A Novel Hybrid Artificial Immune System with Genetic Algorithm for Software Cost Estimation

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Abstract: *Inaccurate estimation of software projects is of the important and obvious causes of project failures. Studying the related literature we notice that different models have been proposed for Software Cost Estimation (SCE) among which COCOMO model is the most prevalent and common one. Lack of a unique standard for measuring the software development costs and heterogeneous estimations are considered two problematic challenges in software industry. Since Meta-heuristic algorithms are among the most widespread algorithms in solving complicated and optimization problems, we have utilized a combination of Genetic Algorithm (GA) and Artificial Immune System (AIS) in evaluating metrics and software criteria in SCE. The present study has used the NASA60 dataset to evaluate the results. PRED, Magnitude of Relative Error (MRE) and Mean MRE (MMRE) assessment indices were used to compare the results of hybrid model. The findings revealed that the hybrid model outperformed the other models regarding estimation accuracy.*

Keywords: *Software Cost Estimation, COCOMO, Genetic Algorithm, Artificial Immune System*

1. Introduction

Success of project based on an accurate SCE is one of the most significant issues in project management. Based on the conducted statistical studies, it has been revealed that a majority of the software projects were not completed within the cost and time schedule on delivery time which leads to dissatisfaction of customers [1]. One of the most important causes to project failure is the improper estimation of cost and timing at the beginning of the project [2, 3]. In software project issues improper estimation of timing and cost at the beginning of deigning phase causes the management and planning of the project to be based on irrational estimations and thus the obtained estimation is unreal and cannot be relied on [4, 5]. On the other hand, wrong estimations brings about false expectations in customers and also imposes financial and time loses on company.

It can be claimed that nowadays SCE is and will be one of the most crucial issues for managers and executives and software system analyst. Studies carried out in SCE results in failure and success in software projects [6, 7]. The way we face a crises seems to be the main point in the failure phenomenon. In other words the problem is related to all staff and the team of project so all should be ready to face and try to solve it. In the success phenomenon we can take on time completion of the project into account along with determined time and budget. The applied mechanism in estimating the soft ware project effort and cost is usually based on the following techniques [8, 9]:

- Estimation based on software experts' comments: it shows the rational and mental process of effort estimation and is often based of prior experiences in developing and managing similar projects.
- Algorithmic estimation: this kind of estimation is used in estimation and production of projects which obviously shows the relationship between the efforts of one or several project

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properties using linear equations. These techniques have been the most prevalent ones in SCE so far.

The most common method in SCE are algorithmic model such as COCOMO [10, 11], SLIM [12] and Function Point (FP) [13]. These models work based on a linier function and series of input factors which highly affect the project. Algorithmic models utilize properties like Line of Code (LOC) and complexity for development estimation of software projects. SCE enables the company to figure out the required effort to complete the project within the determined time and budget before implementation of the software projects. Having adequate knowledge of the similar projects conducted by the company and the good knowledge about effective variables seem too necessary in estimation of cost and effort [14, 15]. Variables such as number of developers contributing the project, average of developers' experience in using developing tools in terms of working years and programming language are highly effective. Each estimator should take the following into account in order to estimate the cost and implementation time of the software project [1, 4]:

- Estimator should give the description of system, rules, assumptions and technical and functional feature. The analysis of cost and timing should be clearly determined to ensure the preparation of final project documentation.
- The whole development team should take part in decision making about the estimated cost and defining system parameters and other data features. And the accuracy perfectness and reliability of the estimation should be independently confirmed.
- Related and appropriate references should be accessible and available. Former data should be used in similar system and these data should be directly related to functional features of the similar system.
- The estimator should make sure that economic changes such as inflation are embedded properly in SCE. Estimator should independently control the investigation and correction of the estimation to ensure the realism and perfectness.

