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Software Cost Estimation by a New Hybrid Model of Particle Swarm Optimization and K-Nearest Neighbor Algorithms

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ABSTRACT

A successful software should be finalized with determined and predetermined cost and time. Software is a production which its approximate cost is expert workforce and professionals. The most important and approximate software cost estimation (SCE) is related to the trained workforce. Creative nature of software projects and its abstract nature make extremely cost and time of projects difficult to estimate. Various methods have been presented in the software project cost estimation for performing a software project in the area of software engineering. COCOMO II model is one of the most documented models among template-based methods that has been proposed by Bohm. Common methods for estimating the time and cost are essentially abstract, accordingly, providing new methods for SCE is required and necessary. In this paper, a new method is presented to solve the problem of SCE by using hybrid particle swarm optimization (PSO) algorithm and K-nearest neighbor (KNN) algorithm. The method was evaluated on 6 multiple datasets with 8 different evaluation criteria. Obtained results show the more accurate performance of the proposed method.

1. INTRODUCTION

Today, increasing needs of software production and development makes software the most expensive components of computer. The success rate of software developer organizations depends on the management and planning of the use of resources, based on estimated cost and time. Managers of the software developers should have ability to manage their resources in the best way in order to prevent project failure. Project managers should be able to determine the requirements such as the labor work (analyst, programmer, designer, etc.), facilities and required equipment, the software features (reliability, reuse, need to document and so on) and project characteristics (size, complexity, management, etc.) for project. After estimating the requirements of the project, the required time or number of each source must be evaluated. For example, how many analysts or developers are needed and for how long must be evaluated. In fact, the project manager can estimate the cost required to complete the project with determining these factors. Success of each project depends on the SCE. If the estimated cost is less than the actual cost, organization will suffer financial losses. If actual costs exceed the estimated cost, the customers will be unhappy. If project managers are able to estimate costs accurately, they can access to the following objectives [1]:

- Improving the performance of software manufacturer with proper and accurate organization of the needed resources for each project.
- Increasing the profit of organizations with projects classification based on business and selection of the best projects.
- Increasing customer satisfaction with equilibrium of real costs with estimated cost.
- Increasing satisfaction of project stakeholders with

appropriate profitability of the project.

Despite the many proposed solutions, none of these solutions are fully able to estimate with one hundred percent precision, as well as this issue exist as raised issue in the field of software engineering that challenges scholars engagingly [16].

This paper is organized as follows. In the Second section the previous studies is reviewed. In Section III, basic concepts such as PSO algorithm, KNN algorithm, etc. are introduced. In Section IV, the proposed method is proposed. In Section V, the proposed method is evaluated and finally in Section VI we offer conclusion.

2. Related Works

The algorithm based method is one of the first methods that have been developed by researchers for SCE. These methods were introduced in late 1970 which among these models the most documented and widely used model i.e. COCOMO II is a pattern-based model [2]. With the lapse of time and introduction of machine learning algorithms in the field of software engineering, researchers have tried to solve this problem with using machine learning algorithms. Accordingly, various methods have been proposed for solving this problem. Some of the solutions can be stated as follow:

To solve the problem of SCE, researchers have used a hybrid model of COCOMO II with fuzzy logic [3]. According to the mentioned work, fuzzy systems are combined with functions of triangular membership, trapezoidal, Gaussian and generalized Bell intermediate COCOMO II models. In these models, evaluation criteria such as MMRE, MRE, PRED, MARE, VAF, VARE, BRE are used for evaluating the hybrid methods. Results obtained by the hybrid COCOMO II model show a better performance in comparison with the COCOMO II model.

For SCE, fuzzy logic was used in [4]. First, the parameters of the COCOMO II model were converted into fuzzy numbers and then these numbers have been emitted from fuzzy state. The results of the proposed method were compared with the COCOMO II and AlaaSheta model. Comparison shows improving the performance in the proposed method. Also, the proposed method had a less marginal error of MMRE, PRED (N), VAF than COCOMO II and AlaaSheta models. In [5], the multiple PSO algorithm was used to optimize the parameters of the COCOMO II model. The proposed model have been tested individually on small and large projects. According to the findings, the MARE amounts for micro projects in COCOMO II model and in the proposed model are 16.1306% and 9.0143%, respectively. In addition, for the large projects, MARE was18.1548% and 20.9717% for the COCOMO II and the proposed model, respectively. The results show that the proposed model have better performance compared to the COCOMO II models.

