International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. #, No.# (Mon-20..)

Optimization of COCOMO II model to Estimate software cost using Squirrel Algorithm

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Received ## Mon. 20##, Revised ## Mon. 20##, Accepted ## Mon. 20##, Published ## Mon. 20##

Abstract: Estimating software effort important highly role of project management which enables Estimate software cost. Inexact results may reason to increment or decrement in estimating effort. A lot of technique concerning software effort prediction was has applied for enhancing models that build optimal prediction accuracy. One of these techniques is Swarm intelligence. The process of choosing an optimal prediction algorithm depends on experts and complexity. The proposed paper enhances the prediction hire the COCOMO idea by executing the Squirrel Search Algorithm(SSA). The search behavior in squirrels is dependent on dynamic jumping and gliding techniques by applying the algorithm on four data sets (NASA 93, NASA 60, NASA 63, Bailey and Basili 18) and assess with the use of Mean Magnitude of Relative Error(MMRE). The score shows that the Squirrel search model has obtained best the coefficient values of the COCOMO model than Algorithms applied in this field.

Keywords: The Squirrel Algorithm, cost Estimation, Constructive Cost Mode, seasonal constant ,NASA dataset.

1. INTRODUCTION

A pivotal work for software evolution in the software engineering group is an effort estimation. As one of the most important processes necessary to predicate product costs in the first stage is estimating the cost of the software. The cost estimate is required to compute the time and budget for the project [1][2].

Costs have concerning to application based on efforts done, which include the many of reviews work everywhere execution and pre-expansion operation, et cetera [3]. There twain important kinds of strategies, the first based on Model, that created based on mathematical methods, while the second kind has Based on Expert-techniques, that depend on personal Supervision, the first kind has been created based on mathematical methods, where the second kind has to depend on personal Supervision. Over there connected particular models of methodologies, such as COCOMO II [4], USE CASE POINT [5], add in more.

All suggested prediction models face the issue of the lack of thoroughness. Most of these methodologies are concentrate on is proven sides connected with the method of software evolution whereas discarding The rest. Additionally, most of these methodologies are conventional and unavailing about IDEs, programming languages, paradigms, In Furthermore to other instruments of development.

One of the main topics in AI is Swarm intelligence. Concerning the characteristics and explains connected to swarm intelligence, many algorithms have enhanced, like algorithms can split into two classes, first class has deemed such the operation algorithm that was to depend on a genetic model which simulates population development's operation, second class is the electronic demeanor algorithm that imitates demeanor type concerning different type search for preys[6].

This paper enhances the COCOMO II model to Estimate software by using one of the modern swarm techniques is Squirrel Algorithm. By execution of the proposed model to two data, this data has taken from NASA-93 project and NASA-60 project [7]. The data set include many projects, each project content (KLOC), actual effort. Of the fifteen cost drivers, each cost driver has one value that ranges between("very low", "low", "normal", "high", "very high", "extra high")in data set projects[7].

The proposed model was evaluated by measures metrics MMRE, the results of the proposed model have compared with several models. The results show that the Squirrel algorithm model gives the best coefficients values for optimization of the COCOMO model.

The remainder of this work has been organized into seven sections. The second section shows the Modern of the linked work, section three depicts the model of COCOMO, whereas section four explains the Squirrel

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search algorithm. In Section Five, the Squirrel Search Algorithm To predict Software cost, section six results and discussion have explained after apply the Squirrel Search algorithm to predict Software cost. Finally, the conclusions and Upcoming works have appeared in section seven.

2. RELATED WORK

To execute the project felicitously, must the Prediction of Software cost convergent Asymptotic of the cost and time demand. The Prediction of effort is essential to the cost Prediction [8]. Several studies have presented to predict the software effort of the projects. Table I show datasets that used in this studies as following:

In 2016, Muhammad Ibrahim proposed to estimate the effort coefficients (a,b) and decrease MMRE, by applying the "bat algorithm" in the COCOMO model [9].

In 2016, Maram and Nejmeddine applied genetic algorithms (GA) to improve coefficients and enhance the thoroughness of estimate the effort and the evolution time for the "COCOMO-II" architecture [10].

In 2017, Alifia and Riyanarto suggested a hybrid model to improve coefficients of COCOMO-II by a Hybrid cuckoo search with a harmony search model to obtain optimal estimation. This model has been executed on the "NASA 93" dataset[11].

