Cluster-based fuzzy regression trees for software cost prediction

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ABSTRACT

The current paper proposes a novel type of decision tree, which is never used for software development cost prediction (SDCP) purposes, the cluster-based fuzzy regression tree (CFRT). This model uses the fuzzy k-means (FKM), which deals with data uncertainty and imprecision. The tree expansion is based on the variability measure by choosing the node with the highest value of granulation diversity. This paper outlined an experimental study comparing CFRT with four SDCP methods, notably linear regression, multi-layer perceptron, K-nearest-neighbors, and classification and regression trees (CART), employing eight datasets and the leave-one-out cross-validation (LOOCV). The results show that CFRT is among the best, ranked first in 3 datasets according to four accuracy measures. Also, according to the Pred(25%) values, the proposed CFRT model outperformed all the twelve compared techniques in four datasets: Albrecht, constructive cost model (COCOMO), Desharnais, and The International Software Benchmarking Standards Group (ISBSG) using LOOCV and 30-fold cross-validation technique.

Keywords:
Decision tree
Fuzzy k-means
Regression tree
Software development cost prediction
Software development effort estimation

1. INTRODUCTION

A growing body of literature on software project management recognizes the importance of software development cost prediction (SDCP). Accurate models assist in efficiently controlling resources, timing, and budgeting even in the earlier phase of the software development process. However, many limitations or conditions could negatively affect the performance of SDCP models and therefore give inaccurate estimations. There are many agile and non-agile effort prediction techniques [1], where researchers propose new methods or optimization for improving existing ones. Generally, decision trees (DTs) are one of the computational intelligence techniques which are largely employed for cost prediction [2], [3].

A DT consists of one root node, different leaves, and branch nodes, where each branch constitutes an option among many options. The effort estimation for a test project is done by traversing the DT nodes according to the project’s attributes values. Once the project hits the leaf node, the estimation is performed based on the instances located at this leaf node [4]. Effort estimation using DT has many significant advantages. First, DTs can be employed for classification and regression tasks (RTs) [3]. Second, DTs are known to be easily comprehensible thanks to their ability to provide a meaningful bit of knowledge about the function(f) that models the inherent hidden relation between features and effort. Third, DTs can also be used for feature selection to reduce misleading data in the SDCP models [5]. Despite the previously mentioned advantages, classical DTs methods suffer from a particular weakness that hinders their ability to make robust estimations. First, DTs are very sensitive to the data used in model construction because numerical features with sharp
boundaries are susceptible to their values. Therefore any change in input values impacts the decision value [6]. Second, crisp DTs cannot handle uncertainty and imprecision in the acquired data and the obtained estimates. Third, DT suffers from the absence of locality due to the crisp boolean nature of tree splits. Two close projects are treated separately by opposite sides of tree branches and hence have distinct effort values [7].

Subsequently, many studies were performed to avoid the limitations mentioned. Consequently, several techniques were employed with DT methods to surmount the traditional DTs challenges. Mainly, according to Najm et al. [8], the fuzzy-logic (FL) is the most employed technique with DT, and the resulting trees are then called fuzzy decision trees (FDTs).

The FDTs include the fuzzy set theory that enables partial membership into the tree's nodes. The FDTs differ from the classical DTs in the fuzzy restriction of splitting criteria and the inference approach [9]. The fuzzy DT approach has several attractive features. First, the knowledge representation is enhanced thanks to fuzzy splits. Second, fuzzification introduces a continuity constraint at the split boundaries that maintain the locality notion where two close projects pursue equal treatment and gain similar effort estimates. Third, FDT perfectly solves the issues related to species preciseness arising from uncertain data or generated by imprecise models. Overall, FDTs have the potential to simulate human reasoning thanks to their ability to perform decisions with high imprecise and volatile datasets besides solving the uncertainty derived from sharp interval boundaries. However, FDTs suffer from some serious issues. First, there are challenges in defining proper fuzzy set partitions and their suitable membership function (MF) [10]. Because the fuzzification closely depends on the dataset used. Therefore, a suitable fuzzy set and MF will produce reasonable effort estimations, while a worse choice will yield inaccurate model estimates. Second, tree growth based on a single attribute selection is also perceived as a conceptual restriction [11], affirmed in [12].

