Effort Estimate with Neuro Fuzzy Use Case Point Based on Exact Weights

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ABSTRACT: *Use case point (UCP) method has been proposed to estimate software development effort in early phase of software project and used in a lot of software organizations. Intuitively, UCP is measured by counting the number of actors and transactions included in use case models . This paper describes the idea to automatically classify the complexity of use cases from use case model.*

Even though several estimation procedures are available the Neural Network and fuzzy models presents advantages over normal estimation procedure. In this paper we develop a fuzzy Neural Network model to estimate the effort of software using Use Case Point approach based on calibrate weights after learning from software projects data . In our proposed system fuzzy neural network use case point has less error and system worked more accurate and appropriative than prior methods.

Keywords: Use case point, Effort, Neuro fuzzy, Neuro Fuzzy Use Case Point

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1. Introduction

Through industry collaboration we have experienced an increasing interest in software effort estimation based on use cases [1].

As the most popular technique for 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[3]. 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 [5][6][7] 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 [8]. 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 [9]. 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 influenced 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 [10]. 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 points 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 scepticism 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 in corporated into the neural network, the result is a neuro-fuzzy system that combines the advantages of both techniques [13].

However, our proposed neuro-fuzzy model goes even further: it is a unique combination of neural networks and fuzzy logic. Specifically, we obtained an equation from step 6 of table 1, 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 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 five sections. After the introduction in section 1, the section 2 also introduces the related works of effort estimation. Section 2 continues with explanations of use case point approaches, the section 3 deals with effort estimation in section 3. The section 4 contains Effort estimate with neuro fuzzy use case point based on calibrate weights . It continues with discussions on the architecture of hybrid learning and fuzzy model validation, the error of observations for training data sets. Section 5 presents the conclusions of the research. The paper ends with a list of references.

2. Literature Review

The use case points method was proposed by Karner 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, 20, 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 [10]. In [10] 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-base 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 in software cost estimation for a long time. Rodrigo extended Use case Size Points (USP) to Fuzzy Use case Size Points (FUSP) by using fuzzy set theory [30]. Ryder researched on the application of fuzzy logic to COCOMO and Function Points models [31].

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 [30], [31], [32].

Neuro-fuzzy systems are one of the most successful and visible directions of that effort. Neuro fuzzy hybridization is done in two ways [33]: 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 adapt-ability (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 [33, 34]. These methodologies are thoroughly discussed in the literature [33].A second and distinct approach to hybridization is the genetic fuzzy systems (GFSs) [35]. 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 [35]. However, genetic fuzzy systems are not the subject of this work.

Marcio Rodrigo Braz, Silvia Regina Vergilio in [36] 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 is done.

3. 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. 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 [37].

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, 38].

4. Study Objectives And Method

The objectives of this study are:

1. Calibration of the use case point factor weight values Exactly to fuzzy further enhanced improvements in the software effort estimation process

2. 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 Point (UFP) in Table 1 are said to reflect the functional size of software [24], Karnerdetermined 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. Researchers Learn from UFP weight values from ISBSG data repository using neural network for calibration to reflect the current software industry trend.

Step	Rule	Output
1	Classify actors: a)Simple , WF (Weight Factors)=1 b)Average , WF=2 c)Complex , WF=3	Unadjusted Actor Weight (UAW)=Σ(#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 then7 transactions, WF=15[2]	Unadjusted Use Case Weight (UUCW)= Σ(#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

Table 1. The UCP estimation method

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 UFP weight values from ISBSG data repository using neural network for calibration to reflect the current software industry trend.

Our Neuro-Fuzzy approach presented in this paper is a novel combination of the above three approaches. It obtains a simple equation from step 6 of table 1, 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

Factor	Description	Weight
T1	Distributed System	2
T2	Response or throughputPerformance 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 trainingfacilities are required	1

Table 2. Technical factor

Factor	Description	Weight
F1	Familiar with RationalUnified 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 programminglanguage	-1

