International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-4, February 2020

A Novel Fuzzy Model for Software Cost Estimation

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Abstract: It predicts the estimated cost at beginning periods of development life cycle is a challenging assignment for the powerful management of any software industry. This model essentially considered on the significance of the datasets was utilized for analysis, kinds of intelligence and Fuzzy Logic were applied to foresee estimated cost lastly, execution assessed of prediction methods. From our model, we found that the COCOMO dataset is the most conspicuous dataset, trailed by NASA, and DESHARNAIS dataset. The MARE and MMRE are noticeable execution assessment methods in the field of study. Further, we found that the Neural Networks technique was repetitively utilized when contrasted with different models pursued by the Hybrid techniques, at that point Fuzzy Logic, Decision Tree and Evolution Computation in a specific order. This model is serving to incredible for research apprentices in the arena of software cost Estimation.

***Keywords** : Fuzzy Logic, Fuzzy Optimization, Software Effort Estimation, Software Cost Estimation (SCE).*

I. INTRODUCTION

The objective of software engineering is to build up the methods and devices expected to grow fantastic presentations that are progressively steady and viable. So as to evaluate and increase the nature of an presentation during the progress procedure, designers and administrators utilize a few measurements. Different business and specialized intentions, for example, shorter expansion cycles, lower expansion costs, improved item quality and access to source code, increasingly more software developers and organizations are putting together their software items with respect to open source parts. Basic association of software affects area of fluctuations during software development. One of the important sorts of such changes is those worried about broadening and altering the actualized usefulness.
The capability of software quality models to exactly perceive basic components licenses for the use of highlighted accreditation exercises going from physical investigation to testing, dynamic and static examination, and mechanized proper examination techniques.

Revised Manuscript Received on February 28, 2020.
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Thus, Software quality models help makes certain the steadfastness of the conveyed items. To conjecture issue inclination of program modules in software engineering, different statistical methods have been recommended. Software size evaluations are imperative to decide the software venture effort. In any case, as per the last research revealed by the Brazilian Ministry of Science and Technology-MCT, in 2001, just 29% of the organizations achieved size appraisals and 45.7% achieved software effort gauge. There is anything but a particular report that distinguishes the reasons for the effort low gauges file, however the unwavering quality degree of the models can be a conceivable reason. Cost estimation is a fundamental part of foundation ventures. Precise estimation will help venture administrators to pick sufficient choices and to abstain from misinterpreting of specialized and monetary arrangements. Software cost estimation by similarity is one of the most prominent AI techniques and is essentially a type of case based thinking. Estimation by relationship depends on the suspicion that comparable software activities have comparative costs. In any case, the system needs improvement particularly while taking care of the all-out factors. The subjects of estimation in the territory of software development are size, effort contributed, quality, technology utilized, development time, and quality. Especially, development effort is the most significant issue.

II. LITERATURE SERVEY

Nassif, et al., (2013) to ascertain the software effort estimation, proposed a different log-straight deterioration model dependent on the utilization case point model. To align the profitability factor in the regression model, fuzzy rationale is utilized. Additionally, to foresee software effort dependent on the software size and group efficiency, a multilayer perceptron (MLP) neural network model was likewise created.
Kusuma Kumari (2014) displayed an outline of current cost estimation models and methods. According to this examination, not one strategy is essentially preferable or more regrettable over the other technique, truth be told, their qualities and shortcomings supplement one another. Comprehension of their qualities and shortcomings is basic while estimating the software projects.
Ghatasheh, et al., (2015) examined the effectiveness of applying the Firefly Algorithm as a meta heuristic optimization strategy to streamline the parameters of various effort estimation models. Results of the models are assessed utilizing VAF, MSE, MAE, MMRE, RMSE and R2 assessment measurements.
Moreover the estimation of Software cost, a few inquiries about have been recommended by analysts. This examination looks at the basics of software cost and estimation.

Various methods of cost estimation ought to be utilized when estimating costs.
Appraisals are made to discover the cost, to the engineer, of creating a software system. Following are the written works utilized for valuation of the condition of-fine art on the estimation of software Cost.