This paper proposes a novel type of regression tree that handles these shortcomings, stated as cluster-based fuzzy regression trees (CFRT) [11]. Essentially, CFRT is conceived to handle the uncertainty management issues and assumed to address the classical FDTs challenges. The essential advantages of using CFRT are:

- Decreasing the imprecision in the prediction model by involving the fuzzy k-means (FKM) during the tree growth of CFRT. In our proposed CFRT model, a project can belong to many nodes at each tree level, which increases the probability of any project being captured by the correct node at each level of the tree. It is also beneficial in handling the uncertainty’s sources, given that the CFRT introduces the FM of projects in tree nodes. Plus, it produces imprecise estimates that offer practitioners the possibility of clearly quantifying the uncertainties in the estimates.

- Surmounting traditional FDT limitations. First classical FDT performs estimation based on a subset of pertinent attributes, which is considered a conceptual drawback because considering more than one attribute may result in good trees and enhanced accuracy [11] as the CFRT, where predictions are made based on the whole set. Second, CFRT does not suffer from the problem of finding a proper fuzzy set and suitable MF, which is done thanks to its particular structure based on the FKM method.

- Maintaining the quality of the historical projects because the generated estimates are directly fitted with the project attribute. The generated estimate of the fuzzy inference is in the form of a single numerical value. Which is more advantageous in enhancing the accuracy of the estimates by preventing the defuzzification step that transforms the fuzzy estimate into a crisp one.

For example, we illustrate the difference between CFRT and traditional FDT with the following example, where we perform a software effort estimation using Kemerer datasets and the leave-one-out cross-validation (LOOCV) method.

A decision tree using classification and regression trees (CART) Figure 1 forms a binary tree. Each node of a tree specifies a condition based on one of the features. Each branch corresponds to possible values or range of values this variable may take, where the decision represents the value of a predicted variable determined based on data in the particular terminal node.

While a decision tree using CFRT Figure 2 is based mainly on the FKM algorithm, which is used for clustering the dataset D into k distinct clusters (k=3 in this example) while each cluster is represented by its center Ci. The tree growth is performed by repetitively splitting the most heterogeneous node from all resulting nodes. In this example, one tree level exists due to the minimum size of the Kemerer dataset and the k=3. Each node of a tree contains more than one attribute. The prediction of a project pi is made as follows: At each tree level, we determine its membership to each node based on each node center ci. After that, we choose the correspondent pathway until the terminal nodes (leaves) are reached (see subsection 2.1.3 for more details about calculating the estimated effort value). By using CART algorithm as shown in Figure 1 we get the following values of errors: MAE=140.5, Pred (0.25)=26.66, MMRE=0.79, MdMRE=0.57, SA=0.53, delta=1.49, MIBRE=0.46, MBRE=1.21. By using CFRT algorithm as shown in Figure 2 we get the following values of errors: MAE=105.88, Pred (0.25)=46.66, MMRE=0.56, MdMRE= 0.27, SA=0.53, delta=1.99, MIBRE=0.32, MBRE=0.82.
We notice that CFRT produces an enhanced accuracy compared to the CART algorithm thanks to its particular structure based on more than one attribute, which is considered a conceptual advantage that results in good trees and then an enhanced accuracy (Pred=46.66). Nevertheless, as seen in Figure 1, CART performs estimation based on a choice of a single attribute, which is considered a conceptual drawback and yet reduces accuracy (Pred=26.66). Therefore, this paper proposed the CFRT model, which is more advantageous in managing uncertainty issues and surmounting the FDT challenges. The performance of the CFRT technique is then compared to four popular ML techniques: linear regression, multilayer perceptron (MLP), KNN, and CART. According to Wen et al. [13], KNN, MLP, and DT are the most employed methods with 37, 26, and 17%. Also, we note that tuning the hyperparameters of the SDCP methods can significantly affect their performance. We used the grid search (GS) method [14].
Hence, we perform the analysis in light of the following research questions:

a) ReQu1: Does the CFRT technique perform better than the four techniques according to the SA measure using LOOCV?

b) ReQu2: Does the CFRT present the most precise (accurate) technique compared to the four SDCP methods using LOOCV?

c) ReQu3: Does CFRT significantly outperform the other SDCP methods according to the statistical test?

Regarding related works, Najm et al. [8] have performed a systematic literature review on decision trees-based SDCP. They outlined 50 studies published from 1985 to 2019. We noted the main results:

- Generally, decision trees perform better than case-based reasoning (CBR), CHAID, MLP, and RBFN models. Moreover, traditional DTs are unable to manage uncertainties.
- FL and regression are the most employed techniques with DT. Moreover, according to Pred(25) and MMRE, the best technique is FL (92.56% MMRE median).

