

TRACE -BASED MODEL FOR KNOWLEDGE ACQUISITION SYSTEM

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ABSTRACT

Aims: This paper presents a trace-based model for Knowledge Acquisition System for Valuing Knowledge.

Study design: The model includes three related stages in solving problems; the first is context – aware retrieved information stage and the second is tracing the user tasks in order to cover all the needed elements in the environment of the given problem. The third stage is the implicitly processed via a back propagation feature exists in the neuro-fuzzy module.

Place and Duration of Study: Evaluation and Analysis of Hospital Disaster preparedness in Jeddah for six months.

Methodology: There are six factors have been utilized in the Adaptive Neural Fuzzy Inference module that covers the second stage of the proposed system alongside with the back propagation process. The training will be based on gathered surveyed data. The purpose of the training is to adjust the model parameters, particularly the input membership function parameters, and the corresponding output values.

Results: After training the model with proper data, a clear target-oriented towards the best usage of knowledge will be revealed. The developed six modules for the second stage with different types of input/output membership functions and trained an input array. The modules are compared based on their ability to train with lowest error values. The Gaussian member function input with either constant or linear Pairing output member function was the best choice for the proposed system to be adopted in its second stage which is Task Analysis Module.

Conclusion: This model can be utilized in firms, societies or even in individuals' life events. The context of knowledge as one of the six factors affecting the knowledge valuation process is the most important factor due to its high changes were more noticeable than others.

Keywords: Artificial Neural Networks, Expert System, Knowledge Acquisition, Knowledge-based Systems, Fuzzy Logic, and Trace-Based.

1. INTRODUCTION

Solving problems is one of many tasks that are strongly related to the survival of human being. There are many methods for solving problems, and there are many differences between these methods used from different perspectives and factors such as the kind of the problem, the domain and the problem space. Considering the problem space representation, find that most of the problem solving methods relying on the problem space representation will depend even if slightly on similar problem solved or observed in past experience [1].

Case-based reasoning is one of the methods in solving problems that all reasoning is based on past cases personally experienced. But depending only on the past experience is not enough to solve some problems, what makes a main problem of the case-based reasoning to appear is the lack of relevant context information in the problem space to be considered in solving new problems [3, 4]. A macro model presented [2], states that how important the context-aware systems are in supporting learning processes. An example of such systems is the "The Knowledge Maturing Process" with its five stages shown in figure1.

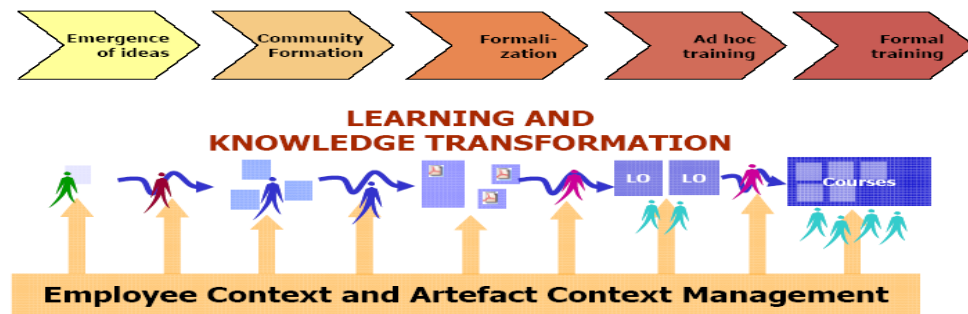


Figure1: The Knowledge Maturing Process [2]

The main important conclusion obtained from this model is that by determining the considered context and relevant artifacts, the system can help the learner in making best use of existing pieces. Therefore, the proposed model in this research work will focus on how to identify the relevant context information and how to use it efficiently.

According to the definition of Case-Based Reasoning (CBR), solving problems is based on the solutions of similar past problems. From the system's point of view, this might be true, but from the user's point of view, identical problems may need different solutions. This is due to that Case-Based Reasoning suffers from the "frame problem": in some situations, the context information is missing.

Other researchers have addressed how useful the contextual retrieved information in search queries [5] they stated that one of the key factors for accurate and effective information access is the user context. The critical elements that make up a user's information context include the semantic knowledge about the domain being investigated, the short-term information need as might be expressed in a query, and the user profiles that reveal long-term interests.

Moving from the Case-Based Reasoning to Trace-Based Reasoning (TBR) is the solution of this problem. Trace-Based Reasoning is an extension of the Case-Based Reasoning, allowing the context to be included in the reasoning process.