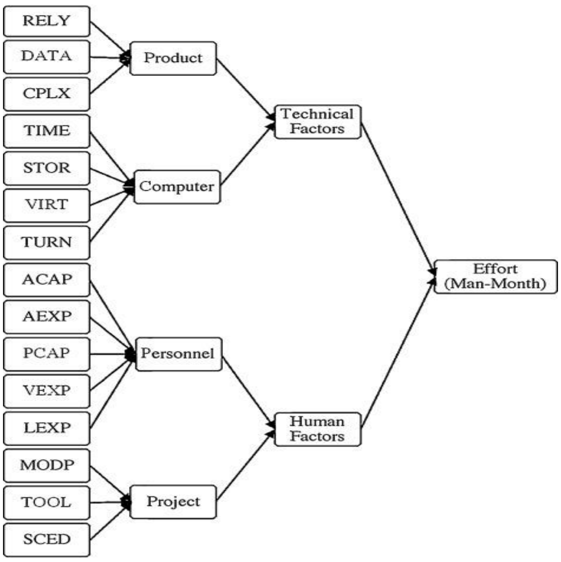
III. PROPOSED METHODOLOGY AND ALGORITHM FOR THE COST ESTIMATION

a) Methodology

The uncertainty about cost estimation is generally exceptionally high, in perspective on prediction of basic segment size, cost drivers and different parameters. By displaying a couple of changes in the interim sort 2 fuzzy logic we can controller the uncertainty. In the present model fuzzy sets are used for exhibiting uncertainty and imprecision in a compelling way. The contributions of the standard cost model join an estimation of adventure size and assessment of the parameters, instead of a single number, the software extent can be seen as a fuzzy set resilient the cost estimate moreover as a fuzzy set. We emphasize a strategy for engendering of uncertainty and ensuring infringement of the consequent effort. Fuzzy sets make an inexorably adaptable, high adaptable development condition. We make information furthermore the consequent uncertainty of the results.

b) Proposed work

The primary objective of our exploration is to utilize idea of soft computing especially fuzzy logic with COCOMO II for accomplishing precise software effort estimation and lessen the uncertainty in COCOMO II model. Engineering of proposed fuzzy model is as below The proposed fuzzy model has for input as Size of the task, and 17 cost drivers whose prices are qualitatively characterized as very low, low, nominal, high, very high, and amazingly high conceived in to two groups relying upon their effect on the effort estimation as OG Optimistic group The range values of these multipliers are contrarily corresponding to effort and PG Pessimistic group The range values of these multipliers are legitimately relative to effort.



We utilized Trapezoidal membership function, Gaussian membership function and Triangular membership function for analysis and the consequences of three are contrasted and the efforts processed by COCOMO II and the genuine aftereffects of the subset of NASA 93 task dataset from PROMISE software Engineering Repository data set which is publically accessible for research reason which comprise of 93 projects data from different focuses of different years. In fuzzification fuzzy rules are characterized by utilizing linguistic variables dependent on connective AND between Input variables.

c) The Effort Estimation by Fuzzy Logic

Fuzzy Logic: is a procedure that has the premise on fuzzy set theory for giving answer for issues, which are gradually complicated for quantifiable recognition. Fuzzy logic involves three phases as pursues:

I) Fuzzification.
II) Inference Engine.
III) Defuzzification.

The fuzzifier changes over the contribution to phonetic terms utilizing membership functions. The membership functions indicate the degree to which a given arithmetical value of a precise variable fits the phonetic term being tended to. The fuzzy induction motor does the mapping between the info membership functions and the yield membership functions with the assistance of fuzzy rules. These fuzzy rules rise up out of expert's thought the relationships being demonstrated. A defuzzifier performs the Defuzzification process, which consolidates the yield into a single mark or arithmetical value according to the necessity.

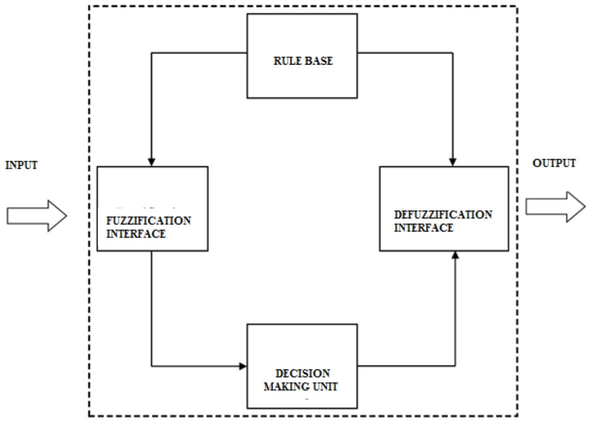


Figure 1 Basic configuration of Fuzzy logic system

d) Fuzzy Membership Function:

A measured definition for a fuzzy set can be created by allocating to every conceivable individual known to mankind of talk, a value depicting its evaluation of membership in the fuzzy set to a greater or littler degree as signified by a bigger or littler membership grade. The cosmos of talk alludes to the info space. A membership capacity is a bend, which depicts the manner in which each point in the info space is plotted to a membership value or degree of membership somewhere in the range of 0 and 1. A membership capacity is utilized to describe the fluffiness in a fuzzy set. A membership capacity sorts the component in the set into distinct or consistent. Different shapes are used for graphical portrayals. Henceforth, the determination of state of the membership capacity is imperative. A few sorts of part functions are accessible. However, here, (TMF)Triangular Membership Function is utilized.

