

Object Oriented Software Effort Estimate with Adaptive Neuro Fuzzy use Case Size Point (ANFUSP)

Mohammad Saber Iraji

Department of Computer science, Young Researchers Club sari Branch, Islamic Azad University, sari, Iran.
E-mail: iraji.ms@Gmail.com

Homayun Motameni

Department of Computer engineering, Islamic Azad University, Sari Branch, Sari, Iran
E-mail: motameni@iausari.ac.ir

Abstract— Use case size point (USP) method has been proposed to estimate object oriented software development effort in early phase of software project and used in a lot of software organizations. Intuitively, USP is measured by counting the number of actors, preconditions, post conditions, scenarios included in use case models. In this paper have presented a Adaptive fuzzy Neural Network model to estimate the effort of object oriented software using Use Case size Point approach. In our proposed system adaptive neural network fuzzy use case size point has less error and system worked more accurate and appropriate than prior methods.

Index Terms— Use case size point, effort, adaptive neuro fuzzy, object oriented effort

I. Introduction

Today the software industry experience and training data in order to estimate the effort of software is important.

Estimation of object oriented software cost and effort is an important and hard management activity. This is due to the lack of information to making decisions in the early phases of the development, frequently characterized by uncertainty. To help the managers in this task, there are in the literature many estimation models that usually include two main metrics: Lines of Code (LOC) and Function Points (FP) [2], both of them with skills and limitations. LOC is dependent on the programming language and the FP Analysis (FPA) is subjective and based on human decisions [3].

As the most popular technique for object-oriented software cost estimation, Use Case Points (UCP) method, however, has two major drawbacks: the uncertainty of the cost factors and the abrupt classification [4]. Software cost estimation is vital for project bidding, budgeting, controlling and planning. Although in the literature many estimation models like Constructive Cost Model (COCOMO), Function Points (FP) have been proposed to

help manager in estimation task, there is no obvious evidence shows that the accuracy is improved in last decades [5]. Achieving a highly accurate estimation is still a challenging issue in software engineering [4].

The subjects of estimation in the area of software development are size, effort invested, development time, technology used and quality. Particularly, development effort is the most important issue. So far, several effort models [6][7][8] have been proposed and most of them include software size as an important parameter. Function point is a measure of software size that uses logical functional terms business owners and users more readily understand [9]. Since it measures the functional requirements, the measured size stays constant despite the programming language, design technology, or development skills involved. To estimate the effort in earlier phase, use case point method has been proposed [10]. Use case point (UCP) is measured from a use case model that develops the functional scope of the software system to be developed. It is intended by the function point methods and is based on analogous use case point. There are several experience reports that show the usefulness of use case point for early estimation of software size.

Unified Modeling Language (UML) is a graphical modeling language that is used for visualizing, specifying, constructing and documenting software systems. To capture the functional requirements of a software project use case models are often employed. Use case modeling is a technique that has been widely used throughout the industry/research to describe and capture the functional requirements of a software system [11]. Since use cases and scenarios are developed as a normal part of requirements gathering and analysis they capture an accurate representation of the user's requirement.

The use case point's method adjusts the size of the functionality of the system based on a number of technical and environmental factors. The technical factors are related to non-functional requirements on the system, while the environmental factors characterize the

development team and its environment. The influence of these factors on the estimate was in this case much smaller (a 16% increase in the estimate) than the increase in actual effort spent by the companies that emphasized the development process and the quality of the code (an increase in actual effort of more than 100%) [1].

Software estimation models combining algorithmic models with machine learning approaches, such as neural networks and fuzzy logic, have been viewed with skepticism by the majority of software managers [12]. Briefly, neural network techniques are based on the principle of learning from historical data, whereas fuzzy logic is a method used to make rational decisions in an environment of uncertainty and vagueness. However, fuzzy logic alone does not enable learning from the historical database of software projects. Once the concept of fuzzy logic is incorporated into the neural network, the result is a neuro-fuzzy system that combines the advantages of both techniques [13].

Many metrics exist based on use case model in object oriented software. We consider use case size point (USP) metric in this paper.

However, our proposed neuro-fuzzy model goes even further: it is a unique combination of neural networks and fuzzy logic. Specifically, we obtained equation 4, defined a suite of fuzzy sets to represent human judgment, and used a neural network to learn from a comprehensive historical database of software projects. A Neuro-Fuzzy use case size Points Calibration model that incorporates the learning ability from neural network and the ability to capture human knowledge from fuzzy logic is proposed and further validated in this paper.

The paper is organized in six sections. After the introduction in Section I, Section II which also introduces the related works of effort estimation. Section II continues with explanations of use case point and use case size point approaches effort estimation in section III, IV. In Section V is proposed Effort estimate with adaptive neuro fuzzy use case size point. It continues with discussions on the architecture of hybrid learning and fuzzy model validation, the error of observations for training data sets. Section VI presents the conclusions of the research. The paper ends with a list of references.

