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RISK BASED DECISION SUPPORT SYSTEM FOR STAKEHOLDER QUANTIFICATION FOR VALUE BASED SOFTWARE SYSTEMS

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ABSTRACT

Stakeholder identification and quantification (SIQ) is one of the core processes in software requirements engineering (RE). The significance of stakeholders becomes more vital when a software project is a value-based software (VBS) and the value-based requirements engineering (VBRE) is involved in it.VBS systems are developed based on business concepts in order to gain market leverage in terms of financial or economic benefits. Different SIQ approaches are presented in literature. However, most of the approaches are partially effective and SIQ process is still immature. The techniques are presented and applied under different conditions in order to monitor the performance of the approach. The presented techniques are vague and difficult to initiate. In this research, a decision support system is presented for stakeholders' quantification. The proposed system predicts the risk associated with the stakeholders using back-propagation neural network (BPNN).

Keywords: *Value-based Software Systems, Stakeholders, Neural Networks, Decision Support System, Expert System.*

1. INTRODUCTION

The importance of requirements elicitation phase (REP) is widely acceptable by the industry professionals due to the criticality of the issues of requirements [1]. Zave (1997) defines that "requirements engineering is the branch of software engineering concerned with the real-world goals for, functions of, and constraints on software systems. It is also concerned with the relationship of these factors to precise specifications of software behavior, and to their evolution over time and across software families" [2]. In this stage all user requirements are gathered in order to realize them in the form of a working system. For realization of the system both functional and non-functional requirements are gathered [3, 4]. Different RE approaches are presented in order to gather highly critical set of requirements which play a vital role in improving quality of the system. In the success and failure of a project the role of key requirements is vital [5]. VBS systems deal with financial matters and innovation is the key aspect of these systems. Innovation is the major cause in the development of these systems and is the result of high complexity. The complexity is the result of unclear requirements so the development of VBS systems also becomes difficult [6].

Stakeholders are the key players in REP. The definition of stakeholders is given in a wide variety by the researchers. "We define stakeholders as these participants together with any other individuals, groups or organizations whose actions can influence or be influenced by the development and use of the system whether directly or indirectly" [7]. A stakeholder may be defined as "any person or organizational group with an interest in, or ability to affect, the system or its environment" [8]. There are many different definitions of the stakeholders that mainly focus on their involvement in the system in terms of interest. This study focuses on software stakeholders however there are different approaches that are presented to identify stakeholders in domains other than software. The selection of wrong stakeholders for a given project will result in the missing requirements and it will result in project failures and higher costs [9] and the selected requirements will deviate from actual needs of the stakeholders [10]. When there is a deviation from actual needs of the stakeholders then it will not result only in over

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budget but also in longer developmental timeframes [11] and ultimately the abandonment of the project occurs [12]. About software development if there are "different views of quality, different requirements, different desired consequences sought result in conflicts leading to software development" [13]. The problems of stakeholders' identification process are discussed in detail in [14].

The practices of value-based software engineering (VBSE) are associated with VBS development. Boehm states VBSE as "the explicit concern with value concerns in the application of science and mathematics by which properties of computer software are made useful to the people" [15]. A diverse range of problems are focused in VBSE studies. The major research issues which are focused in VBSE studies are RE, value or profitability, cost and decision making. However, the importance of stakeholders is recognized in some research studies like [16-21] but the stakeholders are not the direct focus of these studies. VBS systems normally deal with finance and this property of VBS systems make them highly sensitive as compared to traditional systems. The financial streams make the VBS systems highly critical and sensitive and this thing is the cause of uncertainty that either the proposed idea will yield the required output or not in terms of finance. The issues of RE and value creation in case of VBS development are associated with stakeholders directly or indirectly. The due consideration is not given to the plight of stakeholders. The current practices of SIQP are not feasible for VBS systems so there is the need to propose an easy and valuable way to identify and quantify the stakeholders of VBS systems. Stakeholders' analysis is a complex decision based phenomenon and there is almost no decision support in this domain. In this paper a BPNN based an expert decision support system is proposed for stakeholders' analysis of VBS systems.

Rest of the paper is divided into 7 sections. Section 2 is about background in which a brief discussion of existing SIQ approaches is given and the pros and cons of these approaches are described. Section 3 describes the formulation of problem in the form of a metrics or mathematical equation. In section 4 the operational details of NN. Section 5 is about data collection. Section 6 describes the NN optimization in which training, NN architecture selection and initial results are described briefly. In section 7 the results are evaluated and the performance of current approach is compared with the existing approaches. Lastly, section 8 is about a brief summary of the research.