TMF: It is a 3 point capacity set by a lower limit p, a maximum breaking point q and the modular value with the end goal that p<m

$$f(x)=\begin{cases} 0 & \text{if } x\le p \text{ or } x\ge q \\ (x-p)/(m-p) & \text{if } x\in(p,m) \\ (q-x)/(q-m) & \text{if } x\in(p,m) \end{cases} \quad (1)$$

Fuzziness:
Fuzziness of a TMF is demarcated by Equation 2

$$\text{Fuzziness of TMF} = \frac{\lambda-\mu}{2m}, \quad 0<TMF<1 \quad (2)$$

where m shows the model value, μ and λ speak to one side and left limits individually. Higher value of fluffiness uncovers that the TMF is fuzzier.

The Effort Estimation by Fuzzy: In fuzzification, the triangular fuzzy number is used and is characterized by Equation 3

$$T(S)=\begin{cases} 0 & \text{if } (S\le a) \\ (S-\mu)/(m-\mu) & \text{if } \mu\le S\le m \\ (\lambda-S)/(\lambda-m) & \text{if } m\le S\le\lambda \\ 0 & \text{if } S\ge\lambda \end{cases} \quad (3)$$

where S is the magnitude as input, E the effort as yield, μ, m and λ are the limits of membership work T(S), m is the prototypical value, μ and λ are the privilege and left-hand limits individually.

Let (m, 0) split the improper of the triangle in proportion k: 1 inside, where k is a genuine positive number. In this manner, the assessment of m is given by Equation 4.

$$m=\frac{\mu+k\lambda}{k+1} \quad (4)$$

Fuzziness can be currently defined as in Equation 5.

$$F=\frac{\lambda-\mu}{2m} \quad \text{so, nearly} \quad (5)$$

$$\mu=\left(1-\frac{2kF}{k+1}\right)*m \quad (6)$$

$$\lambda=\left(1+\frac{2F}{k+1}\right)*m \quad (7)$$

Hence, the TMF∂( ) E is signified by Equation 8.

$$\delta(E)=\begin{cases} 0 & \text{if } \mathrm{E}\le a\mu^b \\ \dfrac{(E/a)^{1/b}-\mu}{m-\dfrac{\mu}{2}} & \text{if } a\mu^b\le E\le am^b \\ \dfrac{\lambda-(E/a)^{1/b}}{\lambda-\dfrac{m}{2}} & \text{if } am^b\le E\le a\lambda^b \\ 0 & \text{if } \mathrm{E}\ge a\lambda^b \end{cases} \quad (8)$$

Defuzzification:
The productivity fuzzy estimation of E can be planned as a weighted normal of the optimistic (aα b), in all probability (am b) and pessimistic estimate (aβb). Fuzzy effort estimate (E) is given by the recipe in Equation 9.

$$E=\frac{w_1(a\alpha^b)+w_2(am^b)+w_3(a\beta^b)}{w_1+w_2+w_3}+\prod_{i=1}^{15}EM_i \quad (9)$$

where w1, w2 and w3 are the loads of the optimistic, in all probability and pessimistic assessment separately and EMi is the 15 effort multipliers from COCOMO. Supreme weight ought to be given to the most anticipated estimate. Here, the cost of m demonstrates the size in KLOC. The values of α and β, k, F, w1, w2 and w3 are subjective constants. The effort is acquired as far as people every month.

Fuzzy Rules:
The key component of the COCOMO model is used for the age of the fuzzy rules to assessment ostensible effort, free of cost drivers. Along these lines, by separating input and output places into fuzzy locales, the communication between mode, size and coming about effort can be delivered. The parameters of the effort MFs were set up for the given mode, size pair. 3 MFs speaking to effort were acquired for a random size and 3 modes separately. Rules defined relying upon the fuzzy sets of modes, sizes and efforts show up in the accompanying structure:

Fuzzy rules

If mode is organic and size is s_1 then effort is e_{11}
If mode is organic and size is s_2 then effort is e_{12}
If mode is semi-detached and size is s_1 then effort is e_{21}
If mode is semi-detached and size is s_2 then effort is e_{22}
If mode is embedded and size is s_1 then effort is e_{31}
If mode is embedded and size is s_2 then effort is e_{32}
:
If mode is m_j and size is s_i then effort is e_{ji}

In this model, an upgraded fuzzy logic created framework is projected for dealing with the imprecision and vulnerability related with the information at prior phases of the venture and to precisely foresee the software effort also. This structure is built upon the current cost estimation model, called the COCOMO. These formulations give the construction between the size of the system and item, task and group factors and the effort required to build up the system. In COCOMO, effort is expressed by Person Months (PM). Cost drivers have up to six degrees of rating and they are: Very low, low, ostensible, high, high, and additional high. Each appraising has a proportionate genuine number Effort multiplier (EF), in view of the factor and the level to which the factor can control efficiency. Henceforth, a fuzzy model that adopts fuzzy sets can be advantageous for checking the cost drivers in a simpler manner. In the event that the venture cost has been registered as a bit of an undertaking offer to client, at that point a decision must be made about the value referred to the client. Commonly, cost is just cost in addition to benefit. Figure 2 delineates the whole cost estimation process.

