Research Article

Software Cost and Effort Estimation using Ensemble Duck Traveler Optimization Algorithm (eDTO) in Earlier Stage

Shweta.KR[*a], Dr.S.Duraisamy[b], Dr.T.Latha Maheswari[c]
[*a]Ph.D Research Scholar, Department of Computer Science, Chikkanna Govt. Arts College, Tirupur-2, Tamil Nadu
[b]Assistant Professor, Department of Computer Science, Chikkanna Govt. Arts College, Tirupur-2, Tamil Nadu
[d]Associate Professor, Department of Computer Science & Engineering, Sri Krishna College of Engineering & Technology, Cbe

Article History: Received: 11 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 4 June 2021

Abstract: Software engineering is a hot and needed research area for early and also accurate estimation of cost, effort, time to achieving quality of software project. Accuracy is the primary factor involving victim of software cost estimation and increasing the productivity of any workstation. Algorithmic and non-algorithmic models are helped to predict the cost in earlier stage without optimizing any constraints. Nowadays new optimization algorithms based on both the nature inspired based and swarm intelligence based are help to introduce new cost, effort and time estimation in earlier stage of design efficiently. Here, under estimation and over estimation should be optimized using new meta-heuristic algorithm inspired by Duck Flock. For the proposed algorithm eDTO, ACC (Accuracy), VAR (Variance), metrics are used to evaluating the results using NASA 93 standard dataset. Evaluation results are compared with existing COCOMO, NN, SBA and proved that the eDTO having high accuracy and low miscalculation rate.

Key words: Software Cost, Estimated Effort, Actual Effort, Optimization, eDTO, ACC, MMRE.

1. Introduction

Software Engineering is an emerging and trending in IT, Business, Home appliances especially in the research field. The ultimate aim of software engineering is to develop an integrated software component using important phases such as requirements gathering, analysis, planning, designing, testing, coding, maintenance and deployment needed for only customer satisfaction. Customer satisfaction is the final output but concentrated in each and every phase. Prior estimation of software cost, effort, quality and time are the critical to managing the constraints but expected to reach the target with prioritizations.

Maximum profit is the main objective for all the business concerns. Both the employees and the managing directories expect to achieve the profit rather than loss of anything like money, effort, time also. Hard work will never fail in estimation of software cost. But smart work is the gateway to developing the successful software project with maximum satisfaction. All are facing and solving so many complex problems in our daily life. In that particular time period decision making for those kinds of problems is a critical and also needed thing. Either we using accurate prediction results only help to improving the target, or appropriate prediction results. If wrong prediction is occur in estimation then entire project will ready to face the challenges. Any software project needs to manage efficiently using correct prediction.

Software quality has the association with the reliability of good software. In reliable software duration of working is measured. For example we manufacture billing software for super market then after ten years also the organization should having the same output for specified software. In software engineering reliability is the main characteristic for achieving quality of software [1]. Cost estimation includes size, effort, time duration, quality, methods utilized for accurate prediction [2]. In 1981, Barry Boehm introduced **CO**nstructive **CO**st **MO**del (COCOMO) for Estimation used by many researchers now also [3]. There are three types of COCOMO model, Basic model, intermediate model and detailed model is available for calculating the cost [4]. Based on the existing model we observing and need to develop a new optimization model that satisfying the aim of practically relevant in software engineering research filed for computation of cost [5]. Both financial plan and the plan of resources required for the specified application is calculated using cost estimation [6]. For this purpose efficient cost computation well defined optimization algorithms are needed in emergent results [7].

Uncertainty happened in the cost estimation needs careful investigation for calculating effort and time to maintain good software [8]. Uncertainty of Outliers, missing data for calculation are solved by some popular parametric optimization techniques Kapur, Otsu, Tsallis, and so on. Solving uncertainty in cost estimation is the complex and also called as “Parametric Estimation” due to the relationship among parameter scores and outcome of the prediction of cost estimation [9]. In early stage cost estimation is considered as a reliable and having high important in software engineering [10]. Then only the estimator clearly point out the mismatch between the predicted cost and actual cost in initial stage without changing the cost drivers mainly money, schedule, and size [11]. Accurate estimation in initial stage software only adequate to managing the quality, schedule, effort of software and reach the performance of the cost estimation [12]. Outline of the work is needed to start a process in all industrial as well as personnel work especially software project management.In earlier stage software cost estimation gives the overall outline of the project include but not limited to budget, effort, resources, size, quality and so on [13].

Reduce the E^2 (Effort and Error) trial and error based meta-heuristic algorithm is introduced to maintenance of software cost in earlier stage [14]. Botch software due to high error rate (mismatch between predicted cost and original cost) in cost computation leads big challenge to run the organization [15]. Cost assessment model development using optimization algorithm in this research work focusing duck travel algorithm for enrich the model for optimizing uncertainty of under and overestimate during the estimated cost effort process [16-22]. From this analysis duck traveler algorithm was proposed by the nature behavior of duck flock. Several ducks in duck flock make a different group for food foraging activity. Each and every ducks in duck flock start their migration from source to food farm by using their local guide mother duck. Imprinting behavior of duck is very attractive activity using their stack of intelligence and detecting their predators within a second during hunting process. Prediction by optimization is efficient process especially duck travel algorithm to achieving the expected accuracy in the obtained results.

Figure 1: Searching Food by Duck Flock.

Figure 2: Three Primary Factors Involved in Cost Estimation.

Figure 2 predicts three primary factors for cost estimation of specified software projects are effort, duration and size.

In this paper summarization of related work declared in section II. Proposed work is explained in section III. Section IV gives the corpus of cost estimation results. Finally conclusion and work extension part in section V.