2. RESEARCH BACKGROUND

Stakeholders' analysis is a challenging domain in RE in order to find out a set of critical stakeholders for the intended system. Different SIQ approaches are presented in order to resolve the plight of stakeholders' identification. The main problem of SIQ is lack of a uniform approach or framework for the stakeholders' analysis. The stakeholders' attributes used in existing techniques are very abstract and it is difficult to assess the worth of a stakeholder using these attributes. Currently, there is a lack of SIQ approach that may be adopted as generically. Still there is no uniform framework of process for stakeholders' identification [22, 23]. The existing SIQ approaches are not state of the art due to the lack of clear guidelines that may be adopted for SIQ process.

Mitchell is considered as a pioneer in presenting a stakeholders' analysis model. Mitchell has used three main stakeholders' attributes like power, legitimacy and urgency [24]. Based on these three attributes Mitchell has divided stakeholders into eight classes like discretionary stakeholders, non-stakeholders, dormant stakeholders, demanding stakeholders, dangerous stakeholders, dominant stakeholders, definitive stakeholders and dependent stakeholders. Different research studies have used different stakeholders' attributes like roles, relationship and influence or power [24-27]. Most of the proposed techniques are difficult to initiate and very complex. The existing techniques present a very abstract picture of the SIQ process and do not provide nano <low level> descriptions.

A technique for inter-organizational stakeholders is also based on roles and types [28-30]. The stakeholders' attributes used in the technique are domain knowledge, function, and geographical location of the stakeholder. The approach is highly costly in terms of time consumption. The PisoSIA® technique is used to identify the new stakeholders after incorporating a change in the existing system [31]. The technique is not about SIQ process directly. However, the due importance is given to the stakeholders. Boonstra used Mitchell's model in order to identify the stakeholders in an existing ERP after inducing a change in it [32]. There is not new

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contribution with respect to SIQ process and the influence of change is also calculated on the current stakeholders of the system. In a study the stakeholders are divided into three classes like critical, major and minor [33]. The study has divided stakeholders into three major classes without giving process level details that how to initiate the SIQ process. A risk based approach is given which divides the stakeholders into six categories of internal stakeholders, external stakeholders, customers, influencer stakeholders, special interest stakeholders and financial stakeholders [34].

VBS systems are business oriented systems which deals with financial matters. In literature there is no evidence of stakeholders' quantification. As stated that VBS systems deal with financial streams and this thing makes them different from traditional software systems. There is a high risk in the development of VBS systems due to the innovation of the idea. The current SIQ approaches are not suitable for VBS systems. The current approaches are not feasible for VBS development due to higher time consumptions and higher costs [28, 29]. Most of the research studies are applying existing SIQ approaches instead of proposing the new methods [31, 32]. There are several research studies in the domain of VBS requirement prioritization [35-39]. However, there is the need to focus stakeholders in the VBS perspectives.

The current drawbacks of the existing SIQ approaches are the source of motivation for this research. The proposed techniques are highly complex and difficult to initiate due to the lack of in-depth information that how to carry out the SIQ process [31]. It is stated by some researchers that "there is still no Stakeholder Identification Process (SIP) framework or uniform description" [22, 23, 40]. The existing SIQ approaches are not cost effective in terms of time [28-30]. In this research paper a back-propagation neural network (BPNN) based solution is provided in order to solve the plight of software SIQ process for VBS systems. Hence, the current approaches are not only feasible for VBS but they are also not feasible for traditional software systems due to higher time consumptions and higher costs. The existing SIQ approaches are applied in a diverse range of applications. Figure 1 describes the different domains in which these approaches are applied. The existing SIQ approaches focus the domain of information system (IS), generic software practices (GSP), knowledge-based system (KBS), inter-organisational system (IOS), social networks (SN), recommender systems (RS), ERP and agile software development (ASDP). Hence, there is a dire need to propose a technique for stakeholders' analysis of VBS systems.