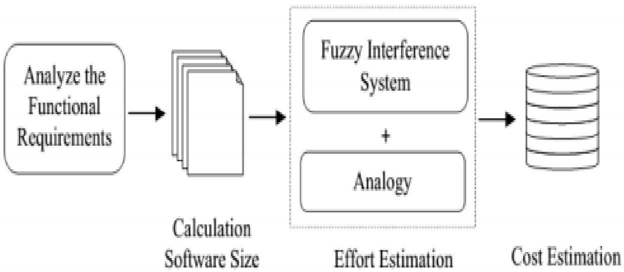


Figure 2 charts for the whole proposed strategy

Fuzzy logic will empower the estimation procedure to deal with the reflection of the data obtained in early periods of a product improvement process. It will help deal with the frailty about the exact significance of semantic values utilized during the estimation procedure. The cost estimation in the proposed method is delineated in the Figure3 as a stream graph

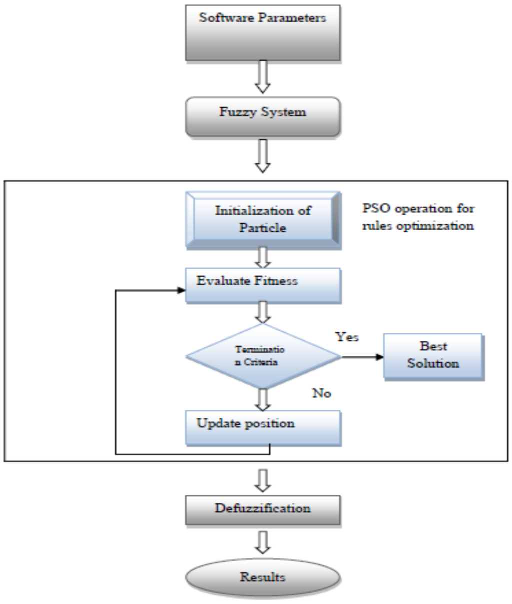


Figure 3 Proposed software cost estimation model

IV. EXPERIMENTAL ANALYSIS

Software cost estimation built on the soft computing method is proposed in this study and the technique is analyzed for different datasets.

The software cost estimation technique used here is compared with various existing method for the evaluation of efficiency. The various error measures are used for performance evaluation.

The dataset utilized in the investigation is the Desharnais dataset (Kemerer 1987), and COCOMO NASA dataset.

The first form of the Desharnai's dataset involves 81 undertakings, of which 4 were prohibited attributable to deficient values.

The dataset has 9 autonomous variables and 1 ward variable. Real Effort in person hours as the tenth variable for the grid B is utilized.

The primary objective of our exploration is to utilize idea of soft computing especially fuzzy logic with COCOMO II for accomplishing precise software effort estimation and lessen the uncertainty in COCOMO II model.

Engineering of proposed fuzzy model is as below The proposed fuzzy model has for input as Size of the task, and 17 cost drivers whose values are qualitatively characterized as very low, low, nominal, high, very high, and amazingly high conceived in to two groups relying upon their effect on the effort estimation as OG Optimistic group The range values of these multipliers are contrarily corresponding to effort and PG Pessimistic group The range values of these multipliers are legitimately relative to effort.

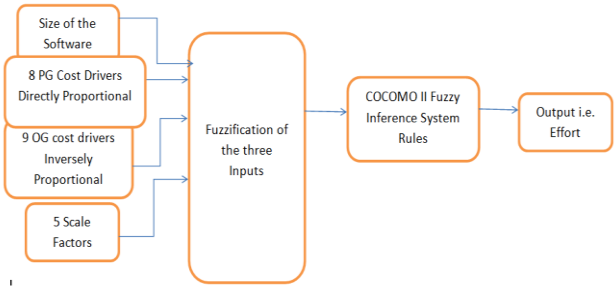


Figure 4 Proposed Methodologies

We utilized Trapezoidal membership function, Gaussian membership function and Triangular membership function for analysis and the consequences of three are contrasted and the efforts processed by COCOMO II and the genuine aftereffects of the subset of NASA 93 task dataset from PROMISE software Engineering Repository data set which is publically accessible for research reason which comprise of 93 projects data from different focuses of different years. In fuzzification fuzzy rules are characterized by utilizing linguistic variables dependent on connective AND between Input variables.