II. Software Effort Estimate Algorithms

The use case points method was proposed by Kerner in 1993, who also validated it on three projects [14]. The method is an extension of MKII Function Points Analysis [15]. The use case points method adjusts the use case points based on a number of technical and environmental factors. This is similar to MKII Function Points, which also adjusts the size based on a number of calibration factors [1,15]. These factors have been criticized for not improving the precision of the estimate [16]. The criticism relates both to the chosen set of factors and to their influence, but little investigation has been done on the effects on effort of the individual factors. Use cases

are often used as input for estimating software development effort. Several studies show that a particular estimation method based on use cases, the use case points method, performs well early in a project [17-18,19,42,21].

In [22, 23, 24, 25] authors have used different neural network models for cost estimation. In [26, 27, 28, 29] the authors have used different case studies for estimating the effort of the software development using use case point approach. Neural Network is an area which is leading the promise of producing consistently accurate estimate. The system effectively learns how to estimate from training set of completed projects [11]. In [11] authors have used neural network models for effort estimation using use case point approach.

Dealing with simple 'black' and 'white' answers is no longer satisfactory enough; degree of membership (suggested by Prof. Zadeh in 1965) became a new way of solving problems by treating data as imprecise or in a fuzzy form, there rule-based allowing the fuzzy system to handle certain degree of randomness without compromising on the efficiency of the system. Fuzzy set is more powerful than classic set, because in real life most of the membership of the set is not a simply absolute "in or out" and fuzzy set mimic the way in which human interprets the terms, so it make is possible to deal with vagueness, imprecise and uncertainty when identifying the category. Fuzzy set theory has been applied software cost estimation for a long time.

Belchior et al [30] show that the metric FP does not have a continuous classification of the functionalities. They propose the Fuzzy Function Point Analysis (FFPA), that introduces a continuous and gradual classification of the system functionalities by using fuzzy numbers to perform the role of the traditional classification tables.

Rodrigo extended Use case Size Points(USP) to Fuzzy Use case Size Points(FUSP) by using fuzzy set theory[31]. Ryder researched on the application of fuzzy logic to COCOMO and Function Points models [32]. Some techniques like fuzzy set and BBNs are introduced for software cost model. Fuzzy set use the degrees of membership in set to replace the absolute "in or out" membership in classic set, which results more precise assessments in software cost estimation[31,32,33].

Neuro-fuzzy systems are one of the most successful and visible directions of that effort. Neuro fuzzy hybridization is done in two ways [34]: a neural network equipped with the capability of handling fuzzy information (termed fuzzy neural network) and a fuzzy system augmented by neural networks to enhance some of its characteristics like flexibility, speed, and adaptability (termed neuro-fuzzy system(NFS) or ANFIS). An adapted neuro-fuzzy system(NFS) is designed to realize the process of fuzzy reasoning, where the connection weights of network correspond to parameters of fuzzy reasoning [34, 35]. These methodologies are thoroughly discussed in the literature [34]. A second and distinct approach to hybridization is the genetic fuzzy systems (GFSs) [36]. A GFS is essentially a fuzzy system

augmented by a learning process based on genetic algorithms (GAs). The parameter optimization has been the approach used to adapt a wide range of dissimilar fuzzy systems, as in genetic fuzzy clustering or genetic fuzzy systems [36]. However, genetic fuzzy systems are not subject of this work.

Marcio Rodrigo Braz, Silvia Regina Vergilio in [3] proposed FUSP (Fuzzy Use Case Size Points), considers concepts of the Fuzzy Set Theory to create gradual classifications that better deal with uncertainty. Results from an empirical evaluation show the applicability and some advantages of the proposed metrics.

Wei xia et al. [13] introduce a new calibration for Function Point complexity weights. A FP calibration model called Neuro-Fuzzy Function Point Calibration Model (NFFPCM) that integrates the learning ability from neural network and the ability to capture human knowledge from fuzzy logic is proposed. The empirical validation using International Software Benchmarking Standards Group (ISBSG) data.

III. Use Case Point Approach

Use case point (UCP) is calculated from use case model in [26]. Table 1 gives a brief overview of the steps of the method.

Table 1 The UCP estimation method [26]

Step	Rule	Output
1	Classify actors: a) Simple, WF (Weight Factors)=1 b) Average, WF=2 c) Complex, WF=3	Unadjusted Actor Weight (UAW)= $\sum(\#Actors * WF)$
2	Classify Use Cases: a) Simple- 3 OR Fewer transactions, WF=5 b) Average- 4 to 7 transactions, WF=10 c) Complex-more then 7 transactions, WF=152	Unadjusted Use Case Weight (UUCW)= $\sum(\#Use Cases * WF)$
3	Calculate the Unadjusted Use Case Point (UUCP)	$UUCP = UAW + UUCW$
4	Assign values to the technical and environmental factors [0..5], multiply by their weights [-1..2], and calculate the weighted sums (Tfactor and Efactor). Calculate TCF and EF as shown	Technical Complexity Factor (TCF) = $0.6 + (0.01 * TFactor)$ Environmental Factor (EF) = $1.4 + (-0.03 * EFactor)$
5	Calculate the Unadjusted Use Case Point (UCP)	$UCP = UUCP * TCF * EF$
6	Estimate Effort (E) in Person-hours	$E = USP * PHperUCP$

