A Novel Hybrid Model of Scatter Search and Genetic Algorithms for Software Cost Estimation

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Abstract: *Software Cost Estimation (SCE) is on the challenging issues in software project management to avoid project failure. The most exact and accurate estimation of costs and efforts in software projects is the one which based on it; the development team can complete the project with specified resources within specified timing. All models of SCE try to do an estimation of the costs and efforts close to the real one with lowest error. COCOMO model is the most common linear model for SCE. In this model which utilizes a simple linear formula, all factors of the project are not fully taken into consideration so those models should be preferred that use training and testing patterns for real estimation. Meta-heuristic algorithms are suitable for SCE due to their nature of diversity and fitness. On conducting the present study we have used a hybrid model of Scatter Search (SS) and Genetic Algorithm (GA) for SCE. Using the proposed model, NASA60 and NASA93 data sets with lower Mean Magnitude of Relative Error (MMRE) in comparison to COCOMO model were obtained.*

Keywords: *Software Cost Estimation, COCOMO, Scatter Search, Genetic Algorithm*

1. Introduction

Nowadays, the necessity of a good and exact estimation in order to get a true estimation of timing and costs of projects and of required resources which directly affect the proper project implementation, management and productivity, plays a vital role in all software development companies [1]. In a world that companies are competing more and more everyday and little differences in offered prices can lead to accomplishment of bankruptcy of companies, providing an accurate estimation which complies with reality and can include all costs in the project model is of utmost importance [2]. By widespread using of an appropriate model for SCE, the duration of project implementation becomes a determining factor in evaluating price offering in tenders and development process. Thus, the managers do not only focus of decreasing the project cost during the development process but also try to make the implementation time shorter, because increased project implementation time leads to gradual increase of the direct costs of the project. Hence, regardless of overhead cost, increase in project implementation duration usually results in increasing its costs.

Including quality factor in addition to time and costs, despite the difficulties in quantifying it for project activities, is another effective factor in choosing estimation models and managers should try to find ways that can both decrease time and costs of the project and at the same time increase its implementation quality [3, 4]. The costs of

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projects are divided in to direct and indirect costs [5, 6]. Project direct costs are the total direct costs of all activities in the project and what are meant by indirect costs are the overhead and management costs which depend on the length of project implementation time. The longer the time of a project, the higher the indirect costs will become. Ideally project implementation costs can be estimated based on similar completed projects. But in some different activities and projects, prior activities and being realistic seems impossible. In addition, if the duration of the project gets longer, we have take the probability of price inflation in coming years and other factors into consideration too. The wages may also change in long term and increase in costs and management, and money management may change for software development process.

In the present industrial world, software production and development projects are look at as economic that generate and software development companies are in such conditions increasing competitive pressures, variety in products, changes in items of costumers' and expectations are increase specifications [7]. While software products should be much qualitative, they can stay in market only for a short time and are replaced by products compatible with the latest tastes and needs of customers. Disregarding customers' demands and failure in timely delivery of the product may cost a lot for the company. The above mentioned conditions cause the SCE issues to be so important for software development companies. Efforts and cost based estimation mainly emphasizes the benefit, success of human resources and investments for development.

One of the most important goals of software development companies is to develop efficient models which can manage software production process accurately and pay adequate attention to SCE. The recent SCE models like COCOMO [8, 9] and Function Point [10] cannot provide exact and accurate estimation due to the fact that mathematical Functions are linear and project factors are not exact. Thus, the applied algorithmic models in cost estimation cannot have required efficiency because of uncertainty in the data. A new hybrid model based on SS [11] and GA [12] is used for time and cost reduction and quality increase in this paper. SS is a suitable algorithm for solving optimization problems that the answers are distributed in the form of a network of point in answer search space. This algorithm is able to start from an initial point and find the best point or point among the possible answers with a high confidence by a targeted point search. Nowadays population based algorithms are widely used optimization [13, 14]. Success of Meta-heuristic algorithms in reaching to the answer generally relies on the type of problem and guarantees gaining an optimized answer. Although algorithmic models even in the cases of being able to solve the problem, do not guarantee that the reached answer is optimal, lose their efficiency by the increase in numbers of designing factors and complexity. Therefore, solving problems with more dimensions and higher complexity using algorithmic models seems impossible.

The overall structure of the present 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, we will take the conclusions and future works.