The NASA 93 dataset involves 93 complete tasks, having 17 autonomous variables of which 15 are all out. This dataset is in COCOMO 81 organization gathered from NASA centers distributed in Predictor Models in Programming Engineering (PROMISE). Here, the DevEffort variable is considered for the age of lattice B. The parameters like TeamExp, Length, Transactions, Entities, Effort are considered in the above said datasets in order to ascertain the standards utilizing the fuzzy. The performance examinations for each of these dataset are assessed and are then contrasted and the existing works so as to demonstrate the adequacy of the proposed methodologies. The different blunder measures like MARE, MMRE and MRE for the datasets are calculated and dependent on these mistake measure values the correlation of the performance of different procedures are utilized. The performance evaluation of the proposed methods are given in the underneath area,

Desharnais dataset:

Different measures for the Desharnais dataset is measured for performance evaluation. Various researchers have used different error measurements. The most popular error measure is Mean Absolute Relative Error (MARE) formula.

$$MARE = \frac{1}{N}\sum_{i=1}^{N}(\left|(est_i - acl_i)/acl_i\right|)/n$$

where,

est_i - Estimated effort from the model

acl_i - Actual effort,

n - Number of projects in the model.

The Horse for the exertion can be contrasted and other existing method referenced in (Idri et al 2001). The correlation values between the proposed method and the existing method is organized in the Table 1 given below,

Table 1 MARE comparison

METHODS	MARE
Proposed Method	7.1E-04
Existing Method	13.8E-04

From the Table 1, it is inferred that the proposed method has better MARE value when compared with that of the existing method. Better MARE values suggest that the proposed approach of software cost estimation is more effective and can be used for cost estimation purpose without any defects.
Once the MARE measure is calculated, the other measures like MRE and MMRE are measured. These two metrics are evaluated in order to find out the effectiveness of the proposed method. These measures are generated based on certain formulas and the values are compared with the existing method of cost estimation.
The MRE and MMRE can be measured by employing the following formula,

$$MRE = |(acl_i - est_i)| / acl_i$$

$$MMRE = \frac{1}{N}\sum_{i}^{N} MRE_i$$

where,
est – Estimated effort from the model
acl – Actual effort
N – Total number of measured errors
The measurements are displayed in Table 2, from which it can be observed that the proposed method has better MMRE value. The MMRE value is then compared with that of the existing method mentioned in (Reddy & Raju 2009). The values show that the proposed method of cost estimation in Desharnais dataset is more effective and has better MMRE value when compared with the existing techniques.

Table 2 Comparison of MMRE values of proposed and existing techniques

Models	MMRE (%)
Proposed Model	2.468
Fuzzy Model	32.651
Neuro-Fuzzy Model	56.46

In this way, the proposed method of cost estimation framework dependent on delicate figuring technique is viably estimated the exertion and cost of the product venture models. Similarly the error measures for the other datasets are also being measured using the same process and are compared with the existing methods.

NASA93 Dataset:

The NASA 93 dataset comprises of 93 complete projects, having 17 independent variables of which 15 are categorical. The above data set is the standard dataset that are used in various cost estimation techniques. The cost estimation value for this dataset is measured based on the proposed study. The measures obtained from proposed method for NASA 93 dataset is given below. The Table 3 given below shows the MARE value for the proposed method using the NASA93 dataset. The proposed value is compared with the existing value to prove the effectiveness.

Table 3 MARE value for the proposed model using the NASA93 dataset

Models	MARE
Proposed Model	5.57 E-04
Existing Model	68.7 E-04

When the MARE measure is estimated, the other measure like MRE and MMRE are calculated. The measurements are tabulated in below table. From the Table 4, it is observed that the proposed method is efficient in NASA 93 dataset when compared to the existing methods (Reddy & Raju 2009)

Table 4 MMRE comparison

Models	MMRE (%)
Proposed Model	5.468
Fuzzy Model	32.651
Neuro-Fuzzy Model	32.46

Thus the MARE, MRE and MMRE measures for the proposed software cost estimation technique for NASA 93 dataset is estimated and from the comparison graph it is inferred that the proposed method has delivered better MMRE value than other existing method which proves the effectiveness of the proposed software cost estimation approach.

COCOMO NASA Dataset:

Similar to the above process the study measures the effectiveness of the proposed approach using the COCOMO NASA dataset as well. The measures obtained from proposed method for COCOMO NASA dataset is given below,
The Table 5 given below shows the MARE value obtained using the proposed method for the COCOMO NASA dataset.

