incapable of describing nonlinear behaviors. In the recent studies, artificial neural networks have widely been employed as nonlinear approximate instruments, in that they can be utilized to tackle above problems. The neural networks can diagnose the linear and nonlinear relationships between input and output products based on training data. They also can discover the fundamental relationships between such data and then generalize them to other data. Consequently, with proper neural network architecture design and training data selection, a structure capable of time series prediction can be obtained.

Artificial neural networks are a group of mathematical models that imitate human brain function. They can extract patterns from the observed data, without any needs for assumptions about the relationships between the variables. These networks are a series of highly accurate comprehensive, flexible, and powerful instruments for data analysis and nonlinear relationships modelling. One of the most common neural networks is the multilayer perceptron neural network. Multilayer perceptron is a standard combination of inputs, linear and nonlinear neural units and outputs. The output of all processing units is transported from each layer to all processing units of the next layer. Processing units of the input layer are all linear. However, neurons with tangent sigmoid, hyperbolic, or any other nonlinear and continuously differentiable function can be used in the hidden layer. Usually, linear form of output layer neurons is selected for increasing the speed. The main debating issue in these types of networks is determination of the number of hidden layers and their neurons. Hidden layers are remarkably significant in neural network models. The adequate number of such layers in the units of a neural network model plays an effective part in learning process. This layer is merely an intermediate result in the process of output value calculation, so is unique in econometrics. The number of hidden nodes is important due to their substantial role in nonlinear configuration properties of the neural networks. The input layer as the recipient of external resources is compared to the five senses with respect to the brain. In determining the number of input nodes, using trial and error method has the highest application. The neural networks with a hidden layer with sigmoid function in the middle layer, and a linear function in the output layer would be able to approximate all of the desired functions with any approximate degrees, providing that there are sufficient neurons in the hidden layer. This is known as global approximation model [8].

Developing economically feasible innovation measurement and intellectual capital forecasting systems using ANNs is possible, although it is clearly a complex task. In many ways, ANNs themselves compound the difficulty. As noted neural methods of back-propagation are designed to reduce network training error. Perhaps a better objective would be to optimize performance to risk, an opportunity not directly afforded by using neural networks.

In this study, a new ANFIS based forecasting model is introduced, to explain how an innovation can be measured and intellectual capital can be predict. After a summary on innovation and innovative behavior, and the Adaptive Neuro-Fuzzy Inference System, the forecast model developed in this study is presented. ANFIS can simply be defined as the combination of ANNs and fuzzy logic [9]. This combined system has the abilities of deducing knowledge from given rules (which come from the ability of fuzzy inference systems (FIS)), learning, generalization, adaptation and parallelism (which come from the abilities of ANN). FIS is a framework based on fuzzy set theory and fuzzy if-then rules. The structure of FIS has three main components: a rule base, a database, and a reasoning mechanism. The rule base contains fuzzy if-then rules. The model is called a first-order Sugeno fuzzy model when f(x, y) is a first-order polynomial as shown below [10].

The intention of this research is to propose a model to describe the variables that determine the Intellectual Capital for competitiveness of industries through the development of knowledge from which innovation can be measured and intellectual capital can be predicted.

2. Literature Review

The main objective of knowledge management system is to identify knowledge and explicate it in a way that it can be shared in a formal manner, and thus reusing it. It helps in transferring the intellectual assets of the firm to value processes such as innovation and knowledge acquisition. It is meant to improve the organization’s ability to executive its core processes more efficiently by capturing intellectual assets for the tangible benefit of the organisation. KMS also aim at codifying knowledge and providing organized ways to find people who possess the required knowledge. Well-organized knowledge use improves competitive benefit and advances organizational success. Knowledge management (KM) has become increasingly important as organizations realize that efficient use of their enormous and diverse knowledge possessions and resources offer them with the capacity to innovate and take action to rapid varying consumer hopes. Organizations expand KM capabilities to help support a series of essential operational and innovative actions. The concentration in organizational competences has created a focus on the enlargement and accomplishment of KM processes and infrastructure necessary to hold up daily work practices [11].

Innovation can be described as the value adding changes in business processes, services, products, marketing or the ways that the works are organized in a company. Schumpeter differentiated between five different types of innovation: new products, new methods of production, new sources of supply, the exploitation of new markets, and new ways to organize business. Companies should manage their innovation performance carefully in order to stay competitive. On the other hand, the innovativeness of the company refers to the capability of making innovations or the degree of success of the innovation management performance. Various factors are shown to be influencing the firm level innovativeness. Among these organizational support enhances the innovativeness particularly at the individual employee level. Organizational support can be shaped by some managerial arrangements, such as work discretion, rewarding systems, management support for generation of new ideas, allocation of time availability, and tolerance for failures in creative undertakings and risky innovation projects [12].

The relationship between intellectual capitals as well as its components, and financial performance of the companies listed in Singapore Stock Exchange is investigated. The results indicate a positive correlation between intellectual capital as well as its components, and financial performance. In addition, the experimental information have provided supportive evidences maintaining that specific classes of intellectual capital positively affect organizational performance [13].

A study has conducted titled “The Performance of Intellectual Capital in Pakistani Companies”. In this study, it was clarified that in addition to financial performance assessment, intellectual capital performance evaluation is also highly significant. The findings show that chemical, oil, gas, and cement sections have high level of intellectual capital, banking section possesses average intellectual capital performance, and public sector companies hold low intellectual capital performance [13].