2. METHODOLOGY

There are many factors expressed for the purpose of knowledge valuation ontology. As per [6], six factors will be used to valuing knowledge. These factors will be utilized an Adaptive Neural Fuzzy Inference System (ANFIS) that covers the second stage of the proposed model alongside with the back propagation process.

The first stage will include context-aware retrieval information algorithm. These stages will be used for valuing knowledge. There are five kinds of components used to specify knowledge in ontology's: concepts, relations, functions, axioms and instances. The aim of knowledge valuation ontology is allowing the users to express factors relevant to valuing a particular chunk of knowledge.

Figure 2 presents the structure and main processes of the model. The proposed model is based on managing the knowledge valuation via the affecting of different factors in order to getting the desired value of the available knowledge.

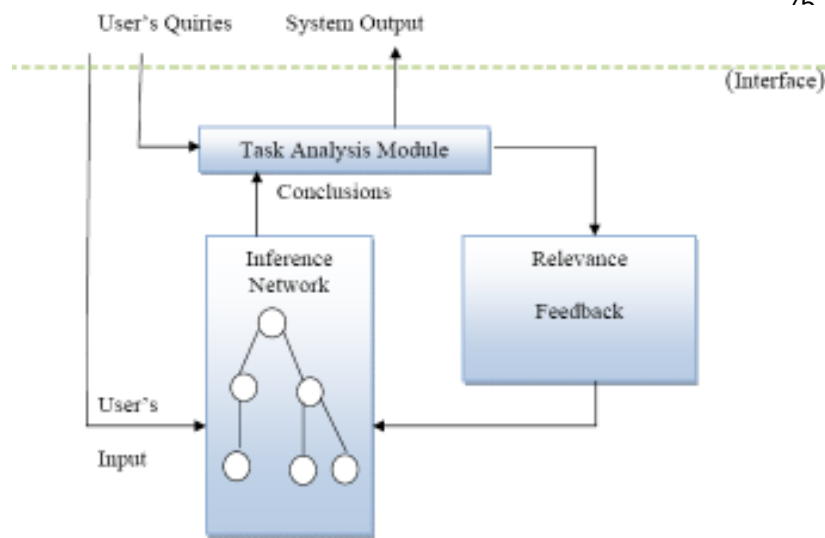


Figure 2: The Structure and main processes of the model

2.1 Inference Network

In this stage has been used a context retrieval information algorithm that integrates the essential elements of user's information context. In this algorithm the user's context is represented taking into account the user's short-term and long-term profiles, as well as relevant concepts from a pre-existing ontology [5].

Via this algorithm solving the faced problems have been transferred from the Case Based Reasoning approach to Trace Based reasoning approach, which in terms achieving one of the aims of this work. The user's context information represented by user's short term and long term profiles, in addition to the past pre-existing ontology, are fed as inputs for the next stage of the model which is Task Analysis Module.

2.2 Task Analysis Module

In this stage, there will be an implementation of the model of Artificial Neural Fuzzy Inference System (ANFIS) via using linguistic variables represented by member function (mf) indicating the degree and the status of each factor on the process of valuing knowledge. These six factors are described in details in the following subsections.

2.1.1 Axioms

As per [6]'s comment cited from Fox and Gruninger, 1999, p.111 that retrieval of information not directly stored in the data base does not require wider search characteristic if ontology's stored the means for relatively straightforward deductions within themselves, i.e. by using axioms. There are five kinds of components used to specify knowledge in ontology's: concepts, relations, functions, axioms and instances. Axioms are model sentences that are always true. Their existence in ontology is to constrain its information, verify its correctness or deduce new information [7].

Table1. Illustrates one of the developed methodology which is an ontology-supported literature search for is specified in the Web Ontology Language OWL DL [8]. Tools have been employed for automated textual analysis to produce a set of document annotations, which was then manually evaluated. Six distinct annotation sets S1 to S6 using different annotation methods for 2,289 logical axioms.

The results of this methodology was that the decision space (means keeping tracking of the dependencies between axioms) saved about 75% of reasoned calls and the appropriate choice of axioms leads to a better performance [9].