SCE plays a significant role in development cycle management decision making and quality of software projects. Estimations should be made to decrease the costs, timing and possible risks in order to prevent the failure of the project [15]. Since accuracy and reliability of effort and cost are vital to the success of the software, companies do their best to develop accurate models in order to achieve effort estimation close to actual level. Thus, in the present study we have used AIS [16, 17] and GA [18] hybrid model for SCE. Meta-heuristic algorithms are more effective in solving optimization problems among Artificial Intelligence (AI) based models while there exists no complicated relationship between the input and output parameters of meta-heuristic algorithm [19]. AIS algorithm which is a search algorithm based on population is inspired by the defense mechanism of immune system in living organism. This algorithm is derived from performance mode of immune system of living organism facing eternal pathogenic factors and protecting the body against them.

This paper is organized as follows: in Section 2, we will describe the studies previous works; in Section 3, we will describe the proposed model; in Section 4, we will describe the evaluation and results of proposed model; finally, in Section 5, presents the conclusions and future works.

2. Previous Works

Most of the developed models used in SCE estimate the cost and effort indirectly using size software. Among the indirect COCOMO model based LOC is widely used. Therefore, there is a need to develop methodologies which consider SCE according to factors like software complexity. Despite the vast studies in SCE field yet there is no general concurrence on the most

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appropriate method to be used by software production and development companies. In most of the models studied in the present study, researchers have used AI based models for SCE.

The Multi Objective Particle Swarm Optimization (MOPSO) hybrid model is proposed for SCE [20]. The evaluation of the model is done on COCOMO dataset with 20 and 21 projects and MOPSO algorithm is used as a means of optimization of COCOMO model parameters. The results of 20 projects show that the MARE value in COCOMO model equals to 16.13 while in MOPSO is 9.01. In addition, PRED (25) accuracy in COCOMO is 20 but in MOPSO is 24. The results obtained from 21 projects show that the MARE value in COCOMO model equals to 18.15 while in MOPSO is 20.97. In addition, PRED (25) accuracy in COCOMO is 17 but in MOPSO is 20. MOPSO model has outperformed the COCOMO model testing on 20 projects. The Clustered GA with Neural Network (CGANN) hybrid model is proposed for SCE [21]. CGANN model is a combination of Fuzzy C-Means (FCM), GA and Artificial Neural Network (ANN) algorithms. In this model, FCM algorithm is used for clustering the input data, GA is used for optimizing the parameters of COCOMO model and ANN model is used to test and train the data. The results of the conducted evaluation on 63 projects showed that MMRE values in training and testing phases for CGANN model are 0.42% and 0.33% and for COCOMO model are 0.51% and 1.23% respectively. PRED (25) accuracy in training and testing phases equal 0.545 and 0.50% for CGANN model and 0.44% and 0.33% for COCOMO model respectively. The Median Magnitude of Relative Error (MdMRE) values in the above mentioned phases are 0.30% and 0.24% for CGANN and for COCOMO model equal 0.333% and 0.38%.

MLP, Radial Basis Function (RBF), Support Vector Machines (SVM) and PSO-SVM models have been tested and evaluated on COCOMO II dataset [22]. PRED (25) and MMRE criteria were measured in these models. MMRE error value during training and testing phases for MLP model are 0.14 and 0.30 respectively and are 0.12 and 0.29 for RBF model. In SVM are 0.20 and 0.16 and for PSO-SVM model are 0.15 and 0.03 respectively. PRED (25) accuracy during the two above mentioned phases for MLP model equal 91.72 and 42.85, for RBF equal 47.61 and 88.17, for SVM model are 85.56 and 94.12 and for PSO-SVM model are 93.65 and 63.44 respectively as well. PSO-FCM and PSO-LA hybrid models are proposed for SCE [23]. The evaluation is carried out on NASA60 dataset. The minimum inter-cluster, total intra-cluster distances and number of clusters are used in PSO-FCM model as fitness and PSO algorithm optimization parameters. Using Fuzzy C-Means (FCM) makes the particles to be accumulated in the best cluster and make the fitness function to have local optimized points. Learning Automata (LA) is used to regulate the behavior of the particles in order to improve efficiency. In PSO-LA hybrid model, all the particles start local search in the search area simultaneously. In this model, the LA strategy provides an opportunity for PSO model sot that the particles can get to several local optimum. The results of the experiments revealed that PSO-FCM hybrid model has lower MRE rate in comparison with PSO-LA hybrid model. The MMRE value respectively 25.36, 24.45, 24.22 and 23.86 for PSO-FCM model and in PSO-LA model were 26.32. PRED (25) accuracy value for COCOMO equaled 40 and for PSO-FCM were 61.6, 58.3, 65 and 68.3. It is also 63.3 for PSO-LA model.