2. Literature Survey

Muhammad Tosan et al., (2016) conducted systematic review of Software Cost Estimation (SCE). SCE implements, approaches and performances also discussed in detailed manner. Software triplex methods are tabulated such as algorithmic, non-algorithmic and hybrid. Their review is inspiration for many researchers especially cost estimator due to the current study of methods also described in a clear manner [23].

Maryam Safavi et al., (2020) utilized artificial neural network based neural network algorithm for optimizing volley estimate locations by meta-heuristic algorithms to solve hydrological complex problems. The proposed algorithm performance are evaluated by comparison of existing whale and election algorithms and depicted results shown the neural network algorithm got prominent results than other existing. Reduce cost maintenance was achieved by the authors through high accuracy of proposed method [24].

AnupamaKaushik et al., (2021) introduced long short term memory (LSM) and recurrent neural network (RNN) for calculating the effort in initial stage of software project management. Different datasets such as NASA 63, COCOMO 81 and MAXWELL used for evaluating the results. The experimental results shown that proposed method with linear activation function having the high precision value comparing with other [25].

David Roch-Dupre et al., (2020) proposed nature inspired (NI) algorithms such as GA, PSO, FA and railway simulator for optimize the profit investment. The operation module and the electrical network module are two basic modules in railway simulator to save the energy. Net present value is calculated by using NI algorithms. Proposed NI algorithms GA and FA having the best performance predicted by the authors [26].

Ken M Nakanishi et al., (2020) examined quantum classical hybrid algorithms based sequential minimal optimization for speed, robust and bug free. Based on the subset of parameters the specified cost function was calculated. Trigonometric functions are used forcalculation of cost estimation. Proposed Cost function is minimum compared with other existing functions [27].

NeelamhabPadhy et al., (2017) suggested novel aging and survivability aware based method for software reusability in forecasting object oriented software. Object Oriented Chidamber and Kemerer (OOCK) metrics are evaluated for proposed method results. The authors proved that Web service products using these OOCK metrics for software reusability [28].

AbolfazalJaafari et al., (2019) studied the significance of hybrid model for explicit prediction in probability of wildfire. Fuzzy inference system with GA, SFLA, PSO, ICA metaheuristic algorithms are used for calculating the weight for each class using Step wise method. Fuzzy with ICA have the high performance result while compared with other optimization algorithms [29].

VahidBeiranvand et al., (2017) reviewed the optimization benchmarking problems and declared the challenges involved in problem solving. They provide the comparison methods and few ideas to eliminate the faults occurring in comparisons. Current benchmarking also rectified some drawbacks in considering future scope [30].

Mariana Dayanara et al., (2020) proposed Particle Swarm Optimization for Statistical Regression Equations applicable to predicting Effort in Software Development. Selection and adjustment based on automation are achieved by proposed method. PSO-SRE was compared with SRE and results shown that the proposed PSO-SRE confidence 99% to improve the efficiency [31].

Muhammad Sufyan Khan et al., (2018) optimized COCOMO effort utilized novel meta-heuristic algorithm inspired by strawberry plant. MRE and MMRE are evaluated using NASA 93 dataset. PSO, GA, HAS are frequently used meta-heuristic optimization algorithms for estimation of cost [32].

AmanUllah et al., (2019) expound flower pollination algorithm used to optimize the COCOMO-II parameters using Turkish dataset. COCOMO-II and bat algorithms are used for comparison and results shows that the proposed algorithm leads better results. MMRE and MD performance metrics are used for evaluating the results [33].

VipanKumari (2019) given a systematic review of software cost estimation model algorithmic and non-algorithmic methods. The author's analyzed algorithmic methods include mathematical equations to solving the specified problems. They predicted non-algorithmic methods are expert judgment, analogy method, and topdown, bottom up methods.Some recommendations are listed by the author's mainly maintained historical databases. Independent methods, monitoring the process and proposed several method and making the comparison and finalize the good method for estimating the cost [34].

Asad Ali et al., (2019) conducted systematic literature review of Estimating Effort in Software Development. Bio inspired algorithms are reviewed from various sources such as IEEE, Springer, ACM, Science direct and Google scholar. PSO and GA algorithms are found that frequently used feature selection algorithm in effort estimation of software development [35].

NazeehGatasheh et al., (2015) proposed firefly algorithm to optimizing the parameters of COCOMO models. VAF, MSE, MAE, MMRE, RMSE, R^2 performance metrics are used for evaluation of results used NASA Dataset. GA and PSO are used for comparison of FA results [36].

ChanderDiwaker et al., (2018) explained general soft computing approaches such as NN, GA, FL, SVM, ACO, PSO, and ABC for achieving reliability of software. Different domains such as medical, computer engineering, software engineering, mechanical engineering also studied for predicting reliability using CBSE [37].

SaurabhBilgaiyan et al., (2019) predicted systematic review of agile model in software development. Agile model having the advantage of cost prediction by changing the customer requirements in easily without affecting the software quality. Preferable software cost estimation methods given the importance to agile based prediction with high successful projects [38].

AnupamaKaushik et al., (2019) introduced deep belief network based on ant lion meta-heuristic optimization algorithm for effort prediction with the help of study about uncertainty. Rather than producing crisp value the estimators predict the cost in ranges are easily by using the proposed method. The proposed DBN-ALO proved that the promising result inboth agile and non-agile methods evaluated by some statistical measurements [39].

SaurabhBilgaiyan et al., (2016) provided systematic review of soft computing approaches like GA, ANN, FL, and PSO for agile based cost prediction. The authors given the detailed review of all the methods and also predicted the future concerns of those kinds of models [40].

