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Ranking of Software Effort Estimation Selection Criteria Based on Fuzzy Set Theory

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ABSTRACT

The selection and evaluation of Software effort estimation models has always been a challenging task for the software developers and the project managers. A lot of research has been done by various researchers on this by considering it as multi-criteria decision making problem. So, a better understanding of various selection criteria and their importance in this regard is required. In this paper, first the identification of the various software effort estimation model selection criteria is done, then by applying fuzzy set theory the local and global weights of these selection criteria are calculated and finally the selection criteria are ranked according to their global weights showing the importance of each criterion.

Keywords: *Selection Criteria; Fuzzy-Set Theory.*

1.0 Introduction

Over the past decades, software has become a crucial component in all aspects of life. The development of the software with a better quality and less effort is the prime motive of the software developers. Several research surveys have focused on software project effort and schedule estimation. Manpower, Effort (usually in person- months), and Project Duration (in calendar time) are the three main elements considered while estimating the effort of any software development.

Effort estimation obtains essential data in the form of how estimates are made, what factors motivate the choice of estimation methods and the current level of estimation accuracy. For both developers and customers the accurate software effort estimation are to be critical which can be used for generating request for proposals, contract negotiation, scheduling, monitoring and control.

To get accurate estimates, effort estimation may be used an input to project plans, iteration plans, budgets, investment analyses and pricing processes and bidding rounds.

Effort estimation methods can be divided into model based and expert-based methods. Model-based methods use some algorithm to summarize old data and make predictions about new projects where as Expert-based methods use human expertise (possibly augmented with process guidelines, checklists, and data) to generate predictions. The precision of size estimation directly impacts the accuracy of effort estimation.

The rest of the paper is structured as: A literature review about the effort estimation model is provide in section 2, in section 3 a brief introduction about Adopted methodology, A ranking procedure is given in section 4, and section 5 contains the conclusion of the paper.

2.0. Literature Review

Tim Menzies et al. [1] proposed a methodology based on heuristic rejection rules named coseekmo to rank various software effort estimation models by considering mean relative error (MRE), mean magnitude of relative error (MMRE) and prediction (PRE) as selection criteria.

Basha and Dhavachelvan [2] proposed mean relative error (MRE), mean magnitude of relative error (MMRE), prediction (PRE), root mean square (RMS), relative root mean square (RRMS) for the ranking of software effort estimation models. In the contemporary work, Kaur et al. [3] used some attributes as mean magnitude of relative error (MMRE), mean square error (MSE), root mean

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square error (RMSE) and RMSSE as the selection criteria.

Kaur Sehra et al. [4] proposed a model based on Fuzzy Analytic Hierarchy Process by accounting reliability (REL), mean magnitude of relative error (MMRE), Prediction (PRE) as selection criteria. Noel Garcia-Diaza et al. [5] developed a methodology based on fuzzy logic for the comparison of two fuzzy logic models for software development effort estimation. Prediction (PRE), mean error relative (MER), (mean magnitude of error relative) MMER were used as selection criteria in this research.

A hybrid model was developed by Predicate.C. Eberendu [6] for the comparison of various software effort estimation models by considering Technical complexity factor (TCF), Environmental complexity factor (ECF), Unadjusted use case points (UCP), Productivity factors (PF) as the selection criteria. Moløkken-Østvold [7] provide mean relative error (MRE), balance relative error bias (BREbias) and balance relative error (BRE) as the selection criteria for the evaluation of software effort estimation models. Leung and Fan [8] published Software Cost Estimation using different criteria as mean relative error (MRE), mean absolute relative error (MARE), balance relative error (BREbias).

3.0 Adopted Methodology

In the present research, fuzzy set theory is adopted to rank the various software effort estimation selection models selection criteria according to their global weights.

3.1 Fuzzy sets

Fuzzy set theory, involving the fuzziness of data, was introduced by Zadeh [8] to solve problems, in which descriptions of activities and observations were imprecise, vague, and uncertain. A fuzzy set is a class of objects, with a continuum of membership grades, in which the membership grade ranges between 0 and 1. A fuzzy subset A of a universal set X is defined by a membership function fA(x) which maps each element x in X to a real number (0, 1). The grade 1 of membership for an element means that the element is in that set. The grade of membership is 0, meaning that the element is not in that set. Ambiguous cases are assigned values between 0 and 1. The theory also allows mathematical operations such as addition, subtraction, multiplication, and division, to be applied to the fuzzy sets [9, 10].