A new model effort estimation for software projects is proposed using PSO algorithm and the effective parameters are evaluated through PSO algorithm too [24]. The evaluation is done with 15 projects on KEMERER dataset. The findings showed that MMRE value for the proposed model is 56.57 and for COCOMO model equals 245.39. The GA and Ant Colony Optimization (ACO) hybrid model are proposed for SCE based on training and testing software project factors [25]. The model is evaluated on NASA60 dataset. Data training phase are done using ACO and testing data is carried out using GA. The results of experiments on 10 projects revealed that the hybrid model in comparison to COCOMO model

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has almost lower MRE value in 0.9 of the projects. MMRE value for 60 projects in hybrid model equals 27.53 and in COCOMO is 29.64. The hybrid model has decreased MMRE value 1.07 times. To estimate cost and effort of the software project, Fuzzy and COCOMO hybrid model is proposed [26]. Evaluation carried out on 30 projects on COCOMO dataset. Fuzzy model is used to optimize parameters of COCOMO model. The results indicate that MMRE Value is 11.00% for COCOMO II and in hybrid model is 7.51%. PRED (25) and PRED (15) are respectively 93.33% and 63.335 for COCOMO II and equal 96.33% and 93.33% for the hybrid model respectively. The Variance Account For (VAF) values in COCOMO II and the hybrid model are 95.86% and 98.77% respectively. The comparisons revealed that the hybrid model have decreased MMRE 1.46 times and increased PRED (25) accuracy 1.47 times.

Support Vector Regression (SVR) ،ANNs ،Liner Regression (LR) and K Nearest Neighbors (KNN) were used for SCE [27]. Dependency of effective traits in SCE is determined using LR model. LR finds the relationship between the dependent and independent variables. ANNs reduces the MRE by training and testing the data. SVR is used to optimize the effective factors in SCE. KNN is a data mining technique which is utilized to categorize the data into an already classified set of data that their traits are determined. KNN also determines the weights of effective traits in SCE. Accuracy of the prediction on training data in LR, ANN, SVR and KNN are 745, 87%, 95% and 68% respectively. Accuracy on tested data in LR, ANN, SVR and KNN are also 39.17%, 12.07%, 36.32% and 1.12%. In addition, Root Mean Square Error (RMSE) values in LR, ANN, SVR and KNN are respectively 11.6%, 2.37%, 20.08% and 0.77%. The findings show that KNN model has lower Mean of Absolute Errors (MAE) compared to other ones. ANN-MLP is one of the most common methods in SCE [28]. In order to determine its efficiency, 60 software projects in NASA dataset were tested and trained that 11 projects were compared with COCOMO and it was revealed that MRE value in COCOMO model was more than ANNs. 80% of the projects were used for training and 20% of them were used for testing. The findings showed that in 90% of the projects, ANNs gave a better estimation compared to COCOMO.

Fuzzy logic hybrid model and PSO are proposed for SCE [29]. Evaluation is done on NASA software project dataset. A triangular membership function was used for fuzzification. In general PSO algorithm is used to perform two fundamental change and reform in triangular membership function. First, training membership function to increase diagnosis rate. Second, removing improper rules in order to decrease the number of fuzzy rules and increase accuracy and generalizability. PSO algorithm is also used for defuzzification of membership function factors. During the implementation and different tests, error rate in estimation and number of required fuzzy rules has decreased a lot for different parameters and using PSO algorithm. The results show that the hybrid model has lower MARE in comparison to COCOMO. Morphological-Rank-Linear (MRL) is proposed for SCE based on linear regression function [30]. The evaluation is done on NASA dataset with 18 projects. The findings of NASA dataset revealed that PRED (25) accuracy in MRL model is 94.44%, in SVR-Linear and SVR-RBF is 83.33%, and in RBF-SG and LR models is 72.22%. MMRE values in MRL equal 0.08% and in SVR-Linear and SVR-RBF models equal 0.1810 and 0.1890 respectively. It equals 18.70 and 0.2330 in RBF-SG and LR models respectively. Project cost estimation of proposed model in comparison to actual model has better accuracy and has been able to minimize the cost estimation.