Accurate SCE has a significant impact on the success of the project. With this aim, in [6] authors tried to solve the SCE problem by using the functional link artificial neural network (FLANN) and genetic algorithm. They used FLANN algorithm for classification of data collection in the training phase and used the genetic algorithm to optimize the parameters of each dataset. In the training phase, they used FLANN algorithm and then after the completion of this stage, the results have been compared with COCOMO II model.

Gharehchopogh and Dizaji [7] used hybrid artificial bee algorithm and chaos optimized algorithm to solve SCE problem. Tenet mapping as chaos mapping was mixed with the proposed algorithms. Then, the results of the proposed method were compared with the COCOMO II model on NASA63 dataset. The results of the MARE comparison in this case can be stated as below: COCOMO II was0.2952, artificial bee algorithm was0.1925, combined artificial bee algorithm and Tenet mapping was0.18, bee optimization algorithms was0.2538, combined optimized bee algorithms and Tenet mapping was0.1202 and the proposed method (multiple factors) was0.07.

In [8], the researchers used data mining algorithms for SCE. They compared and evaluated data mining algorithms with COCOMO II algorithm model. For this purpose, the algorithms of linear regression, artificial neural networks, support vector machines and KNN algorithm were compared with COCOMO II models. It should be noted that the datasets available in NASA63wasused as dataset and MRE evaluation criteria was used to evaluate the listed models. The results showed that applying the data mining methods in comparison to the algorithm methods had a higher speed and accuracy. As well as the findings showed that the artificial neural network algorithms and support vector machine had better performance than the other listed models. Dizaji and Gharehchopogh [9] used combination of PSO algorithm and chaos optimization algorithm to solve the problem of estimating the cost of software projects. In this paper, tent mapping was used as the agent of chaos and NASA63 dataset was used. At each stage of optimization, each algorithm of PSO and PSO+chaos were implemented, individually. Each one of these algorithms which offered better results was used as the solution to estimate the cost at that stage. The result of the proposed method was compared with COMOCO model as the most documented mathematical model to estimate the cost of software projects. It should be noted that the evaluation criterion in this article was mean of absolute relative error. Based on the obtained results, PSO algorithm performance was better than the COMOCO model, also the performance of the hybrid algorithm was more efficient than PSO algorithm and COMOCO model.

3. Basic Concepts

A. SCT and COCOMO II

The SCE is one of the most challenging tasks in project management, because based on the estimated costs, the organization will decide and plan the time, budget and resources required to complete project. In fact, it can be said that the success and failure of a project depends on the accuracy of manager's prediction about the cost amount required for the project. COCOMO II stands for COnstructive COst MOdel which has been published first in 1981 by David Bohm in [2]. This model is an algorithmic approach to SCE. The formula used to calculate the SCE is according to the formula (1) [10, 15] .

$$PM = a * (size)^b * \prod_{i=1}^{15} EM_i \quad (1)$$

In formula (1), variable size identifies the size of the project and variable EM identifies decisive factors the SCE. The values of the parameters a and b are fixed and are determined based on the type of project. The values of these parameters are shown in table 1.

Table 1
Constant Parameter Value for Different Project

B	A	Project Type
1.05	2.4	Organic
1.12	3.0	Semi Organic
1.2	3.6	Embedded

B. Evaluation Criteria in SCE

Evaluation criteria represent the accuracy of the proposed models and the difference between the actual cost and the predicted costs. There are different criteria for evaluating which a number of these criteria can be briefly stated as follow [11, 12]. It should be noted that in these criteria, variable N included the total number of data in dataset; variable "act" represents the real costs, variable "est" represents the amount of estimated expenses and variable i represents the index of any data that its range is from 1 to N.