In step 4, there are 13 technical factors, which are basically non-functional requirements on the system, see Table 2. There are also eight environmental factors that relate to the efficiency of the project in terms of the qualifications and motivation of the development team, see Table 3. The weights and the formula for technical factors are borrowed from the Function Points method

proposed by Albrecht [20]. Karner himself proposed the weights and the formula for the environmental factors based on interviews with experienced developers and some estimation results. In step 6, the adjusted use case points (UCP) is multiplied by a productivity factor. The literature on the UCP proposes from 20 to 36 person hours per use case point (PHperUCP) depending on the values of the environmental factors [14,37].

Table 2 Technical factor [14]

Factor	Description	Weight
T1	Distributed System	2
T2	Response or throughput Performance objectives	2
T3	End-user efficiency	1
T4	Complex internal processing	1
T5	Reusable Code	1
T6	Easy to install	0.5
T7	Easy to use	0.5
T8	Portable	2
T9	Easy to change	1
T10	Concurrent	1
T11	Includes security features	1
T12	Provides access for third parties	1
T13	Special user training facilities are required	1

Table 3 Environmental factor [14]

Factor	Description	Weight
F1	Familiar with Rational Unified Process	1.5
F2	Application experience	0.5
F3	Object-oriented experience	1
F4	Lead analyst capability	0.5
F5	Motivation	1
F6	Stable requirements	2
F7	Part-time workers	-1
F8	Difficult programming language	-1

IV. Use Case Size Point (USP)

USP measures the functionality by considering the structures and sections of a UC, counting the number and weight of scenarios, actors, precondition and post conditions [3]. To determine the USP, the sections of an expanded UC are analyzed and its elements must be classified. The USP for the whole system is given by the sum of the USP for each UC. The following steps show how to calculate USP [3].

Step1:

total complexity of actors (TPA), total complexity of the preconditions (TPPrC), complexity of the scenario (PCP), total complexity of the alternative scenarios (TPCA), total exceptions complexity (TPE) and total complexity of postconditions (TPPoC) calculates from tables 4-8 and computes Unadjusted Use-case Size Point (UUSP) value from Equation 1.

$$UUSP = TPA + TPPrC + PCP + TPCA + TPE + TPPoC \tag{1}$$

Step2:

Technical Adjustment Factors calculate from table 9 by Equation 2. ($0 \leq I_i \leq 5$)

$$FTA = 0.65 + (0.01 * \sum_{i=1}^{14} I_i) \quad (2)$$

Step3:

Environmental Adjustment Factor (FAA) calculate from table 10 by Equation 3.

$$FAA = 0.01 * \sum_{i=1}^5 I_i \quad (3)$$

Step4:

The final value for a UC is given by Equation 4:

$$USP = UUSP * (FTA - FAA) \quad (4)$$

Table 4 UCP actor classification [3]

Complexity	Tested Expressions	UUSP
Simple	1 logical expression	1
Average	2 or 3 logical expressions	2
Complex	> 3 logical expressions	3

Table 5 USP precondition classification [3]

Complexity	Entities	UUSP
Simple	≤ 3	1
Average	4 to 6	2
Complex	> 6	3

Table 6 USP scenario classification [3]

Complexity	Entities + Steps	UUSP
Very Simple	≤ 5	4
Simple	6 to 10	6
Average	11 to 15	8
Complex	16 to 20	12
Very Complex	> 20	16

Table 7 USP exception classification [3]

Complexity	Tested Expression	UUSP
Simple	1 logical expression	1
Average	2 or 3 logical expressions	2
Complex	3 logical expressions	3

Table 8 USP postcondition classification [3]

Complexity	Entities	UUSP
Simple	≤ 3	1
Average	4 to 6	2
Complex	> 6	3

Table 9 Technical factors[45]

Factor	Requirement	Influence
F1	Data communication	I1
F2	Distributed processing	I2
F3	Performance	I3
F4	Equipment utilization	I4
F5	Transaction Capacity	I5
F6	On-line input of data	I6
F7	User efficiency	I7
F8	On-line update	I8
F9	Code reuse	I9
F10	Complex processing	I10
F11	Easiness of deploy	I11
F12	Easiness operation	I12
F13	Many places	I13
F14	Facility of change	I14

Table 10 Environmental factors [46]

Factor	Description	Influence
E1	Formal development process existence	I1
E2	Experience with the application being developed	I2
E3	Experience of the team with the used technologies	I3
E4	Presence on an experienced analyst	I4
E5	Stable requirements	I5

V. Study Objectives And Method

The objectives of this study are:

- calibration of the use case point factor weight values Exactly to fuzzy further enhanced improvements in the software effort estimation process
- Artificial neural network approach to calibrate the function point weight values provides improvement in the software size estimation process.