Radial Basis Neural Network (RBNN) and Regression Neural Network (GRNN) has been proposed for SCE [31]. Efficiency evaluation of the model is carried out on COCOMO81 dataset. The results indicate that MARE value in COCOMO model is 19.45 and PRED (25) accuracy is 87.3 while in RBNN and GRNN models, MARE values equal 7.13 and 14.19 and PRED (25) accuracy are 90.48 and 84.13

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respectively. Comparing RBNN model with GRNN model, MMRE is lower in the former one. Another model based on ANNs is proposed for SCE [32]. For higher efficiency of the network, Single Layer Artificial Neural Network (SLANN) mode is used combining SLANN-Back Propagation (SLANNBP) and SLANNRPROP (SLANN-Resilient Back Propagation Algorithm) algorithms for training. The evaluation is done on COCOMO II dataset. PRED (40) accuracy in COCOMO model equals 41.65 and in SLANNBP and SLANNRPROP 76.92 respectively. MMRE value in COCOMO model equals 41.65 and in SLANNBP and SLANNRPROP are 32.72 and 30.22 respectively. PRED (40) accuracy in SLANNBP and SLANNRPROP models has increased 1.42 times in comparison to COCOMO model. MMRE in SLANNBP and SLANNRPROP models compared to COCOMO model has decreased as well.

AI based methods such as data mining techniques, ANNs and meta-heuristic algorithms are proposed as complements or alternatives to algorithmic and experts' experience based methods. Nowadays it has been proved that artificial intelligence based methods in different conditions compensate for the efficiency weaknesses of the former methods and produce better results applying learning methods on the data.

3. Proposed Model

Planning and determining the cost is one of the most important activities in software projects to produce and develop software projects. SCE is considered one of the most difficult issues of management in software projects. Effort Multipliers (EM) factors determine the required effort to complete the software project and SCE factors in NASA60 dataset projects include programmer development tools data set size and etc. [33]. Development team cost, testing and implementation, software management cost and control management cost consist the most important project cost which all requires acceptable result and estimation with an error value close to the real value [33]. SCE deals with estimation of probable cost and time for project completion. In general SCE is based on anticipation of LOC size. The obtained estimation seems to be inaccurate and impossible during first phases of software development cycle due to the insufficient information about the system at that period of time. This estimation is vital to companies and software developers since it can provide them with cost control delivery precision and other advantages [33]. Currently we have few model develop for SCE most of which function based on measuring LOC and FP. It is clear that size estimation accuracy directly affect cost estimation accuracy thus new alternatives such as Meta-heuristic algorithms can be a good option for SCE. The flowchart of the proposed model is illustrated in Figure (1).