In 2018, proposed Deepak and Om Prakash hybrid "bat algorithm" with the "gravitation search algorithm (GSA)" to improve the COCOMO-II architecture. The bat algorithm explains hunting. The exploration bat algorithm has then optimized by applied GSA as gravitation imposes an impact on the velocity of the bat[12].

In 2019, Varinder and Jatinder they shown regression depend on the training of AI which creates the prediction model more precise[13].

In 2020, Anfal, Rasha, and Atica improved the COCOMO II models using two datasets by hybrid dolphin and bat algorithm to predict software cost [6].

In 2020, Anfal and Rasha proposed the whale algorithm to optimize coefficient values of COCOMO-II (a,b) to estimate Software Project Effort using one dataset [14].

In 2021, Marrwa, Najla, and Taghreed proposed the antlion algorithm to optimize coefficient values of COCOMO using four datasets to estimate Software Project Effort[15].

TABLE I. show datasets that used in related work Mentioned

year	model	dataset
2016	bat algorithm	NASA 60
2016	genetic algorithms	NASA 93
2017	Hybrid cuckoo search with harmony search model	NASA 93
2018	bat with the gravitation search algorithm	NASA 60 NASA 93 kemerer
2019	regression based training of AI	UML diagrams
2020	hybrid dolphin and bat algorithm	NASA 60 NASA 93
2020	Whale algorithm	NASA 93
2021	antlion algorithm	Bailey and Basili NASA 60 NASA 93 NASA 63 NASA 15

3. THE MODEL OF COCOMO II

In 1981 retreating depend model to predict cost was proposed by Barry Boehm and adjust to the environment of software developments, the model is the Constructive Cost Model (COCOMO II). COCOMO II has advanced from previously COCOMO cost prediction models. It has been derived through gathering data from enormous software projects. And it a well-documented predict model, where analyze data to find formulae that better to observations. And it became The most popular model used to predict software effort in the industry. The COCOMO II Used in the early phase of software engineering, After fixing requirements, and build user interfaces.

The COCOMO II model depends on the modern strategy to software development by component created and use database programming[16]. And It is a soft-to-understand model that estimates the effort and time of a project. Depend on inputs connected to the size of the systems(kilo line of code KLOC) and cost drivers that Boehm consider influence productivity as shown in Eq.(1) [17].

$$\text{Effort} = \quad a * (\text{Size}^{b}) * \prod_{i=1}^{15} \text{emi} \tag{1}$$

where the coefficient “a” is represented as the productivity coefficient, the coefficient “b” represents the scale factor. The proposed model help to estimate the best values of a, b. the " emi" known 15 effort multipliers and every multiplier takes on of value between (ver low-extra high) depend on the NASA dataset[18]. There are many reasons became usage COCOMO model is spread in any software cost prediction, which are [19]:

- COCOMO criteria over historical data.

- COCOMO is quite documented which will be used as an instruction to explain how the predicted costs are obtained.
- COCOMO is a parametric model that let users set the parameters to depend on their project Characteristics
- COCOMO has flexibility in volume input as function points, SLOCs, and application points.
- 5-COCOMO is a multi-model contain various sectors.

There are also other advanced models from the COCOMO model, such as Sheta's Model [20] is considered a modification of the COCOMO model as given in Eq.(2).

$$\text{Effort} = a * (\text{Size}^{b}) + (C^{*} \prod_{i=1}^{15} \text{emi}) \quad (2)$$

Where C is constant are consider from coefficients of COCOMO.

4. Squirrel Search Algorithm(SSA)

Mohit, Vijander, and Asha in 2018[21] presented a new algorithm has The squirrel search(SSA), which is considered a modern and strong algorithm nature-inspired. This algorithm imitates the dynamic search strategy. The discovery process starts when flying squirrels begin to search for the food.