2. Previous Works

In the last few decades, different models of SCE have been presented in order to estimate the time, cost and production quality of software projects. Having considered the efforts and costs as the basic criteria in the success of the projects, most of the researches in this area are allotted to the simultaneous optimization of time and implementation costs.

The hybrid models of PSO-FCM and PSO-LA are proposed for SCE [15]. The evaluation of the model is done on NASA60 dataset. The minimum distance between clusters, the total intra-cluster distances and number of clusters have been used as the fitness and improvement parameters of PSO algorithm in the PSO-FCM combined model. Using Fuzzy C-Means (FCM) causes the particles to accumulate in the best possible cluster and fitness function to have many optimal local points. Learning Automata (LA) is used for adjusting the practical behavior to improve efficiency of PSO algorithm. In LA-PSO combined model, all the particles look for a location in the search space simultaneously. The LA strategy in the PSO-LA model with taking the reward criteria for PSO algorithm into account enables the particles to reach several local optimizations. The results show that PSO-FCM combined model has got lower MRE error rate compared to PSO-LA hybrid model. The MMRE in PSO-FCM equals to 25.36, 24.56, 24.22 and 23.86 while in PSO-LA is 26.32. The PRED (25) accuracy in COCOMO model equals to 40 and in PSO-FCM model is 61.6, 58.3, 65 and 68.3. And also in PSO-LA model is 63.3. The hybrid model of Ant Colony Optimization (ACO) and GA is proposed for SCE based on the training and testing software project factors [16]. The evaluation of the hybrid model is done on the NASA60 dataset. The training phase of data is conducted using ACO and tasting phase by using GA. The obtained results from 10 projects reveals that the hybrid model in comparison to COCOMO model has lower MRE error in 0.9 of projects. Also the MMRE in 60 projects is 27.53 in combined model and 29.64 in COCOMO model. The hybrid model has reduced the MMRE 1.07 times. Localized Multi-Estimator Software (LMES) model is proposed for SCE based on choosing the most optimal effort and cost factors [17]. The evaluation of this model is done on COCOMO, Maxwell and ISBSG datasets. The results of ISBSG dataset reveal that the MMRE value in LMES model equals to 0.31 and in Multiple Linear Regression (MLR), Stepwise Regression (SWR) and Artificial Neural Network (ANN) models are 1.49, 0.93 and 1.22 respectively. The PRED (25) accuracy in LMES model is 0.61 and in MLR, SWR and ANN models are 0.12, 0.21 and 0.17 respectively. The obtained results from Maxwell dataset indicate that the MMRE value in LMES model equals to 0.41 and in MLR, SWR and ANN models are 1.08, 1.42 and 0.97 respectively. In addition, the PRED (25) accuracy in LMES model is 0.57 and in MLR, SWR and ANN models are 0.23, 0.19 and 0.28 respectively. The results of COCOMO dataset reveal that the MMRE value in LMES model equals to 0.35 and in MLR, SWR and ANN models are 1.54, 1.25 and 0.75 respectively. The PRED (25) accuracy in LMES model is 0.66 and in MLR, SWR and ANN models are 0.15, 0.17 and 0.29 respectively. In most of the cases results show that LMSE model has outperformed MLR, SWR and ANN models.

The hybrid model of Particle Swarm Optimized Functional Link ANN (PSO-

FLANN) is proposed for SCE [18]. The evaluation of the model is done on COCOMO81, NASA93 and Maxwell datasets. PSO algorithm is used for training FLANN network as well as optimization of hidden layer by particles. The results of COCOMO81 dataset reveals that in PSO-FLANN model the MMRE in training and testing phases are 0.43 and 0.37 respectively and the Median Magnitude of Relative Error (MdMRE) are 0.48 and 0.42 respectively and the PRED (25) accuracy are 0.39 and 0.52 respectively. Training phases and data test for the MMRE in FLANN model are 0.45 and 0.38 respectively and for the MdMRE are 0.49 and 0.47 respectively and for the PRED (25) accuracy are 0.35 and 0.49 respectively. The results of NASA93 dataset reveals that training phases and data test for the MMRE in PSO-FLANN model are 0.49 and 0.34 respectively and for the MdMRE are 0.44 and 0.45 respectively and for the PRED (25) accuracy are 0.39 and 0.50 respectively and in FLANN model, training and testing phases for the MMRE are 0.42 and 0.49 respectively and for the MdMRE are 0.46 and 0.48 respectively and for the PRED (25) accuracy are 0.38 and 0.48 respectively. The results of Maxwell dataset indicates that training phases and data test for the MMRE in PSO-FLANN model are 0.55 and 0.38 respectively and for the MdMRE are 0.49 and 0.42 respectively and for the PRED (25) accuracy are 0.32 and 0.48 respectively and in FLANN model, training and testing phases for the MMRE are 0.48 and 0.42 respectively and for the MdMRE are 0.39 and 0.40 respectively and for the PRED (25) accuracy are 0.45 and 0.28 respectively. ANN-MLP is one of the prevalent methods in SCE [19].