The weight values of Unadjusted use case size Point (UUSP) in Tables 4-8 are said to reflect the functional size of software [24], Kerner determined them in 1993. Since 1993, software development has been growing steadily and is not limited to one organization or one type of software. Thus, there is need to calibrate these weight values to reflect the current software industry

trend. The ISBSG Development and Enhancement repository has over 5,600 projects from 29 countries and 11 major industry types. This industry data can be used to estimate, benchmark and improve the planning and management of projects. Learning UUSP weight values helps for calibration to reflect the current software industry trend from ISBSG data repository using neural network.

Our Neuro-Fuzzy approach presented in this paper is a novel combination of the above three approaches. It obtains a simple equation 4, defines a suite of fuzzy sets to represent human judgment Exactly, and uses neural network to learn the calibrated parameters from the historical project database. The equation from statistical analysis is fed into neural network learning. The calibrated parameters from neural network are then utilized in fuzzy sets and the users can specify the upper and lower bounds from their human judgment.

The first, the neural network technique is based on the principle of learning from previous data. This neural network is trained with a series of inputs and desired outputs from the training data so as to minimize the prediction error. Once the training is complete and the appropriate weights for the network links are determined, new inputs are presented to the neural network to predict the corresponding estimation of the response variable. The final component of our model, fuzzy logic, is a technique used to make rational decisions in an environment of uncertainty and imprecision. It is rich in its capability to represent the human linguistic ability with the terms of fuzzy set, fuzzy membership function, fuzzy rules, and the fuzzy inference process (figure 1). PHperUSP proposes 2.5 person hours per use case Size point.

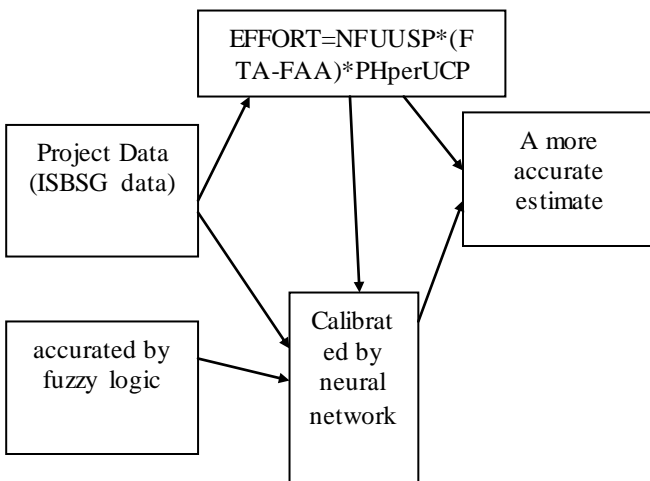


Figure 1. neuro fuzzy use case size point model

A. Neuro fuzzy

It immediately comes to mind, when looking at a neural network, that the activation functions look like fuzzy membership functions. Indeed, an early paper from 1975 treats the extension of the McCulloch-Pitts neuron to a fuzzy neuron (Lee & Lee, 1975; see also Keller & Hunt, 1985).

The one neuron in the output layer, with a rather odd appearance, calculates the weighted average corresponding to the center of defuzzification in the rule base. Backpropagation applies to this network since all layers are differentiable. Two possibilities for learning are apparent. One is to adjust the weights in the output layer, i.e., all the singletons weight until the error is minimized. The other is to adjust the shape of the membership functions, provided they are parametric. also rule weight can be changed with training data. in Neuro fuzzy model is not necessary output be linear [43].

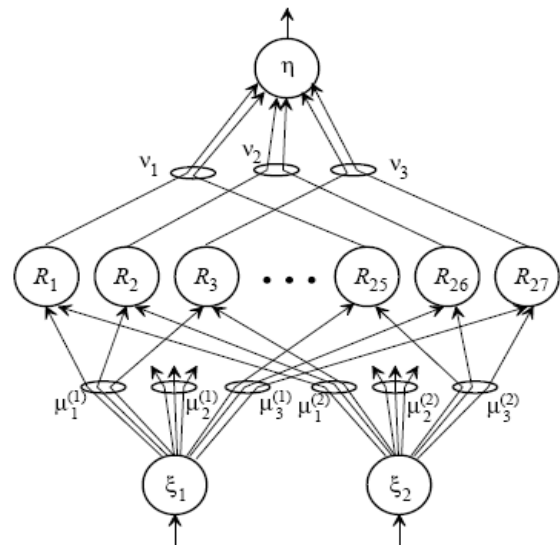


Figure 5. Neuro fuzzy model control system

A.1 Neural network

Developing a neural net solution means teaching the net a desired behavior. This is called the learning phase. Either sample data sets or a “teacher” can be used in this step. A teacher is either a mathematical function or a person that rates the quality of the neural net performance. Since neural nets are mostly used for complex applications where no adequate mathematical models exist and rating the performance of a neural net is difficult in most applications, most are trained with sample data (figure 2).