Mean Magnitude Error Relative (MMER): To calculate this error, the formula (2) is used.

$$\text{MMER} = \frac{1}{N}\sum_{i=1}^{n}\frac{|act_i - est_i|}{est_i} * 100 \quad (2)$$

Mean Magnitude of Relative Error (MMRE): To calculate this error, the formula (3) is used.

$$\text{MMR}E = \frac{1}{N}\sum_{i=1}^{n}\frac{|act_i - est_i|}{act_i} * 100 \quad (3)$$

Median Magnitude of Relative Error (MDMRE): To calculate this error, the formula (4) is used.

$$\text{MDMRE} = Median\left(\frac{1}{N}\sum_{i=1}^{n}\frac{|act_i - est_i|}{act_i} * 100\right) \quad (4)$$

PRED(N): To calculate this error the formula (5) is used.

$$\text{PRED(N)} = \frac{1}{N}\sum_{i=1}^{n}\begin{cases}1, if MRE \le m\\ 0, Otherwise\end{cases} \quad (5)$$

Mean Squared Error (MSE): To calculate this error, the formula (6) is used.

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{n}(act_i - est_i)^2 \quad (6)$$

Root Mean Square Error (RMSE): To calculate this error, the formula (7) is used.

$$R\text{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(act_i - est_i)^2} \quad (7)$$

Mean of Absolute Errors (MAE): To calculate this error, the formula (8) is used.

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{n}|act_i - est_i| \quad (8)$$

Mean Absolute Percentage Error (MAPE): To calculate this error, the formula (9) is used.

$$\text{MAPE} = \sum_{i=1}^{n}\frac{\frac{|act_i - est_i|}{act_i}}{n} * 100 \quad (9)$$

C. KNN Algorithm

One of the best classifications is KNN classification algorithm which was first described in 1967 [13]. In this method, instead of assuming a general function, some local functions for any given class and in input space is estimated. In this classification, the test sample belongs to the class that has the most votes in the KNN. To obtain the nearest neighbors of a sample, usually the Euclidean distance is used. Since KNN algorithm has the simplicity, performance as well as the use of a small number of training patterns or the same sample, then it has been used in the field of pattern recognition since 1967. The KNN algorithm is a method for classifying objects based on the nearest training samples in space-based features that make it an example of learning or lazy known example. Where all training samples are stored at the beginning and until an unknown sample does not require classification, classification would not be taken.

D. PSO Algorithm

PSO Algorithm (birds) first was proposed in 1995 by Eberhart and Kennedy [14]. PSO algorithm is comprised of specific number of particles that randomly take an initial value; for each particle two status of values and speed are defined which are modeled by a position vector and a speed vector, respectively. Particles update their speed and position in terms of the best absolute and local solutions according to the formulas (10) and (11).

$$V_{I,J}(T+1) = WV_{I,J}(T) + C_1 R_1(T)\,(PBEST_{I,J}(T) - X_{I,J}(T)) + C_2 R_2(T)\,(GBEST_I(T) - X_{I,J}(T)) \quad (10)$$