In order to show the efficiency of ANN, 11 projects with COCOMO model were compared out of 60 ones in NASA software dataset which were trained and tested using ANN and it has been revealed that MRE error value for COCOMO model is higher than ANN model. 80% of the projects were used for training and 20 of them for testing. The results indicate that in more than 90% of the projects, the ANN model has shown a better estimation compared to COCOMO model.

The hybrid model of GA-Optimizing Feature Weights for Functional Link Neural Network (GA-OFWFLANN) is proposed for SCE [20]. Evaluations are carried out on NASA93 dataset. The GA algorithm is used for training FLANN network as well as optimization of hidden layer. The results of the evaluation show that the training and data testing phases of MMRE in GA-OFWFLANN model are 0.33 and 0.38 respectively and for the MdMRE are 0.28 and 0.39 respectively and for the PRED (25) accuracy are 0.38 and 0.30 respectively and in FLANN model, the training and testing phases of MMRE are 0.37 and 0.43 respectively and for the MdMRE are 0.33 and 0.37 respectively and for the PRED (25) accuracy are 0.39 and 0.46 respectively. The training and testing phases in hybrid model are more accurate due to optimizing of the factors by GA.

The carried out studies in SCE has utilized the data mining techniques [21]. Liner Regression (LR), ANN, Support Vector Regression (SVR) and K Nearest Neighbors (KNN) techniques were used for SCE. Dependency of the effective characteristics in SCE can be determined by using LR model. LR model can find the relationship between dependant and independent factors among data. ANN model tries to decrease the MRE error by training and testing data. SVR model is used to optimize the effective factors in SCE. KNN is a data mining technique which is used in classifying the previously categorized data that their characteristics were formerly determined. The value of effective characteristics in SCE is determined by KNN. The findings show that SVR model has got lower MRE compared to other models. Modified GA (MGA) model is also proposed for SCE [22]. In this model, the Gradient and combining GA performances are used for optimizing effort and cost factors. The evaluation is done on COCOMO, Desharnais, Kemerer, Albrecht and KotenGray datasets. The results obtained from Desharnais dataset indicate that PRED (25) accuracy in MGA model is 90% and in SVR-Linear [23] and SVR-RBF [23] models are 55% and 60% respectively. In addition to, MMRE value for MGA model is 0.08 and for SVR-Linear and SVR-RBF models are 0.48 and 0.45 respectively. The results of the done evaluations on COCOMO dataset show that PRED (25) accuracy in MGA model is 90.90% and in SVR-Linear and SVR-RBF models are 81.82% and 72.73% respectively. In addition MMRE value for MGA model is 0.10 and for SVR-Linear and SVR-RBF models are 0.15 and 0.18 respectively. The results obtained from Albercht data set indicate that PRED (25) accuracy in MGA model is 75% and in SVR-Linear and SVR-RBF models are 58.33% and 66.66% respectively. In addition MMRE value for MGA model is 0.35 and for SVR-Linear and SVR-RBF models are 0.50 and 0.67 respectively. Also the results of the done evaluations on Kemerer dataset show that PRED (25) accuracy in MGA model is 73.33% and in SVR-Linear and SVR-RBF models are 60% and 60% respectively. In addition MMRE value for MGA model is 0.25 and for SVR-Linear and SVR-RBF models are 0.46 and 0.44 respectively. The results obtained from KotenGray data set indicate that PRED (25) accuracy in MGA model is 94.12% and in SVR-Linear and SVR-RBF models are 88.24% and 88.24% respectively. In addition MMRE value for MGA model is 0.05 and for SVR-Linear and SVR-RBF models are 0.11 and 0.11 respectively. GA-M5P, GA-MLP, GA-SVR-Linear and GA-SVR-RBF hybrid models were also proposed for SCE [23]. M5P model acts based on decision Making tree. The evaluations have been carried out on Albrecht, COCOMO, NASA, Desharnias, Koten&Gray and Kemerer datasets. The results of Desharnias dataset reveal that the PRED (25) accuracy in GA-SVR-RBF, GA-SVR-Linear, GA-MLP and GA-M5P models are 72.22, 66.67, 72.22 and 61.11 respectively. Furthermore, the MMRE values in the models are 0.4051, 0.3685, 0.3154 and 0.5945 respectively. The PRED accuracy in GA-SVR models compared to others is better. The obtained results from NASA dataset show that the PRED (25) accuracy in GA-SVR-RBF, GA-SVR-Linear, GA-MLP and GA-M5P models are 94.44, 94.44, 94.44 and 83.33 respectively. In addition, the MMRE values in the models are 0.1778, 0.1650, 0.1950 and 0.1838 respectively. The PRED accuracy in GA-M5P models compared to others is lower.