In a study it is addressed to profitability of the resources, competitive intellectual capitals, and corporate performance in the health care industry. The experimental findings indicate a significant correlation between intellectual capital and corporate performance. These results also demonstrate that initiative capacities and modification are counted to be the first process. In addition, corporate performance improvement can be achieved by corporate human capital value added [13].

Chaos is a creative state in which order and disorder mingle. Chaotic view of the world is currently preferred by many researchers over the previously famous orderly view in explaining how the world works. In this chaotic world, disequilibrium is the norm and comes along with both threats and opportunities that have economic implications subject to the reactions of entrepreneurs, hence economic progress. Human systems including business organizations and economies are non-linear feedback systems because they exhibit both stability and instability at the same time. Chaotic theory posits that while economic forecasting and econometric model-building are at best hazardous pursuits, this does not rule out useful observations about economic relationships. The conclusion is that the simple linear relationships may not be the perfect basis for allocating indirect costs. Nevertheless, the firm should consider possible non-linear relationships as posited by the theory of chaos. However, this complex costs allocation analysis should bear in mind the cost benefit analysis [13].

Artificial Neural Networks (ANNs) have earned themselves an excellent reputation as non-linear approximates. Out of all the AI techniques available, ANNs are the technique which deals best with uncertainty. Like other forms of soft computing, ANNs exhibit a high tolerance to imprecision and perform well in noisy data environments. According to the researches, the neural networks have been accused that they are not being able to recognize the degree to which an input can influence the output of the model and that the “black box” syndrome that characterizes them restricts their applicability. Also, another limitation of the neural network is that it should be of feed forward type and due to this restriction; the adaptive network’s applications are immediate and immense in various areas [14].

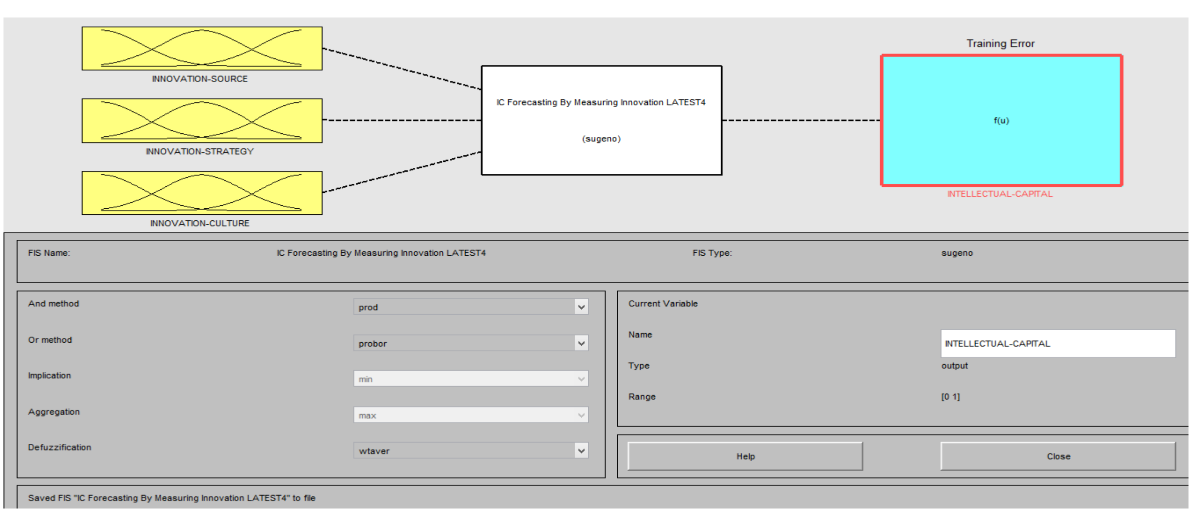
The ANFIS method has been widely used in literature. Jang first introduced the ANFIS method by embedding the Fuzzy Inference System (FIS) into the framework of adaptive networks. ANFIS has a feed-forward neural network structure where each layer is a neuro-fuzzy system component. ANFIS is capable to learn and generalize the training data. The consequents of the Takagi-Sugeno (TS) fuzzy rules are linear combinations of their preconditions in this method [12].

3. Adaptive Neuro-Fuzzy Inference System Mechanism

In 1965 Loft Zadeh introduced the fuzzy sets theory. Fuzzy logic controls have successively been implemented to solve the problems of real time automatic systems i.e. autonomous robot navigation, image analysis, autofocus cameras, diagnosis systems, automobile transmissions, washing machines, aerospace and many more adaptive systems.

In order to evolve the new setup of fuzzy logic based hardware and software solution are required to face new challenges in this field. To avoid computational complexity Fuzzy logic helps multidimensional problems of decision making for uncertain distributed environment in dynamic mode.

Fuzzy logic Systems are more efficient and accurate due to the variable environment. The input and output variables vary according to the situation. The values of output variables are achieved according to the variation in the input values using the rule base of fuzzy logic system. In other automated systems the values entered are fix where as in fuzzy logic systems the values entered vary due to which it gives much more accurate results then other automated systems and make them more close to real time systems because they work on real time scenarios.



Figur-1. Sugeno Type Fuzzy Inference System for Intellectual Capital Forecasting

The fuzzy inference mechanism consists of three stages: in the 1st stage, the values of the numerical inputs are mapped with membership function, this operation is called fuzzyfication. In the 2nd stage, the fuzzy system processes the rules with the firing strengths of the inputs. In the 3rd stage, the resultant fuzzy values are converted into numerical values; this operation is called defuzzyfication. Essentially, this procedure makes the use fuzzy categories in representation ideas in accordance to human beings in description of decision taking procedure.