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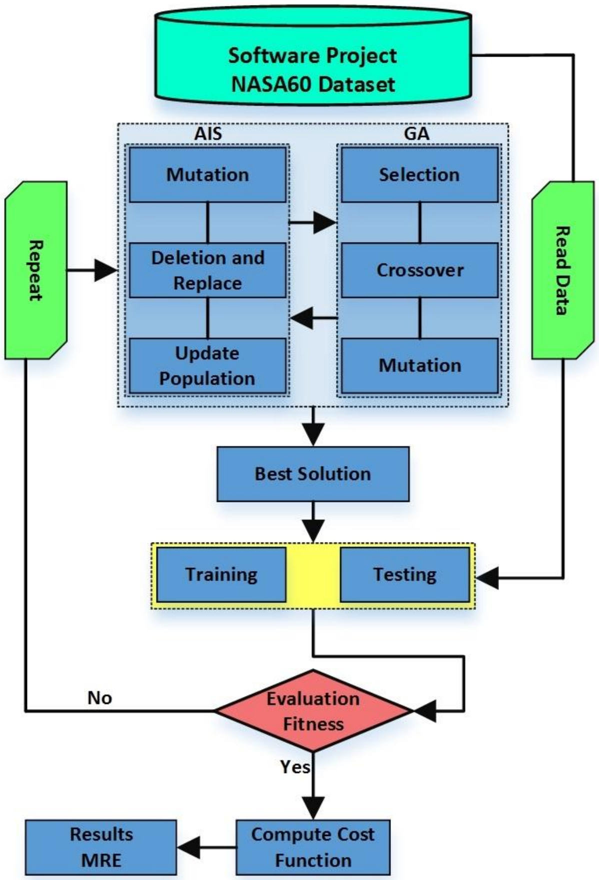

Figure. 1. Flowchart of the Proposed Model

A combination of AIS and GA operators have been used in the hybrid model to find the most optimized value for dataset aiming at estimating cost and effort. Fifteen EM factors were analyzed to obtain a better and integrated estimation. In the hybrid model the AIS algorithm tries to find the most optimized values based on LOC for the project and GA works on value training through re-optimization and selecting the most optimized values. At the end the objective function is evaluated and the values are tested on the dataset if the problem has reached an optimized condition. In the hybrid model, MMRE is considered as a fitness function which aims at minimizing the MMRE value in comparison to GA and AIS algorithms and COCOMO model. MMRE is repeated to reach a desired amount. The fitness function for the hybrid model is defined in Eq. (2) [34].

$$MRE_i = \frac{|act_i - est_i|}{act_i} \times 100 \tag{1}$$

$$MMRE = \frac{1}{n}\sum_{i=1}^{n} MRE_i \, , i = 1,2,...,n \tag{2}$$

The total errors obtained from estimation models can be compared using Eq. (2). In addition PRED is regarded as an important criterion in estimation accuracy. The most commonly used methods of investigating the estimation accuracy are MMRE and PRED. PRED(x) is defined as Eq. (3) [34].

$$PRED(x) = \frac{1}{n} \times \sum_{i=1}^{n} MRE \le x \tag{3}$$

PRED(x) which is defined based on MRE is mostly used in estimation accuracy and provides a good illustration of performance of the models. A model which has got lower MRE in comparison to the one with higher MRE is better in estimation model evaluation and also models with lower MMRE outperform models with higher MMRE. It also should be mention that models with higher PRED are desired more.

4. Evaluation and Results

The evaluation of hybrid model was done on 60 projects of NASA60 dataset projects and the simulation of the hybrid model was done using VC#.NET 2013 programmer. Factors such as initial values of the parameters and fitness function were taken into consideration since they play a vital role in achieving convergence and optimized solution. The parameter values are shown in Table (1).

Table 1. Values of the Parameters

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Parameters	Value
N_P	50
P_C	0.7
P_M	0.3
N_G	50
Elitism	0.20
Selection	30%
D_R	0.2
R_R	0.6
Fitness Function	MMRE

In Table (1), N_P represents the number of initial population, P_C parameter shows the crossover rate, P_M mutation rate, N_G is the number of generation to achieve an optimized solution, D_R is the removal rate of the genes which do not affect the optimization and R_R represents the replacement rate of the genes which are highly effective on achieving an optimized solution.

The MRE values of the models are shown in Table (2). As it can be observed, estimation accuracy in COCOMO model is lower than AIS, GA and hybrid model. It can also be seen that accuracy of AIS and GA models is remarkably low in comparison to hybrid model. It cannot be strongly claimed that AIS and GA models are better than COCOMO model due to the fact that in some projects COCOMO mode better but based on the results MRE value in hybrid model is better than COCOMO model.