Krishnaveni et al., (2021) proposed chaotic duck travel algorithm for selecting beast features for classification of mammogram in MIAS dataset and DDSM dataset. Here Linear Discriminant Algorithm (LDA) also used for classification. Finally obtained results are compared with the existing related works and results shown as well as proved that the proposed cDTO having the high accuracy rather than LDA and bDTO [41].

Shweta K R et al., (2021) given anoptimized cost estimation model for minimizing under and overestimate in earlier stage software review. Their review was very useful to identify the purpose of optimization in software engineering and also various researchers work in different years with variety of models. They conducting a systematic review of various software cost estimation models and their pros, cons and significance in detail. They also point out all the models and said the importance of independency of proposed algorithm. Both algorithmic and non-algorithmic models also explained. [42-43].

3. Proposed Method

MATLAB 2015a software is used with NASA dataset for optimizing the effort estimation of COCOMO by proposed algorithm Ensemble Duck Traveler Optimization (eDTO).

Methodology

Prevention is better than cure is the famous proverb. In similarly prediction is better than occurrence. Total cost estimation (CE) is calculated from difference between actual cost (AC) and predicted cost (PC).

$$CE = AC - PC \tag{3.1}$$

Balance between actual cost and predicted cost must be optimized using the proposed algorithm. Otherwise underestimate and overestimate problem has been occurring. Both under and overestimate yields organization loss. Total Optimized cost estimation (OCE) is calculated from difference between actual cost (OAC) and predicted cost (OPC).

$$OCE = OAC - OPC \tag{3.2}$$

Here minimization of overestimate and underestimate is achieved by using the proposed Ensemble Duck Travel (eDTO) algorithm. Total Optimized Cost Estimation (OCE) is calculated from difference between Actual Cost (OAC) and Predicted Cost (OPC) which is optimized by eDTO.

$$OCE = eDTO(OAC - OPC) \tag{3.3}$$

$$Effort\ Activation\ (EA) = P * [SIZE]^{Q} * \prod_{j=1}^{15} EM_j \tag{3.4}$$

$$Effort\ (E) = P_j(KLOC)^{Q_j} * ETF \tag{3.5}$$

$$Development\ Time\ (DT) = R_j(E)^{S_j} \tag{3.6}$$

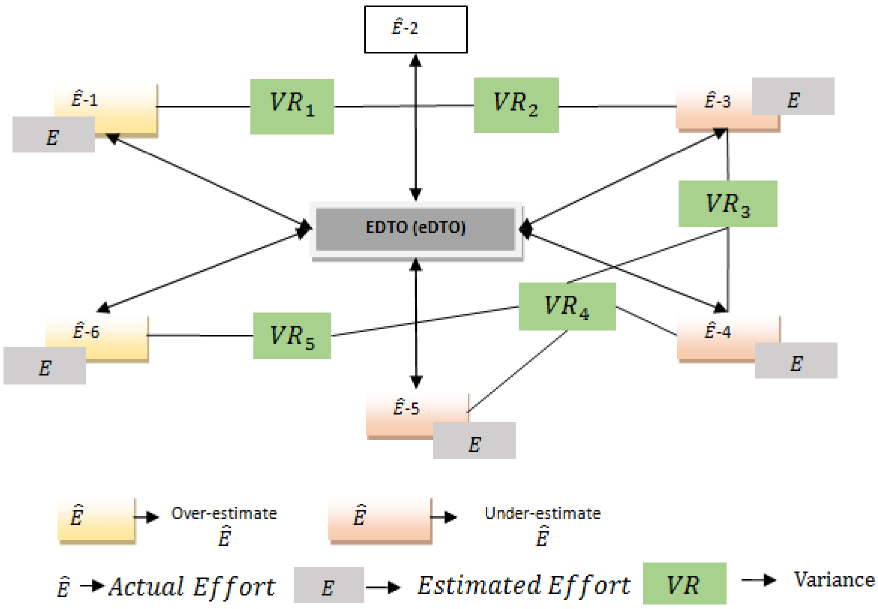

Figure 3: Overall Process of Ensemble Duck Traveler (eDTO) Algorithm.

Algorithm for eDTO:

Begin
$\boldsymbol{for}(each\ E\ and\ \hat{E})$
Compute the cost estimation; using eq (3.1)
Consider the mixture of under and over estimates;
Estimate the customer demands;
$\boldsymbol{if}(uncertainty\ occurs)$
Model $\mathcal{G} = (\hat{E}, E)$;
$\boldsymbol{for}(each\ over\ and\ under\ estimates)$
Choose the $\hat{E}$ and construct the set of optimized cost functions to send over and under estimates among E;
Define VR and other evaluation metrics;
Compute the estimates and over & under estimate ratio to be assigned;
$\boldsymbol{for}(each\ pair\ of\ communicating\ E)$
Determine the multiple cost-disjoint least-uncertainties estimated (3.3);
Partition the uncertainties at cost flow level;
Achieve the maximum prevention grade;
Assign the estimates for each cost flow using (3.2);
Avoid the customer demand wastage of variance at top layers;
Prevent the uncertainties and estimate failure;
$\boldsymbol{end\ for}$
$\boldsymbol{end\ for}$
$\boldsymbol{end\ if}$
$\boldsymbol{end\ for}$

Dataset Description for Proposed Algorithm

The ultimate aim of our exploration is to utilize idea of swarm intelligence especially duck flock with COCOMO for realizing accurate software determination estimation. Software Engineering Fountain "PROMISE" which given the detail about the dataset NASA 93 in variety of sources and various years only for investigation purpose.Actual Effort is described by $\hat{E}$ *and* Estimated Effort is denoted by E. Evaluation is also done with the help of Low, Very Low, Nominal, High, Very High, Extra High.