Similarly, Artificial Neural Networks (ANN), as one of the computational intelligence methods structured after the human brain, started to be developed in 1943 in paper of McCulloch and Pits. Since then, they are constantly being developed, so the computational intelligence based on the learning theory enhanced the possibility of using prior knowledge (via expert systems and fuzzy logic) and data (via ANN) for complex information processing.

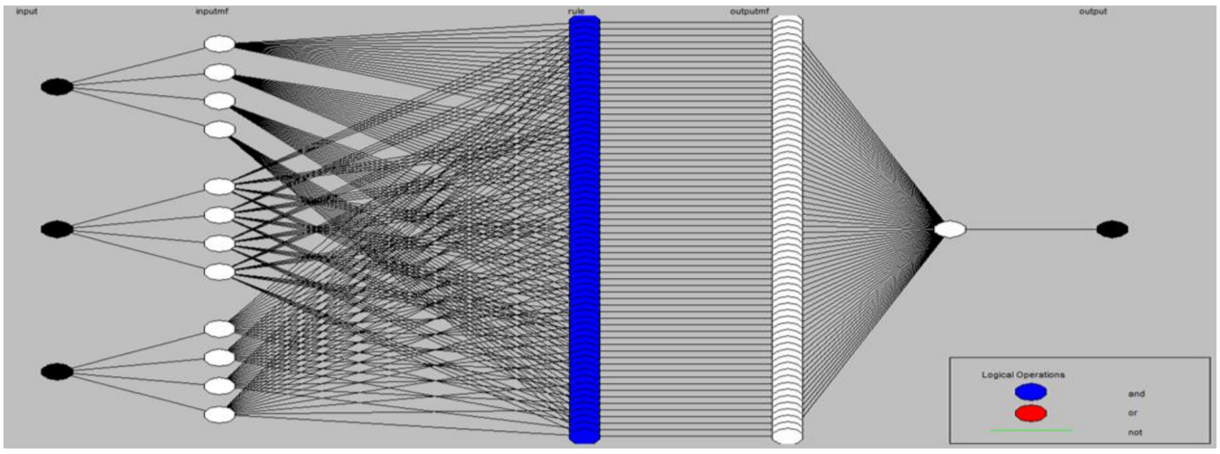


Figure-2. ANFIS Processing Mechanism

These models are often used for predicting bankruptcy and stock market trends, but the field of implementation is spreading to the financial analyses, research of interdependencies of certain metrics and business optimization as well. Next to production and operations, finances and investments, and company valuation are business areas that most frequently use computational intelligence in economics.

These very tools enabled a contemporary approach to business valuation and especially integration of financial, strategic, managerial and other information of quantitative and qualitative nature as the value's moving force, and using fuzzy logic, which further exposed the shortcomings of the standard valuation process and the necessity of implementing different methods and analytical techniques.

The ANFIS model has been successfully applied to a variety of scientific areas such as energy, stock market, financial indexes, robotic applications and others. Atsalakis and Valavanis in 2009, have developed an ANFIS controller that forecasts stock market short-term trends using the Elliott Wave Theory and neuro-fuzzy systems

This paper is dealing with the development of a forecasting system based on ANFIS, which differs from the traditional Artificial Neural Networks (ANN) in that it is not fully connected and not all the weights or nodal parameters are modifiable. The model uses a hybrid learning algorithm to identify the parameters for the Sugeno-type fuzzy inference systems. It applies a combination of the least-squares method and the back-propagation gradient descent method for training the Fuzzy Inference System (FIS) membership function parameters to match the given training data set. Specifically, a back-propagation algorithm is used to optimize the fuzzy sets of the premises and a least-squares procedure is applied to the linear coefficients in the consequent terms. In addition, it uses a testing data set for checking the model over fitting. ANFIS is a multilayer neural network-based fuzzy consisted of five layers, in which the training and predicted values are represented by the input and output nodes and the nodes functioning as membership functions (MFs) and rules are presented in the hidden layers. Its topology is shown in Figure 1. During the learning phase of ANFIS, the parameters of the membership functions are changing continuously in order to minimize the error function between the target output and the calculated values. ANFIS has a feed-forward neural network structure where each layer is a neuro-fuzzy system component. ANFIS is capable to learn and generalize the training data. The consequents of the Takagi-Sugeno (TS) fuzzy rules are linear combinations of their preconditions in this method. ANFIS can simply be defined as the combination of ANNs and fuzzy logic. This combined system has the abilities of deducing knowledge from given, learning, generalization, adaptation and parallelism. FIS is a framework based on fuzzy set theory and fuzzy if-then rules. The structure of FIS has three main components: a rule base, a database, and a reasoning mechanism. This model is called first-order Sugeno model.

$$
\begin{aligned}
&\textit{if } \text{x is } A_1 \text{ and y is } B_1 \text{ and } C_1 \text{ then } f_1 = p_1x + q_1y + r_1z + t_1 \\
&\textit{if } \text{x is } A_2 \text{ and y is } B_2 \text{ and } C_2 \text{ then } f_2 = p_2x + q_2y + r_2z + t_2 \\
&\textit{if } \text{x is } A_3 \text{ and y is } B_3 \text{ and } C_3 \text{ then } f_3 = p_3x + q_3y + r_3z + t_3
\end{aligned}
$$

Equation-1.