Table 2. MRE Comparison Diagram of the Models

No.	KSLOC	Actual Effort	MRE COCOMO	MRE AIS	MRE GA	MRE Hybrid Model
1	2.2	8.4	24.15	13.65	8.95	6.32
2	3.5	10.8	3.95	5.26	4.69	1.13
3	5.5	18	7.36	5.21	6.75	4.35
4	6	24	58.88	34.10	27.63	28.02
5	9.7	25.2	20.05	11.50	13.49	7.61
6	7.7	31.2	23.91	12.35	7.54	12.42
7	11.3	36	30.83	17.45	12.45	13.35
8	8.2	36	29.55	16.68	14.23	11.21
9	6.5	42	28.22	18.52	11.64	13.42
10	8	42	22.22	13.21	15.47	9.34
11	20	48	27.21	14.65	16.32	12.16
12	10	48	41.66	23.98	19.84	19.84
13	15	48	46.19	28.04	23.11	26.74
14	10.4	50	34.90	25.47	17.02	21.95
15	13	60	9.36	6.53	5.31	7.15
16	14	60	25.88	15.41	17.54	8.46
17	19.7	60	6.10	7.21	4.21	2.54
18	32.5	60	93.91	47.35	56.47	36.10
19	31.5	60	3.81	6.52	5.46	1.07
20	12.8	62	27.96	13.11	10.84	4.31
21	15.4	70	22.51	10.13	12.76	7.02
22	20	72	60.76	45.68	33.82	27.11
23	7.5	72	41.75	32.61	24.15	15.04
24	16.3	82	29.79	23.40	17.37	7.46
25	15	90	39.54	27.68	21.51	19.01

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26	11.4	98.8	42.04	25.10	19.07	21.74
27	21	107	36.75	24.55	16.53	9.02
28	16	114	34.48	18.65	15.21	8.30
29	25.9	117.6	27.85	19.36	11.57	17.09
30	24.6	117.6	31.65	21.87	16.34	14.82
31	29.5	120	18.94	11.15	7.13	6.44
32	19.3	155	35.78	17.30	21.06	16.72
33	32.6	170	29.88	19.54	15.19	5.68
34	35.5	192	32.10	16.35	8.37	13.06
35	38	210	28.46	13.19	19.50	15.43
36	48.5	239	24.31	8.43	12.07	7.94
37	47.5	252	37.81	21.36	18.64	11.83
38	70	278	21.28	9.42	11.46	6.24
39	66.6	300	23.76	11.30	16.79	9.22
40	66.6	352.8	35.17	19.25	11.20	13.62
41	50	370	36.90	23.54	13.48	7.42
42	79	400	45.74	31.29	22.97	18.06
43	90	450	38.29	20.11	31.73	15.94
44	78	571.4	24.50	13.64	8.03	5.21
45	100	215	120.66	86.14	61.42	51.04
46	150	324	49.50	26.80	13.09	23.83
47	100	360	44.97	17.67	25.07	12.62
48	100	360	15.85	6.23	8.62	9.84
49	190	420	1.89	4.87	3.84	2.65
50	115.8	480	11.37	16.49	5.32	5.42
51	101	750	19.87	10.67	6.46	12.71
52	161.1	815	4.76	10.25	8.41	5.95
53	284.7	973	38.36	21.43	17.09	10.14
54	227	1181	3.93	2.36	6.31	4.62
55	177.9	1228	3.64	9.84	5.08	2.06
56	282.1	1368	17.21	9.46	11.36	7.92
57	219	2120	29.00	21.03	15.81	8.31
58	423	2300	25.78	16.07	7.44	9.02
59	302	2400	0.46	3.24	5.64	2.54
60	370	3240	25.21	8.62	3.21	6.87

MRE comparison diagram of the models is shown in Figure (2). As we see, the MRE value diagram has dropped in hybrid model compared to COCOMO model and in a number of the projects MRE error value in comparison to AIS and GA models has increased.