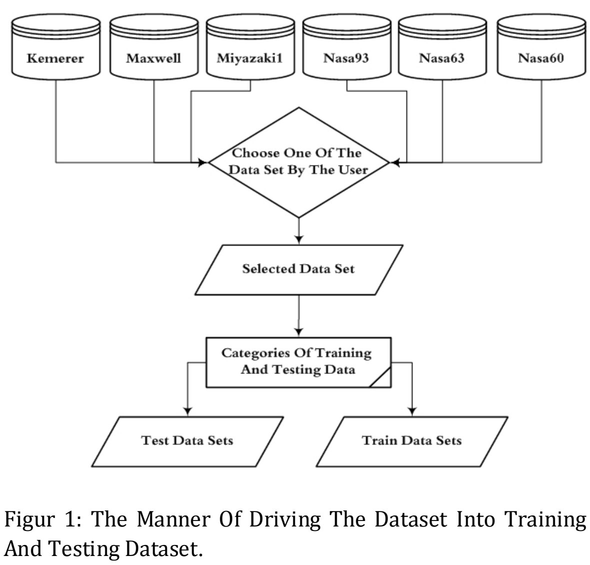
and

$$X_I(T+1) = X_I(T) + (V_I(T+1)) \quad (11)$$

In formula (10), w is inertia coefficient and depending on the need can be fixed, variable with number of repetitions or random. The existence of inertia coefficient ensures that the particles that gain the best answer of population is not stopped and continues to move in the previous direction. The coefficients of c_1 and c_2 are also learning coefficients, which are usually in the range of 0 to 2. In addition, r_1 and r_2 are random numbers which are considered usually as uniformly distributed and in the range of 0 to 1. Pbest is the best answer has ever been found by particle i. Gbest is also the best answer has been proposed by the entire particles in the community.

4. PROPOSED MODEL

In this paper, model based PSO and KNN algorithms are used to solve the problem of SCE. In the other words, first the selected dataset of user is classified based on KNN algorithm and then PSO algorithm is applied. It means that before the implementation of the proposed method, the data available in dataset are normalized and vague and empty data has been deleted. After this stage, the proposed method is implemented and in the first stage of implementation, data available in dataset are classified completely randomly into two dataset of training and testing with the ratio of 20% to 80%. In order to understand, the way of dividing dataset into training and test datasets is shown in Fig. 1.



Figur 1: The Manner Of Driving The Dataset Into Training And Testing Dataset.

After the classification of the selected data collection, data in the training and test datasets are classified based on KNN algorithm and in order to teach the training datasets is applied on PSO algorithm. The way of training is displayed in Table 2 and Fig. 2.

TABLE 2
PSEDU CODE OF THE PROPOSED METHOD

Inputs: User selected data set includes: Factors effective in estimating, project type and the number of project in data sets. Outputs: The values for fixed parameters of COCOMO model and classified data. Step 1: Read the data in the dataset. Step 2: Breakdown of training and testing data. Step 3: KNN algorithm of training and testing data based on classification algorithms. Step 4: Calling the mass of particles for each category. Step 5: Give the value for particles and also the initialize value for the fixed parameters of COCOMO model. Step 6: Calculate the merit for each particle mass. Step 7: Evaluate the performance of each particle: in order to evaluate the performance of each particle, the mean absolute relative error is used. Step 8: Find pbest: If the fitness function is better solution to the current solution, then this solution is regarded as the solution of the best bit. Here Pbest for each particle obtained to evaluate and compare current and previous estimation of the obtained parameters. Step 9: Find Gbest: select the best value from the Pbests, in fact, a particle with the least difference between the existed value and estimated value conducted by operating is elected. Step 10: Update position and velocity of every particle. Step 11: Until the optimal solution is not achieved, repeat the sixth to the tenth steps. Step 12: Take values of parameters from Gbest as the optimal values. Step 13: Finish the action of mass of the particles.

In the first phase of training, the basic parameters of PSO algorithm such as the number of particles and their repetition, as well as the coefficients of C_1, C_2, and Ware quantified. After completion of this step, the amount of merit for each of the particles is calculated by using the fitness function and attached values.

In the next phase, based on the competency of particles, Gbest and Pbest values are determined and in the next steps until the algorithm is not completed, the value of particles is updated on the basis of these two quantity and coefficients, C_1, C_2, W, R_1, R_2, then the particle merit is re-calculate. It is necessary to mention that the condition for the completion of algorithm is the number of iterations or a minimum value that achieving this minimum value represents the achieving to the goal.

In order to understand the proposed method, the way of its work is displayed in Fig. 2.