Table 3. Enviromental factor

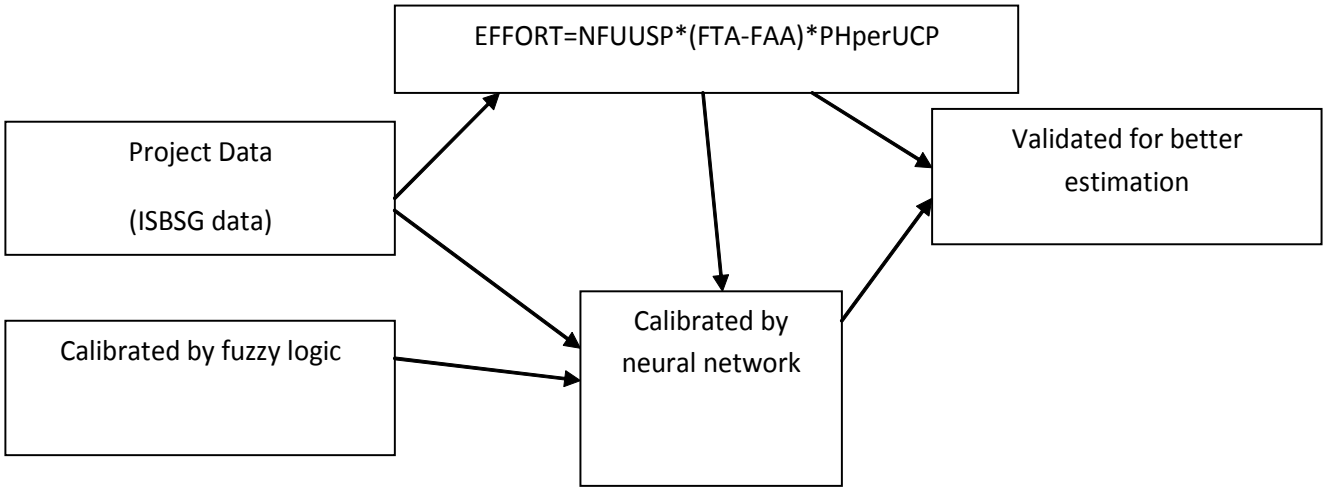

Figure 1. Neuro fuzzy use case point model

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).

4.1 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).

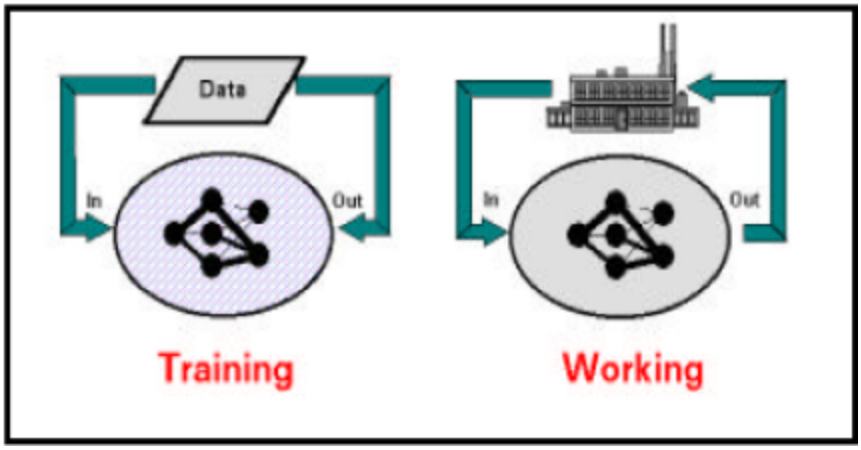

Figure 2. Training and working phase for supervised learning

4.1.1 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.

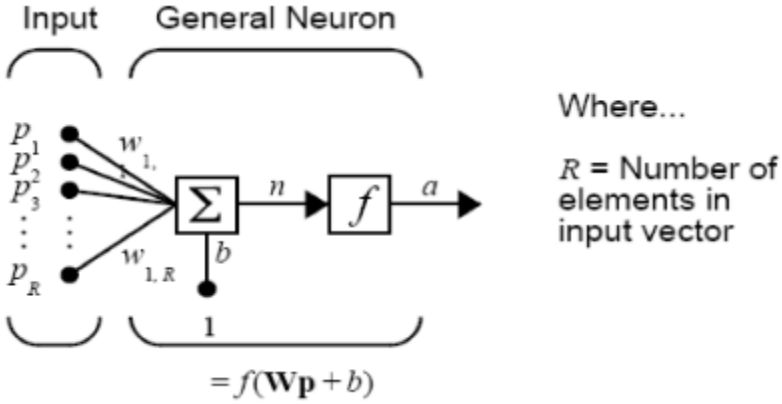

Figure 3. Structure a neuron

Feed forward 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 log sig). 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 [2].