Table1. Shows revision results for OWL DL Axiom Ontology

	<i>S</i> ₁ (54, 94%)			<i>S</i> ₂ (60, 100%)		
<i>impact</i> ⁺	69%	4,677	36,773	83%	2,584	18,702
<i>guaranteed</i>	48%	11,860	51,677	65%	8,190	55,273
<i>impact</i> ⁻	9%	17,828	46,461	12%	20,739	67,625
upper bound	74%	4,110	11,399	83%	2,645	27,850
random	45%	-	1,291	60%	-	1,090

	<i>S</i> ₃ (40, 45%)			<i>S</i> ₄ (35, 48%)		
<i>impact</i> ⁺	20%	3,137	26,759	29%	2,198	15,601
<i>guaranteed</i>	43%	3,914	27,629	43%	3,137	18,367
<i>impact</i> ⁻	28%	9,947	46,461	31%	7,309	10,217
upper bound	48%	3,509	13,202	51%	2,177	7,002
random	31%	-	764	31%	-	534

	<i>S</i> ₅ (26, 26%)			<i>S</i> ₆ (72, 12%)		
<i>impact</i> ⁺	8%	1,778	11,443	13%	9,352	212,041
<i>guaranteed</i>	39%	1,290	6,647	54%	8,166	99,586
<i>impact</i> ⁻	54%	954	1,438	76%	6,797	16,922
upper bound	54%	801	1,989	76%	5,219	19,861
random	41%	-	212	57%	-	1,065

2.1.2. Network Effects

Network effects are characteristic of advanced technology and information based sectors of the economy. The more a piece of knowledge is used, the more valuable it is [6]. The added value in every incident of networking lies in its contributions to the knowledge of the participants and to the enhancement of its value to them [10].

The Research and Development (R&D) is one of a corporate activity, as a mutually beneficial formal relationship between two or more parties, i.e. via network activities for increasing the stock of knowledge .Figure. 3. Shows the strong correlation between patents and the Research and Development (R&D).

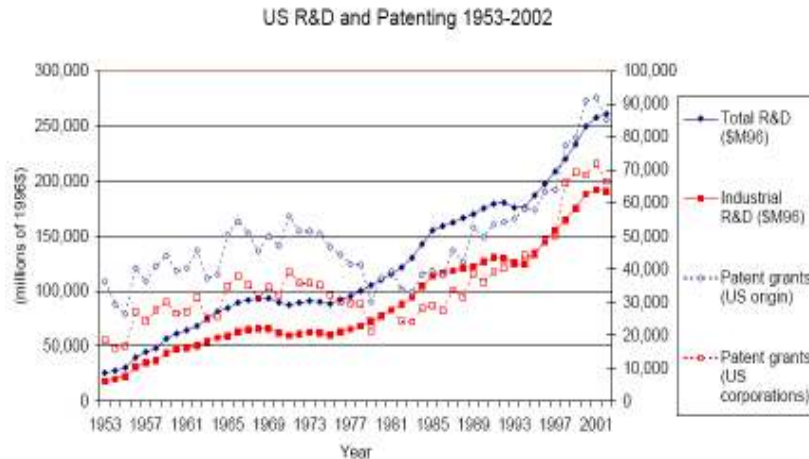


Figure 3: Shows R&D and Patenting Time Series Relationship [11].

Referring to the World Intellectual Property Organization (WIPO) Indicators in 2010 and as shows that the direct proportional relationship between patent applications across the world versus years (1985 – 2008) as seen in Figure 4. The overall percentage growth rate was positive through years excluding some slowdown periods had been occurred due to the global economic decline in that time which was in 2008.