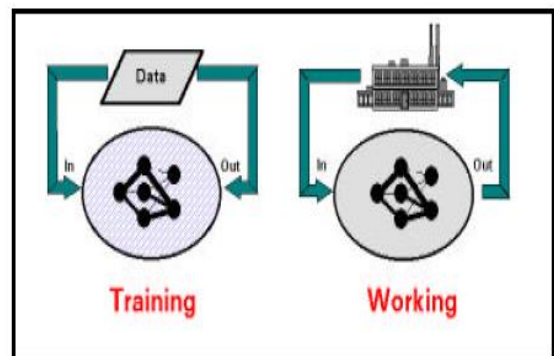


Figure 2. Training and working phase for supervised learning

A.1.1 Neuron Model

An elementary neuron with R inputs is shown figure 3. Each input is weighted with an appropriate w . The sum of the weighted inputs and the bias forms the input to the transfer function f . Neurons may use any differentiable transfer function f to generate their output.

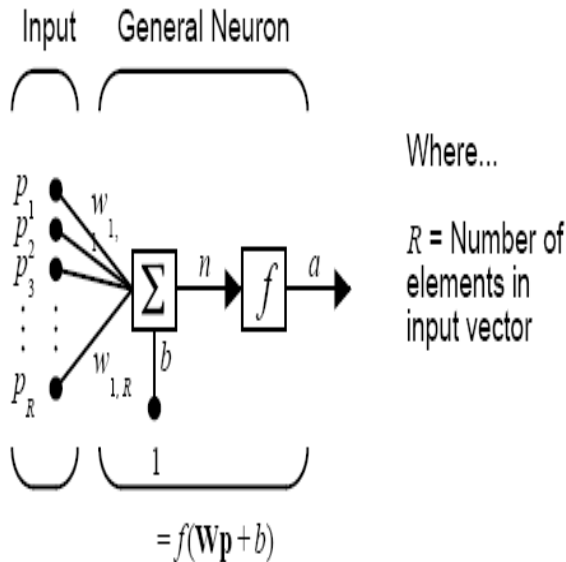


Figure 3. Structure a neuron

Feedforward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors (figure 4). The linear output layer lets the network produce values outside the range -1 to $+1$. On the other hand, if you want to constrain the outputs of a network (such as between 0 and 1), then the output layer should use a sigmoid transfer function (such as logsig). This network can be used as a general function approximator. It can approximate any function with a finite number of discontinuities, arbitrarily well, given sufficient neurons in the hidden layer [38].

A.1.2 Neural network step for estimating use case weight

Back-propagation feed forward neural network approach is used to predict the size of the software using USP approach. A neural network is constructed with 38 inputs and 1 output effort .

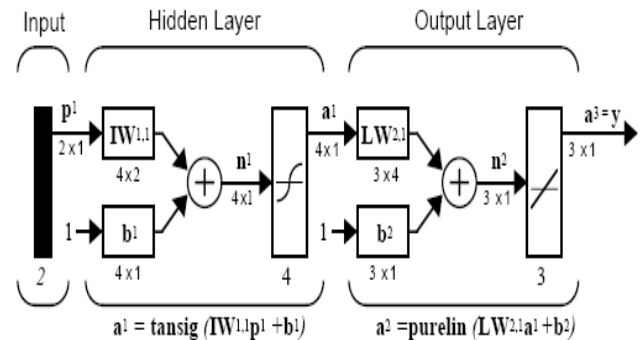


Figure 4. feed forward neural network with two layers

The input nodes represent the distinguishing parameters of use case size point approach and the output nodes represent the effort . The network is constructed by using MATLAB. In our experiment the training function we have considered is traingda , the adaptation learning function considered was learnngdm , and the performance function used was Mean Square Error (MSE). The projects considered for this research are taken from the use case point ISBSG data . The input nodes represent the following features of software projects:

1. Number of simple actor
2. Number of average actor
3. Number of complex actor
4. Number of simple Precondition
5. Number of average Precondition
6. Number of complex Precondition
7. Number of very simple Scenario
8. Number of simple Scenario
9. Number of average Scenario
10. Number of complex Scenario
11. Number of very complex Scenario
12. Number of simple Exception
13. Number of average Exception
14. Number of complex Exception
15. Number of simple Post condition
16. Number of average Post condition
17. Number of complex Post condition
18. Technical cost Factor (FTA)
19. Environmental Factor (FAA)
20. Data communication - F1
21. Distributed processing - F2
22. Performance - F3
23. Equipment utilization - F4
24. Transaction Capacity - F5
25. On-line input of data - F6
26. User efficiency - F7
27. On-line update - F8
28. Code reuse - F9
29. Complex processing - F10
30. Easiness of deploy - F11
31. Easiness operation - F12
32. Many places - F13
33. Facility of change - F14
34. Formal development process existence - E1