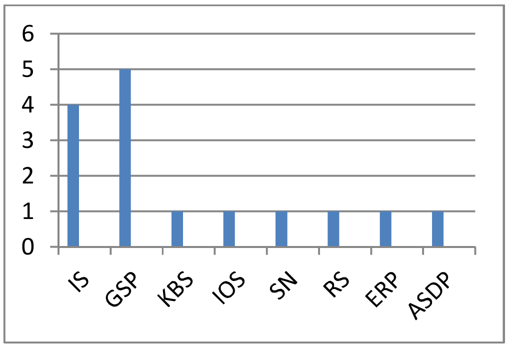

Figure 1. Application domains of SIQ approaches

3. PROBLEM FORMULATION

This section of the technique deals with the problem formulation. The value of a stakeholder is accessed through risk associated with the stakeholder. The value of risk is going to depict the extent of risk after making a stakeholder the part of REP. Risk is inversely proportional to the value of a stakeholder if the risk is higher the worth of stakeholder will be lower and vice versa. Different aspects or attributes of the stakeholders are considered in order to find out the key importance of a stakeholder. The risk factor associated with the stakeholder is denoted by F_{SR} and the different aspects or attributes of the stakeholders are denoted by T.

The values of aspects or attributes are taken on the ranking scale of 0 to 5. The stakeholder attributes used in the stakeholders' factor computation are communication (T_{CM}), interpretation (T_{IT}), decision making (T_{DM}), cognitive load (T_{CL}), complexity (T_{CP}), language barriers (T_{LB}), experience (T_{EX}). Communication is the ability of a stakeholder to describe the needs fluently without any ambiguity. Interpretation deals with explanations of the objectives to the point for a given system. The attribute of decision is about the ability of a stakeholder that either he or she is able to take a decision or not. The aspect of cognitive load explains the ability that at which level the stakeholder is able to manage the stress of the memory. Complexity is associated with the ability of the stakeholder to explain complex needs in a

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simple and elaborative way. The language barrier describes the risk associated due to the difference of the language of the stakeholders. The aspect of experience explains the professional ability of the stakeholder in the domain of value-based business. These seven attributes are chosen with the help of industry professionals after long discussions and can be used to evaluate the risk associated with a stakeholder.

$$F_{SR} = 0.2(T_{CM} + T_{IT} + T_{DM} + T_{CL} + T_{CP} + T_{LB} + T_{EX}) + 0.2$$

$$F_{SR} = 0.2\left(\sum_{i=1}^{n} F_{SR_i}\right) + 0.2 \quad (1)$$

The value of F_{SR} is in the range of 0.2 to 7.2 with a geometric progression of 0.2. In equation 1, 0.2 is taken as a weight factor in order to get manageable data in smaller data bounds. The weights lower than 0.2 are the cause of fuzzification, while the weights greater than 0.2 result in higher value which are not easily manageable. Different weights are applied in a range of 0.05 to 1.0 and it is found that 0.2 is a more feasible weight to manage the data. The values to the attributes are assigned by the industry experts on a ranking scale of 0 to 5 where 0 means no risk and 5 means high risk. As there is the involvement of highly expert judgment and it makes the SIQ process more complex and non-linear. The expert judgment also affects the final results in terms of stakeholders' values. So in order to solve this problem a NN based solution is given. The NN will help to predict the values of the stakeholders based on key inputs and outputs.

4. PROPOSED EXPERT SYSTEM

Artificial neural networks (ANNs) are widely used in different scientific and engineering domains in order to solve complex non-linear problems using backpropagation algorithm. ANN is an approach for prediction and approximation [41]. ANNs are a simulation of biological neural network (BNN). The components of a BNN are soma, dendrite, axon, and synapse while in ANN the components are neuron, input, output and weight. Neurons in ANN perform the duties of Soma, Input signals serves as Dendrites, Output signals serve as Axon and weight adjustment is performed like synapse. The key features which are common in both ANN and BNN are learning and generalization, adaptability, robustness, associative storage of information, massive parallelism, generalization, and spatiotemporal information processing [42].

In this SIQ approach BPNN is used. The learning method of BPNN is supervised. The input data set is given to input layer or source neurons. BPNN predicts the output of the given input data set and based on error threshold the back-propagation algorithm (BPA) is called each time in order to minimize the Mean Squared Error (MSE) and to optimize the output or result. BPA actually calculates the error gradient [43]. An error is a difference between expected output and predicted output. During call of BPA the adjustment of the weights is carried out to optimize the results or to minimize the error. BPNN training algorithm is comprised of following 4 steps.