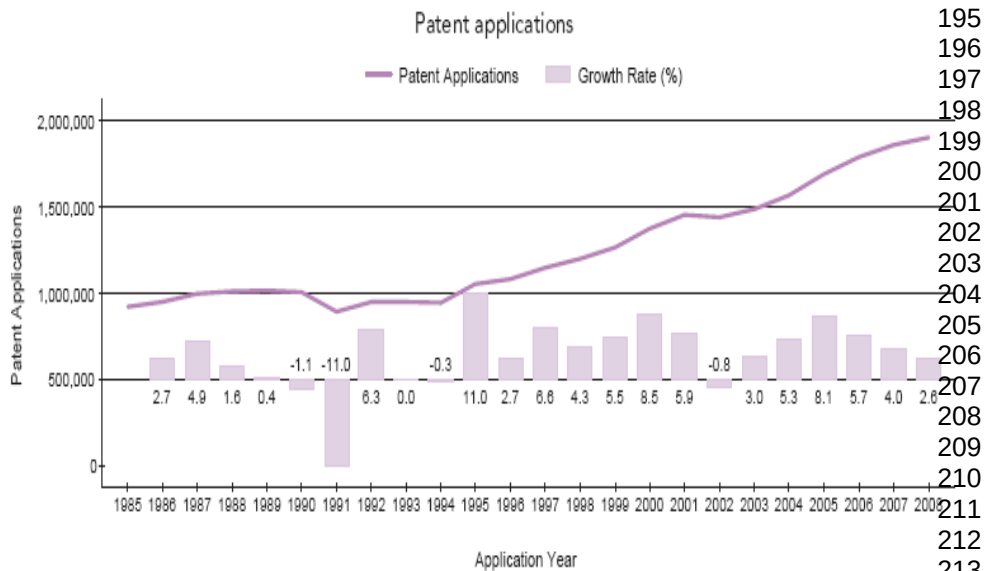


Figure 4: Shows trend in total patent applications across the world

2.1.3 Cumulatively

To understand and acquire a chunk of knowledge is strongly influenced by other chunk of knowledge that are related to it [6]. Jeffrey, Furman & Stern (2006[12] mentioned that the cumulative nature of the knowledge is recognized as central to economic growth. Using the cumulative nature of innovation development in the semiconductor industry, an analysis was achieved indicating how much new innovative outputs (patents) are based on already existing technological knowledge.

Table 2 shows the correlation coefficient for each year which was calculated at first by calculating the intensity of each technological combination, and then correlating the combination vector of each year with the observations of the previous year [13].

Table 2: Shows revision results for OWL DL Axiom Ontology [9]

Year	Cumulativeness	Year	Cumulativeness
1963	.5288	1980	.9195
1964	.7443	1981	.8862
1965	.8288	1982	.8971
1966	.8532	1983	.8802
1967	.8581	1984	.894
1968	.8621	1985	.9245
1969	.8713	1986	.9359
1970	.8731	1987	.9439
1971	.8873	1988	.9353
1972	.8777	1989	.9442
1973	.8538	1990	.9575
1974	.8716	1991	.9684
1975	.8917	1992	.9746
1976	.9057	1993	.9723
1975	.8917	1994	.9737
1976	.9057	1995	.9793
1977	.9006	1996	.9822
1978	.9074	1997	.9899
1979	.8982	1998	.9816

The ranges of the high or low effects of the cumulatively factor which will be figured out later in the paper were depending on the number of patents and patent growth in semiconductor technology space as shown in Figure 5 for each year mentioned in Table 2.

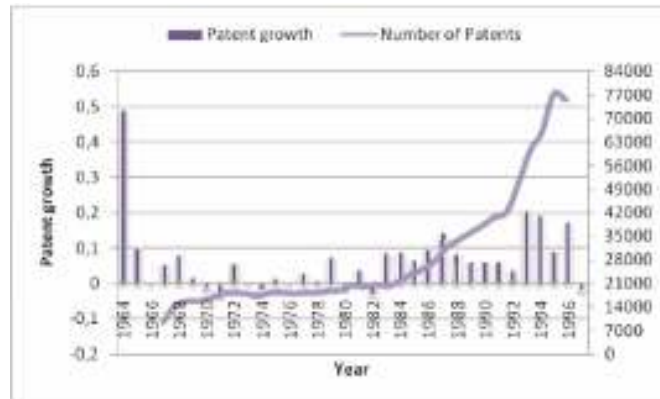


Figure 5: Shows the evolution of the patents and patent growth in semiconductor technology space (Dibiago & Nasiriya, 2008).

2.1.4 Sources of Knowledge

Sources of knowledge are the fourth factor affecting the valuation process of the knowledge. Referring to intellectual capital Stewart's definition mentioned in [14]: "the intellectual material – knowledge, information, intellectual property, experience – that can be put to use create wealth".

According to the intellectual capital, there are three sources of knowledge assets: External Capital, Human Capital and Structural Capital (O'Hara and [6]. A questionnaire obtained by a research team in Amsterdam 1999 from four companies: Institution of Higher Education, High-Tech Firm, Petroleum Exploration & Production Firm and Energy Delivery, has resulted in the chart shown in Figure 6 for indicating the usefulness of each (Human, Structural and External (Customer)) capital in each of the four samples of companies [15].