- 35. Experience with the application being developed -E2
- 36. Experience of the team with the used technologies -E3
- 37. Presence on an experienced analyst -E4
- 38. Stable requirements -E5

A.2 Fuzzy Use Case Size Point (FUSP)

In use case size counting method, each component, such as actors is classified to a weight level determined by the numbers of its entities (step 1 of section 4). Such weight classification is easy to operate, but it may not fully reflect the true color of the software complexity under the specific software application. For example, a software project with two use cases, A with 10 entities and B with 6 entities. According to the weight matrix, A and B are classified as having the same complexity and are assigned the same weight value of 4. However, A has 4 transactions to more than B and is certainly more complex. They are now assigned the same complexity, which is recorded as Observation 1: ambiguous classification?[13]

The metric USP presents new elements for measuring the functionality of the UCs. However, it also uses a discrete classification of the functionalities complexity, like UCP and FPA[3]. The use of the classification tables does not allow a gradual change from one complexity category to another. To allow such gradual change, we extended the metric USP by adopting the same FFPA steps [39] with Learning ability of neural networks and The accuracy of the fuzzy system introduced a metric named NFUSP (Neuro Fuzzy Use Case Size Points).

A.2.1 Fuzzy logic calibration step

The classification tables are transformed into a continuous classification, this process is called fuzzyfication (a more formal definition to fuzzyfication could be found in [40]). This can be made through the generation of a trapezoidal fuzzy number to each complexity category found on the classification tables. Then, each classification table for a UC (actors, preconditions, exceptions, etc) is represented by a graph. The graphs obtained for each USP classification table are present in Figure 5[3].

Membership functions for output actor weight are the triangular type, because these types of membership functions are appropriate to use in preserving the values in the complexity weight matrices (Figure 6).the fuzzy inference process using the Mamdani approach [41] is applied to evaluate use case component weight degree when the linguistic terms, the fuzzy sets, and the fuzzy rules are defined.

Fuzzy Logic Rules:

- If Input =simple entities then weight output = simple
- If Input = average entities then weight output = average
- If input =complex entities then weight output=complex

The antecedent result as a single number implies the consequence using the min (minimum) implication method. Each rule is applied in the implication process and produces one consequence. The aggregation using the max (maximum) method is processed to combine all the consequences from all the rules and gives one fuzzy set as the output. Finally, the output fuzzy set is defuzzified to a crisp single number using the centroid calculation method.

An example of the complete fuzzy inference process is shown in Figure 10. Input values are set to entities: 10. The antecedent parts of the fuzzy rules whose degrees are not equal to zero are activated and represented by the light gray shades. Here, rules 2,3 are activated for the antecedent part input. Finally, the consequent fuzzy set is defuzzified, using the centroid calculation method, and the output is achieved as a single value of 4.36 the bold black line in the output fuzzy set located in the bottom right of the Figure 7.

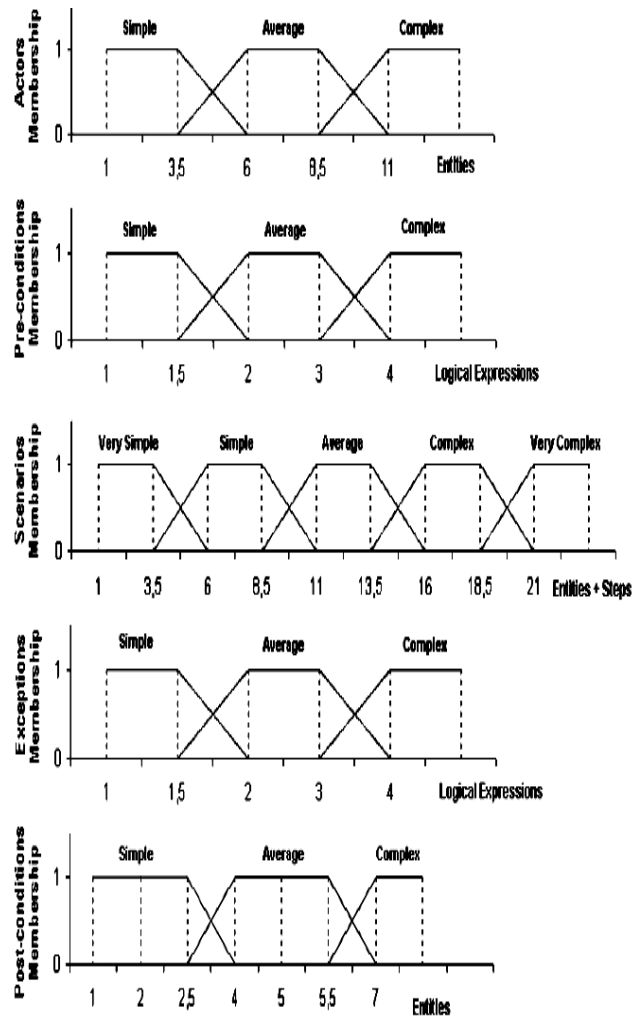


Figure 5. fuzzy graph for USP tables[3]