1. Initialization
2. Activation
3. Weight Adjustment
4. Iteration/Loop

In initialization all required parameters are initialized based on threshold levels. The weights and threshold values are initialized by a uniform distribution of the random numbers. In activation step of BPNN the application of target inputs and target outputs is carried out. The target inputs and outputs serve as input and output patterns for BPNN. The sigmoid activation function is used in the hidden layer in order to calculate the outputs. The sigmoid activation function is represented as:

$$y_j(p) = sigmoid\left[\sum_{i=1}^{n} x_i(p).w_{ij}(p) - \theta_j\right] \quad (2)$$

In sigmoid activation function of hidden layer, *n* represents the total inputs to neuron *j*. The word *sigmoid* is used for sigmoid activation function. For output layer the outputs are calculated using the function:

$$y_k(p) = sigmoid\left[\sum_{j=1}^{m} x_{jk}(p).w_{jk}(p) - \theta_k\right] \quad (3)$$

In sigmoid activation function of output layer, *m* represents the total inputs to neuron *k*.

In third step the weights are adjusted using back propagation phenomenon or algorithm. In back propagation the error is moved backward in order to re-adjust the weights for minimization of error or optimization of the results. In order to reduce the error the error gradients of output layer

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and hidden layer are calculated. Using error gradients the weights are corrected and updated at output and hidden layers. Then feed-forward propagation is applied once again to calculate the outputs.

The fourth and the last step is the iteration. The iteration or loop is carried out until the output error or MSE is not going to reach the predefined threshold and the expected output is a stable output. An expert system is proposed based on the formulated problem and NN. Figure 2 describes the model of the proposed expert system for SIQ process. The expert systems are knowledge based systems which are based on knowledge of the experts [42]. The application of expert systems is widely accepted in all domains of sciences and engineering in order to resolve the complex problems. The SIQ process is a highly complex process and industry needs a highly reliable way to predict the value of a stakeholder for a given VBS system. Simply, for requirements engineers stakeholders are the only tools which can make a system successful or a collapse. In order to design high quality VBS systems the requirements must be in align with the key needs of the system and users. Hence, in this research an expert system for stakeholders' analysis is proposed for requirements engineers in order to quantify the stakeholders. The stakeholders have an immense influence not only on the quality of the system but also on the key business values in the market. Currently, the domination on the market leverage is highly essential. The NN is used for prediction of the value of stakeholders in a reliable way.

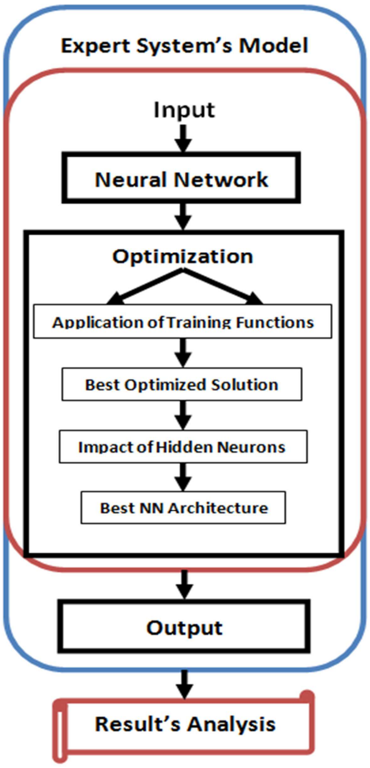

Figure 2. Expert Decision Support System Model

5. DATA COLLECTION

The supervised and unsupervised learning techniques are the two key techniques for learning in NN. The historical data is required in supervised learning method of BPNN. In supervised learning the training data must represent the all possible situations of the target data. Simply, the mapping between domain and solution space must be one to one in order to predict the class of the data. However, in unsupervised learning the data is used for the data similarities [44]. In case of SIQ process the historical dataset is lacking so equation 1 is used to collect the data. Three projects are taken as case studies in this research. The case studies are online car showroom (OCSR), hospital management system (HMS), and restaurant management system (RMS). The OCSR system provides better business opportunities to run the vehicle business which may be the sell and purchase or rent of a vehicle. The OCSR system is a VBS system as it deals with both managerial and financial matters. The HMS system provides better process in order to manage the routine activities of the hospital and to provide better medical services to patients. HMS also deals with