3. Proposed Model

In software projects usually for each activity there are a number of factors or procedures that can be selected for conducting that activity. For instance, preliminary and advanced programmers can be used for project programming which can be done during either work hours or overtime work hours. Each project consists of a set of Effort Multipliers (EMs) that some of them can be done simultaneously or in parallel forms and also some of them can be done

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observing the priority of time due to the fact that they are interdependent [24]. There are different methods of doing each factor that can be different in terms of time, cost and implementation quality. Hence, to run a project consisting of several implementation factors from the beginning to the end, various implementation programs can be used each having their own duration, cost and quality. As a resolution for running a project, each of EMs will have its own duration, cost and quality [24]. In SCE, the equilibration of time, cost and qualities in the suitable models to conduct some project activities during the whole process should be chosen in a way that a compound objective function defined time, cost and quality of the whole project is minimized. The proposed model emphasizes on optimizing EMs to reduce the costs and time. In Figure (1), flowchart of hybrid model is shown.

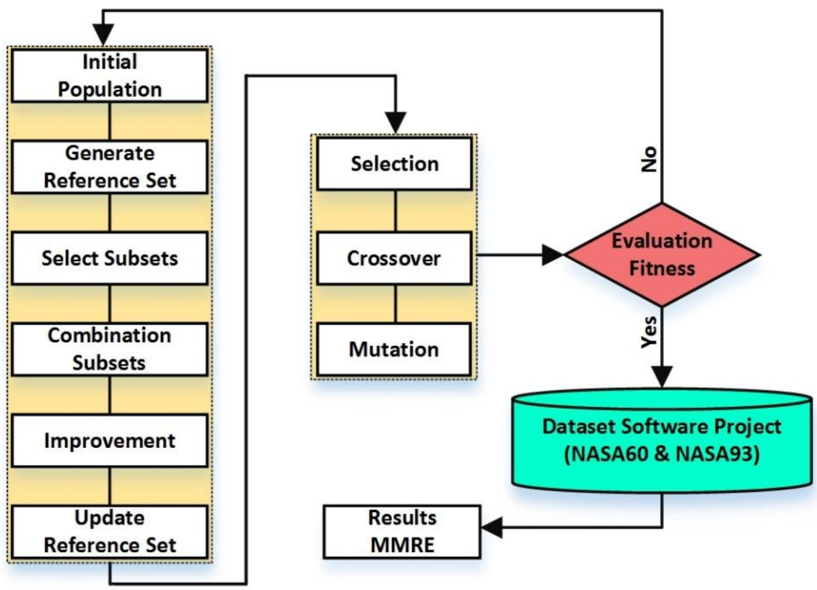

Figure. 1. The Flowchart of Hybrid Model

In the beginning of algorithm the initial population generating various members and sets is formed then an optimizing stage is carried out to upgrade the generated set members. Updating the reference set in terms of fitness and implementation variety is done to form a set best achieved answers. In subset forming stage, the categorized members are generated after combining the answers for each subset. Afterwards, combining the answers with one or several members is done to covert each subset. In the next stage the new members are optimized. In GA model, possible states are investigated with the generation of series of initial random answers and the answers which seem to be close to ultimate optimal answers are generated and investigated using a search around superb ones in the set of answers. Later, the process of generating and investigating series of initial random answers is repeated to get closer to the ultimate optimal answer. Furthermore, in most cases, the obtained answers are the same as ultimate optimal answers; therefore, not optimized factors are changed using a GA model according to the problem conditions that a suitable value is obtained for them. This process is repeated till the condition like number of generation or the most suitable resolution is determined. In