First Layer: This layer consists of input variables (membership functions-MF). Here, triangular or bell shaped MF can be used. Triangular functions minimize Root Mean Square Error (RMSE) so that it is used in this study. To simplify the structure x and y are assume to be the input nodes, A, B and C are the linguistic labels, μ_{Ai}, μ_{Bi} and μ_{Ci} are the membership functions. Outputs obtained from these nodes are expressed as:

$$
\begin{aligned}
O_{1,i} &= \mu_{Ai}(x), \text{ for i} = 1,2 \\
O_{1,i} &= \mu_{Bi-2}(y), \text{ for i} = 3,4 \\
O_{1,i} &= \mu_{Ci-4}(z), \text{ for i} = 5,6
\end{aligned}
$$

Equation-2.

O is the output of the node i in the first layer. A typical membership function is triangular function with, where a, b, c are referred to as the premise parameters.

$$f(x;a,b,c) = \begin{vmatrix} a, & x \le a \\ \frac{b-x}{b-a} & a \le x \le b \\ \frac{c-x}{c-b} & b \le x \le c \end{vmatrix}$$

Equation-3.

Second Layer: This layer is called membership layer. It checks for the weights of each MF receives the input values x_i, y_i, z_i from the 1st layer and act as MFs to represent the fuzzy sets of the respective input variables. Further, it computes the membership values which specify the degree to which the input value xi belongs to the fuzzy set, which acts as the inputs to the next layer (Fig.1).

$$O_{2,i} = w_i = \mu_{Ai}(x)\mu_{Bi}(y)\mu_{Ci}(y), \text{ for } i = 1,2,3$$

Equation-4.

Third Layer: Every node is a fixed node labelled N and calculates the ratio of the ith rule‘s innovation ranking strengths to the sum of all rule‘s innovation ranking strengths in this layer.

$$O_{3,i} = w_i = \frac{\overline{w}_i}{w_1 + w_2 + w_3}, \text{ for } i = 1,2,3$$

Equation-5.

Fourth Layer: All nodes are adaptive nodes with a node function in this layer.

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i z + w_i), \quad \text{for } i = 1,2,3$$

Equation-6.

Where w_i is the output of layer 3; p_i, q_i and r_i are the parameters set. Parameters in this layer are referred to as the consequent parameters.

Fifth Layer: This node computes the overall output of ANFIS as the summation of all incoming signals from the 4th layer.

$$O_{5,i} = \sum \overline{w}_i f_i = \frac{\sum w_i f_i}{\sum w_i}, \text{ for } i = 1,2,3$$

Equation-7.

The final output of adaptive neuro-fuzzy inference system is expressed as:

$$f_{out} = \overline{w}_1 f_1 + \overline{w}_2 f_2 + \overline{w}_3 f_3 = \frac{w_1}{w_1+w_2+w_3} f_1 + \frac{w_2}{w_1+w_2+w_3} f_2 + \frac{w_3}{w_1+w_2+w_3} f_3 = (\overline{w}_1 x)p_1 +$$
$$(\overline{w}_1 y)q_1 + (\overline{w}_1 z)r_1 + t_1 + (\overline{w}_2 x)p_2 + (\overline{w}_2 y)q_2 + (\overline{w}_2 z)r_2 + t_2 + (\overline{w}_3 x)p_3 + (\overline{w}_3 y)q_3 + (\overline{w}_3 z)r_3 + t_3, \quad \text{for } i = 1,2,3$$

Equation-8.

4. Proposed Model: Adaptive Neuro-Fuzzy Inference System for IC Forecasting

The purpose of this study is to predict the intellectual capital on the basis of innovation performance using the ANFIS model. We implement a new ANFIS based model as a forecasting mechanism for intellectual capital. The ANFIS model consists of input-output indicators, training-test algorithms, as well as fuzzy inference rules. The structure of the adaptive neuro-fuzzy inference systems and components of proposed model is summarized below:

Identify input and output: In the first step, input and output of the intellectual capital forecasting model are identified. Nine innovation objectives are used as input variables and ten innovation performance measurements are as output used to forecast intellectual capital. The proposed input/output factors are obtained from literature on innovation, intellectual capital and their relationship. Output of the proposed model has ten different criteria for intellectual capital forecasting.

Determine model parameters: There are two learning methods widely used in ANFIS to specify the Evaluation criteria of the proposed model are given in Table 1. Relationship between input and output to determine optimized distribution of membership functions. These are propagation and hybrid. The hybrid system is a combination of propagation and least squares method. Hybrid method has been selected for fuzzy inference system (FIS) optimization method. Three membership functions are assigned to each input. Triangular membership function (trimf) is chosen to train the model criteria.

Execution of model: We placed the training data to the ANFIS model using MATLAB ANFIS editor. Membership functions are assigned to each input for the training purpose. Each input has three membership functions. Rules are generated using FIS editor. The rule structure of the model is obtained after training, as seen in

Fig.3. The rule viewer displays a roadmap of the whole fuzzy inference process and allows organizational training planners to change input values and obtain new output values.