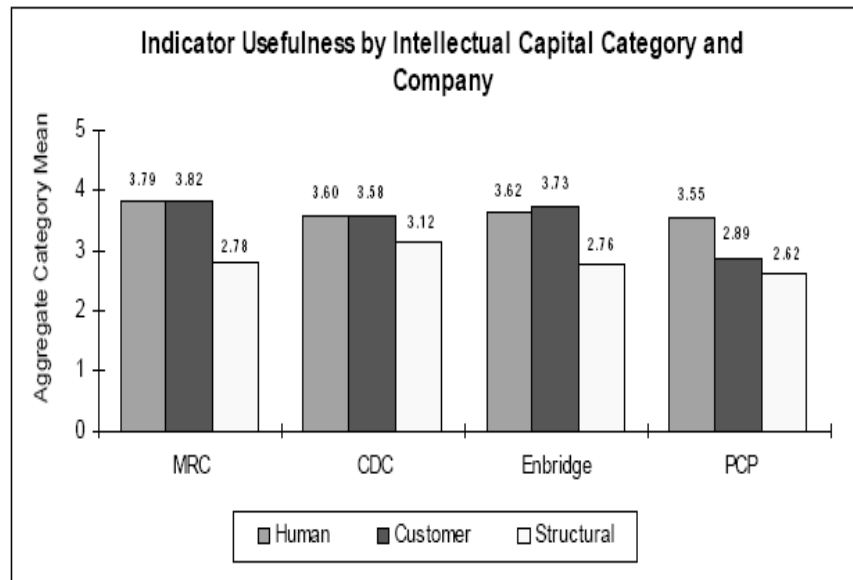


Figure 6: Shows the intellectual capital types effect on four sample firms [15].

2.1.5. Context of Knowledge

Knowledge's context refers to circumstances or events that form the environment within which something exists or takes place. Because of this relation between knowledge and these circumstances, they have their effects on improving and valuating knowledge [16]. By referring to a questionnaire had been adopted for the purposes of an organization's information management practices, information behavior and values, and information uses. Table 3 shows the questionnaire items for this survey. For the purposes of studying the effects of the context of knowledge on knowledge valuation process, we have focused on the Knowledge Management Environment (KME) items only which are listed in the table 3 (as seen in column 2, which are KME1, KME2, KME3 and KME4), and Table 4 presents the analyzing their impact after observing the values of convergent validities of the four previously mentioned items with both Organizational Information Behavior (OIB) and Personal Information Behavior (PIB).

Table 3: Shows matrix of loadings and cross-loadings of the survey's items

Construct	Item	Statement
KME	KME1	My organization has a culture intended to promote knowledge and information sharing.
	KME2	Knowledge and information in my organization is available and organized to make it easy to find what I need.
	KME3	Information about good work practices, lessons learned, and knowledgeable persons is easy to find in my organization.
	KME4	My organization makes use of information technology to facilitate knowledge and information sharing.
OIB	OIB1	The people I work with regularly share information on errors or failures openly.
	OIB2	The people I work with regularly use information on failures or errors to address problems constructively.
	OIB3 (Reversed)	Among the people I work with regularly, it is normal for individuals to keep information to themselves.
PIB	PIB1	I often exchange information with the people with whom I work regularly.
	PIB2	I often exchange information with people outside of my regular work unit but within my organization.
	PIB3	I often exchange information with citizens, customers, or clients outside my organization.
	PIB4	I often exchange information with partner organizations.

Table 4 Analysis of the impact of values observed

	KME	PIB	OIB	Age	Sex	Job Category	Sex*Job Category	Years in Org.
KME1	0.797	0.161	0.341	-0.052	-0.062	-0.103	-0.041	-0.045
KME2	0.832	0.151	0.267	0.000	-0.121	-0.089	-0.097	-0.080
KME3	0.838	0.175	0.398	0.008	-0.128	-0.121	-0.067	-0.075
KME4	0.806	0.209	0.297	-0.002	-0.070	-0.067	-0.047	-0.020
PIB1	0.259	0.680	0.342	0.020	0.027	0.096	0.058	-0.027
PIB2	0.089	0.720	0.116	0.194	0.085	0.139	0.082	0.152
PIB3	0.121	0.782	0.055	0.227	0.213	0.310	0.282	0.129
PIB4	0.142	0.758	0.132	0.163	0.082	0.129	0.079	0.176
OIB1	0.323	0.151	0.871	-0.018	-0.132	-0.125	-0.132	-0.166
OIB2	0.363	0.241	0.879	-0.050	-0.032	-0.074	-0.049	-0.118
OIB3	0.343	0.165	0.757	-0.087	-0.017	0.101	0.018	-0.057
Age	-0.014	0.209	-0.061	1.000	0.009	0.005	-0.002	0.534
Sex	-0.119	0.150	-0.072	0.009	1.000	0.478	0.884	0.152
JobCat	-0.120	0.243	-0.041	0.005	0.478	1.000	0.602	0.235
Sex.JobCat	-0.077	0.187	-0.065	-0.002	0.884	0.602	1.000	0.202
YearsInOrg	-0.068	0.140	-0.135	0.533	0.152	0.235	0.202	1.000