3.2 Triangular fuzzy numbers

In this study, triangular fuzzy numbers due to their easy calculation are used as membership functions, corresponding to the elements in a set. A fuzzy number is a triangular fuzzy number if its membership function can be denoted as follows [9].

$$f_{(A)}(x) = \begin{cases} \dfrac{x-c}{a-c}, c \le x \le a \\ \dfrac{b-x}{b-a}, a \le x \le a \\ 0, otherwise \end{cases}$$

where a, b, and c are real numbers and c ≤ a ≤ b.

In this study, addition and multiplication from the Zadeh extension principle are used to calculate the membership functions. Let we have two triangular fuzzy numbers A_1 and A_2 represented by triplets as

A1= (c1, a1, b1) and A2 = (c2, a2, b2), the addition and multiplication operations these can be expressed as follows:

Addition: if $\oplus$ denotes addition.

$$A1 \oplus A2 : (c1,a1,b1) \oplus (c2,a2,b2)=(c1+c2,a1+a2,b1+b2) \quad (2)$$

Multiplication: if $\otimes$ denotes multiplication.

$$A1 \otimes A2 : (c1,a1,b1) \otimes (c2,a2,b2)=(c1\times c2,a1\times a2,b1\times b2),c1\geq 0,c2\geq 0 \quad (3)$$

3.3. Linguistic terms in triangular fuzzy numbers

In this study, we are using linguistic terms for the weight of various criteria. A linguistic term can be defined as a variable whose values are in words rather than numbers. The weights can be evaluated by linguistic terms such as Extremely More Important, Very More Important, More Important, Important, Less Important, Less Important, Very Less Important, Extremely Less Important. These linguistic terms can be expressed in a triangular fuzzy numbers, as shown in Table I.

3.4 A Fuzzy algorithm for selection criteria ranking problem

A systematic approach for the ranking of various selection criteria related to software effort estimation model based on fuzzy set theory is described in this section. A lot of operators as mean, median max etc. can be used to aggregate the expert's opinion but in this study average is applied for this purpose. For software effort estimation selection criteria ranking problem, Let us assume that there are a group of *n* experts (*E*1, *E*2, ..., *En*), who evaluate the weights of *k* criteria *(C*1,*C*2, . . .,*Ck)* and Let *Wte (t* =1, 2,....,*k; k* ; *e*=1,2, . . .,*n)* be the weight given to *Ct* by expert E_e

$$W_t = 1/n \otimes (W_{t1} \oplus W_{t2} \oplus \cdots \oplus W_{tn}) = \frac{1}{n}\sum_{e=1}^{n} W_{te} \quad (1)$$

Where *Wt* is the average weight of criterion

Table 1: Linguistic Terms for the Weight of Each Criterion

Linguistic term	**Membership function**	**Linguistic term**	**Membership Function**
Extremely More important (EMI)	**(1,1,1)**	Less Important (LI)	**(0.2,0.3,0.4)**
Very More Important (VMI)	**(0.8,0.9,1)**	Very Less Important (VLI)	**(0,0.1,0.2)**
More Important (MI)	**(0.6,0.7,0.8)**	Extremely Less Important (ELI)	**(0,0,0)**
Important (I)	**(0.4,0.5,0.6)**		

3.5 Conversion of fuzzy numbers to crisp scores

In this research, maximizing and minimizing methods are used to convert the triangular fuzzy numbers into crisp score.