Table-1. Intellectual Capital Forecasting Criteria

Input	Membership Function	Description
Innovation Source	INSO1=mf α1	Innovative organizational patient obtained from self R&D
	INSO2=mf α2	Innovation development groups consisting of staff members
	INSO3=mfα3	R&D alliance with organizational employees
	INSO4=mfα4	Innovation inspiration from internal and external environment
Innovation Strategy	INST1=mf β1	Relationship with employees
	INST2=mf β2	An interaction mechanism with organizational production sites
	INST3=mf β3	Full cooperation between innovation and operation strategies
	INST4=mf β4	Strategies for external environment
Innovation Culture	INCU1=mf µ1	Flexible and well communicated organizational culture
	INCU2=mf µ2	Learning category organization
	INCU3=mf µ3	Ability to response the new technologies
	INCU4=mf µ4	Organization emphasize on staff education and training
Output	**Membership Function**	**Description**
Intellectual Capital	IC1=mfπ1	Creativity and invention in organizational studies
	IC2=mfπ2	Responsibility of the staff officer
	IC3=mfπ3	Execution in real-time
	IC4=mfπ4	Field performance learning
	IC5=mfπ5	Problem solving
	IC6=mfπ6	Meet organizational regulations and standards
	IC7=mfπ7	Education and training of foreign delegates
	IC8=mfπ8	Professional conferences, meetings and journals
	IC9=mfπ9	Computer based information social networks
	IC10=mfπ10	Time usage improvement in field simulations
	IC11=mfπ11	Solution innovation
	IC12=mfπ12	Intellectual capacity of all employees

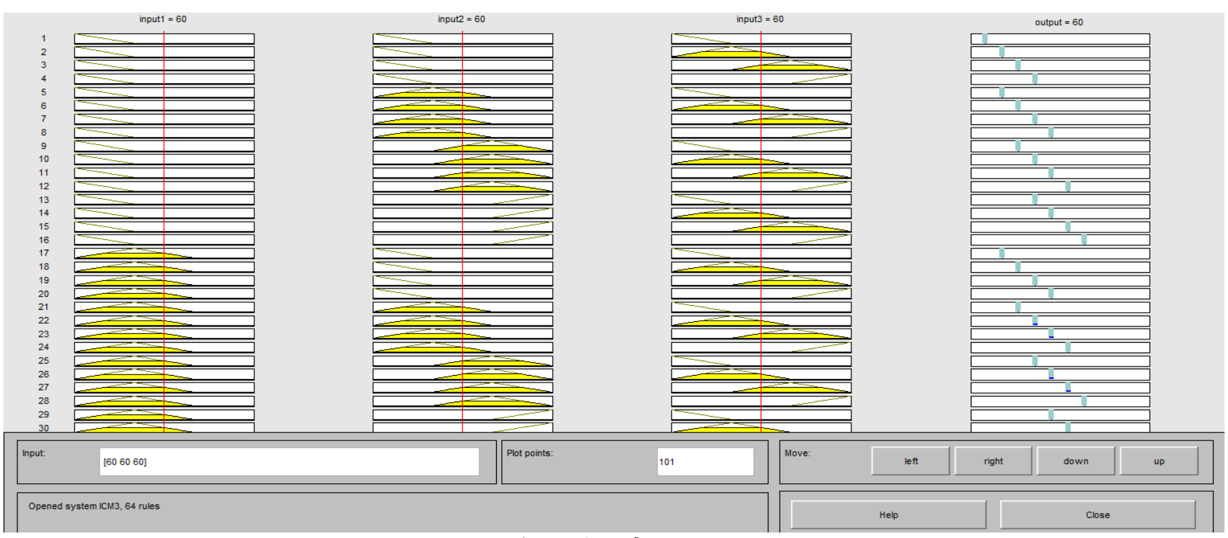
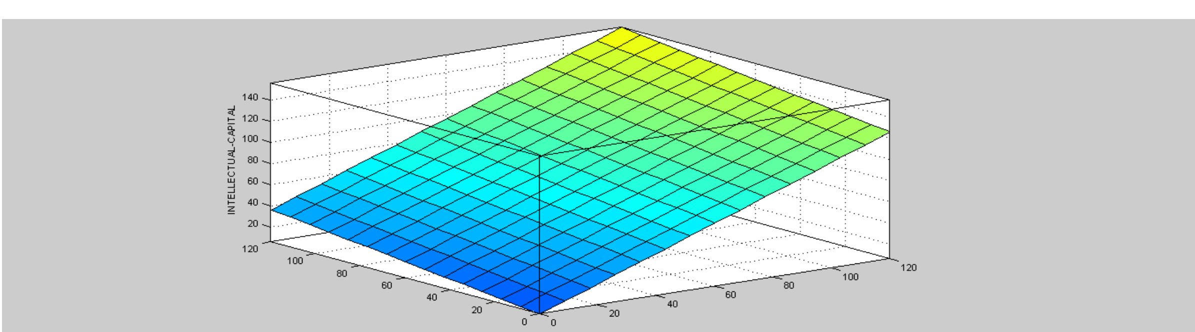


Figure-3. Rules Viewer

Check Results: In this step, we test data are placed into the ANFIS model using MATLAB ANFIS editor. After running MATLAB ANFIS module, testing and training data were compared to test the model‘s performance. The 3D surface plot shown in Fig. 3 depicts the relationship among certain inputs Innovation Source, Innovation Strategy, Innovation Culture and the output Intellectual Capital obtained by the developed ANFIS system, where other inputs are fixed at a certain value.