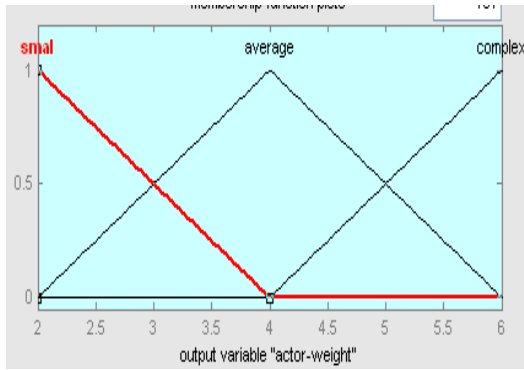


Figure 6. membership function for actor weights

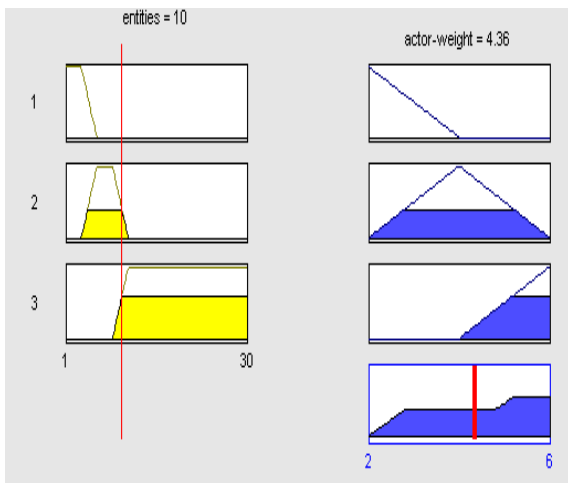


Figure 7. fuzzy inference process of neuro-fuzzy use case size point model

Afterwards, a fuzzy complexity measurement system that takes into account all elements of use case size point in tables 4-8 is built after the fuzzy logic system for each use case size point component is established, as shown in Figure 8. Each USP element is into a Fuzzy Logic System (FLS). The outputs of all five FLS are summed up and become the neuro fuzzy Unadjusted Use Case Size Points(NFUUSP) Which is used to calculate effort(figure 8).

$$EFFORT = NFUUSP * (FTA - FAA) * PHperUSP \quad (5)$$

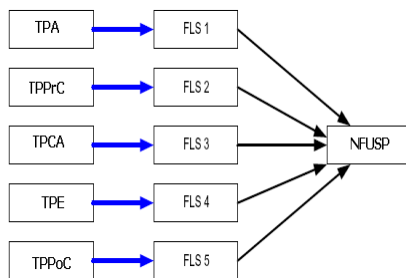


Figure 8: fuzzy inference process of neuro-fuzzy use case size point model

B. Sugeno model

A typical rule in a Sugeno fuzzy model has the form If Input 1 = x and Input 2 = y, then Output is z = ax + by + c.

For a zero-order Sugeno model, the output level z is a constant (a=b=0).

The output level zi of each rule is weighted by the firing strength wi of the rule. For example, for an AND rule with Input 1 = x and Input 2 = y, the firing strength is wi=AndMethod (F1(x), F2(y)) ;where F1,2 (.) are the membership functions for Inputs 1 and 2. The final output of the system is the weighted average of all rule outputs, computed as:

$$FinalOutput = \frac{\sum_{i=1}^N w_i z_i}{\sum_{i=1}^N w_i}$$

A Sugeno rule operates as shown in the following diagram(Figure 6).ANFIS (Adaptive Neuro Fuzzy Inference System) is an architecture which is functionally equivalent to a Sugeno type fuzzy rule base (Jang, Sun & Mizutani, 1997; Jang & Sun, 1995). Under certain minor constraints the ANFIS architecture is also equivalent to a radial basis function network. Loosely speaking ANFIS is a method for tuning an existing rule base with a learning algorithm based on a collection of training data. This allows the rule base to adapt.

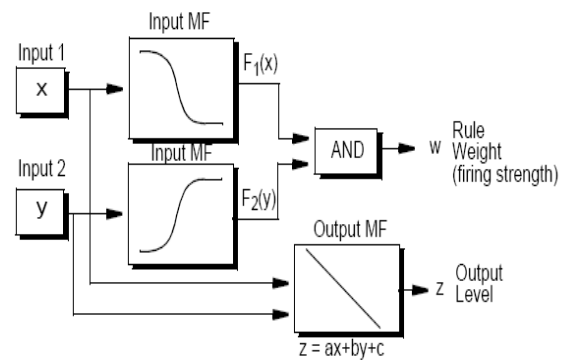


Figure 6. Sugeno model

B.1 Anfis

Consider the fuzzy neural network in figure 7. The output of the first layer nodes are the degree of membership of linguistic variables. Typically, in this layer bell-shaped functions are used. Bell-shaped function is shown in Relationship 6. The purpose of learning in this layer is adjusting the parameters of membership function of inputs.

$$f(x) = \exp \left[\frac{-1}{2} \left(\frac{x - a_i}{b_i} \right)^2 \right] \quad (6)$$

The second layer is 'rules layer'. In this layer, the condition part of rules is measured by usually Min fuzzy logic operator, and the result will be the degree of activity of rule resultant. Learning, in this layer, is the change of the amount of activity of rules resultant, regarding to the 'training data', given to the network. In the third layer, we'll get the linear combination of rules resultant rate, and in order to determine the degree of belonging to a particular category, Sigmund function is used in layer 4 [44].