For maximizing

$$f_{m(y)} = \begin{cases} \dfrac{y - y_{\min}}{y_{\max} - y_{\min}}, y_{\min} \le y \le y_{\max} \\ 0, otherwise \end{cases}$$

For minimizing

$$f_A(x) f_G(x) = \begin{cases} \dfrac{x - x_{\max}}{x_{\min} - x_{\max}}, x_{\min} \le x \le x_{\max} \\ 0, otherwise \end{cases}$$

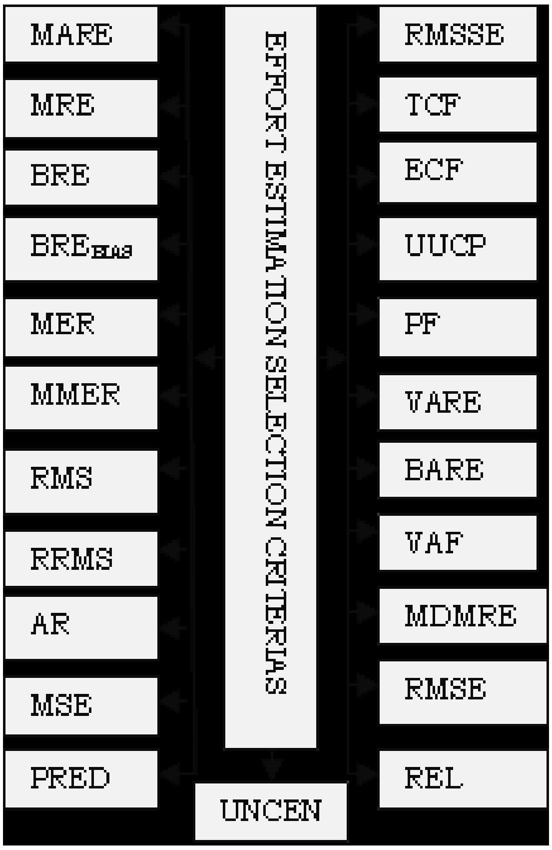
where xmin=inf S, xmax=sup S, S=∪mi =1 Fi , Fi ={x| fFi (x)>0}, i =1,2, . . .,m.

4.0 Ranking Procedure

4.1 Effort estimation model selection criteria

In the open literature, a lot of selection criteria were used by the various researchers for the selection of software effort estimation model. After the extensive study of past researches, total twenty four criteria were identified as shown in figure 1.

Fig 1: Software Effort Estimation Model Selection Criteria



4.2 Expert identification and selection

In existing literature review, there was no sufficient data available which can lead to find out the importance of each selection criteria. So, we rely on different expert's opinion to overcome the problem of collecting relevant data. In this research, a team of five experts (E1, E2, E3, E4, E5) from software development companies, academia as well as laboratories was constituted who provide the weights of each selection criteria in linguistic terms as defined in table 1. These experts have a wide experience in the field of software development.

Table 2: Aggregated Triangular Fuzzy Numbers

S No	Criteria	Local Weight	Global Weight	S No.	Criteria	Local Weight	Global Weight
1.	MARE	0.84	0.05740842	2.	MMER	0.7	0.04784035
3.	VAF	0.62	0.042372881	4.	RMSE	0.86	0.058775287
5.	REL	0.88	0.060142154	6.	RMSSE	0.42	0.02870421
7.	MMRE	0.76	0.051940951	8.	TCF	0.46	0.031437944
9.	PRE	0.78	0.053307818	10.	ECF	0.34	0.023236741
11.	UNC	0.3	0.020503007	12.	UUCP	0.38	0.025970476
13.	MSE	0.66	0.045106616	14.	PF	0.1	0.006834336
15.	AR	0.58	0.039639147	16.	VARE	0.26	0.017769273
17.	BRE	0.72	0.049207217	18.	BRE bias	0.74	0.050574084
19.	RME	0.54	0.036905413	20.	MRE	0.94	0.064242756
21.	RRME	0.82	0.056041553	22.	MMRE	0.632	0.043193002
23.	MER	0.5	0.034171679	24.	MDMRE	0.8	0.054674686