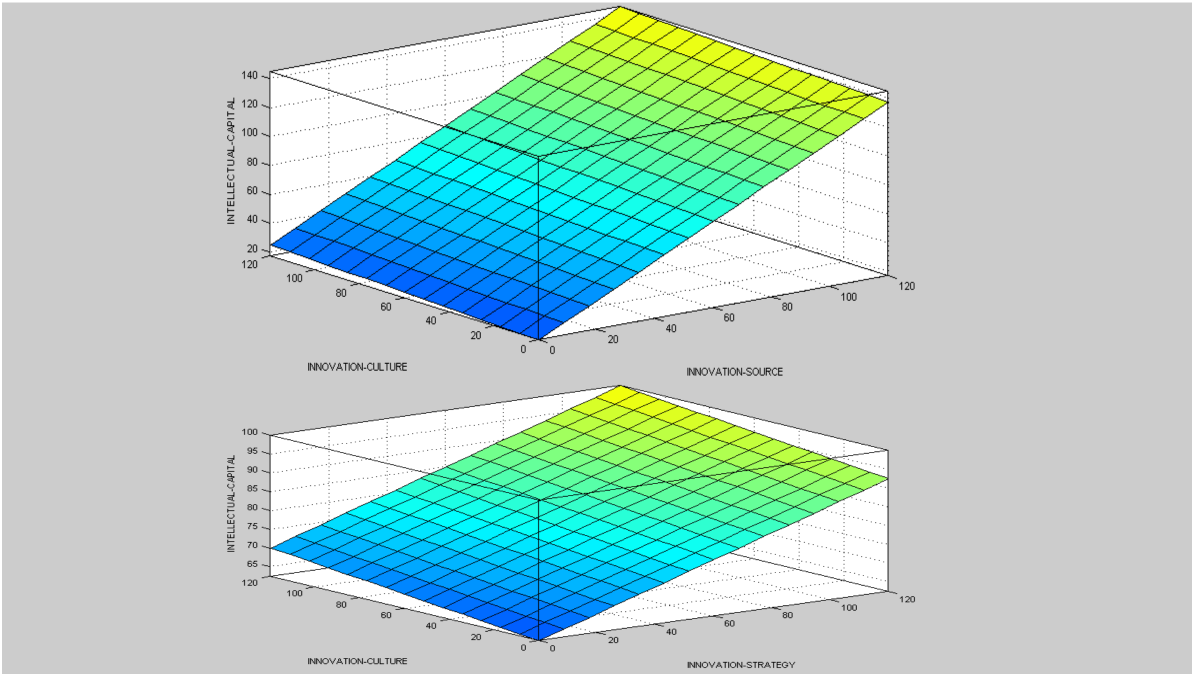


Figure-4. Surface Viewer Indicating Relationships among IC, INSO, INST, INCU

Figure below depicts the training procedure for the data under observation according to the constructed model for intellectual capital forecasting.

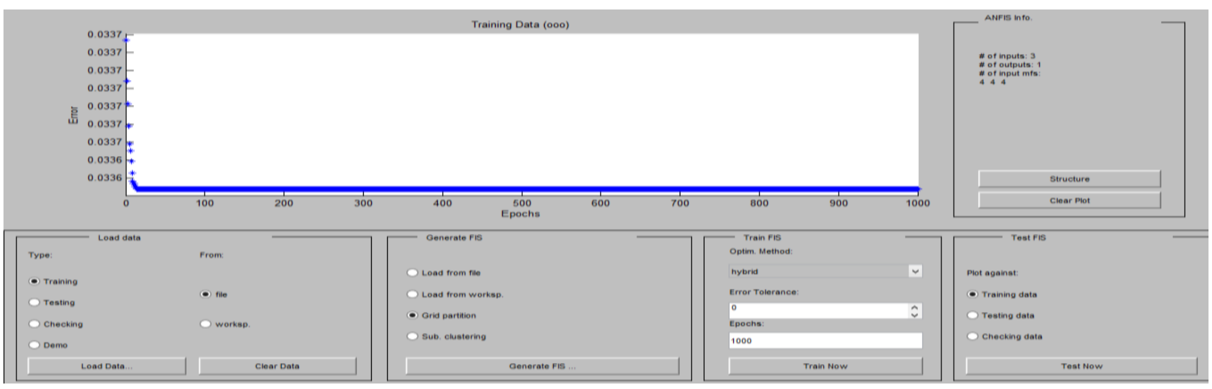


Figure-5. Final Result after Training

Now a Graphical User Interface is created in evaluation with Matlab ANFIS simulation to verify and compare the results. The figure below shows the GUI of the simulated ANFIS which produces the results after taking three inputs. The first input indicates the innovation source, second input indicates innovation strategy and the last input indicates innovation culture. The output forecasts the intellectual capital management,