Table 5 MARE comparison with proposed and existing models

Models	MARE
Proposed Model	246.7 E-04
Existing Model	1627.4E-04

After MARE evaluation the investigation assesses the MMRE measure and the relating MMRE esteem got utilizing the proposed method is organized in the table beneath. From Table 6, it is seen that proposed investigation is effective in COCOMO NASA dataset when contrasted with the existing methods (Reddy and Raju 2009) .

Table 6 MMRE comparison

Models	MMRE (%)
Proposed Model	12.052
Fuzzy Model	32.651
Neuro-Fuzzy Model	37.15

In this manner, the proposed method of cost estimation framework dependent on delicate processing technique is successfully gauge the exertion and cost of the product venture models.
As referenced, three diverse dataset for programming cost estimation has been utilized. From the chart it is seen that the NASA 93 informational index has low MARE esteem when contrasted with the other 2 datasets. The values are recorded in Table 7.

Table 7 MARE measures of all the datasets

DATASETS	MARE
Desharnais Dataset	0.000713
NASA 93 Dataset	0.000557
COCOMO NASA Dataset	0.024674718

FUZZY LOGIC WITH THE AID OF OPTIMIZATION ALGORITHMS FOR SOFTWARE COST ESTIMATION

Programming cost estimation technique utilizing fuzzy logic with the guide of optimization algorithm is proposed as an improvement to the cost estimation technique utilizing delicate figuring. The proposed technique in assessed utilizing three distinct data sets. For each of these datasets the blunder measure like MRE and MMRE are calculated so as to discover the adequacy of the proposed framework. The datasets utilized in the investigation is the Desharnais dataset. The first form of the Desharnais dataset involves 81 projects, of which 4 were barred inferable from deficient values. The dataset has 9 autonomous variables and one ward variables. Genuine Effort in person hours as the tenth variable for the grid B is utilized.

The MARE measures for the Desharnais dataset on exertion estimation process is estimated and discovered to be 0.14634.

Different scientists have utilized distinctive blunder measurements. The most prominent mistake measure is Mean Absolute Relative Error (MARE).

$$MARE = \sum_{i=1}^{N} (|(E_i - A_i) / A_i|) / n$$

E_i - Estimated effort

A_i -Actual effort

The *MRE and* MMRE can be measured by employing the following formula

$$MRE = |E_i - A_i)| / A_i$$

where,

E_i - Estimated effort

A_i -Actual effort.

The MMRE for the estimated effort can be calculated by using the equation given below. The MMRE for the proposed method seems to be better than other works where fuzzy is used.

$$MMRE = \frac{1}{N} \sum_{i}^{N} MRE_i$$

where,

MRE - Mean relative error for ith measured error

n - Total number of measured errors.

Performance evaluation:

The Table 8 given below indicates the experimental results obtained in proposed method. For various sizes the actual effort as well as the estimated efforts is calculated. The Magnitude of Relative Error (MRE) for each entry is calculated. The actual effort has remained to be more reduced when compared with the estimated effort. The MMRE for the efforts are calculated using the expression given in equation $MMRE = \frac{1}{N} \sum_{i}^{N} MRE_i$ in the below performance evaluation section.

Table 8 Effort Estimates and MRE

No	Estimated Effort	Actual effort	MRE
1	65.9432	52.0	0.2681398531948195
2	138.3309	124.0	0.11557240503182262
3	64.5942	60.0	0.07657145153747227
4	133.1731	119.0	0.11910186417687778
5	103.9609	94.0	0.10596778071185663
6	97.03521	89.0	0.09028332481758743
7	49.1576	42.0	0.17042080408984633
8	63.0460	52.0	0.2124247062834734
9	99.4889	88.0	0.13055616859855187
10	43.6095	38.0	0.14761961722488037

Once the effort values are calculated, the MRE for corresponding errors are measured using the formula. Now using the MRE value the MMRE of the proposed method is measured using respective formulas and the measures are tabulated. The proposed method is then compared with some existing methods in order to assess the efficiency of the proposed technique. The MMRE measurements for the proposed and existing methods are given in Table 9. The MMRE measure is estimated in percentage values.

Table 9 MMRE measurements for the proposed and existing models

Models	MMRE (%)
Proposed Model	1.1588
Fuzzy Model	32.651

NASA 93 Dataset:

As per the above process, the study evaluates the effectiveness of the proposed method by utilizing the other datasets as well. The NASA 93 dataset is employed for cost estimation process which is explained in the below section.

Performance evaluation:

The Table 10 had given below shows the experimental results obtained in the proposed method. For various sizes the actual effort as well as the estimated efforts is calculated. The Magnitude of Relative Error (MRE) for each entry is calculated. The actual effort has remained to be more reduced when compared with the estimated effort. The MMRE for the efforts are calculated using the expression given in equation $MMRE = \frac{1}{N} \sum_{i}^{N} MRE_i$ in the below performance evaluation section.