Table 1: Cost Drivers used in COCOMO Model [44]

Cost Drivers	Assessments					
	Very Low (VL)	Low (L)	Nominal (N)	High (H)	Very High (VH)	Extra High (EH)
PRODUCT ATTRIBUTES						
Required S/w Reliability (RELY)	0.75	0.88	1.00	1.15	1.40	-
Size of Application Database (DATA)	-	0.94	1.00	1.08	1.16	-
Complexity of the Product (CPLX)	0.70	0.85	1.00	1.15	1.30	1.65
COMPUTER ATTRIBUTES						
Run Time Performance Constraints (TIME)	-		1.00	1.11	1.30	1.66
Memory Constraints (STOR)	-		1.00	1.06	1.21	1.56
Virtual Machine Volatility (VIRT)	-	0.87	1.00	1.15	1.3	-
Turnaround Time (TURN)	-	0.87	1.00	1.07	1.15	-
PERSONAL ATTRIBUTES						
Analyst Capability (ACAP)	1.46	1.19	1.00	0.86	0.71	-
Application Experience (AEXP)	1.29	1.13	1.00	0.91	0.82	-
Programmer Capability (PCAP)	1.42	1.17	1.00	0.86	0.70	-

Table 1: Contd.,

Virtual M/c Experience (VEXP)	1.21	1.10	1.00	0.9	-	-
Programming Language Experience (LEXP)	1.14	1.07	1.00	0.95	-	-
PROJECT ATTRIBUTES						
Modern Programming Practices (MODP)	1.24	1.10	1.00	0.91	0.82	-
Use of Software Tools (TOOL)	1.24	1.10	1.00	0.91	0.83	-
Required Development Schedule (SCED)	1.23	1.08	1.00	1.04	1.10	-

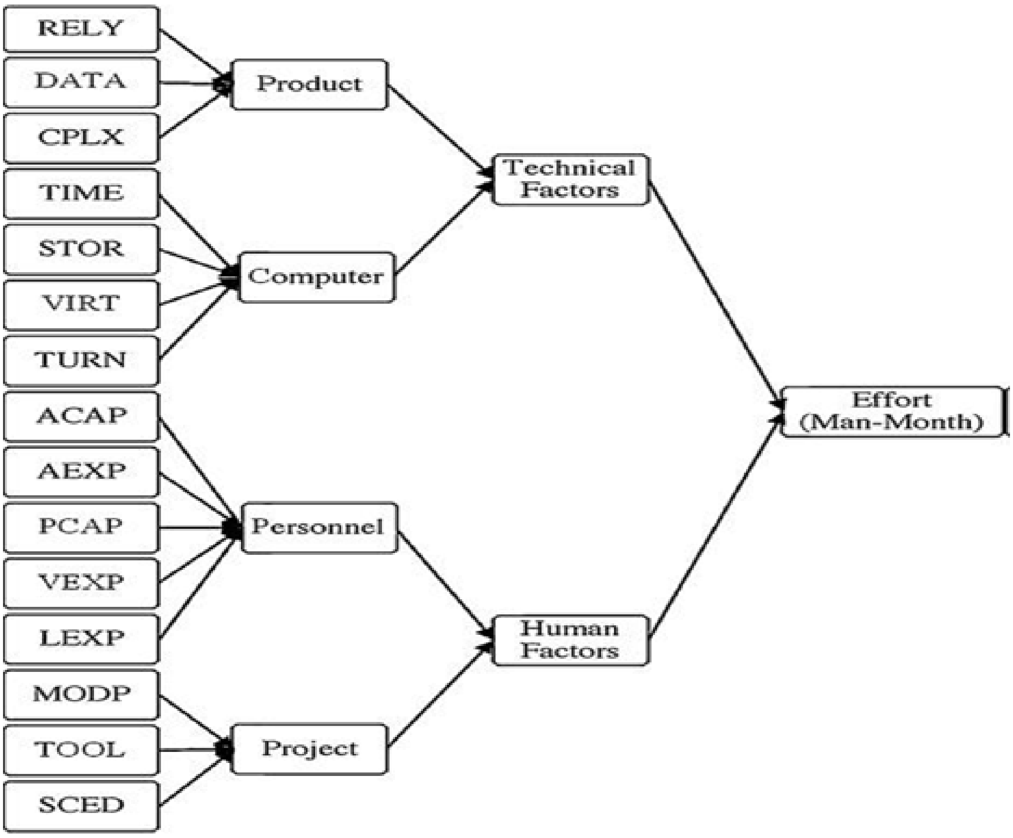

Figure 4: COCOMO-II Cost Drivers Used for Effort Calculation.

Cost estimation is mainly focused on early concentrate on size, effort (m^2) money and manpower needed for completing the specified project, and also budget for prioritization of all expenses needed for accomplishing works in work planned activity. To reduce the overestimate and underestimate issues in COCOMO-II, the Duck Travel Algorithm calculates the cost function using cost drivers and effort multipliers in fig.4 are used for effort calculation. Effort Activation using 15 cost drivers are calculated using size metric and coefficients P & Q for calculating the manpower in unit of months. Lines of Code are the key term in COCOMO model. So KLOC is mentioned for Effort Tuning Function (ETF).ETF is the item for consumption of all Effort multipliers. Finally Development Time duration is calculated using another two coefficients R & S. 0.9 to 1.4 is the assortment of (ETF).