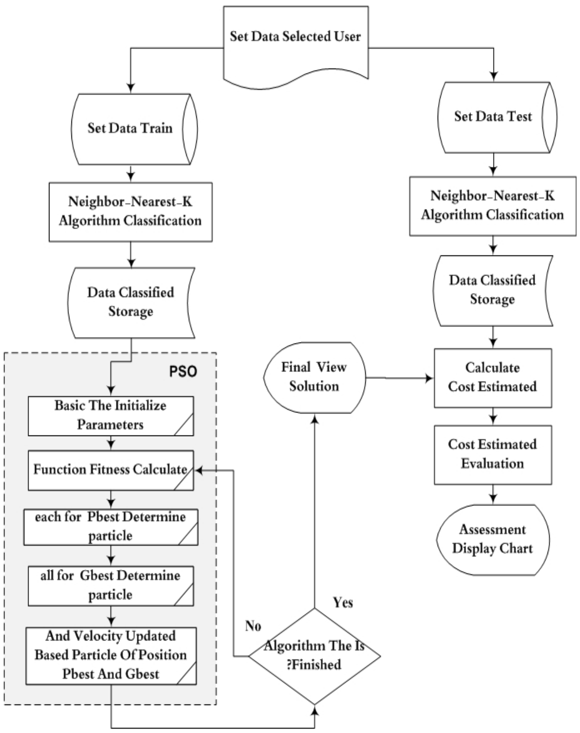


Figure 2: The Manner Of Performance Of The Proposed Method.

As it is represented in Fig. 2, after completion of training stage the results obtained from this stage which are fixed parameters of COCOMO model is applied on the test dataset. In the next stage, the results obtained from test stage are evaluated by the evaluation criteria. Finally, based on the results of evaluation the charts are prepared and presented in order to better understand the results.

5. Result and Discussion

In this paper, PSO and KNN algorithms and NASA60, NASA63, NASA93, MAXWELL, KEMERER, MIYAZAKI datasets are used to solve the problem of SCE. The mentioned dataset is divided into two training and testing datasets with a ratio of 80 to 20 and the results are displayed in tables 3 to 8.

TABLE 3
EVALUATION OF THE PROPOSED METHOD ON THE NASA 60 DATASET

Approach / Datasets	COCOMO II	KNN	PSO	Proposed Method
MMER	19.43	16.67	13.19	12.61
MMRE	16.9	14.52	14.98	14.02
MDMRE	16.27	14.68	14.16	14.09
RMSE	92.31	83.64	67.52	65.77
MAPE	16.09	14.52	14.98	14.02
MAE	50.34	43.30	36.61	35.10
PRED(N)	0.83	0.92	0.83	0.92
MSE	8521.4	6995.79	4558.43	4325.98

According to Table 3, it is clear that the results of the proposed method for evaluating MMER is 12.61, MMRE is 14.02, MDMRE is 14.09, RMSE is 65.77, MAPE is 14.02, MAE is 35.1, PRED(N) is 0.92, and MSE is 4325.98. Based on these values, the proposed method has acted in all criteria better than other comparative methods and only PRED(N) criteria has acted the same as KNN algorithm.

TABLE 4
EVALUATION OF THE PROPOSED METHOD ON NASA63 DATASET

Approach / Datasets	COCOMO II	KNN	PSO	Proposed Method
MMER	19.43	16.67	12.73	11.96
MMRE	16..9	14.52	13.49	12.93
MDMRE	16.27	14.68	10.21	10.15
RMSE	92.31	81.44	75.49	64.27
MAPE	16.09	15.16	13.49	12.93
MAE	50.34	43.64	40.48	32.89
PRED(N)	0.83	0.92	0.92	0.92
MSE	8521.4	6633.15	5698.75	4131.13

According to Table 4, it is clear that the results of the proposed method to measure the amount of MMER is 11.96, MMRE is 12.93, MDMRE is 10.15, the RMSE is 64.27, MAPE is 12.93, MAE is 32.89, PRED(N) is 0.92, and MSE is 4131.13. Based on these values, it can be said that the proposed method has acted in all criteria better than comparative methods and only in PRED(N) criterion it is equal to KNN and PSO algorithms.