Several works have been done to manage the SDCP model uncertainties. Hence, the researchers explain the uncertainty's sources or propose solutions to manage imprecision in software effort prediction environments. Mainly, in [5], [15], [16], the authors investigated the use of the fuzzy ID3 decision tree in SDCP by incorporating the principle of fuzzy theory. Idri and Elyassami [15], the experiments show that based on Pred(25) and MMRE, the Fuzzy ID3 outperforms crisp ID3, CART, and C4.5 over the TUKUTUKU dataset. Moreover, in Elyassami [16], the use of the ISBSG dataset enhances the performance. Also, in Elyassami and Idri [17] the authors are interested in testing the accuracy of fuzzy C5 and the effect of the confidence factor of pruning on the accuracy of fuzzy C5 using the ISBSG dataset [18]. The comparison was made utilizing fuzzy ID3, and the results show that increasing the confidence factor of pruning produces the best estimates of fuzzy C5.

Additionally, other studies focus on enhancing the accuracy of FDT by incorporating a hybrid DT model with FL. Which is the case for [19]-[21]. The authors in [20] suggested a fuzzy scheme (framework) that integrates FL with CART and CHAID. Besides, a fuzzy inference system (FIS) for defuzzification of generated rules. The suggested framework was applied to Desharnais, constructive cost model (COCOMO), and ISBSG datasets and the subsets available in the first stage of software development. The results revealed that the framework gives accurate results and can be used even in the first stages of software development.

By carefully analyzing the studies on FDTs, we affirmed that they deal with uncertainty management issues, a severe challenge of SDCP models. Also, they are enhanced compared to the crisp version. Nevertheless, the proposed models are still suffering from some weaknesses. For example, in [16], the author does not compare with other SDCP methods, which hinders the validity of the results. Also, in [5], the authors compare the proposed models just with the crisp version of the models or with just one model like in [17], [18], which is not enough for generalizing the results and affirming their superiority. Also, experimentation made in [15] is still limited due to using just one dataset and the absence of other Non-DT models in the comparison.

Some existing works use CFDT in classification and regression problems but not for software cost prediction concerns. For example, Chiu et al. [22] have proposed an enhanced CFDT method that uses an adjusted version of the FKM algorithm and the linear model in the leaf nodes where its parameters are determined using the recursive SVD-based least squares estimator. The empirical results indicate that the enhanced model generated a small (mean square) error compared to the initial model. Generally, the optimization calculation techniques of FKM are highly susceptible to the initially chosen parameters. Also, there is a risk of local extrema problems resulting from the optimization of cluster criteria. That is why some optimization algorithms exist in the literature, even inspired by nature, like particle swarm optimization [23], bee colony, and firefly method.

Alternatively, algorithms inspired by the biological domain, such as genetic algorithms [24], and artificial immune networks [25], were used to achieve global optimization of the Fuzzy k-means method. The use of GA with FKM in building decision trees (GCFDT) was previously employed for reactive ion etching (RIE) modeling as a data mining approach [26]. The main finding of this paper is that the accuracy of GCFDT outperforms that of classical CFDT and C4.5 algorithms. Also, Gadomer and Sosnowski [27] have proposed a fuzzy random forest with CFDT and proved that the proposed model performs better than the singular « CFDT » model and C4.5 rev. 8 classifiers. Therefore, in this paper, we proposed the CFRT model which is more advantageous in managing uncertainty issues and surmounting the FDT challenges.

The remainder of this study is organized as follows. Section 2 explains the method used, the overall design of the proposed "CFRT" model, and a detailed description of the used SDCP methods and the used optimization technique and datasets, while the results are explained in section 3. At last, section 4 concludes the study and provides information about future work.
2. METHOD
2.1. C-fuzzy regression trees: the tree growth and expansion

In this study, the construction of the tree blocks as shown in Figure 3 is based mainly on the FKM algorithm used for clustering the dataset D into k distinct clusters, while each cluster is represented by its center vi (or prototype). The variability criterion controls tree growth, which measures the data heterogeneity according to the target value y (effort) in a certain node (a cluster is perceived as a tree node). Let \( H = \{H_1, ..., H_k\} \) be a set of heterogeneity criteria of the corresponding k clusters. The node \( N_j \) with the highest \( H_k \) is chosen to be more refined (we refer the reader to [1] for more details about the calculation of \( H_i \)).