The squirrels discover food sources by skid through trees in snug weather (autumn). During that, they alteration their position and discover new areas of food search. In the fall, the heat is sufficient to meet their daily energy needs because acorns are abundant, so the squirrels consume the acorns as soon as they find them. After complete their need for daily Food, they begin to search for good food origin for winter "hickory nuts". Save of food origin will assist to keeping their need for food in cruel winter and decrease the process search of food costly and thence rise the chance of endurance to stay. In the winter, the Squirrels do not hibernate but become less active because of falling leaves from trees and a rise chance of predation. And in the spring season, the squirrels will be active again [21]. The food is obtained by searching, where each squirrel search in vast, multi-distance areas. In SSA, each squirrel changes its location and transfers to the best location. That includes having n squirrels in the forest With fallen leaves that one squirrel per tree. there three kinds of tree in the forest are presumed available and the forest space included N trees as following:

1- one tree of hickory.
2-Na trees of the acorn.
3- normal trees are remaining.

The better food space for the squirrels is the hickory tree. The activity of each squirrel is affected by the operations following ("Divided the population, dynamic foraging behavior, seasonal acclimate intelligence, and random re-location at the end of the winter")[22].

1. *Divided the population*

The location of N squirrel individuals is indiscriminately created. Then has arranged the population in ascending to decrease the issue. And the squirrels are divided into a subset and as :

1- f_h individuals existing on hickory trees.
2- f_a individuals existing on acorn trees.
3- f_n individuals existing on normal trees.

The squirrel individual has a minimum fitness value is f_h, the individuals that have the fitness position from 2 to Na + 1 is f_a , and the residual individuals are indicating as f_n.

2. *Dynamic foraging behavior*

A mathematically represented moveable foraging behavior can be three cases as follows[21]:

a. Flying squirrels locations that are sliding from "acorn trees" to "hickory tree" (fs_{at}) are modified as :

$$fs_{at}^{t+1} = \begin{cases} fs_{at}^{t} + d_s \times G_c \times (fs_{ht}^{t} - fs_{at}^{t}) & r_1 > p_{dp} \\ random\ location & otherwise \end{cases} \quad (3)$$

where d_s is the random sliding distance, fs_{ht} is the position of individuals that arrived "hickory nut tree", t refers to the existing iteration and Gliding constant G_c=1.9 according to rigorous analysis for the proposed algorithm.

b. The remaining flying squirrels' locations, that are sliding from "normal trees" (fs_{nt}) to " acorn nut trees" are adjusted as :

$$fs_{nt}^{t+1} = \begin{cases} fs_{nt}^{t} + d_s \times G_c \times (fs_{at}^{t} - fs_{nt}^{t}) & r_2 > p_{dp} \\ random\ location & otherwise \end{cases} \quad (4)$$

c. Get the new location of squirrels that are in "normal trees" and used a "corn nuts" may occur about to "hickory nut tree" because save "hickory nuts" may be used at the time of food lack. can get as follows:

$$fs_{nt}^{t+1} = \begin{cases} fs_{nt}^{t} + d_s \times G_c \times (fs_{ht}^{t} - fs_{nt}^{t}) & r_3 > p_{dp} \\ random\ location & otherwise \end{cases} \quad (5)$$

where r1,r2,r3 is a number randomly, between [0, 1] and $p_{dp} = 0.1$ is likelihood Predator presence. The sliding distance d_s can be compute by:

$$d_s = \frac{h_g}{\tan(\varphi)} \quad (6)$$

Where h_g=8 and tan (φ) appear the sliding angle which is compute by:

$$\tan(\varphi) = D/L \quad (7)$$

$$D= \frac{1}{2pv^2 sc_D} \quad (8)$$

$$L= \frac{1}{2pv^2 sc_L} \quad (9)$$

Where p represent the density of air which is equal (1.204kgm− 3), v is speed Which is equal(5.25 ms−1), s is the surface area which is equal(154 cm2), c_D is defined as drag coefficient and c_L is defined as lift coefficient[22].

3. seasonal acclimate intelligence

The behaviors of search food in squirrels influence by seasonal fluctuation. The SSA eschews local optimal solutions. The squirrels are more efficacious in autumn and less efficacious in winter. the seasonal acclimate intelligence has computed seasonal constant (S_c) using Eq.(10)

$$S_c^t = \sqrt{\sum_{k=1}^{d} (fs_{at,k}^t - fs_{h,k}^t)^2} \quad (10)$$

Where $i = 1,2,3.$ The less value of a seasonal constant is computed by using Eq.(11):

$$S_{min} = 10e^{-6} / (365)^{t/(t_{max/2.5})} \quad (11)$$

The big value of S_{min} support exploration while the minimal value enhance the ability of the squirrels algorithm.