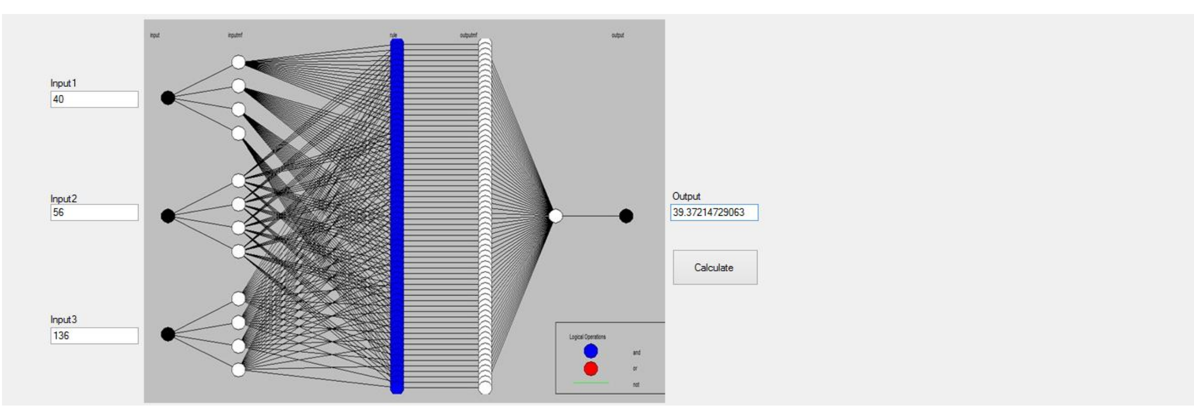


Figure-6. GUI of the Simulated ANFIS

```
using System;
using System.Collections.Generic;
using System.ComponentModel;
using System.Data;
using System.Drawing;
using System.Linq;
using System.Text;
using System.Windows.Forms;

namespace basic
{
```

```
public partial class Form1 : Form
{
   public Form1()
   {
      InitializeComponent();
   }

   private void button1_Click(object sender, EventArgs e)
   {
      // Declaration of Input Variables
      double num1, num2, num3, result;

      // Declaration of Hidden Layer A Variables
      double hla1, hla2, hla3, hla4, hla5, hla6, hla7, hla8, hla9;
        hla1 = Convert.ToDouble(0);
      hla2 = Convert.ToDouble(0);
      hla3 = Convert.ToDouble(0);
      hla4 = Convert.ToDouble(0);
      hla5 = Convert.ToDouble(0);
      hla6 = Convert.ToDouble(0);
      hla7 = Convert.ToDouble(0);
      hla8 = Convert.ToDouble(0);
      hla9 = Convert.ToDouble(0);
        num1 = Convert.ToDouble(textBox1.Text);
      num2 = Convert.ToDouble(textBox2.Text);
      num3 = Convert.ToDouble(textBox3.Text);

      // IS
      int a = 0;
      int b = 40;
      int c = 80;
      int d = 120;
        // Variables for layer 1
      double r1, r2, r3, r4, r5, r6, r7, r8, r9, r10, r11, r12;

      if (num1 > 0 && num1 <= 40) { hla1 = (num1-a)/(b-a); }
      else if (num1 > 40 && num1 <= 80) { hla1 = (num1 - b) / (c - b); }
      else if (num1 > 80 && num1 < 120) { hla1 = (d - num1) / (d - c); }
      else if (num1 >= 120) { hla1 = 120; }
      else { hla1 = 0; }

      if (num2 > 0 && num2 <= 40) { hla2 = (num2 - a) / (b - a); }
      else if (num2 > 40 && num2 <= 80) { hla2 = (num2 - b) / (c - b); }
      else if (num2 > 80 && num2 < 120) { hla2 = (d - num2) / (d - c); }
      else if (num2 >= 120) { hla2 = 120; }
      else { hla2 = 0; }

      if (num3 > 0 && num3 <= 40) { hla3 = (num3 - a) / (b - a); }
      else if (num3 > 40 && num3 <= 80) { hla3 = (num3 - b) / (c - b); }
      else if (num3 > 80 && num3 < 120) { hla3 = (d - num3) / (d - c); }
      else if (num3 >= 120) { hla3 = 120; }
      else { hla3 = 0; }

      r1 = Math.Pow(hla1, 0.5);
      r2 = Math.Pow(hla1, 1);
      r3 = Math.Pow(hla1, 1.5);
      r4 = Math.Pow(hla1, 2);

      r5 = Math.Pow(hla2, 0.5);
      r6 = Math.Pow(hla2, 1);
```

```
r7 = Math.Pow(hla2, 1.5);
r8 = Math.Pow(hla2, 2);

r9 = Math.Pow(hla3, 0.5);
r10 = Math.Pow(hla3, 1);
r11 = Math.Pow(hla3, 1.5);
r12 = Math.Pow(hla3, 2);

double[] array1 = { r1, r5, r9 };
double[] array2 = { r1, r5, r10 };
double[] array3 = { r1, r5, r11 };
double[] array4 = { r1, r5, r12 };
double[] array5 = { r1, r6, r9 };
double[] array6 = { r1, r6, r10 };
double[] array7 = { r1, r6, r11 };
double[] array8 = { r1, r6, r12 };
double[] array9 = { r1, r7, r9 };
double[] array10 = { r1, r7, r10 };
double[] array11 = { r1, r7, r11 };
double[] array12 = { r1, r7, r12 };
double[] array13 = { r1, r8, r9 };
double[] array14 = { r1, r8, r10 };
double[] array15 = { r1, r8, r11 };
double[] array16 = { r1, r8, r12 };
double[] array17 = { r2, r5, r9 };
double[] array18 = { r2, r5, r10 };
double[] array19 = { r2, r5, r11 };
double[] array20 = { r2, r5, r12 };
double[] array21 = { r2, r6, r9 };
double[] array22 = { r2, r6, r10 };
double[] array23 = { r2, r6, r11 };
double[] array24 = { r2, r6, r12 };
double[] array25 = { r2, r7, r9 };
double[] array26 = { r2, r7, r10 };
double[] array27 = { r2, r7, r11 };
double[] array28 = { r2, r7, r12 };
double[] array29 = { r2, r8, r9 };
double[] array30 = { r2, r8, r10 };
double[] array31 = { r2, r8, r11 };
double[] array32 = { r2, r8, r12 };
double[] array33 = { r3, r5, r9 };
double[] array34 = { r3, r5, r10 };
double[] array35 = { r3, r5, r11 };
double[] array36 = { r3, r5, r12 };
double[] array37 = { r3, r6, r9 };
double[] array38 = { r3, r6, r10 };
double[] array39 = { r3, r6, r11 };
double[] array40 = { r3, r6, r12 };
double[] array41 = { r3, r7, r9 };
double[] array42 = { r3, r7, r10 };
double[] array43 = { r3, r7, r11 };
double[] array44 = { r3, r7, r12 };
double[] array45 = { r3, r8, r9 };
double[] array46 = { r3, r8, r10 };
double[] array47 = { r3, r8, r11 };
double[] array48 = { r3, r8, r12 };
double[] array49 = { r4, r5, r9 };
double[] array50 = { r4, r5, r10 };
double[] array51 = { r4, r5, r11 };
double[] array52 = { r4, r5, r12 };
```

```
        double[] array53 = { r4, r6, r9 };
        double[] array54 = { r4, r6, r10 };
        double[] array55 = { r4, r6, r11 };
        double[] array56 = { r4, r6, r12 };
        double[] array57 = { r4, r7, r9 };
        double[] array58 = { r4, r7, r10 };
        double[] array59 = { r4, r7, r11 };
        double[] array60 = { r4, r7, r12 };
        double[] array61 = { r4, r8, r9 };
        double[] array62 = { r4, r8, r10 };
        double[] array63 = { r4, r8, r11 };
        double[] array64 = { r4, r8, r12 };
        double[] arrayForAverage = { array1.Max(), array2.Max(), array3.Max(), array4.Max(), array5.Max(),
array6.Max(), array7.Max(), array8.Max(), array9.Max(), array10.Max(), array11.Max(), array12.Max(),
array13.Max(), array14.Max(), array15.Max(), array16.Max(), array17.Max(), array18.Max(), array19.Max(),
array20.Max(), array21.Max(), array22.Max(), array23.Max(), array24.Max(), array25.Max(), array26.Max(),
array27.Max(), array28.Max(), array29.Max(), array30.Max(), array31.Max(), array32.Max(), array33.Max(),
array34.Max(), array35.Max(), array36.Max(), array37.Max(), array38.Max(), array39.Max(), array40.Max(),
array41.Max(), array42.Max(), array43.Max(), array44.Max(), array45.Max(), array46.Max(), array47.Max(),
array48.Max(), array49.Max(), array50.Max(), array51.Max(), array52.Max(), array53.Max(), array54.Max(),
array55.Max(), array56.Max(), array57.Max(), array58.Max(), array59.Max(), array60.Max(), array61.Max(),
array62.Max(), array63.Max(), array64.Max() };
        result = arrayForAverage.Average();
        textBox13.Text = Convert.ToString(result);
      }
   }
}
```