Table 5 shows the construct validity and variance extracted for each of the factors listed to obtaining the survey's purposes mentioned above. We have focused on the last item which is Knowledge Management effectiveness for this paper. The calculation of the construct reliability of each factor leads the researcher to conclude whether or not the various items of a construct as a set are reliable, in the sense of producing similar construct metrics every time is used by different researchers for similar contexts [17].

Table 5: Shows construct reliability and variance extracted for survey's items

Items	λ_{hi}	R_{hi}^2	ΣR_{hi}^2
Leadership			
LED1	0.79	0.38	0.6241
LED2	0.49	0.16	0.2401
LED3	0.53	0.28	0.2809
LED4	0.73	0.47	0.5329
0.73 construct reliability	2.54	2.33	1.6780
Culture			
CUL1	0.89	0.90	0.1024
CUL2	0.86	0.25	0.7396
CUL3	0.86	0.20	0.7921
CUL4	0.80	0.36	0.6400
CUL5	3.70	2.02	2.9630
0.87 construct reliability			
Strategy			
STR1	0.87	0.24	0.7569
STR2	0.92	0.16	0.8464
STR3	2.85	0.27	0.7225
2.64	0.67	2.3258	
0.91 construct reliability			
Technology			
TEC1	0.75	0.44	0.5625
TEC2	0.80	0.36	0.2025
TEC3	0.57	0.68	0.3249
TEC4	0.69	0.53	0.4761
TEC5	0.71	0.50	0.5041
TEC6	0.51	0.73	0.2601
3.68	3.68	2.3302	
0.79 construct reliability			
People			
PEP1	0.41	0.83	0.1681
PEP2	0.41	0.83	0.1681
PEP3	0.84	0.30	0.7056
PEP4	0.93	0.13	0.8649
2.59	2.09	1.9067	
0.76 construct reliability			
KM effectiveness			
KM1	0.98	0.04	0.9604
KM2	0.89	0.21	0.7921
KM3	0.80	0.36	0.6400
KM4	0.68	0.54	0.4624
KM5	0.69	0.53	0.4721
KM6	0.85	0.27	0.7225
4.89	1.94	4.0535	
0.92 construct reliability			
Firm performance			
KMF1	0.85	0.27	0.7225
KMF2	0.93	0.13	0.8649
1.78	0.4	1.5874	
0.89 construct reliability			
0.80 variance extracted			

3. IMPLEMENTATIONS AND RESULTS

In this section will be overview the practical results obtained after submitting an ANFIS editor by using MATLAB for the input and out membership functions plus J48 Classifier by using the machine learning software.

3.1 Neuro-Fuzzy Models

The fuzzy model for all the input factors and the output valuation is shown in Figure 7. The models are done using MATLAB ANFIS editor with the input member functions of Gaussian Bell.

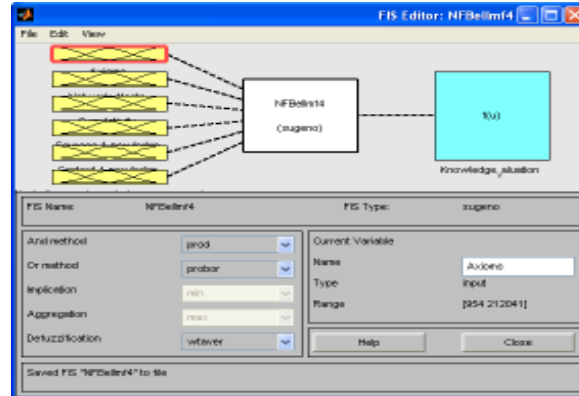


Figure 5: Fuzzy model of the 6 input mfs

MATLAB ANFIS editor supports only the Sugeno type, and the Fuzzy Inference System (FIS) supports two types of output functions types, the constant, and the linear function. The rule in Sugeno fuzzy model has the form:

If (input 1 = x) and (input 2 = y) then output z = ax +by +c.