4. random re-location at the end of the winter

In case $S_c^t \leq S_{min}$ the winter is ended. In this case position of the flying squirrels are randomly re-location by using Eq.(12) [23].

$$fs_{nt}^{new}=fs_L + le'vy(n) \times (fs_u - fs_L) \quad (12)$$

Levy distribution enhances the universal exploration power and gets new results out of the way from the current better results. The Levy flight has computed by Eq.(13):

$$le'vy(n)=0.01\times\frac{R_a\times\sigma}{|R_b|^{1/\beta}} \quad (13)$$

Where β is a fixed number equal 1.5, R_a and R_b random numbers between [0,1] and σ is computed by Eq.(14):

$$\sigma=\left[\frac{\Gamma(1+\beta)\times\sin(\frac{\pi\beta}{2})}{\Gamma(\frac{1+\beta}{2})\times\beta\times2^{(\frac{\beta-1}{2})}}\right]^{1/\beta} \quad (14)$$

Where $\Gamma(x) = (x-1)!$.

5. THE SQUIRREL ALGORITHM TO PREDICT SOFTWARE COST

This paper has applied the Squirrel search algorithm on

1- COCOMO II model to obtain best coefficients value(a,b) to Predict the cost of the software. And was done generate matrix form of a two dimensional, the first dimensional symbolize the number of projects in NASA dataset, and second dimensional symbolize the "coefficients values of COCOMO II (a, b)" .

2 -Sheta's Model to obtain best coefficients value(a,b,c) to Predict the cost of the software. And was done to generate matrix form of a three dimensional, the first dimensional symbolize the number of projects in Bailey and Basili dataset [24], and second dimensional symbolize the "coefficients values of COCOMO (a, b,c)".

Where exacted it in Matlab language at the beginning work, the algorithm for squirrels a random population has been created. The algorithm has executed for 100 iterations and for each iteration, the fitness function for the population has been calculated based on MMRE Eq.(15)[25].

$$MMRE=1/n\sum_{i=1}^{n}\frac{|Estimate\ Effort(i)-Actual\ Effort(i)|}{Actual\ Effort(i)} \quad (15)$$

where N =(93 or 60 or 63) represents a number of projects in the NASA dataset or N=(18) represents a number of projects in the Bailey and Basili dataset. And its order in ascending. New locations are calculated for f_a and f_n based on Eq.(3,4,5). Then the calculation of S_c and is S_{min} done using Eq.(10,11). If the S_c is less than or equal to S_{min}, then the position is updated using Eq.(12) and the algorithm works next iteration.

When alliteration has executed the output of optimal solution (the best position of the squirrel on "hickory tree"), are represent coefficients values of COCOMO (a, b,c). And Fig. 1 represents the stage of the "Squirrel search algorithm" that was applied to Predict estimate software cost.