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financial management and comes in the domain of VBS system. The RMS is a business oriented system that is normally used to provide better services to its customers. The system is normally used to keep track of all the transactions that are related to food sales and room bookings by the customers. Hence, all these case studies are associated with the financial streams of the business so these as taken as VBS systems in this research. During RE phase experts have evaluated the stakeholders based on the key aspects used in F_{SR} by assigning value to each aspect or attribute in the range of 0 to 5. Experts were also asked to randomly assign an FSR value in the range of 0.2 to 7.2. The input vector P to BPNN is represented as:

$$P = (p_1, p_2, p_3, \ldots, p_n)$$

The data is gathered about 431 stakeholders of 3 projects and 1 team of 4 persons was assigned to each project. Out of 3 teams 2 of the teams were from Malaysia while 1 team was from Pakistan. The main purpose to select the teams from 2 countries is to avoid biasness and to generalize the implementation of F_{SR}. For example, the values assigned to the stakeholders aspects or characteristics by an expert are *P = (2, 4, 2, 5, 3, 1, 3)* for the seven factors. The input to F_{SR} is 20 and the F_{SR} value is 4.2.The range of input data P is 0-35 and the range of target data T is 0.2 to 7.2 with geometric progression 0.2. There are a total of 36 data classes. These data classes present all possibilities of the F_{SR} value for a stakeholder. The sum of 7 stakeholders' aspects is given as an input to NN and is mapped to the target data. As the aspect value is assigned by expert so it induces a sense of bias which affects the final results of F_{SR} and experts may vary their opinion based on their expert judgment. The use of NN will increase the efficiency of the SIQ process. Table 1 represents the partial sample data.

Table 1: Partial Sample Data

T_{CM}	T_{IT}	T_{DM}	T_{CL}	T_{CP}	T_{LB}	T_{EX}	$\sum_{i=1}^{n} F_{SR_i}$	F_{SR}
2	3	3	3	4	3	1	19	4.0
3	4	2	3	2	3	4	21	4.4
3	3	5	2	2	2	2	19	4.0
0	0	0	0	0	0	0	0	0.2
1	1	1	1	1	1	1	7	1.6
1	2	1	2	1	2	1	10	2.2
2	0	1	4	0	0	1	8	1.8

6. NEURAL NETWORK OPTIMIZATION

The NN is trained to get the optimized results. The training phase is used to feed an implicit knowledge to the NN [45]. For optimization purpose different training functions are used in this approach in order to find out the most optimum results. For optimization the data is normalized and a dataset range of -1 to 1 is obtained. The data normalization helps in even distribution of the data. In hidden layer the hyperbolic tangent function is used in all training functions. Figure 2 describes the optimization process in the proposed expert system's model. The NN optimization is carried out in three different phases. The main purpose of these phases is to get an optimized solution for the research problem of this study.

6.1 Phase 1: Application of Training Functions

In this phase the performance of NN is measured by applying different training functions. The main purpose of apply different training functions is to get an optimized NN solution for the focused problem. The different training functions that are applied to simulate the NN are *trainlm, trainbfg, traincgf, traingdx, traingdm* and *traingd.* The performance of the different networks' training functions is shown in Table 2.

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Table 2: NN Results

NN Architecture	Actual data	*Trainlm*	*trainbfg*	*traincgf*	*traingdx*	*traingdm*	*traingd*
1-15-1	0.2	0.1977	0.1674	0.2178	0.2195	0.2407	0.1331
1-15-1	0.4	0.3953	0.4644	0.4128	0.5419	0.4890	0.3841
1-15-1	0.6	0.5944	0.6552	0.5383	0.6774	0.6047	0.4984
1-15-1	0.8	0.7913	0.7790	0.7780	0.7163	0.7043	0.5995
...							
1-15-1	2.6	2.6061	2.4844	2.5908	2.6223	2.8788	2.7186
1-15-1	2.8	2.7978	2.7832	2.8964	2.6620	3.2583	2.7564
1-15-1	3.0	2.9765	3.0545	3.0468	2.8126	3.3216	2.7834
1-15-1	3.2	3.2091	3.1846	3.1449	3.1971	3.3350	2.8658
...							
1-15-1	5.4	5.4474	5.3448	5.3909	5.2909	4.8892	5.8541
1-15-1	5.6	5.5934	5.5351	5.6086	5.6697	5.1933	5.9335
1-15-1	5.8	5.7511	5.8052	5.7748	5.9434	5.7862	5.9573
1-15-1	6.0	6.0253	6.0472	5.9438	6.0537	6.3801	6.0174
...							
1-15-1	6.6	6.5493	6.5586	6.5667	6.6248	6.8220	6.6201
1-15-1	6.8	6.8534	6.8438	6.7920	6.9486	6.8308	6.6872
1-15-1	7.0	7.0442	7.0382	7.0541	7.0359	6.8333	6.7044
1-15-1	7.2	7.1006	7.1163	7.1481	7.0509	6.8338	6.7028