Table 10 Effort Estimates and MRE

No	Actual effort	Estimated Effort	MRE
1	68.5	67.251	0.0182336
2	147.1	143.13	0.0270224
3	75.25	74.165	0.0144186
4	133.17	129.25	0.0294506
5	102.22	101.23	0.0096849
6	97.23	89.12	0.0834105
7	47.125	48.12	0.0211114
8	65.23	59.16	0.0930553
9	112.35	110.25	0.0186915
10	46.25	41.22	0.1087567

The proposed method is then contrasted and some existing method so as to assess the adequacy of the proposed technique. The MMRE measurements for the proposed and existing methods are given in Table 11. The MMRE measure is estimated in rate values.

Table 11 MMRE quantities for the proposed and existing models

Models	MMRE (%)
Proposed Model	2.86
Fuzzy Model	32.651

COCOMO NASA dataset:

The MARE measures for the COCOMO NASA dataset on effort estimation process is and the various measure are given in the below sections.

Performance evaluation:

The table 12 given below shows the experimental results obtained in proposed method. For various sizes the actual effort as well as the estimated efforts is calculated. The Magnitude of Relative Error (MRE) for each entry is calculated. The actual effort has remained to be more reduced when compared with the estimated effort. The MMRE for the efforts are calculated using the expression given in equation $MMRE = \frac{1}{N}\sum_{i}^{N} MRE_i$ in the below performance evaluation section.

Table 12 Effort Estimates and MRE

No	Actual effort	Estimated Effort	MRE
1	67.251	59.23	0.0168833
2	143.125	132.21	0.0762620
3	74.165	59.63	0.1959819
4	129.25	112.35	0.1307543
5	101.23	87.52	0.1354346
6	89.12	68.23	0.2344030
7	48.12	35.62	0.2597672
8	59.16	41.87	0.2922582
9	110.25	101.23	0.0818140
10	41.22	29.25	0.2903930

The proposed method is then compared with some existing method in order to evaluate the effectiveness of proposed technique. The MMRE measurements for the proposed and existing methods are given in Table 13. The MMRE measure is estimated in percentage values.

Table 13 MMRE measurements for the proposed and existing methods

METHODS	MMRE (%)
Proposed Method	9.32
Fuzzy method	32.651

The MMRE values for all the datasets such as Desharnais dataset, NASA 93 and COCOMO NASA dataset are estimated for the proposed approaches and are compared with the other existing techniques. The values that obtained here as output shows that the proposed approaches has better MARE and MMRE values when compared with the other methods of software cost estimation. The overall MMRE comparison of the proposed approaches for different data set is performed to simplify the effectiveness of the studied approach. The table 14 given below shows the MMRE values obtained for Desharnais dataset, NASA 93 and COCOMO NASA datasets using the proposed approaches like soft computing based approach and fuzzy- optimization based approaches.

Table 14 MMRE values for different datasets using the proposed approaches

Cost estimation Methods	MMRE values (%)		
	Desharnais dataset	NASA 93 Dataset	COCOMO NASA dataset
Proposed Soft computing based approach	2.468	5.468	12.052
Proposed Fuzzy-Optimization Approach	1.1588	2.86	9.32

The graphical representation of the above comparison value is shown in the below figure. The proposed approaches have MMRE values with better rate for all the datasets and provide better error measure which can be an added advantage of the proposed approach for software cost estimation.

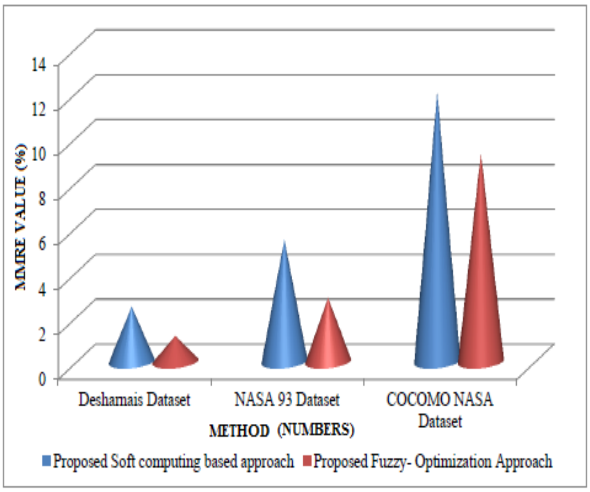


Figure 5 Graphical representation MMRE values for different datasets using the proposed approaches

The NASA data set was considered for experimentation. The terminating interims got after the fuzzification are [0.7362, 0.8998]. The parameters acquired subsequent to tuning PSO approach a=3.131606, b=0.820175, c=0.045208 and d= -2.020790. While performing defuzzification w1=1, w2=10 and w3=10. Table 15 shows the efforts the proposed model. The projected efforts are near the measured efforts. The proposed model outcomes are contrasted and the existing models in the writing and the outcomes are appeared in the Table 15.