![Figure 3. The expansion of the tree nodes with k=3](image)

2.1.1. Clustering technique: fuzzy K-means method

Generally, the tree's growth is based on constructing fuzzy clusters through the fuzzy K-means method (FKM). The FKM is a widespread method of information granules that Bezdek described in [28]. It is a technique that helps assign each input in the dataset to more than one cluster. Essentially, the FKM is an optimization procedure where we perform a recursive updating of the membership matrix and cluster centers until specific stopping criteria are reached.

2.1.2. The criterion of node splitting

The overall tree growth is performed by measuring the data diversity accrued at the tree nodes. The split of tree nodes is made through the variability criterion, and we choose precisely the node in which the diversity criterion is maximum and split it into k subsequent nodes. We note that each dataset pattern is assigned to the clusters with distinct membership grades.

Besides, we mention two stopping criteria conditions that depend on the nature of node patterns. The first condition depends on the number of elements located at the node. We split the node if the number of its elements exceeds the clusters' number (k). The second condition depends on the data structure index. We refer the reader to [11] for more details about the splitting criteria and the quantization of this index. We stop expanding the node once the number of patterns (projects) is less than k (number of clusters) or the data structure ability is too weak.

2.1.3. Software cost prediction using the tree

Generally, we use the regression tree to predict the software development cost (\( \hat{y} \)) from a training data or software project (\( p_i \)). For this purpose, we calculate the membership degrees for each tree node (or cluster) \( \varphi_{ij} \). We choose the correspondent pathway until the terminal nodes (leaves) are reached. At each tree
level, we determine the path \( t_0 \) based on \( t_0 = \arg\max_k \phi_k(p_i) \). We repeat this procedure at each tree level. Finally, the estimated effort value (\( \hat{y} \)) calculation at the terminal node is equivalent to the \( \phi_1 \) value of the (1).

\[
\phi_1 = \frac{\sum_{(p_k,y_k) \in P \times Y} \phi_{ik}^k y_k}{\sum_{(p_k,y_k) \in P \times Y} \phi_{ik}^k}
\]  

\[ (1) \]

2.2. SDCP techniques and optimization approach

We introduce in this subsection all SDCP methods used in comparison with the CFRT technique. Mainly the linear regression, multi-layer perceptron, k-nearest neighbor, and CART. Besides, the employed optimization technique.

2.2.1. Linear regression

LR is among the popular (famous) SDCP methods [2]. The LR estimates the effort required by building a linear equation. This linear equation models the relationship between the input variables \((p_{j1}, ..., p_{jn})\) and the output \((y_j)\).

2.2.2. Multi-layer perceptron

MLP was used efficiently to deal with many problems like time-series forecast, classification, and regression [29]. MLP is a neural network composed of an input layer, hidden layers (\( \geq 1 \)), and an output layer that reflects the output variable (the cost). The performance of the MLP network depends on various parameters, which are: the number of hidden layers (\( H \)), their neurons, and the value of training epochs (\( E \)) plus the learning rate (\( L \)) and the momentum. These parameters were selected carefully in this study by performing a GS method.

2.2.3. K-nearest neighbor

KNN is one of the SDCP methods employed for classification and regression problems [30]. It is a kind of case-based reasoning, which is based on the following logic: identical inputs (projects) have a potentially identical output (effort/cost) [31]. Consequently, the cost prediction of a novel unseen project depends on the costs of analog historical projects. The KNN includes three phases: case recognition, similar projects’ extraction, and adaption of cases. We note that in this paper, we firstly made a min-max normalization to the project features to have a similar impact when performing the prediction; also, we used the Euclidian distance to compute the analogy between the new project and the available projects in the dataset. And then, we average the costs of the \( N \) identical projects.

2.2.4. CART

CART [32] is an ML technique that uses the project attributes to construct a binary tree to deal with classification problems and regression issues. To get any prediction of any project, we must traverse the nodes of the constructed tree by starting from the root node and then choosing its subsequent nodes according to the project attributes’ values. Then, the cost prediction is calculated from the values available in the final reached node (leaf).