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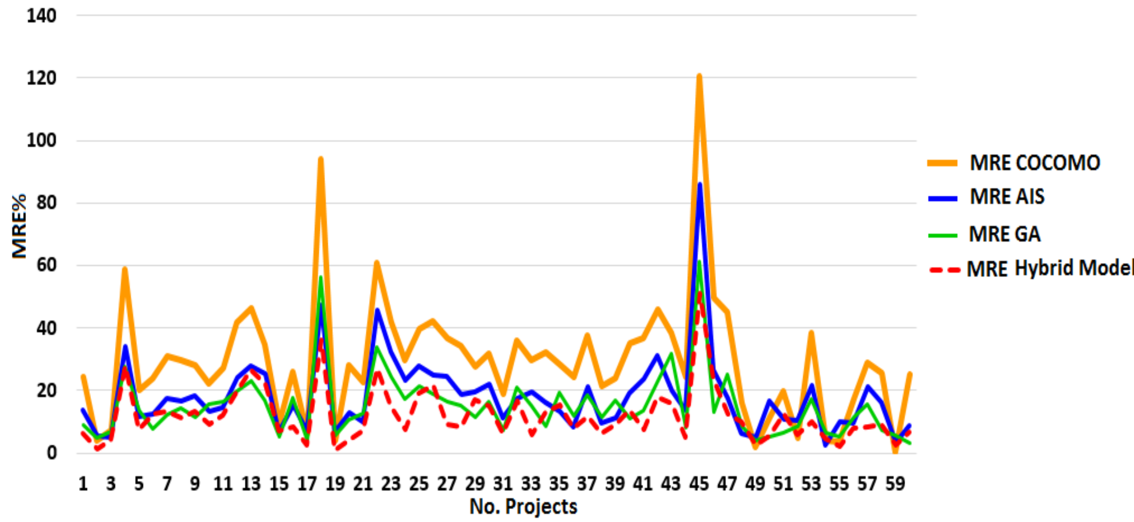

Figure. 2. Comparing MRE of the Models on NASA60

In Table (3) the evaluation criteria are compared. PRED (20) accuracy equal to 40 and 93.33 in COCOMO and hybrid models respectively that shows higher accuracy of the hybrid model. GA and AIS models were also able to increase accuracy 2.25 and 1.95 times more compared to COCOMO model.

Table 3. Evaluation of the Models

Criterion	Models			
	COCOMO	**AIS**	**GA**	**Hybrid Model**
MMRE	29.64	18.20	15.15	12.04
PRED(20)	40	78.33	90.00	93.33

In Figure (3) we can see that PRED (20) criterion is tested on 60 projects and the red area shows low PRED (20) accuracy and blue area represents high PRED (20) accuracy. PRED accuracy is determined in terms of MRE criterion. The model in which the MRE value is lower than PRED (20) is more accurate.

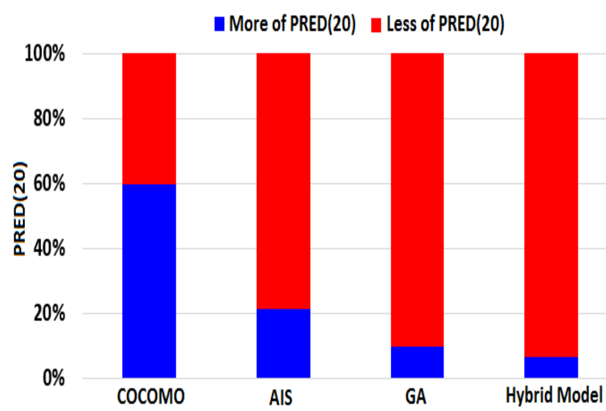

Figure. 3. Comparison of PRED on the Models.

5. Conclusion and Future Works

An accurate estimation of cost and effort in software projects in the initial stages is of utmost importance knowing the fact that a lot of causes

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and factors affect the development of a project. Not only the effort estimation techniques affect the prediction accuracy, but also the factors of software project dataset are effective too. Thus, comparing different SCE techniques is often necessary and always finding a technique with higher estimation accuracy should be the goal. The present study used the GA and AIS hybrid models for SCE. The findings revealed that the hybrid model owns a higher PRED accuracy in comparison to COCOMO model and has increased it 2.33 times. This study hopes that more accurate estimation can be achieved combining COCOMO model with other meta-heuristic algorithms in future.

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