Table 3: Crisp Scores (Local and Global Weights) of Selection Criteria

S. No.	Criteria	Aggregate Weight	S. No.	Criteria	Aggregate Weight
1.	MARE	0.76,0.84,0.92	2.	MMER	0.6,0.7,0.8
3.	VAF	0.52,0.62,0.72	4.	RMSE	0.8,0.86,0.92
5.	REL	0.84, 0.88, 0.92	6.	RMSSE	0.32,0.42,0.52
7.	MMRE	0.72, 0.76,0.8	8.	TCF	0.36,0.46,0.56
9.	PRE	0.68,0.78,0.88	10.	ECF	0.24,0.34,0.44
11.	UNC	0.2,0.3,0.4	12.	UUCP	0.28,0.38,0.48
13.	MSE	0.56,0.66,0.76	14.	PF	0,0.1,0.2
15.	AR	0.48,0.58,0.68	16.	VARE	0.16,0.26,0.36
17.	BRE	0.64,0.72,0.8	18.	BRE bias	0.64,0.74,0.84
19.	RME	0.44,0.54,0.64	20.	MRE	0.92,0.94,0.96
21.	RRME	0.72,0.82,0.92	22.	MMRE	0.88,0.92,0.96
23.	MER	0.4,0.5,0.6	24.	MDMRE	0.72,0.8,0.88

4.3 Data collection

The weight in linguistic terms was assigned to each selection criteria by all five experts. The weight so obtained is represented in table 2 and given in appendix-1 with their membership function.

4.4 Selection criteria weight calculation

The aggregate triangular fuzzy numbers for each selection criteria are obtained by using equation1 and are given in table 3.

$$W1 = \frac{1}{5}\left[(1, 1, 1) \oplus (0.8, 0.9, 1) \oplus (0.8, 0.9, 1) \oplus (0.4, 0.5, 0.6) \oplus (0.8, 0.9, 1)\right]$$

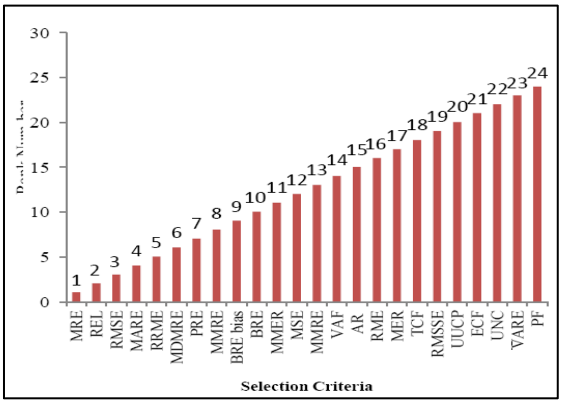
$$= \frac{1}{5}(3.8, 4.2, 4.6) = (0.76, 0.84, 0.92)$$

After analyzing all criteria weight as in table 2, the crisp score (local and global weight) for each selection criteria is obtained and given in table 3.

4.5 Final ranking

The software effort estimation model selection criteria are ranked according to global weights as shown in figure 2.

Fig 2: Ranking of Software Effort Estimation Model Selection Criteria



The figure depicts that mean relative error (MRE) is ranked at number-1 due to its largest global weight followed by reliability (REL) at number-2 and relative mean square error (RMSE) at number-3. It also depicts that product factor (PF) is ranked at last or number-24 due to the smallest value of its global weight.

5.0 Conclusions

In this research, fuzzy set theory is applied to rank the various software effort estimation model selection criteria identified. The ranking of selection criteria relates to the importance of each selection criteria. Simply, it can be stated that ranking represents that which selection criteria is more important than another one. The better understanding of the importance of selection criteria can lead to the more precise and accurate selection and evaluation of software effort estimation model.

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APPENDIX- 1

Table 2: Linguistic Value with Their Corresponding Membership Function for Selection Criteria