For the constant Sugeno model, the output level z is constant c , where $a = b = 0$. The output level z_i of each rule is weighted by firing strength w_i of the rule. Six distinct neuro-fuzzy models are used to demonstrate the correlation and delectability of knowledge valuation using the 6 factors presented earlier. The classifications of the models are given in Table 6. Each model is characterized by the type of the input/output membership function and constant or linear output type.

Table 6: Model Specifications

Model Name	Input member function	Output member function
Generalized Bell	Gbellmf	Constant
Generalized Bell	Gbellmf	Linear
Gaussian	Gaussmf	Constant
Gaussian	Gaussmf	Linear
Gaussian2	Gauss2mf	Constant
Gaussian2	Gauss2mf	Linear

For each of the models shown in Table 6, we build the neuro-fuzzy structure. The structure of the J48 rules based neuro-fuzzy model is shown in Fig.6.

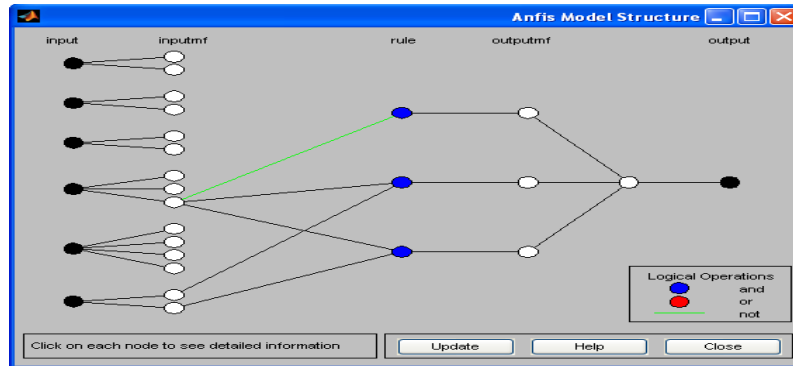
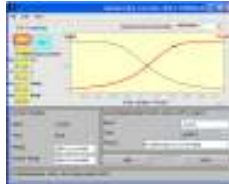
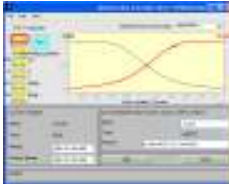
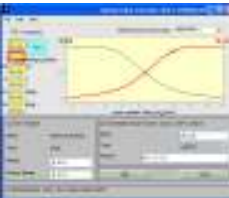
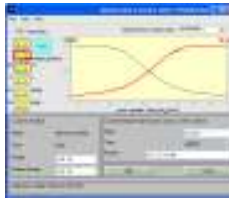
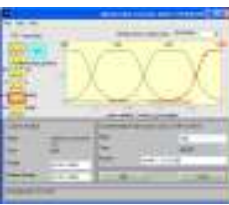
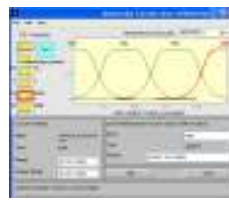
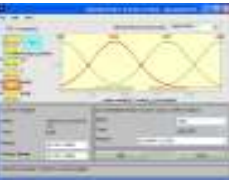
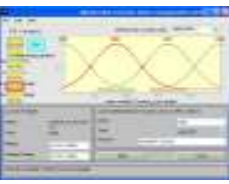
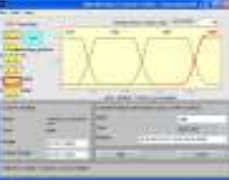
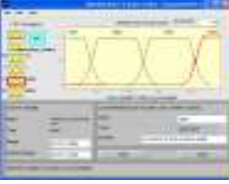


Figure 6: Shows the Structure of the j48 rules based neuro/fuzzy model

3.2 Training

The purpose of the training is to adjust the model parameters, particularly the input membership function parameters, and the corresponding output values. The adjustment and tuning depend on the accuracy of the training data, as will be shown later. Training needs two kinds of arrays, the first is the training array and the other one is the testing array. A training array is a two dimensional array $[m \times n]$, where (m) is the number of rows containing input values, and (n) is the number of input factors plus one for the output column.; in our model, $n = 7$ since there are 6 distinct input variables and one output variable. Each row of the array contains some of the possible values for each input corresponding to the first $n-1$ columns representing the 6 variables, and the last column holds the desired output values. The testing array holds the data in the same way as the training array, but the data in this array is more accurate than the data of the training array. The possible combinations for 6 inputs variables and 2 output values. Each input factor has on the average two linguistic variables, thus making the total combinations = 26, which equal to 64. The training array used was having $m = 64$ and $n = 7$ containing randomly chosen data.