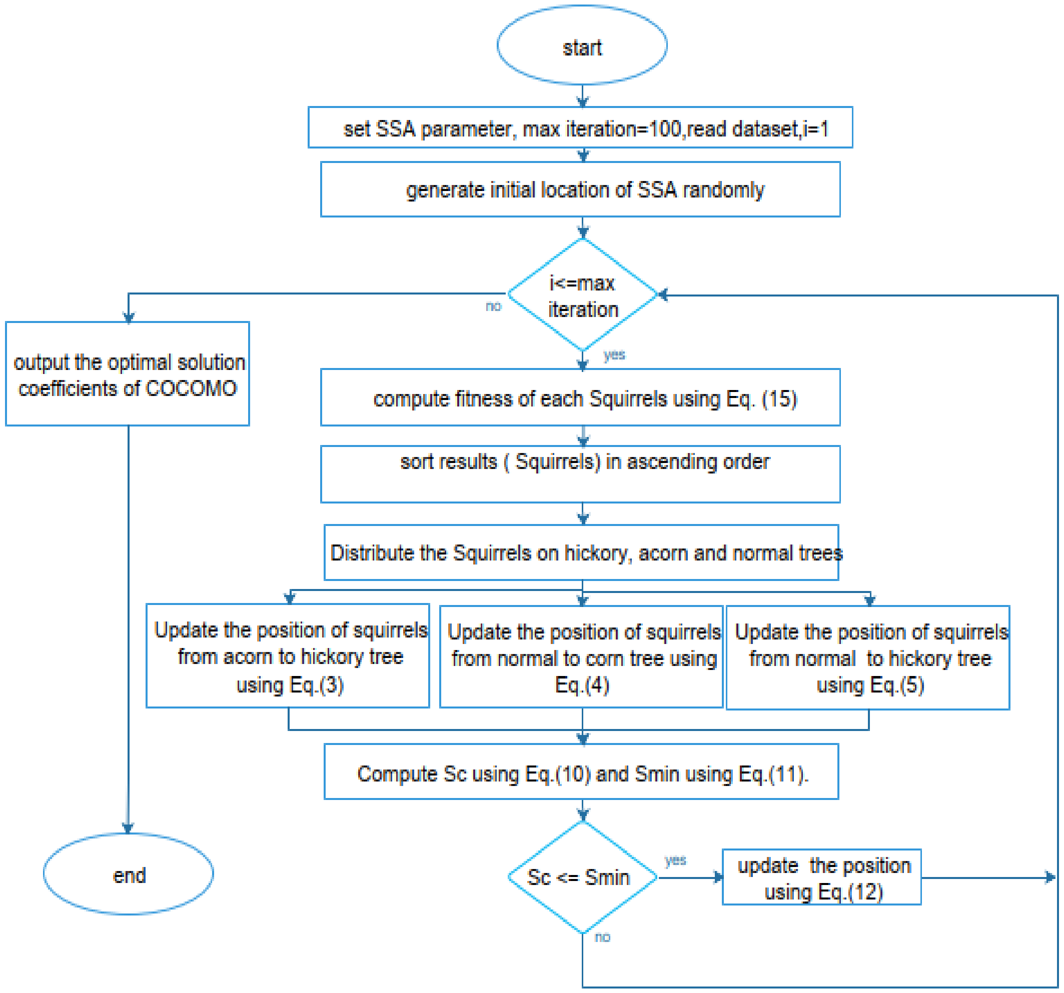

Figure 1. procedures of the Squirrel search algorithm to Predict software cost

6. THE RESULTS AND DISCUSSION

The Squirrel search has executed on four types of datasets :

a) NASA-93 that include information for 93 projects:

The proposed algorithm has compared with several models (COCOMO II model, whale algorithm[14], Bat algorithm [9], CSHS algorithm [11], Genetic algorithm [10], and Dolphin Bat algorithm[6]) on this dataset to Predict the software cost and Table II shows the actual effort and estimate effort for The proposed algorithm and other algorithms for 14 projects. Table III shows the value of the "coefficients (a, b)" and MMER of the suggested model and the models to which it has been compared. Fig. 2 shown the Efficiency of the Squirrel algorithm depending on MMRE least, where it has got the best result for MMRE (48.2993) and thus surpassed DolphBat, which was the value of MMRE(50.2757) and other algorithms.

TABLE II. The estimated effort Squirrel search model with other models for the NASA dataset(93 projects)

Project No	Models							
	Actual effort	COCOMO II	Whale	Bat model	CSHS	GA	DolphBat	Squirrel search

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1	117.6	49.9115	77.5587	80.3913	56.7804	58.1863	69.5742	84.8143
2	117.6	53.8387	84.1708	85.7097	61.5642	62.9535	74.5823	91.0459
3	31.2	18.709	33.5421	22.8864	24.0286	23.411	22.5192	28.366
4	36	19.8114	35.256	24.5832	25.2848	24.6996	24.0283	30.2156
5	25.2	23.0837	40.2739	29.7562	28.9705	28.4985	28.5722	35.7668
6	8.4	5.9834	12.4347	5.5091	8.7103	8.0552	6.189	8.0641
7	10.8	9.1295	17.9621	9.3392	12.6872	11.962	9.9889	12.853
8	352.8	133.2616	185.2574	265.9137	137.9384	147.0223	208.2492	247.474
9	72	21.4708	38.6133	26.1086	27.6484	26.9083	25.7614	32.473
10	72	17.2299	27.6026	26.1715	20.1144	20.3918	23.278	28.5757
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
90	8211	1162.6478	1394.424	3082.0243	1061.7935	1192.284 7	2114.1515	2428.8322
91	480	132.0381	216.6908	191.4675	157.3287	158.146	174.0251	214.8142
92	12	54.788	100.7674	63.8074	71.9074	69.4301	64.2395	81.3931
93	38	28.3002	56.7015	27.9558	39.9397	37.4157	30.3919	39.2696