Selection Criteria	E1	E2	E3	E4	E5
MARE	EMI(1,1,1)	VMI(0.8,0.9,1)	VMI(0.8,0.9,1)	Imp(0.4,0.5,0.6)	VMI(0.8,0.9,1)
VAF	MI(0.6,0.7,0.8)	LI(0.2,0.3,0.4	MI(0.6,0.7,0.8)	M.I(0.6,0.7,0.8)	MI(0.6,0.7,0.8)
REL	EMI(1,1,1)	EMI(1,1,1)	EMI(1,1,1)	M.I(0.6,0.7,0.8)	MI(0.6,0.7,0.8
MMRE	E.M.I(1,1,1)	EMI(1,1,1)	EMI(1,1,1)	L.I(0.2,0.3,0.4	Imp(0.4,0.5,0.6)
PRE	MI(0.6,0.7,0.8)	MI(0.6,0.7,0.8)	VMI(0.8,0.9,1)	M.I(0.6,0.7,0.8)	VMI(0.8,0.9,1)
UNC	LI(0.2,0.3,0.4)	LI(0.2,0.3,0.4)	LI(0.2,0.3,0.4)	LI(0.2,0.3,0.4)	LI(0.2,0.3,0.4)
MSE	Imp(0.4,0.5,0.6)	VMI(0.8,0.9,1)	VMI(0.8,0.9,1)	Imp(0.4,0.5,0.6)	Imp(0.4,0.5,0.6)
AR	MI(0.6,0.7,0.8)	Imp(0.4,0.5,0.6)	Imp(0.4,0.5,0.6)	MI(0.6,0.7,0.8)	Imp(0.4,0.5,0.6)
BRE	MI(0.6,0.7,0.8)	MI(0.6,0.7,0.8)	Imp(0.4,0.5,0.6)	EMI(1,1,1)	Imp(0.4,0.5,0.6)
RME	Imp(0.4,0.5,0.6)	Imp(0.4,0.5,0.6)	Imp(0.4,0.5,0.6)	MI(0.6,0.7,0.8)	Imp(0.4,0.5,0.6)
RRME	VMI(0.8,0.9,1)	Imp(0.4,0.5,0.6)	VMI(0.8,0.9,1)	VMI(0.8,0.9,1)	VMI(0.8,0.9,1)
MER	Imp(0.4,0.5,0.6)	Imp(0.4,0.5,0.6)	Imp(0.4,0.5,0.6)	Imp(0.4,0.5,0.6)	Imp(0.4,0.5,0.6)
MMER	MI(0.6,0.7,0.8)	Imp(0.4,0.5,0.6)	VMI(0.8,0.9,1)	VMI(0.8,0.9,1)	Imp(0.4,0.5,0.6)
RMSE	EMI(1,1,1)	EMI(1,1,1)	VMI(0.8,0.9,1)	MI(0.6,0.7,0.8)	MI(0.6,0.7,0.8)
RMSSE	Imp(0.4,0.5,0.6)	LI(0.2,0.3,0.4)	Imp(0.4,0.5,0.6)	Imp(0.4,0.5,0.6)	LI(0.2,0.3,0.4)
TCF	Imp(0.4,0.5,0.6)	Imp(0.4,0.5,0.6)	LI(0.2,0.3,0.4)	Imp(0.4,0.5,0.6)	Imp(0.4,0.5,0.6)
ECF	LI(0.2,0.3,0.4)	LI(0.2,0.3,0.4)	LI(0.2,0.3,0.4)	Imp(0.4,0.5,0.6)	LI(0.2,0.3,0.4)
UUCP	Imp(0.4,0.5,0.6)	LI(0.2,0.3,0.4)	LI(0.2,0.3,0.4)	LI(0.2,0.3,0.4)	Imp(0.4,0.5,0.6)
PF	VLI(0,0.1,0.2)	VLI(0,0.1,0.2)	VLI(0,0.1,0.2)	VLI(0,0.1,0.2)	VLI(0,0.1,0.2)
VARE	LI(0.2,0.3,0.4)	LI(0.2,0.3,0.4)	VLI(0,0.1,0.2)	LI(0.2,0.3,0.4)	LI(0.2,0.3,0.4)
BRE bias	MI(0.6,0.7,0.8)	Imp(0.4,0.5,0.6)	VMI(0.8,0.9,1)	MI(0.6,0.7,0.8)	VMI(0.8,0.9,1)
MRE	EMI(1,1,1)	EMI(1,1,1)	EMI(1,1,1)	EMI(1,1,1)	MI(0.6,0.7,0.8)
MMRE	EMI(1,1,1)	EMI(1,1,1)	EMI(1,1,1)	VMI(0.8,0.9,1)	MI(0.6,0.7,0.8)
MDMRE	EMI(1,1,1)	MI(0.6,0.7,0.8)	MI(0.6,0.7,0.8)	VMI(0.8,0.9,1)	MI(0.6,0.7,0.8)