Table 2 shows the predicted value of F_{SR} based on different training functions but with same training parameters. Different NN architectures are applied and the best training results are achieved by NN architecture of 1-15-1 which means one input, 15 hidden neurons and 1 output. It is observed that the results of *trainlm* function are highly optimized than other training functions. The results given in the Table 2 depict that the stakeholders' problem can be solved by using *trainlm* function. The MSE of *trainlm* function is shown in Figure 3.

For assessment of error in BPNN the parameter of MSE is used. The MSE graph helps in validating the NN after every iteration or epoch [46]. When the value of MSE decreases and the number of epochs increases then it ensures the efficient working of NN [46]. The decrease in MSE is highly desirable in BPNN otherwise it is required to retrain the network.

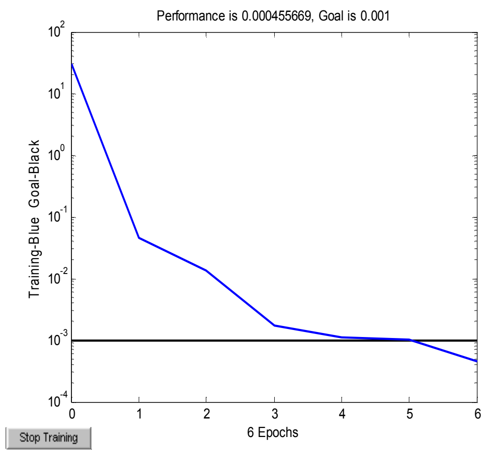

Figure 3. MSE Graph of Trainlm Function

The training results in Table 2 show that the best possible training function for stakeholder quantification problem is *trainlm* which is also default training function of PBNN. In validation phase different NN architectures are applied in order to achieve the optimized results. The number of hidden units is changed in order to analyse the results of different NN architectures. The change in hidden units helps in measuring the performance of BPNN. However, there is only one hidden layer in all the experiments. The results of validation data are given in Table 3

Journal of Theoretical and Applied Information Technology
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Table 3: Validation Data Results

Sr. No.	Input	Target	trainlm Predicted Output	Error Difference (Target-Predicted)
1.	16	2.2000	3.4040	-1.2040
2.	5	3.4000	1.1936	2.2064
3.	14	2.8000	3.0068	-0.2068
4.	12	1.6000	2.6004	-1.0004
5.	9	4.4000	2.0200	2.3800
6.	18	3.4000	3.7981	-0.3981
7.	7	0.4000	1.6130	-1.2130
8.	8	1.2000	1.7766	-0.5766
9.	10	0.8000	2.1908	-1.3908
10.	13	2.2000	2.7947	-0.5947
11.	9	1.8000	2.0200	-0.2200
12.	11	0.8000	2.4029	-1.6029
13.	17	1.2000	3.6015	-2.4015
14.	5	2.4000	1.1936	1.2064
15.	16	1.6000	3.4040	-1.8040
16.	24	2.0000	4.9977	-2.9977
17.	19	3.2000	3.9917	-0.7917
18.	8	4.8000	1.7766	3.0234
19.	16	2.6000	3.4040	-0.8040
20.	4	1.4000	0.9899	0.4101

Table 3 describes the results of *trainlm* training function. Input, target, *trainlm* predicted output are shown and based on target and predicted output the error difference is calculated. The linear fit of the function *trainlm* is shown in Figure 4.