Figure (2), quasi code of hybrid model is shown.

```
Initialize Parameters
N_P: No. Population
R_S= No. Reference Set
P: The Population From Which the Reference Set is Selected
Pc: Rate Crossover
Pm: Rate Mutation
Ng: No. Generation
Hybrid Model
While (not Terminate Condition) do
Repeat
    Create Population
    Generate Reference Set
  Repeat
     Repeat
       Select Subsets;
       Combination Subsets;
       Improvement Combined;
    until (Stopping Criterion)
    Update Reference Set;
  until (Stopping Criterion)
until (Stopping Criterion)
   Evaluate Fitness
   (a) Selection
   (b) Mutation with probability Pm
   (c) Crossover with probability Pc
   (d) Reproduction population
End while
Dataset Software Project
Dataset Software Projects
   NASA60
   NASA93
Fitness Function
MMRE
```

Figure. 2. Quasi Code of Hybrid Model

In the hybrid model MMRE is considered as a fitness function. The objective of fitness function in this model is to minimize the MMRE value in comparison

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to SS and GA algorithms and COCOMO model. The hybrid model is repeated to obtain a minimal desired MMRE value. Fitness function for combined model is defined as eq.2 [25].

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

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

The obtained error sets from estimation models can be compared using eq. 2. PRED is also considered as an important criterion in estimation accuracy. The most prevalent method of investigating prediction accuracy are PRED and MMRE. PRED(x) is defined as eq.3 [25].

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

PRED (x) criterion which is defined in terms of MRE has the most application in estimation accuracy and provides a suitable presentation of performance of models and is also used to show the superiority of hybrid model in terms of combined criteria of PRED and MMRE as the evaluation function according to eq.4 [26].

$$EF = \frac{PRED(25)}{1 + MMRE} \tag{4}$$

In evaluating the estimation of the criteria the model with lower MRE is better than models with higher MRE and models with lower MMRE are better in comparison to models with higher MMRE. It should also be mentioned that models with higher PRED are better than the ones with lower PRED.

4. Evaluation and Results

In this section the hybrid model is evaluated and tested on NASA60 and NASA93 datasets. The simulation of the hybrid model is done using VC#.NET 2013 programming language. The parameter values are shown in Table (1). Determining the population size strongly affects the whole procedure of the algorithm. Generally if the initial population size is chosen small the combined model will not adequate number of samples for computing and the probability of being stuck in a relative optimization increases. On the other hand with an increase in the number of the population, the computation size within a generation increases and the convergence speed is reduced. Since selection is based on probability rules, there is no guarantee for the answers to be better in the new generation because we may face a situation in which the best member of the generation may be omitted which causes deviation from the answer the problem may not be divergent. Consequently, the best values are given the parameters based on the test and repeat.

Table 1. Values of Parameters

Parameters	Values
NP	50
RS	4
P	NP/RS
Selection	%30
Pc	0.7
Pm	0.2
Ng	20
Fitness Function	MMRE

Table (2) shows the PRED and MMRE criteria on NASA60 and NASA93 datasets. As it is observed, the hybrid model in comparison to COCOMO model has reduced the MMRE value on NASA60 dataset almost as 3.92 times. Also, the hybrid model in comparison to COCOMO model has reduced the MMRE value on NASA93 dataset almost as 2.46 times. The hybrid model has increased the PRED (25) accuracy on NASA60 and NASA93 dataset almost as 2.29 and 1.68 times compared to COCOMO model. The EF criterion shows that the hybrid model in comparison to COCOMO, GA and SS is more efficient.

Table 2. Evaluating EF, PRED and MMRE Criteria

Models	**Datasets**					
	NASA60			**NASA93**		
	MMRE	**PRED(25)**	**EF**	**MMRE**	**PRED(25)**	**EF**
COCOMO	29.64	40	1.30	58.80	51.61	0.86
GA	19.63	78.33	3.79	36.51	73.11	1.94
SS	15.21	85	5.24	29.15	76.34	2.53
Hybrid Model	7.56	91.66	10.70	23.85	87.09	3.50

Figure (3) shows the MMRE diagram of hybrid model on NASA60 dataset. The hybrid model in comparison to GA and SS models has reduced the MMRE value quite as 2.59 and 2.01 times respectively.