Table 2: COCOMO Coefficients used for Intermediate Type of Project

Project	P_j	Q_j	R_j	S_j
Organic	3.2	1.05	2.5	0.38
Semidetached	3	1.12	2.5	0.35
Embedded	2.8	1.2	2.5	0.32

Table 3: eDTO Algorithm used for Estimation of Cost Mainly Focused (E),$(\widehat{E})$, DT, for NASA Projects using VR, BRE, MRE, MMRE Metrics for Software Model

S.NO	KLOC	Actual Effort$(\widehat{E})$	Estimated Effort (E)	Development Time	BRE	MRE
1	20	72	28.5	8.9316	1.5241	152.4079
2	6	24	9.9	5.9741	1.4244	142.4398
3	100	215	475.9	21.6304	1.2134	54.8208
4	32.5	60	117.5	15.2931	0.9576	48.9176
5	15	48	25.9	8.6109	0.8527	85.2665
6	100	360	200	15.971	0.7996	79.9629
7	11.4	98.8	57.3	11.64	0.7252	72.5153
8	7.5	72	42.1	10.3571	0.7095	70.9481
9	10	48	28.1	8.8806	0.7082	70.825
10	15	90	54.9	11.4549	0.6392	63.9215
11	47.5	252	158.1	17.1225	0.5936	59.3604
12	16	114	75.1	12.9012	0.5185	51.8476
13	150	324	491.4	21.8753	0.5168	34.0706
14	50	370	234.2	19.8771	0.5801	58.0133
15	19.3	155	99.5	14.361	0.5571	55.7103
16	10.4	50	32.9	9.4258	0.5212	52.1193
17	35.5	192	131.6	15.9704	0.4585	45.8452
18	24.6	117.6	81.2	13.2894	0.4489	44.8854
19	79	400	279.8	17.9618	0.4295	42.9463
20	11.3	36	25.2	8.521	0.4284	42.8433
21	32.6	170	120.4	15.4365	0.4122	41.2216
22	16.3	82	58.1	11.7068	0.4104	41.0417
23	219	2120	1509.6	32.3997	0.4044	40.4357
24	8.2	36	25.6	8.573	0.4057	40.5715
25	190	420	436.9	20.9935	0.0403	3.8749
26	284.7	973	1353.8	31.1874	0.3913	28.126
27	38	210	151	16.8231	0.3911	39.1109
28	6.5	42	30.2	9.1281	0.3904	39.0416
29	12.8	62	45.1	10.6304	0.3745	37.4523
30	25.9	117.6	85.7	13.5653	0.3726	37.2593
31	21	107	146.6	16.6383	0.3704	27.0293
32	20	48	35	9.6583	0.3697	36.9655
33	14	60	44.9	10.6127	0.336	33.6029
34	423	2300	1731.7	27.18	0.3282	32.8189
35	48.5	239	182.7	18.0878	0.3083	30.8277
36	2.2	8.4	6.4	5.0716	0.3057	30.5674
37	7.7	31.2	24	8.3605	0.3015	30.1483
38	8	42	32.7	9.4036	0.2858	28.5751
39	15.4	70	54.8	11.4445	0.278	27.8003
40	370	3240	4068.6	35.7241	0.2557	20.3648
41	90	450	360.5	19.6267	0.2484	24.8352
42	101	750	602.7	23.495	0.2444	24.4395
43	29.5	120	98.2	14.2883	0.2217	22.1708
44	66.6	352.8	290.5	18.199	0.2144	21.441
45	9.7	25.2	30.5	9.1674	0.2123	17.5123
46	282.1	1368	1139.6	29.3628	0.2005	20.0467
47	100	360	418.2	20.6741	0.1617	13.9177
48	115.8	480	539.8	22.6058	0.1246	11.0767
49	13	60	54.4	11.4137	0.1032	10.3222
50	19.7	60	64.3	12.1623	0.0714	6.6615
51	5.5	18	16.8	7.3102	0.069	6.9033
52	161.1	815	862.2	26.6315	0.0579	5.4699
53	227	1181	1236.7	30.2153	0.0471	4.5005
54	31.5	60	62.7	12.0448	0.0444	4.2477

Table 3: Contd.,

55	78	571.4	548.7	22.7349	0.0415	4.1463
56	302	2400	2419.3	30.2497	0.008	0.7978
57	177.9	1248	1202.7	29.9226	0.0376	3.7634
58	66.6	300	290.5	18.199	0.0327	3.2662
59	3.5	10.8	10.5	6.1039	0.031	3.0983
60	70	278	278	17.9197	0.0002	0.0168

$\text{Accuracy (ACC)} = 95.2453, \text{VAR} = 95.0891 \text{ and MMRE} = 0.3531.$

The proposed Ensemble Duck Traveler Optimization (eDTO) Algorithm having the high accuracy and high variance, minimum BRE, MRE and MMRE values for software cost estimation. It is evaluated using ACC, VAR, BRE, MRE, MMRE and also compared with Gaurav Kumar et al [4], shown VAR=93.5542 and MMRE=0.3642. They mentioned about importance of Metaheuristics algorithm for optimizing the cost estimation in software project management. So we proposed Ensemble Duck traveler Optimization (eDTO) Algorithm to getting the cost estimation accuracy higher than the existing neural network. MATrix LABoratory (MATLAB) tool is used for experiments of project cost estimation in NASA.

4. Evaluation Metrics for Cost Model in Software Engineering

Proposed eDTO algorithm predicts the KLOC, Actual Effort, and Estimated Effort, Development time, BRE, and MRE values mentioned in the above Table 3.

$$\text{Accuracy (ACC)} = \left(\frac{TP + TN}{TP + FP + TN + FN}\right)$$

$$\text{Variance (VAR)} = \left(1 - \frac{Variance(E - \hat{E})}{Variance\ E}\right)$$

$$Scheduled\ Variance\ (SV) = E - \hat{E}$$

$$\text{Relative Error (RE)} = \frac{E - \hat{E}}{\hat{E}}$$

$$\text{Balance Relative Error (BRE)} = \frac{|E - \hat{E}|}{\min\ (E - \hat{E})}$$

$$\text{Magnitude of Relative Error (MRE)} = \frac{\left|E - \hat{E}\right|}{E} * 100$$

$$\text{Mean Magnitude of Relative Error (MMRE)} = \frac{1}{N}\sum j\,\frac{E_j - \hat{E}_j}{E_j}$$

Activation of Authentic Effort is described by $\hat{E}\ and$ Predictable Effort is denoted by E. Results are evaluated using ACC, BRE, MRE and MMRE software metrics for cost estimation using eDTO Algorithm.