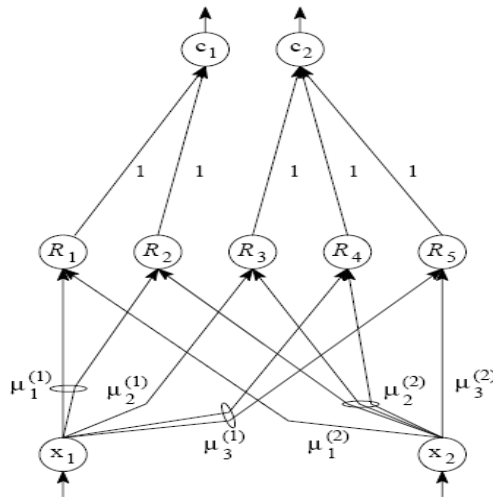


Figure 7. Adaptive neuro fuzzy Network (ANFIS)

If a series of training vectors is given to the network in the form of the formula 7:

$$\{(x^k, y^k), k = 1, \dots, K\} \tag{7}$$

Where x^k refers to the K-th input pattern, then we have:

$$y^k = \begin{cases} (1, 0) \\ (0, 1) \end{cases}$$

$$\text{if } x^k \text{ belongs to class 1} \tag{8}$$

$$\text{if belongs to class 2 } x^k$$

The error function for K pattern can be defined by relationship 9:

$$Pr\ edicatedEffort_i \tag{9}$$

where y^k is desired output, and O^k is computed output.

VI. Discussion And Conclusion

Several methods exist to compare cost estimation models. Each method has its advantages and disadvantages. In this work, The Magnitude of Relative Error (MRE) will be used. MRE for each observation i can be obtained as:

$$MER_i = \frac{|ActualEffort_i - Pr\ edicatedEffort_i|}{Pr\ edicatedEffort_i} \tag{10}$$

MMRE can be achieved through the summation of MRE over N observations:

$$MMER = \frac{1}{N} \sum_1^N MER_i \tag{11}$$

After training neural network by ISBSG data ,we have applied Our proposed neuro fuzzy system on seven samples of projects. The results are shown in the table below .

TABLE 11. EVALUATION RESULTS FROM SAMPLE PROJECTS

PROJECT #	Actual effort	effort in Use case size point	Effort in Neuro fuzzy use case point(mamdani)	Effort in Adaptive Neuro fuzzy use case point(sugeno)	MER (USP)	MER(NFUSP)	MER(ANFUSP)
1	2905	2610	2873	2880	0.113027	0.011138	0.008681
2	2200	2176	2196	2190	0.011029	0.001821	0.004566
3	1759	1591	1638	1751	0.105594	0.073871	0.004569
4	1542	1364	1538	1540	0.130499	0.002601	0.001299
5	1025	992	1015	1019	0.033266	0.009852	0.005888
6	2784	2600	2725	2783	0.070769	0.021651	0.000359
7	2961	2891	2927	2957	0.024213	0.011616	0.001353
MMER					0.069771	0.018936	0.003816

As you can see in the table 11 Thus effort estimation with Adaptive neuro fuzzy Unadjusted Use Case Size Points(ANFUUSP) MMER is less and ANFUUSP accuracy further. For future work can be other different

types of membership functions, different types of neural network and optimization algorithms like genetic algorithm considered. However, software development is a rapidly growing industry and these calibrated weight

values will not reflect tomorrow's software. The advantage of Neural Networks is it has the learning capability to adapt new data. On the other hand, Fuzzy Systems has the capability to handle numerical data and linguistic knowledge simultaneously. In the future, when modern project data is available, the USP weight values will again need to be re-calibrated to reflect the latest software industry trend. The Adaptive neuro-fuzzy USP model is a framework for calibration and the neuro-fuzzy USP calibration tool can automate the calibration process when data becomes available.

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Mohammad Saber Iraj received B.Sc in computer software engineering from shomal university ,iran ,amol; M.Sc1 in industrial engineering (system management and productivity) from khatam university iran ,Tehran and M.Sc2 in computer science from Islamic azad university , sari branch . Currently, he is engaged in research and teaching on computer graphics, image processing , fuzzy and artificial intelligent , data mining, software engineering.

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