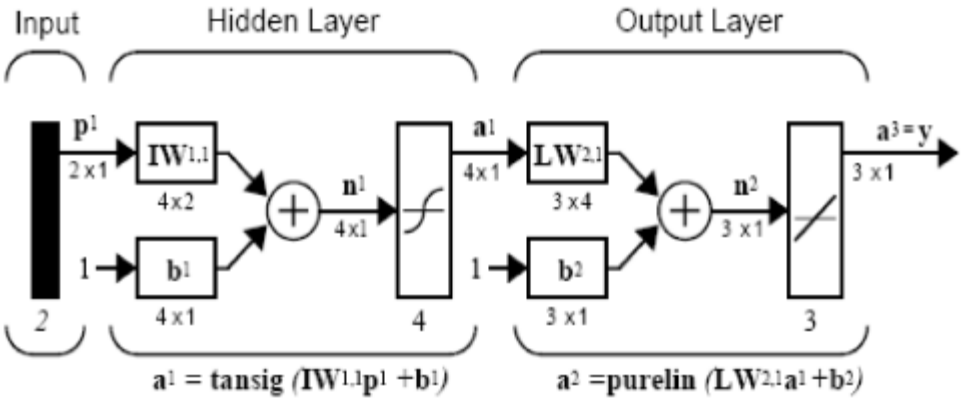

Figure 4. Feed forward neural network with two layers

4.1.2 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 UCP approach. A neural network is constructed with 27 inputs and 1 output effort. The input nodes represent the distinguishing parameters of use case 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 learngdm, 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 Use case
2. Number of average Use case
3. Number of complex Use case
4. Unadjusted Actor weight
5. Technical cost Factor
6. Environmental Factor
7. Distributed System
8. Response Time
9. End User Efficiency
10. Complex Internal Processing
11. Reusable code
12. Installation ease
13. Easy use
14. Portable
15. Easy to change
16. Concurrent
17. Security objectives
18. Direct access to third parties
19. User training facilities
20. Familiarity with the project
21. Application experience
22. Object oriented programming experience
23. Lead analyst capability
24. Motivation
25. Stable requirement
26. Part time staff
27. Difficult Programming Language

4.2 Fuzzy Use Case Point (FUCP)

In use case counting method, each component, such as use case is classified to a weight level determined by the numbers of its transactions(step 2 table 1), 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 7 transactions and B with 5 transactions. According to the weight matrix, A and B are classified as having the same complexity and are assigned the same weight value of 10. However, A has 2 more transaction than B and is certainly more complex. They are now assigned the same complexity, which is recorded as Observation: ambiguous classification?[13]

The metric UCP 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. 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 UCP by adopting the same FFPA steps [11] and introduced a metric named NFUCP (Neuro Fuzzy Use Case Points).

m1	n1	a1	b1	m2	n2	a2	b2	m3	n3	a3
1	2.5		4		6	2.5	8	8		6

Table 4. values for the fuzzyfication of the terms

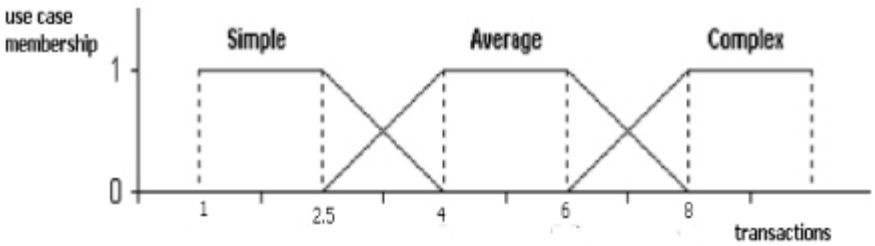

Figure 5. Fuzzy graph for use case Terms of transactions

4.2.1 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 [39]). This can be made through the generation of a trapezoidal fuzzy number to each complexity category found on the classification tables. Then, classification table for a UC (use case) is represented by a graph, To generate the graph, that is the trapezoidal number, the following variables are calculated, for each category in the classification table ($1 \leq i \leq n$, and n is the number of linguistic terms in the classification table being analyzed).
Shortly [36]:

- mi = lower value of the linguistic term Ti in the classification table
- ni = (mi+mi+1)/2
- ai = ni”1
- bi = mi+1

Table 4 shows the values of the above variables for the UCP classification tables. For example, the table for use case Classification has three linguistic terms: Simple (T1), Average (T2) and Complex (T3). The graph obtained for use case classification table are present in Figure 5.

Membership functions for output i.e use case 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 [40] 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 transactions then weight output = simple

If Input = average transactions then weight output = average
If input = complex transactions 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.