TABLE III. value of the "coefficients (a, b)" and MMER for the Squirrel model and different models for the NASA dataset(93 projects)

Coefficient	models						
	COCOMO II	**Whale**	**Bat**	**CSHS**	**GA**	**DolphBat**	**Squirrel search**
A	2.94	6.7051	2.2637	4.631	4.1444	2.7643	3.6793
B	0.91	0.7921	1.1368	0.81	0.85163	1.031	1.004
MMRE	57.40	50.6122	53.528	54.04	53.0498	50.2757	48.2993

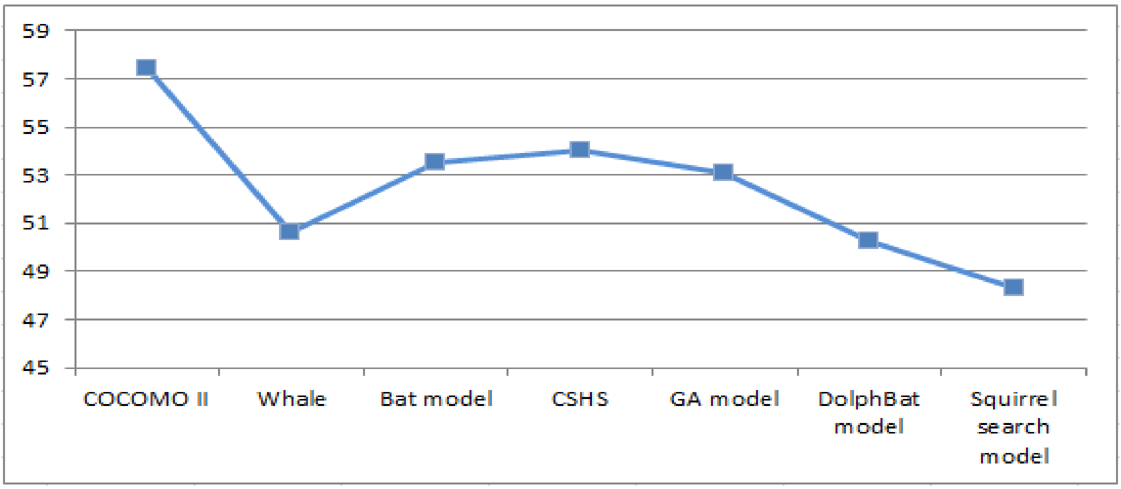

Figure 2. MMER for the Squirrel search model and different algorithms for NASA dataset(93 projects)

b) NASA-60 that include information for 60 projects:

many models as(COCOMO II, bat algorithm[9], Genetic algorithm[10], and Dolphin Bat algorithm[6]), were compared with The proposed algorithm on this dataset to predict the software effort. Table IV shows the actual effort and estimates effort for The proposed algorithm and other algorithms for 14 projects. Table V shows the value of the "coefficients (a, b)" and MMRE of the suggested model and the models to which it has been compared. Fig. 3 shows the values of MMRE. from Table V and Fig. 3 Been noted the Squirrel algorithm gave a slight improvement (by 0.06) over the dolphinbat algorithm in this dataset.

TABLE IV. The estimated effort of the Squirrel search model and other models for the" NASA-60 dataset"

Project No	models					
	Actual effort	COCOMO II	Bat	GA	Dolph Bat	Squirrel search
1	8.4	5.293	5.2376	7.1257	6.9184	9.2288
2	10.8	8.0761	9.0842	10.5817	11.5821	14.6822
3	18	12.1851	15.5272	15.5499	19.1265	23.0721
4	24	7.0772	9.2376	8.9858	11.3037	13.5059
5	25.2	20.4202	30.4322	25.2102	35.9006	40.6908
6	31.2	16.5503	23.142	20.7097	27.7849	32.3009
7	36	16.4896	25.632	20.1769	29.8881	33.3129
8	36	17.5254	24.9348	21.8496	29.7943	34.3984
9	42	21.3547	28.4959	26.9873	34.6576	41.0471
10	42	22.4314	31.6982	28.0064	37.9471	43.93
. . .	. . .	. . .	. . .	. . .	. . .	. . .
60	3240	768.8659	3130.3904	767.4658	2798.0869	2126.2524