2.2.5. Optimization technique: grid search

The performance of any ML method depends essentially on the chosen hyperparameters. We note that, for each technique, the selected hyperparameters change depending on the used dataset. Therefore, an optimization process is applied to get the optimal parameter settings that generate the best accuracy. In this study, we used the GS. The GS method uses the cross-validation technique to determine the most optimal values from a set of parameters by testing all possible combinations and selecting the best one. We refer the reader to [33] for more details about the GS principal phases.

2.3. Experimental design

This subsection gives insight into the practical design. Mainly, it briefly describes the employed datasets, the performance criteria, and the evaluation process description. In addition, the employed statistical test and the configuration of the SDCP methods.

2.3.1. Datasets

The characteristics of datasets significantly impact the evaluation of SDCP methods like the size of the dataset, the nature of its features, the presence of outliers, and missing values [34]. We note that the eight datasets used in this paper originated from two repositories: the repository PRedictOr Models In Software Engineering (PROMISE) [35] and the International Software Benchmarking Standards Group (ISBSG)

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Table 1. Datasets descriptive statistics

| Dataset   | Size | Nb. Features | Min | Max   | Mean | Std  | Median | Skewness | Kurtosis |
|-----------|------|--------------|-----|-------|------|------|--------|----------|----------|
| Albrecht  | 24   | 7            | 0.50| 105.20| 21.88| 28.42| 11.45  | 2.30     | 4.67     |
| Atkinson  | 16   | 14           | 109.00| 912.00| 456.06| 241.07| 427.00 | 0.47     | -0.66    |
| COCOMO    | 252  | 13           | 6.00| 11,400.00| 683.44| 1,810.62| 98.00  | 4.39     | 20.51    |
| China     | 499  | 15           | 546.00| 23,940.00| 4,833.91| 4,188.19| 3,542.00| 2.04     | 5.30     |
| Desharnais| 77   | 8            | 5.60| 1,586.00| 87.48| 228.76| 38.10  | 6.26     | 41.36    |
| ISBSG     | 151  | 6            | 24.00| 60,270.00| 5,039.13| 8,471.11| 2,449.00| 4.17     | 21.10    |
| Kemerer   | 15   | 6            | 23.20| 1,107.31| 219.25| 263.06| 130.30 | 3.07     | 10.59    |
| Miyazaki  | 48   | 7            | 5.60| 1,586.00| 87.48| 228.76| 38.10  | 6.26     | 41.36    |

2.3.2. Evaluation methods and criteria

We notice that, for all the eight datasets mentioned, we used the LOOCV, where the estimation of one project is performed by leaving this project out of the training set and making the prediction. Also, the standard accuracy (SA) and the effect size ($\Delta$) measures were employed as evaluation criteria. Generally, a better model has a positive SA value, whereas a poorly predictive model has an SA value near zero, and negative SA values signify poor model predictions. The effect size measure ($\Delta$), as explained in [37], was used to check whether the model estimates were produced by chance or not.

Three categories are defined as follows: large (for value close to 0.8), medium (for value close to 0.5), and small (for value close to 0.2). The large and medium categories mean that the model performs good predictions. Nevertheless, the SA measure reflects only the acceptance of the model, so it is not convenient enough to conclude the method's accuracy [38], [39]. Therefore, we used other criteria in (4-8) in conjunction with SA, which are characterized by being unbiased and insensitive to dissymmetry: mean absolute error (MAE), mean balanced relative error (MBRE), mean inverted balanced relative error (MIBRE) and logarithmic standard deviation (LSD).

We used the Borda counting technique to point out the most accurate methods as described in [40].

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} AbE_i$$

$$\text{MBRE} = \frac{1}{N} \sum_{i=1}^{N} \frac{AR_i}{\min(y_i, \hat{y}_i)}$$

$$\text{MIBRE} = \frac{1}{N} \sum_{i=1}^{N} \frac{AR_i}{\max(y_i, \hat{y}_i)}$$

$$\text{LSD} = \sqrt{\frac{\sum_{i=1}^{n}(\delta_i + z^2)^2}{n-1}}$$

$$\delta_i = \ln(y_i) - \ln(\hat{y}_i)$$

Where $y_i$ is the actual cost, $\hat{y}_i$ reflects the estimated cost of project number $i$, and $z^2$ reflects the residual variance estimate.