TABLE 5
EVALUATION OF THE PROPOSED METHOD ON THE NASA 93 DATASET

Approach / Datasets	COCOMO II	KNN	PSO	Proposed Method
MMER	23.01	21.27	14.47	13.35
MMRE	18.23	17.24	13.01	12.53
MDMRE	20.98	18.18	12.37	11.8
RMSE	77.03	70.5	52.83	52.18
MAPE	18.23	17.24	13.01	12.53
MAE	44.49	40.04	30.13	29.18
PRED(N)	0.84	0.89	0.95	1
MSE	5933.62	4970.08	2717.17	27940.85

According to the Table 5, it can be said that the results of the proposed method to measure MMER amount is 13.35, MMRE is 12.53, MDMRE is 11.8, RMSE is 52.18, MAPE is 12.53, MAE is 29.18, PRED(N) is 1, and MSE is 2790.85. These values show that the proposed method has acted in all criteria better than the comparative methods and only in MSE criterion acted worse than particle mass algorithm.

TABLE 6
EVALUATION OF THE PROPOSED METHOD ON THE MAXWELL DATASET

Approach / Datasets	COCOMO II	KNN	PSO	Proposed Method
MMER	118.44	118.44	102.13	99.8
MMRE	43.76	43.76	38.22	37.98
MDMRE	36.58	36.58	33.72	32.8
RMSE	3809.67	3809.67	4605.67	4558.54
MAPE	43.76	43.76	38.22	37.98
MAE	2603	2603	2950.53	2917.86
PRED(N)	0.38	0.38	0.46	0.46
MSE	14513	14513	21212	20780

According to Table 6 the, results of the proposed method to measure the amount MMER is 99.8, MMRE is 37.98, MDMRE is 32.8, RMSE is 4558.54, the MAPE is 37.98, MAE is 2917.86, the PRED(N) is 0.46, and MSE is 20780. Based on these values, the proposed method in criteria of RMSE, MSE, MAE acts better than PSO algorithm and worse than KNN algorithm and COCOMO model.

TABLE 7
EVALUATION OF THE PROPOSED METHOD ON THE KEMERER DATASET

Approach / Datasets	COCOMO II	KNN	PSO	Proposed Method
MMER	79.23	79.23	59.93	59.71
MMRE	687.64	687.64	46.27	45.6
MDMRE	626.6	626.6	43.9	35.6
RMSE	1883.09	1883.09	262.72	261.65
MAPE	687.64	687.64	46.27	45.6
MAE	1375.95	1375.95	121.32	120.56
PRED(N)	0	0	0.33	0.33
MSE	35460	35460	689	684

According to the Table 7, it is clear that the results of the proposed method to measure the amount of MMER is 59.71, MMRE is 45.6, MDMRE is 35.6, RMSE is 261.65, MAPE is 45.6, MAE is 120.56, PRED(N) is 0.33, and MSE is 684. Based on these results, we can say that the proposed method has acted in all criteria better than the comparative methods and only in PRED(N) criteria has acted equally to the PSO algorithm.

TABLE 8
EVALUATION OF THE PROPOSED METHOD ON THE MIYAZAKI DATASET

Approach / Datasets	COCOMO II	KNN	PSO	Proposed Method
MMER	70.83	70.83	78.4	70.6
MMRE	272.79	272.79	40.11	36.07
MDMRE	277.48	277.48	51.6	46
RMSE	137.7	137.7	30.34	27.93
MAPE	272.79	272.79	40.11	36.07
MAE	122.16	122.16	24.07	22.47
PRED(N)	0	0	0.3	0.4
MSE	18960.4	18960.4	920.48	780.28

According to the Table 8, it can be said that the amount of MMER in the proposed method is 70.6, MMRE is 36.07, MDMRE is 46, RMSE is 27.93, MAPE is 36.07, MAE is 22.47, PRED(N) is 0.4, and MSE is 780.28.

Based on these results we can say that the proposed method has acted in all criteria better than the comparative approaches.

6. CONCLUSION

Due to the fact that the complexity of a project increases by increasing its size, it will be helpful to reduce the error rate significantly by determining the most important aspects of software initially.

In fact, it can be said that the success and failure of a project depend on the accuracy of managers' prediction about determining the cost of a project. Several methods have been proposed to solve this problem in the field of engineering but neither of them could estimate accurately, so in this paper, we proposed a hybrid approach using a combination of two classification of K nearest algorithms and PSO algorithms on Kemerer, Maxwell, Miyazaki1, Nasa60, Nasa63, Nasa93 datasets to resolve this issue.