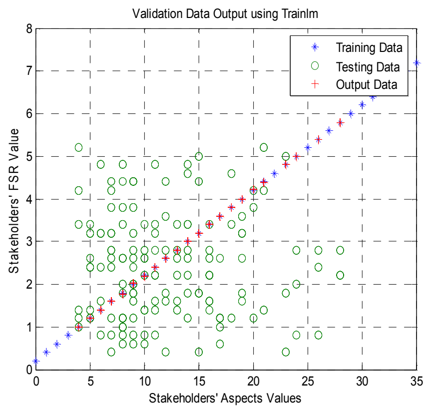

Figure 4. Linear Fit for Trainlm

The F_{SR} values of the stakeholders are mapped with the training data values. The values on X axis are values of stakeholders' aspects or attributes while values on Y axis are predicted F_{SR} values of the stakeholders using BPNN. The predicted data values in case of trainlm have lesser deviation from the actual or training data values and the trainlm function is acceptable in order to solve the plight of stakeholders' quantification. For more optimized results we have applied different architectures of BPNN. The architectures of BPNN vary based on the hidden nodes in the hidden layers and activation functions.

The MSE graph for validation data is shown in Figure 5. The MSE graph shows that the NN is working efficiently for validation data also. As the error reduces with the number of epochs the results achieved are more optimized. The graph shows the achieved performance of the NN.

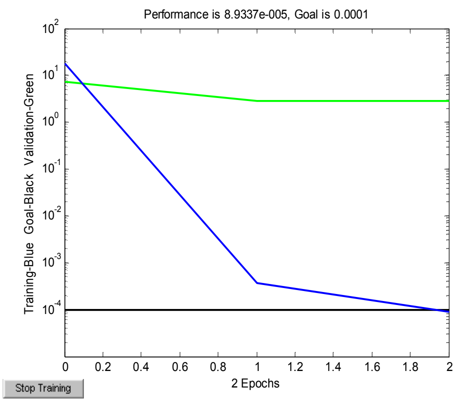

Figure 5. MSE Graph of Trainlm for Validation Data

6.2 Phase 2: Impact of Hidden Neuron

The selection of an NN is based on the results produced by the NN. For stakeholders' problems different NN architectures are applied by changing the hidden nodes in the hidden layer.

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The accuracy of all NN architecture is monitored, and architecture of 1-16-1 is selected based on the most optimized results in terms of reduced error and high accuracy. Where the first 1 shows a single input, the middle number 16 shows the number of hidden nodes and in the last the 1 represents the final output. The NN architectures with hidden nodes less than 16 are rejected based on increased error. However, the NN architectures with hidden nodes greater than 16 are also rejected due to the problem of over-fitting. The results produced and performance by these NN architectures cannot be generalized due to minor errors. As the number of hidden nodes increases in the hidden layer it results in the problem of over-fitting of training data. The bad performance generalizations are the result of over-fitting of the training data [47].

Table 4: Change of Hidden Nodes and Impact on Results

NN Architecture	Hidden Nodes	Input	Target	trainlm Output	Error Difference (Target-Predicted)
1-3-1	3	35	7.2000	7.1782	0.0218
1-4-1	4	35	7.2000	7.1817	0.0183
1-5-1	5	35	7.2000	7.1797	0.0203
1-6-1	6	35	7.2000	7.1801	0.0199
1-7-1	7	35	7.2000	7.1851	0.0149
1-8-1	8	35	7.2000	7.1895	0.0105
1-9-1	9	35	7.2000	7.1836	0.0164
1-10-1	10	35	7.2000	7.1970	0.0030
1-11-1	11	35	7.2000	7.1835	0.0165
1-12-1	12	35	7.2000	7.1902	0.0098
1-13-1	13	35	7.2000	7.1961	0.0039
1-14-1	14	35	7.2000	7.1925	0.0075
1-15-1	15	35	7.2000	7.1935	0.0065
1-16-1	16	35	7.2000	7.1994	0.0006
1-17-1	17	35	7.2000	7.1998	0.0002
1-18-1	18	35	7.2000	7.2000	-0.0000
1-19-1	19	35	7.2000	7.2000	-0.0000
1-20-1	20	35	7.2000	7.2000	-0.0000

7. RESULTS AND ANALYSIS

The results produced by selected NN architecture (1-16-1) are shown in Table 5. Stakeholders are considered as key entities in REP. The requirements are gathered from these key entities. This expert system is proposed for quantification of these key entities based on the risk associated with each entity. Higher the value of F_{SR} then higher risk is associated with the concerned stakeholder and vice versa. From Table 5 the F_{SR} values like 7.1988, 5.9802, 7.0027, 4.5945, 4.9973, 4.0030, 5.4003, 4.9973, 4.7982, and 5.8106 shows the higher risk associated with these stakeholders. The F_{SR} values other than these depict the association of low risk with other stakeholders. The results given by the chosen NN architecture can be generalized due to the low and acceptable errors. As stated previously the results produced by NN architectures having hidden nodes greater than 16 are the cause of over-fitting which results in bad performance of the NN architecture.