468 **3.3. Membership functions of Input and Output Factors**
469 The results of these training processes are shown below in Table 7. , and brief the first
470 model of Generalized Bell function/Constant the only factors have been affected after
471 training are: Axioms, Network Effects and Context of Knowledge. For linear output for the
472 same input function (Generalized Bell) only Context of Knowledge has been affected. For
473 the Gaussian function with either constant or linear output then, no changes have been
474 resulted and an example of the six factors showing this result is Context of Knowledge as
475 shown below in (2) in Table 7. Finally for the Gaussian2 function with either constant or
476 linear output, also as in Gaussian function, no changes have been resulted, an example
477 showing this result is Context of Knowledge in (3) in Table 7.
478 **Table 7: Results of training the six example models**

1. Generalized Bell function (gbellmf)/Constant				
Input	Before Training	After Training	Parameters values before training	Parameters values after training
AXIOMS (ALowI)			a = 1.055e+005 b = 2.5 c = 2.12e+005	a = 1.06e+005 b = 2.5 c = 2.12e+005
Network Effects NLowE			a = 4.7 b = 2.5 c = 11	a = 4.7 b = 2.5 c = 10.98
Context of Knowledge KM4			a = 0.04117 b = 2.5 c = 0.398	a = 0.04117 b = 2.5 c = 0.3967
2. Gaussian function (gaussmf)/Constant or Linear				
Context of Knowledge KM2			$\sigma = 0.03497$ C = 0.2333	$\sigma = 0.03497$ C = 0.2333
3. Gaussian2 function (gauss2mf)/Constant or Linear				
Context of Knowledge KM4			$\sigma_1 = 0.03497$ C ₁ = 0.2333 $\sigma_2 = 0.03497$ C ₂ = 0.2333	$\sigma_1 = 0.03497$ C ₁ = 0.2333 $\sigma_2 = 0.03497$ C ₂ = 0.2333

3.4 Results

We have measured the impact of training array on the performance of the models. In particular, we observe the error rate of the models under same numbers of epochs which is 800 epochs. An epoch in the ANFIS is one full cycle starting from the application of input at layer 1 of the model, until the firing weight of the rule is adjusted. At the end of an epoch, the error, which is defined as the difference between the desired output and the computed output value, is measured. The models are trained by using testing array its inputs have been chosen carefully.

Table 8 shows the different values of the average testing errors for the three used membership functions (generalized bell, Gaussian, Gaussian2).

Table 8: Error values after testing the models for constant/Linear models

Model Name	Number of Epoch	The value of Error
Generalized Bell/Constant/Linear	800	0.46043
Gaussian/Constant/Linear	800	0.45846
Gaussian2/Constant /Linear	800	0.4641

4. CONCLUSION

the following can be conclude during the design and implementation of A Knowledge Acquisition System for valuing knowledge using with three stages, The first stage has been deduced from a previously existing algorithm which has achieved the purpose of converting the case based reasoning to trace based reasoning.

1. The second stage has been built by using a neuro-fuzzy model feeds by 6 factors. Each of these factors has been translated into membership functions reflecting their degree in impacting the process of valuing knowledge. ANFIS editor is a digital data processing in the computer and needs figures to work and have results. Although of these factors are being intangible ones but by surveys and questionnaires in the needed field, they have been figured out.
2. The fuzzy rules used and deducted by using a machine learning software written in Java called WEKA. The models were trained and the output parameters representing knowledge valuation can be adjusted using an array of training data. The results presented in this study show that knowledge can be valued using a neuro-fuzzy model. The performance of the model is measured in terms of error value obtained between the expected outputs. The experiments in this study were conducted using MATLAB neuro-fuzzy tool. The experiments show that the model is sensitive to the choice of input membership functions.
3. The Gaussian function is the most optimal in terms of trainability and producing low error values. In plus the choice of Sugeno either linear or constant output function is convenient accompanied to the Gaussian function.
4. The context of knowledge as one of the six factors affecting the knowledge valuation process is the most important factor due to its high changes were more noticeable than others. Context of information in terms and Trace Based Reasoning are both very important to be used in solving any faced problems.

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