Table 4: Metrics Involved in Cost Estimation of Software Projects NASA 93

Metrics	COCOMO	NN	SBA	eDTO
ACC	91.8012	92.6120	94.3217	95.2453
VAR	90.7325	91.6732	93.5542	95.0891
BRE	0.2101	0.2002	0.101	0.002
MRE	0.2001	0.1982	0.1052	0.0168
MMRE	0.6536	0.5789	0.3642	0.3449

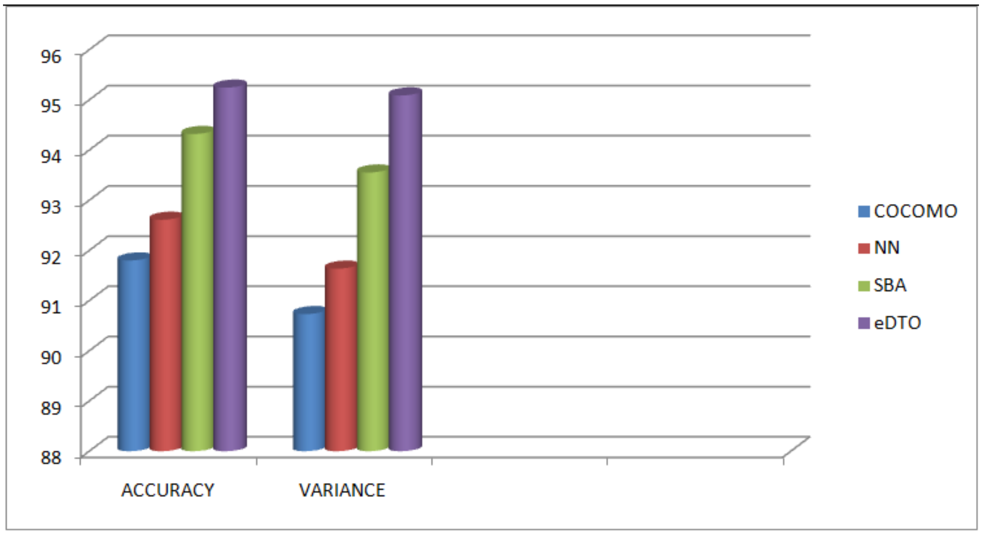

Figure 5: High ACC & VAR Values of eDTO Algorithm with Comparison of Existing COCOMO, NN, SBA.

In Figure 5, the existing COCOMO model having ACC = (91.8012), Neural Network having ACC = (92.6120), Strawberry Algorithm having ACC = (94.3217) and proposed eDTO having highest variance ACC = (95.2453). From this analysis we proved that high Accuracy value of eDTO optimize cost and effort estimation in a perfect manner. High variance values of eDTO having high risk and high return value (95.0891) than all existing algorithms.

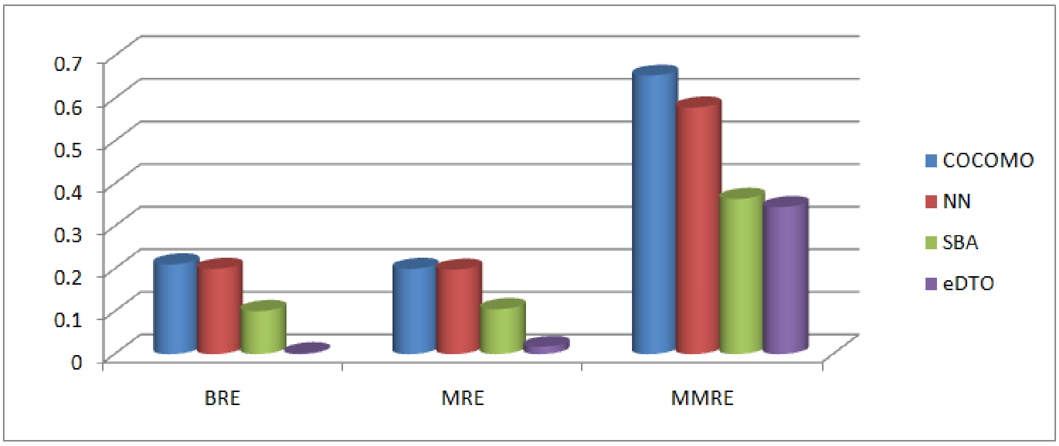

Figure 6: Minimum RE values of eDTO Algorithm with Comparison of Existing COCOMO, NN, and SBA.

5. Conclusions & Further Work

In this research work to reduce the uncertainty of cost estimation during over estimate and under estimate, new optimization algorithm enhanced duck traveler (eDTO) was proposed. According to the customer demand the estimation flow was generated using the architecture of software process model. Actual effort and Estimated Effort values are used to calculate the error rate. Performance metrics ACC, BRE, MRE and MMRE are evaluated the performance results of proposed algorithm. In addition to comparison between proposed and existing algorithm had been done and demonstrate that the proposed optimization algorithm having high variance value and minimum error rate. COCOMO model input values are passed to eDTO for calculating effort, development time for NASA projects. Proposed eDTO calculate the estimation of effort for all types of COCOMO. Results are compared with the existing COCOMO Model, Neural Network and Strawberry algorithm. Results of high variance value of eDTO and minimum Relative Error (RE) had shown the performance of the proposed eDTO algorithm efficiency. Many researchers working on cost estimation of software projects and all of them are tried to reduce the difference between actual cost and estimated cost. So balance between actual and predicted should be optimized using eDTO is achieved in this research work. In future, eDTO algorithm with new cost estimation model four Point Capability of Rectangular Relationships Mapping Function (4PCR2MF) will plan to be proposed for further improvements.