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Table 5: Results of Selected NN Architecture

Sr. No.	NN Architecture	Input	Target	trainlm Predicted Output	Error Difference (Target-Predicted)
1.	1-16-1	35	7.2000	7.1988	0.0012
2.	1-16-1	29	6.0000	5.9802	0.0198
3.	1-16-1	34	7.0000	7.0027	-0.0027
4.	1-16-1	14	3.0000	2.9946	0.0054
5.	1-16-1	22	4.6000	4.5945	0.0055
6.	1-16-1	24	5.0000	4.9973	0.0027
7.	1-16-1	12	2.6000	2.5948	0.0052
8.	1-16-1	8	1.8000	1.7947	0.0053
9.	1-16-1	19	4.0000	4.0030	-0.0030
10.	1-16-1	5	1.2000	1.1957	0.0043
11.	1-16-1	26	5.4000	5.4003	-0.0003
12.	1-16-1	6	1.4000	1.3999	0.0001
13.	1-16-1	24	5.0000	4.9973	0.0027
14.	1-16-1	23	4.8000	4.7982	0.0018
15.	1-16-1	28	5.8000	5.8106	-0.0106

The different parameters of the selected NN architecture are shown in Figure 6.

```
net.trainParam.goal=1e-4;            % - Performance goal
net.trainParam.time=0.4;             % - Maximum time to train
net.trainParam.max_fail=5;           % - Maximum validation failures
net.trainParam.mem_reduc=1;          % - memory/speed trade off.
net.trainParam.min_grad=1e-06;       % - Minimum performance gradient
net.trainParam.mu=0.001;             % - Initial Mu
net.trainParam.mu_dec=0.1;           % - Mu decrease factor
net.trainParam.mu_inc=10;            % - Mu increase factor
net.trainParam.mu_max=1e+010;        % - Maximum Mu
net.trainParam.epochs =10;           % - Maximum number of epochs to train
net.performFcn='mse';                % - Performance Function
```

Figure 6. NN parameters

The proposed expert system provides a way to software professionals to analyse the stakeholders based on the risk associated with them. The proposed system helps in finding out the F_{SR} value of the stakeholders. Higher the F_{SR} value higher the stakeholder is highly risky and vice versa. The approach helps in finding key stakeholders for VBS systems' development. The selected stakeholders will help in elicitation of requirements for VBS system. The requirements given by these key stakeholders will help in gaining market leverage. The proposed expert system helps in removing the problems of the existing approaches. Based on the problem formulation the approach is easy to initiate as compared to other approaches. Other approaches lack in providing any metric however the F_{SR} equation can be used as a metric in order to evaluate the stakeholders for VBS systems. The proposed intelligent system is also cost effective in terms of time as compared to other SIQ approaches.

8. CONCLUSION

This research paper presents an approach for identification and quantification of stakeholders of VBS systems. Stakeholders are the key entities in REP in order to get valuable requirements for VBS systems. The proposed approach is easy to initiate the SIQ process and to identify the key stakeholders for VBS systems based on the risk associated with them. This research supports business analysts in analysis of stakeholders and requirements. The current SIQ approaches are not successful hence an intelligent approach is presented in this research which is based on BPNN. The research focuses on an expert system for SIQ process. The proposed F_{SR} metrics proved useful in predicting the risk associated with a stakeholder. The results show that the proposed expert system helps well in solving the stakeholders' problem. There are certain validity threats to this approach. The lack of expert judgement in the domain of SIQ process may be the cause of incorrect results. There is a need that the proposed SIQ approach must be initiated by expert domain analysts. Currently the dataset is very limited and the approach is applied in smaller projects with few stakeholders. There is a need to apply the approach in larger projects with hundreds and thousands of stakeholders. For future works some clustering algorithm like k-means, c-means or self-organizing map may be used in order to find out a most critical bunch of stakeholders with lowest risk value. The use of a clustering algorithm will also help in defining the base for inclusion and exclusion of a stakeholder in REP.

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