Moreover, the results of this hybrid method is compared with KNN algorithm, optimization of particle masses and the COCOMO 2 based on the evaluation criteria of MMER, MMRE, MDMRE, RMSE, MAPE, MAE, PRED (N), MSE. The results in all datasets apart from Maxwell dataset showed that the proposed method has better performance compared to the others.

In Maxwell dataset, the proposed method in the evaluation criteria of MSE, MAE, MSE has not acted better than KNN classification algorithm and COCOMO model. It is due to the lack of consistent data.

References

[1] L. Zhangf, "Software Cost Estimation in Handbook of Software Engineering and Knowledge Engineering," World Scientific Pub. Co, River Edge, NJ, 2001.

[2] B.W. Boehm, S. Chulani, and D. Reifer, The Rosetta Stone: Making COCOMO 81 Files Work with COCOMO II,1998.

[3] F. S.Gharehchopogh, L. Ebrahimi, I. Maleki, and S. Jodati, "A new novel PSObased approach with hybrid of fuzzy c-means and learning automata in software cost estimation," *Indian Journal of Science and Technology*, vol. 7, pp. 795-803, 2014.

[4] Ziauddin, Sh. Kamal, Sh. Khan, and J.A. Nasir, "A fuzzy logic based software cost estimation model," *International Journal of Software Engineering and Its Applications*, vol. 7, no. 2, pp. 7-18, 2013.

[5] P.V.G.D.P. Reddy, CH.V.M.K. Hari, and R.T. Srinivasa, "Multi objective particle swarm optimization for software cost estimation," *International Journal of Computer Applications*, vol. 32, no.3, pp. 13-17, 2011.

[6] T.R. Benala, S. Dehuri, S.C. Satapathy, and S. Madhurakshara, "Genetic algorithm for optimizing functional link artificial neural network based software cost estimation," in *Proc.* 2012 *International Conference on Information Systems* Design, pp. 75–82.

[7] F. S.Gharehchopogh, Z.A. Dizaji, "A new approach in software cost estimation with hybrid of bee colony and chaos optimizations algorithms," *MAGNT Research Report*, vol. 2, no. 6, pp. 1263-127, 2014.

[8] Z.A.Khalifelu, F.S.Gharehchopogh,"Comparison and evaluation data mining techniques with algorithmic models in software cost estimation," *Procedia-Technology Journal*, vol. 1, pp. 65-71, 2012.

[9] Z.A. Dizaji, F. S.Gharehchopogh, "A hybrid of ant colony optimization and chaos optimization algorithms approach for software cost estimation," *Indian Journal of Science and Technology*, vol. 8, no.2, pp.128–133,2015.

[10] E.E. Miandoab, F.S. GHAREHCHOPOGH, "A novel hybrid algorithm for software cost estimation based on cuckoo optimization and k-nearest neighbors algorithms," *Engineering, Technology & Applied Science Research*, vol. 6, no. 3, pp. 1018-1022, 2016.

[11] L.F. Capretz, V. Marza, "Improving effort estimation by voting software estimation models," *Advances in Software Engineering*, pp. 1-8, 2009.

[12] S. Kumari, S. Pushkar, "Performance analysis of the software cost estimation methods: a review," *International Journal of Advanced Research in Computer Science and Software Engineering*, vol. 3, no. 7, pp. 229-238, 2013.

[13] T.M. Cover, P.E. Hart, "nearest neighbor pattern classification," *IEEE Trans. Inform. Theory*, vol. 13, pp 2-21, 1967.

[14] J. Kennedy, R.C. Eberhart, "Particle swarm optimization," 1995 *IEEE Conference on Neural Networks*, Perth, Australia; pp. 1942–1948.

[15] F.D. Mokri, M. Molanli, "software cost estimation using adaptive neuro fuzzy inference system," *International Journal of Academic Research in Computer Engineering*, vol. 1, no. 1, pp. 34-39, 2016.

[16] F. S.Gharehchopogh, S. Jodati, and I. Maleki, "object oriented software engineering models in software industry," *International Journal of Computer Applications*, vol. 95,no.3, pp. 13-16, 2014.

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