5. Conclusion

Modern economic growth comes from knowledge and information. This has caused increased intellectual capital importance as a research and economic subject. The role and contribution of intellectual capital in management, technical, and socioeconomic development have been picked as the topic for recent studies. In that, organizational knowledge has been known as the main factor in competitive advantage and value creation. The purpose of this study is to investigate the performance of artificial neural networks in predicting intellectual capital performance of the companies

Today‘s global competition needs more efficient staff and officers. Organizations should design an effective advanced organizational training and education system and select appropriate technology by applying instructors, institutes and international organizations. In this paper, we present a new Intellectual Capital forecasting technique for advanced organizational education based on the ANFIS model. The proposed model has been implemented in Matlab (The Math Works Inc., USA) environment by using the Neuro-Fuzzy toolbox. Results show that inputs [innovation source, innovation strategy and innovation culture] and the selection of Intellectual Capital as output are convenient for this study.

From the organizational point of view, this structure can be applied to future Intellectual Capital forecasting in advanced organizational training and education. To apply this strategy, organizational instructors and decision makers from the organization should evaluate inputs for expected Intellectual Capital in future.

Then, proposed ANFIS model calculates expected Intellectual Capital as output. Using these results, organization decision makers could decide on necessary changes in training and education system. In doing so, the emphasis is put on the application of the ANN in determining the interdependencies of significant quantitative and qualitative metrics, that create the value of the company, on the one hand, and on the development of FIS, by which the value of the company, which can objectively and reliably be considered fair market value on the basis of intellectual capital, can be determined. The value of the company estimated in this manner could be of great significance for the potential sellers and purchasers, business appraisals, investment bankers, as well as all other entities within the organization.

ANFIS is simple to maintain and apply on forecast practically. It combines the capabilities of fuzzy systems and neural networks. Fuzzy rule based system incorporates the flexibility of human decision making by means of the use of fuzzy set theory and makes use of fuzzy linguistic terms described by MFs. It requires fewer and simpler trials and errors for optimization of their architecture. It is nonlinear and capable of adapting and learning fast from numerical and linguistic knowledge. ANFIS is a model-free, easy to implement approach. In contrast to traditional time-series methods, little training is needed to calculate predictions with ANFIS. It Implements a single-fitting procedure to nonlinear situations, without the need of establishing a formal model for the problem being resolved. Thus, no a priori information is required to determine the empirical relationship between explanatory and predicted variables and the method suitability is always tested a posteriori. The transparent rule structure of ANFIS allows the researcher to extract information about the empirical relationship between the inputs and the outputs over time and to provide concise explanations.

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