References

1. Juan M-M, C.Q-L opez, C.C-Herrera and M. Jenkins, “An Empirical Evaluation of NASA-MDP Data sets using a Genetic Defect-Proneness Prediction Framework” IJERT Vol. 4 issue 1 (2008).
2. S. S Ch, S. P Singh, “A Novel Fuzzy Model for Software Cost Estimation International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-4, pp. 111-119 February (2020)
3. Dhana Sekar S.P.S, Askarunisa. A, “Optimization Technique For Software Cost Estimation Using Neural Network”, Innovare Journal Of Engineering And Technology, Vol 2, Issue 4, 5-9, (2014)
4. Gaurav K, Pradeep K B, “Automation of Software Cost Estimation using Neural Network Technique”, International Journal of Computer Applications (0975 – 8887) Volume 98 – No.20, July (2014)
5. P.Rijwani∗and S.Jain, “Enhanced Software Effort Estimation using Multi Layered Feed Forward Artificial Neural Network Technique” Twelfth International Multi-Conference on Information Processing-2016 (IMCIP-2016) Procedia Computer Science 89 307 – 312, (2016)
6. Deepak N, Om Prakash S, “Software Cost Estimation by Optimizing COCOMO Model Using Hybrid BATGSA Algorithm”, International Journal of Intelligent Engineering and Systems, Vol.11, No.4, (2018)
7. Neha S, Amit S, Bhupendra V, “Software Assessment Parameter Optimization using Genetic Algorithm”, International Journal of Computer Applications (0975 – 8887) Volume 72– No.7, May (2013)
8. A Kaushik, S Verma, H J Singh, G Chhabra, “Software cost optimization integrating fuzzy system and COA-Cuckoo optimization algorithm”, Int J SystAssurEngManag, Springer (2017)
9. Syed Ali M Z, Vinodani K, S. Q Abbas, “Development of A Framework for Software Cost Estimation: Design Phase”, International Journal of Technical Research and Applications E-Issn: 2320-8163, Www.Ijtra.Com, Volume 5, Issue 2, Pp. 68-72 March - April (2017)
10. Anfal A. Fadhil ,RashaGh. Alsarraj, And Atica M. Altaie, “Software Cost Estimation Based on Dolphin Algorithm”, VOLUME 8, pp.75279- 75287, IEEE Access (2020)
11. E EMiandoab, F S Gharehchopogh, “A Novel Hybrid Algorithm for Software CostEstimation Based on Cuckoo Optimization and K-Nearest Neighbors Algorithms”, Engineering, Technology & Applied Science Research, Vol. 6, No. 3, 1018-1022, (2016)
12. Alifia P, Riyanarto S, “A Hybrid Cuckoo Optimization and Harmony Search Algorithm for Software Cost Estimation”, 4th Information Systems International Conference 2017, ISICO 2017, 6-8 November 2017, Bali, Indonesia, Procedia Computer Science 124 461–469, (2017)
13. Shivani S, Aman K, Abhishek T, “Software Cost Estimation using Hybrid Algorithm”, International Journal of Engineering Trends and Technology (IJETT) – Volume 37 Number 2- July (2016)
14. Shailendra P S, “Cost estimation model using enhance-based differential evolutionAlgorithm”, Iran Journal of Computer Science, Springer (2019)
15. Seyed H H, Seyedeh N H, “Determining The Parameters of Object-Oriented Software Cost Estimation Using Cuckoo Search Optimization Algorithm”, Journal of Xi'an University of Architecture & Technology ISSN No : 1006-7930 Volume XII, Issue IX, pp.420-442 (2020)
16. Krishnaveni A, Shankar R, Duraisamy S, “A Survey on Nature Inspired Computing (NIC): Algorithms and Challenges”, Global journal of computer science and technology: D Neural & Artificial Intelligence volume 19 issue 3 version 1.0 Year (2019)
17. A.Krishnaveni , R. Shankar and S. Duraisamy, “A Review on various Image Thresholding Methods for Mammogram Image Segmentation” Compliance Engineering Journal ISSN NO: 0898-3577 Volume 11, Issue 2, (2020)
18. A.Krishnaveni, R.Shankar, S.Duraisamy, “Duck Cluster Optimization Algorithm with K-Means Clustering for Mammogram Image Segmentation”, Solid State Technology, SCOPUS Indexed ISSN NO: 0038-111X Volume 63, Issue 6, (2020)
19. A.Krishnaveni, R.Shankar, S.Duraisamy, “An Efficient Methodology for Breast Tumor Segmentation using Duck Traveler Optimization Algorithm”, PalArch’s Journal of Archaelogy of Egypt/Egyptology, SCOPUS Indexed ISSN NO: 1567- 214X Volume 17, Issue 9, (2020)
20. Krishnaveni Arumugam, Shankar Ramasamy, Duraisamy Subramani “Improved Duck and Traveler Optimization (IDTO) Algorithm: A Two-way efficient approach for breast tumor segmentation using multilevel thresholding”, European Journal of Molecular & Clinical Medicine ISSN 2515-8260 Volume 7, Issue 10, (2020)
21. Krishnaveni A, Shankar R, Duraisamy S “Swarm Intelligence Algorithms with K-Means Clustering for Mammogram Image Segmentation”, IRJMETS, ISSN 2515-8260 Volume 3, Issue 2, (2021)