TABLE V. value of the "coefficients (a, b)" and MMER for the Squirrel model and different models for "NASA dataset" (60 projects)

Coefficient	models				
	COCOMO II	Bat	GA	Dolph Bat	Squirrel search
A	2.94	2.3403	4.1444	3.2827	4.775
B	0.91	1.186	0.85163	1.1098	1
MMRE	33.9581	16.98	29.9469	14.576	14.5123

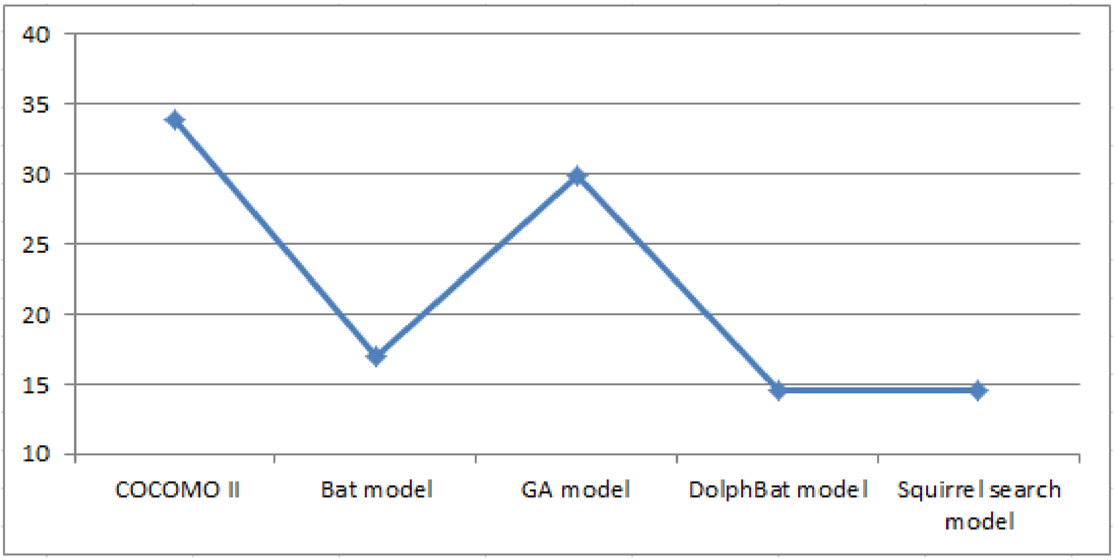

Figure 3. MMER for the Squirrel search model and other models for "NASA-60 dataset"

c) NASA-63 that include information for 63 projects:

many models such as(COCOMO II, Whale algorithm[14], Bat algorithm [9], CSHS algorithm [11], Genetic algorithm [10], and Dolphin Bat algorithm[6]) were compared with The proposed algorithm on this dataset to predict the software effort. Table VI showed the results for 14 projects. Table VII shows the value of the "coefficients (a, b)" and MMER of the suggested model and the models to which it has been compared. The Squirrel search model gave improvement (by 0.36) over the dolphin algorithm, and gave improvement (by 0.36) over the bat algorithm in this dataset.

International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. #, No.# (Mon-20..)

TABLE VI . The estimated effort of the Squirrel search model and other models for "NASA-63 projects"

Project No	Models							
	Actual effort	**COCOMO II**	**Whale**	**Bat model**	**CSHS**	**GA**	**DolphBat**	**Squirrel search**
1	2040	496.7371	648.8235	1117.4711	487.6926	531.3769	827.536	969.4687
2	1600	435.1573	507.9963	1215.0759	388.4069	440.3212	813.5329	928.8588
3	243	86.5871	111.0441	201.7767	83.6996	91.7888	146.9876	171.4767
4	240	121.8027	171.4236	237.363	127.3999	135.2012	187.9537	223.986
5	33	24.0499	39.5553	34.7279	28.7097	28.8365	31.6263	39.0587
6	43	19.3602	37.4959	20.414	26.5479	25.1699	21.5276	27.6007
7	8	6.8525	12.4453	8.1766	8.898	8.6298	8.1393	10.283
8	1075	269.8337	427.4472	418.8217	312.0192	317.5801	368.7798	451.5457
9	423	130.779	199.73	217.7813	146.6065	151.1586	185.5699	225.3229
10	321	108.9465	167.0531	180.0349	122.5465	126.1733	153.9577	187.1099
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
60	57	35.2805	64.2981	41.8176	45.9467	44.5072	41.7568	52.7963
61	50	27.2382	41.9389	44.6545	30.7461	31.6098	38.3286	46.6261
62	38	25.386	44.6254	32.2535	32.064	31.4579	31.18	39.0987
63	15	9.2273	16.0411	11.977	11.5453	11.3716	11.4634	14.3382