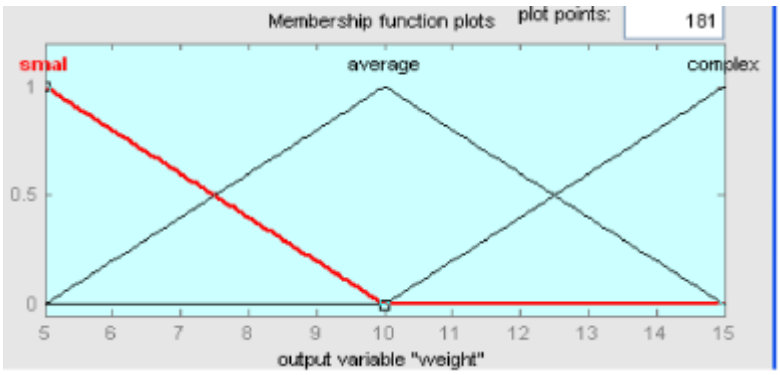

Figure 6. Membership function for use case weights

An example of the complete fuzzy inference process is shown in figure 7. Input value are set to transaction: 7. 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 10.6 the bold black line in the output fuzzy set located in the bottom right of the figure 7.

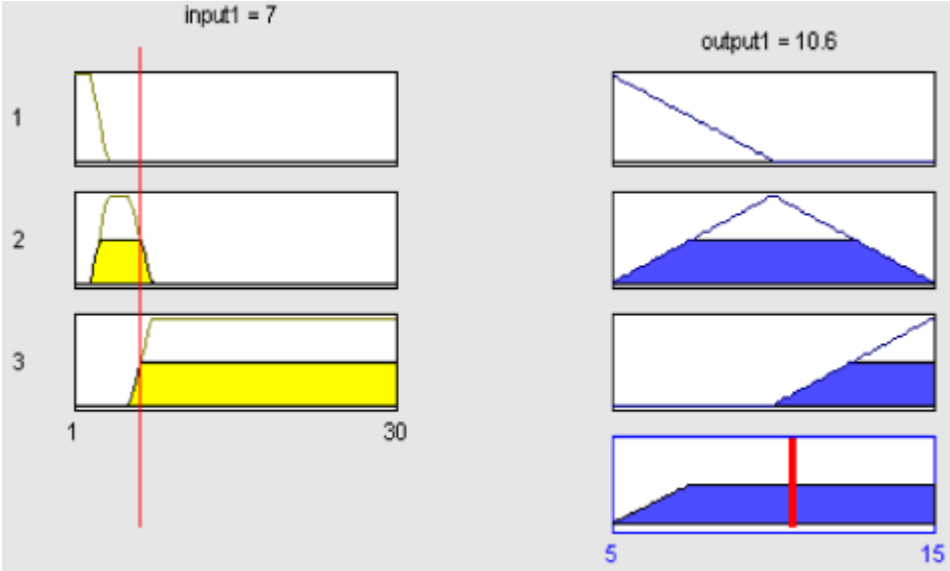

Figure 7. Fuzzy inference process of neuro-fuzzy use case point model

Afterwards, a fuzzy complexity measurement system that takes into account all elements of use case point in table 1 is built after the fuzzy logic system for each use case point component is established, as shown in figure 7. Use cases weights is into a Fuzzy Logic System (FLS). Use cases weights obtained in this way are called neuro fuzzy unadjusted use case weight (NFUUCW).The

outputs of all use case point elements are summed up and become the neuro fuzzy Unadjusted use case Points(NFUUCP) Which is used to calculate effort.

5. 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

$$MER_i = \frac{|\,Actual\ Effort_i - \Pr edictedEffort_i\,|}{\Pr edictedEffort_i}$$

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

$$MMER = \frac{1}{2}\sum_{1}^{N} MER_i$$

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

PROJECT #	Actual effort	effort in Use case point	Effort in Neuro fuzzy use case point	MER(UCP)	MER(NFUCP)
1	2905	2501	2859	0.161535	0.01609
2	2200	2130	2175	0.032864	0.011494
3	1759	1402	1642	0.254636	0.071255
4	1542	1112	1359	0.386691	0.134658
5	1025	963	1011	0.064382	0.013848
6	2784	2581	2690	0.078652	0.034944
7	2961	2720	2907	0.02603	0.018576
MMER				1.067363	0.300864

Table 5. Evaluation results from sample projects

As you can see in the table 5 The effort estimation with neuro fuzzy Unadjusted Use Case Points(NFUUCP) MMER is less and NFUUCP accuracy is further. . In future work other different types of membership functions, different types of neural network and optimization algorithms like genetic algorithm will be considered.

However, software development is a rapidly growing industry and these calibrated weight values will not reflect tomorrow's software. In the future, when modern project data is available, the UCP weight values will again need to be re-calibrated to reflect the latest software industry trend. The neuro-fuzzy UCP model is a framework for calibration and the neuro-fuzzy UCP calibration tool can automate the calibration process when data becomes available.

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