22. A.Krishnaveni, R.Shankar, S.Duraisamy, “Versatile Duck Traveler Optimization (VDTO) Algorithm Using Triple Segmentation Methods for Mammogram Image Segmentation to Improving Accuracy” (March 13, 2021) SSRN:https://ssrn.com/abstract=3803814
23. Muhammad T B, Massila K, “A Review of Software Cost Estimation: Tools, Methods, and Techniques”,https://www.researchgate.net/publication/310599686 (2016)
24. Maryam S & Abbas K S &Seyed R H, “New optimization methods for designing rain stations network using new neural network, election, and whale optimization algorithms by combining the Kriging method”, Environ Monit Assess (2021) 193:4
25. AnupamaKaushik, NishaChoudhary, and Priyanka, “Software Cost Estimation Using LSTM-RNN”, Advances in Intelligent Systems and Computing, Proceedings of InternationalConference on Artificial Intelligence and Applications Volume 1164, ICAIA Springer (2020)
26. David R-D, Tad G, Asuncion P. C, Ramon R. P,Alvaro J. L-L, Antonio F-C, “Determining the optimum installation of energy storage systems in railway electrical infrastructures by means of swarm and evolutionary optimization algorithms”, Electrical Power and Energy Systems 124, 106295 (2021)
27. Ken M. N, Keisuke F, Synge T, “Sequential minimal optimization for quantum-classical hybrid algorithms”, Physical Review Research 2, 043158 (2020)
28. Neelamdhab P, R.P. Singh, Suresh C S, “Software reusability metrics estimation: Algorithms, models and optimization techniques”, Computers and Electrical Engineering 1–16, (2017)
29. Abolfazl J, Eric K. Z, Mahdi P, Himan S, “Hybrid artificial intelligence models based on a neuro-fuzzy system and metaheuristic optimization algorithms for spatial prediction of wildfire probability”, Agricultural and Forest Meteorology 198–207 (2019)
30. Vahid B, Warren H, Yves L, “Best practices for comparing optimization algorithms”, OptimEng, Springer (2017)
31. Mariana D A-T, Cuauhtemoc L-M, Yenny V-R, “Particle Swarm Optimization for Predicting the Development Effort of Software Projects”, Mathematics8, 1819 (2020) doi:10.3390/math8101819
32. Muhammad S K, CH Anwar ul H, Munam A S, Azra S, “Software Cost and Effort Estimation using a New Optimization Algorithm Inspired by Strawberry Plant”, Procedia technology (2018)
33. Aman U, Bin W, Jinfan S, Jun L, Muhammad A, Faiza R, “A Novel Technique of Software Cost Estimation Using Flower Pollination Algorithm”, International Conference on Intelligent Computing, Automation and Systems (ICICAS) (2019)
34. Dr. VipanKumari, “Software Development Cost Estimation Methods and Particle Swarm Optimization Model”, IJIRST –International Journal for Innovative Research in Science & Technology| Volume 5, Issue 11, ISSN (online): 2349-6010 April (2019)
35. Asad A, Carmine G, “Using Bio-inspired Features Selection Algorithms in Software Effort Estimation: A Systematic Literature Review”, 2019 45th Euromicro Conference on Software Engineering and Advanced Applications (SEAA) IEEE (2019)
36. Nazeeh G, Hossam F, Ibrahim A, Rizik M. H. Al-S, “Optimizing Software Effort Estimation Models Using Firefly Algorithm”, Journal Of Software Engineering And Applications, 8, 133-142 Published Online March 2015 In Series (2015)
37. Chander D, Pradeep T, Ramesh C. P, Vijander S, “Prediction of Software Reliability using Bio Inspired Soft Computing Techniques”, Journal of Medical Systems 42:93 Springer(2018)
38. SaurabhBilgaiyan, SantwanaSagnika, Samaresh Mishra and Madhabananda Das, “A Systematic Review on Software Cost Estimation in Agile Software Development”, Journal of Engineering Science and Technology Review 10 (4) 51-64(2017)
39. Anupama K, Devendra Kr. T, Kalpana Y, “A Comparative Analysis on Effort Estimation for Agile and Non-agile Software Projects Using DBN-ALO”, Arabian Journal for Science and Engineering, Springer(2019)
40. Saurabh B, Samaresh M, Madhabananda D, “A Review of Software Cost Estimation in Agile Software Development Using Soft Computing Techniques”, 2016 International Conference on Computational Intelligence and Networks IEEE (2016)
41. Krishnaveni Arumugam, Shankar Ramasamy, Duraisamy Subramani, “Chaotic Duck Traveler Optimization (cDTO) Algorithm for Feature Selection in Breast Cancer Dataset Problem”, Turkish Journal of Computer and Mathematics Education, Vol.12 No.4 250-262, (2021)
42. Shweta K R, Duraismy S, LathaMaheswari T, “Optimized Software Cost Estimation in earlier stage software: A Review”, Elementary Education Online - EEO. 20(1): 1877-1887. (2021) doi:10.17051/ilkonline.2021.01.200
43. Shweta K R, Duraismy S, LathaMaheswari T, “Comparative Analysis of Algorithmic, Non Algorithmic and Machine Learning Models For Software Cost Estimation: A Survey”, IRJMETS ISSN 2515-8260 Volume 3, Issue 3, (2021)

44. B. W. Boehm, "Software engineering economics," IEEE transactions on Software Engineering, pp. 4-21, 1984.
45. Prabu P, Duraisamy S, “Impact of pair programming for effective software development process”, International Journal of Applied Engineering Research(2015)
46. E. Ramarajand S. Duraisamy, “Design Optimization Metrics for Uml Based Object-Oriented Systems”, International Journal of Software Engineering and Knowledge Engineering, Vol.17, No.03, pp.423-448 (2007)