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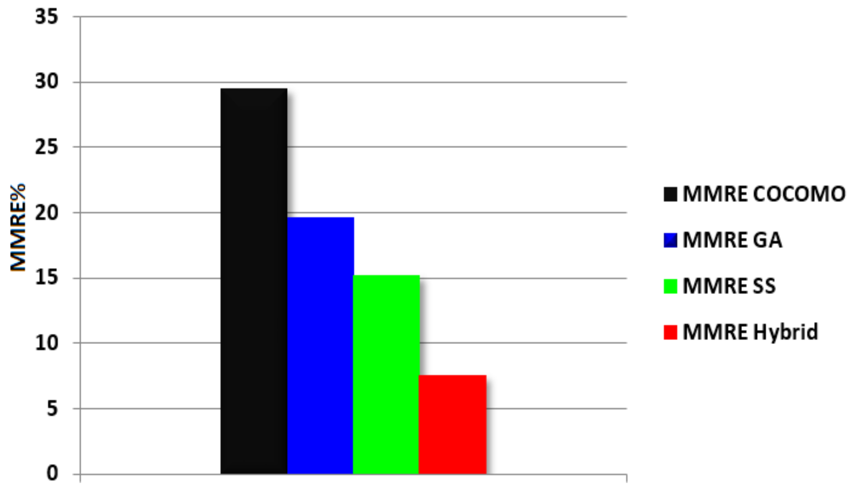

Figure. 3. MMRE Diagram of Hybrid Model on NASA60

MMRE diagram of hybrid model on NASA93 dataset is shown in Figure (4). The hybrid model in comparison to GA and SS models has reduced the MMRE value quite as 1.53 and 1.22 times respectively.

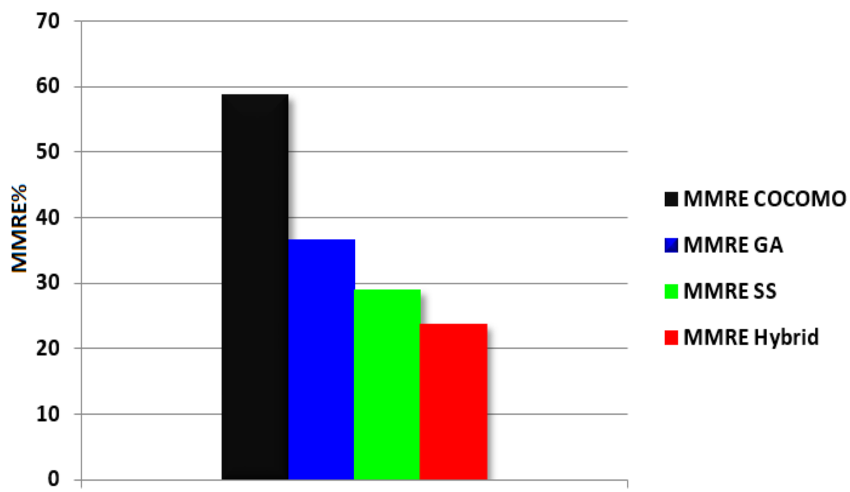

Figure. 4. MMRE Diagram of Hybrid Model on NASA93

According to the results the EF criterion in combined model on NASA60 and NASA93 datasets in comparison with COCOMO model had higher efficiency. The EF criterion in hybrid model on NASA60 dataset is 10.70 and in COCOMO model is 1.30. In addition, on NASA93 dataset the EF criterion in hybrid model is 3.50 and in COCOMO model is 0.86.

5. Conclusion and Future Works

Scheduling and cost estimation is one of the most important activities for software development in any software project. SCE of software projects is one of the most difficult issues in software management; hence, in SCE, a definite cost must be determined for all phases of scheduling and needs analysis, designing and coding, unit testing and overall testing till final verification test. In the present paper, a new hybrid model using GA and SS is proposed for SCE. The efficiency of the hybrid model was evaluated by implementing it on NASA60 and NASA93 datasets and obtained results were compared with COCOMO model. The results of the experiments was indicator of the fact that the hybrid model not only presents relatively better answers but also has a better convergence. The evaluation findings reveal that hybrid model has increased the PRED accuracy on NASA60 and NASA93 datasets as 2.29 and 1.60 times in comparison to COCOMO model. The present paper proposes Meta-heuristic algorithms as an effective instrument in effort and cost estimation.

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