TABLE VII . value of the "coefficients (a, b)" and MMER for the Squirrel model and different models for "NASA dataset" (63 projects)

Coefficient	models						
	COCOMO II	**Whale**	**Bat**	**CSHS**	**GA**	**DolphBat**	**Squirrel search**
A	2.94	6.7051	2.2637	4.631	4.1444	2.7643	3.6893
B	0.91	0.7921	1.1368	0.81	0.85163	1.031	1.00
MMRE	30.5664	30.3357	23.8258	29.2126	28.2772	23.9121	23.5453

All previous datasets have been taken from The "PROMISE Repository of Software Engineering Databases".

d - Bailey and Basili dataset :

that includes information for 18 projects and compare (Artificial Bee Colony[26], ALO[15]) to Predict the software cost. Table VIII shows the results of 18 projects. Table IX shows the value of the "coefficients (a, b,c)" and MMER .the Squirrel search model gave improvement (by 0.3) over the ALO. And given high improvement (by 16.37) over the DABC algorithm in this dataset.

TABLE VIII . The estimated effort Squirrel search model with other models for Bailey and Basili dataset(18 projects)

Project No	Models			
	Actual effort	**Artificial Bee Colony**	**ALO**	**Squirrel search**
1	115.8	124.8585	15.7999	115.6646
2	96	74.8467	58.3195	63.4677
3	79	75.4852	58.6023	63.8058
4	90.8	85.4349	68.8641	73.5436
5	39.6	50.5815	40.7873	45.0676
6	98.4	99.0504	125.1979	89.2865
7	18.9	24.148	17.4059	20.5778
8	10.3	18.0105	15.4182	17.5753
9	28.5	37.2724	28.5000	32.5049
10	7	4.5849	5.9414	6.2915
11	9	8.9384	6.5270	7.8271
12	7.3	13.5926	11.9109	13.5965
13	5	1.51	5.0000	4.7134
14	8.4	8.2544	8.4268	9.3529
15	98.7	110.5249	101.2579	102.4408
16	15.6	18.2559	13.7817	16.2307
17	23.9	23.369	17.1413	20.1884
18	138.3	135.4825	129.9849	127.8461

TABLE IX. value of the "coefficients (a, b,c)" and MMER for the Squirrel model and different models for Bailey and Basili dataset(18 projects)

Coefficient	models

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	Sheta's Model	DABC	ALO	Squirrel search
A	3.1938	5.4507	1.9174	2.001
B	0.8209	0.7082	0.90948	0.89948
C	− 0.1918	− 0.3184	0.024546	0.029046
MMRE	23.27	23.79	7.2	6.9

7. CONCLUSIONS AND FUTURE WORKS

One of the main problems in software development projects is to estimate software cost. The Inaccurate estimate leads to problems and difficulties in project management and monitoring. This paper has used the Squirrel search algorithm to enhance the COCOMO coefficients that are required in cost estimation for a software project. Where the Squirrel search is Equivalent for the boost job, with fewer persons and extra fitness function By Dynamic foraging behavior to getting the food and compute seasonal constant (Sc). That represents a difference of strategies to get the solution effectively. The suggested algorithm has implemented on two models:

first, the COCOMO II where have executed on three types of the dataset when applying the algorithm on the NASA-93 dataset has been obtaining the value of MMRE equal (48.2993), and on NASA-60 dataset has obtained the value of MMRE equal (14.5123), and on the NASA-63 dataset has obtained the value of MMRE equal (23.5453).

The second, Sheta's model that applied to the Bailey and Basili dataset and value of MMRE has equal (6.9).

The results confirm that the applied algorithm in this work is better than the previous algorithms.

In future work, Could develop by merging a Squirrel search model with new models or apply modern approaches to estimate the cost of the software project.

ACKNOWLEDGMENT

The author wants to express to thank the University of Mosul/ College of Computer Sciences and Mathematics for their supplied help, which assisted to enhance of this work.

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