Table 15 Effort Estimates and MRE

P.No	Size	Actual	Estimated	MRE
1	18	301	293	2.657807
2	50	1063	984	7.431797
3	40	605	537	11.23967

4	22	243	201	17.28395
5	13	141	127	9.929078
6	12	112	121	8.035714
7	3	16	16	0
8	11	91	82	9.89011
9	42	781	722	7.554417
10	16	233	249	6.866953
11	21	334	318	4.790419
12	52	982	890	9.368635
13	23	305	281	7.868852
14	27	421	401	4.750594
15	9	45	41	8.888889
16	15	189	192	1.587302
17	4	17	17	0
18	6	22	22	0
19	2	8	8	0
20	7	34	29	14.70588
21	13	84	79	5.952381
22	18	274	268	2.189781
23	24	403	379	5.955335
24	26	371	362	2.425876
25	61	1241	1102	11.20064
26	29	677	638	5.760709
27	19	291	263	9.621993
28	10	110	119	8.181818
29	21	239	213	10.87866
30	12	145	189	30.34483

Table 15 shows estimated efforts of the model. It likewise shows MRE of the model for each gauge. Table 4.16 shows examination of the proposed model with different models. The estimation results are graphically appeared in Figure 6.

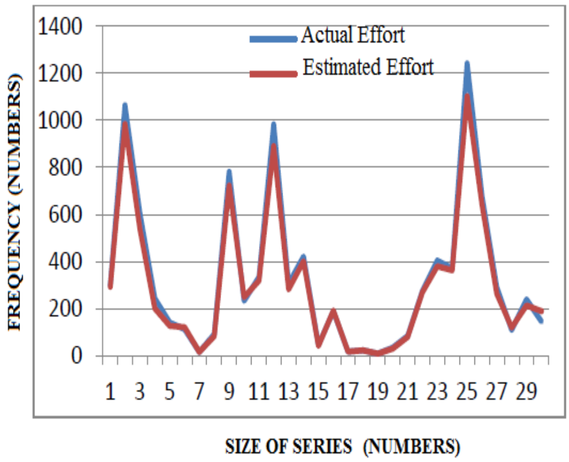


Figure 6 Actual Vs Estimated Effort with respect to frequency and Size of Series

Examination of the model outcomes in Table 16 shows that the proposed model has better estimation exactness when contrasted with different models having 7.512% MMRE with 98.77% likeliness to have a similar proportion of MMRE if the model is tried under various condition with various data. So as to additionally confirm the prediction (PRED), we have broken down the prediction (PRED) for 25%, 15%, 10% and 8% forecast. The prediction (PRED) show that the proposed model is 63. 33% and 40% for COCOMO II sure to have its normal MRE, which shows the dependability of its evaluations.

Table 16 Comparison with other Models

	Alaa Sheta	COCOMO II	Proposed
MMRE	16.838%	11.003%	7.512%
PRED(25)	80%	93.33%	96.33%
PRED(15)	53.33%	63.33%	93.33%
PRED(10)	20%	50%	80%
PRED(8)	10%	40%	63.33%

This examination reports the got outcomes from all the four led tests. The principal test is directed to look at all five algorithmic models which utilize the KLOC property in the data sets and other three trials are for the non-algorithmic models. The performances of the models improved in explore 3 and 4 with lower MAE, MBRE and MIBRE.

This model shows the significance of the three variables Human Perception and Performance Index (HPPI), Machine Requirement and Performance Index (MRPI) and Process Requirement and Performance Index (PRPI). At the point when the size factor alone is utilized, it will prompt vulnerability in estimation.

V. CONCLUSION

Predict the estimated cost at early stages of development life cycle is a challenging task for the effective management of any software industry. This review basically attention on the importance of the datasets was employed for analysis, types of intelligence and machine learning techniques were applied to predict estimated cost and finally, performance evaluated of prediction methods. From our review, we found that the COCOMO dataset is the most prominent dataset, followed by NASA, and DESHARNAIS dataset. The MMRE and PRED are prominent performance evaluation methods in the field of study. Further, we found that the NEURAL NETWORKS technique was recurrently used when compared to the other models followed by the HYBRID techniques, then FUZZY LOGIC, DECISION TREE and EVOLUTION COMPUTAION in that order. This review is helping to great for research beginners in the field of software cost Estimation. Programming cost estimation depends on a probabilistic model and subsequently it doesn't produce definite values. In this paper, we have displayed a Software Effort Estimation Model utilizing Fuzzy Logic.

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