2.3.3. Statistical testing

The statistical test is still required to evaluate the significant difference between methods [41]. The statistical test used in this study is the Wilcoxon test, with a significance level of 0.05. This test aims to check if the evaluated SDCP methods are statistically different by using their absolute error (AbE). One reason why this test has been used is that the distribution of AbEs is not normal.
2.3.4. SDCP techniques configuration

To tune the hyperparameter values of all SDCP methods, we perform a series of GS evaluations by checking every possible parameter combination listed in Table 2. These parameters originated from the available studies assessing ML methods’ performance [42], [43]. Hence, to search for the optimal parameter of each method using the GS technique, we evaluate all eventual combinations as shown in Table 2 based on the value of MAE. Then the best hyperparameter is the one that produces minimal MAE.

Table 2. Grid search hyperparameters

| Method | Parameters |
|--------|------------|
| KNN    | K={1,2,4,8,12} |
| MLP    | Learning rate={0.01, 0.02, 0.03, 0.04, 0.05} |
|        | Momentum={0.1, 0.2, 0.3, 0.4, 0.5} |
|        | Layers={3, 5, 9, 16} |
|        | Epochs={100, 500, 1000, 2000} |
| CART   | Minimum instances per leaf (I) = {1, 2, 3, 4, 5} |
|        | The minimum number of samples required to split an internal node (S)= {1, 2, 4, 6, 8, 10} |
|        | Max depth (M) = {1, 2, 4, 6, 8} |

3. RESULTS AND DISCUSSION

We present in this section all the experimental results attained from the evaluation of the CFRT and the remaining four SDCP methods. Firstly, we tune the SDCP methods using GS, and after that, we used SA and Δ measures to assess their performance. Table 3 shows the values of SA and the effect size measures resulting from the empirical evaluation of the five SDCP methods throughout eight datasets.

According to Table 3, all SDCP methods perform better than randomly guessing over all datasets (positive value of SA measure). Nevertheless, some methods perform better than randomly guessing but with low SA values: (SA=0.19 for LR with the Kemerer dataset and SA=0.26 for MLP in Albrecht).

- CFRT has the highest values of SA in COCOMO (SA=88%), Albrecht (SA=77%), and Atkinson (53%).
- MLP has the highest values of SA in COCOMO (72%), ISBSG (64%), and china (58%).
- LR has the highest values of SA in ISBSG (64%), Albrecht (59%), and china (54%).
- CART has the highest values of SA in COCOMO (95%) and China (74%).
- KNN has the highest values of SA in COCOMO (89%) and Albrecht (65%).

The Δ values are all large for all methods in all datasets (Δ>0.74). So, the totality of estimations was not produced by chance:

- CFRT with COCOMO (9.04), China (8.93), and ISBSG (4.80).
- LR with China (10.3), ISBSG (6.3), and Desharnais (5.37).
- MLP with china (11.5), COCOMO (7.6), and ISBSG (6.5).
- CART with COCOMO (14.14), COCOMO (10.06), and ISBSG (5.05).
- KNN with China (10.6), COCOMO (9.2), and ISBSG (5.5).

Table 3. Evaluation of the five SDCP techniques in terms of SA and effect size, bold values reflect the highest SA in the corresponding dataset using LOOCV

| Datasets  | LR  | MLP  | CART | KNN       | CFRT       |
|-----------|-----|------|------|-----------|------------|
|           | SA  | [Δ]  | SA   | [Δ]       | SA         | [Δ]       | SA       | [Δ]       |
| Albrecht  | 0.591 | 2.960 | 0.261 | 1.274 | 0.504 | 2.637 | 0.655 | 3.327 | 0.771 | 4.058 |
| Atkinson  | 0.416 | 2.587 | 0.494 | 3.056 | 0.390 | 2.489 | 0.414 | 2.647 | 0.532 | 4.337 |
| China     | 0.548 | 10.388 | 0.586 | 11.589 | 0.746 | 14.144 | 0.547 | 10.647 | 0.462 | 8.93 |
| COCOMO    | 0.446 | 4.484 | 0.729 | 7.620 | 0.957 | 10.061 | 0.891 | 9.291 | 0.882 | 9.04 |
| Desharnais| 0.504 | 5.371 | 0.408 | 4.149 | 0.424 | 4.421 | 0.448 | 4.855 | 0.437 | 4.850 |
| ISBSG     | 0.641 | 6.344 | 0.641 | 6.533 | 0.496 | 5.065 | 0.515 | 5.538 | 0.460 | 4.809 |
| Kemerer   | 0.196 | 0.741 | 0.492 | 1.945 | 0.382 | 1.452 | 0.463 | 1.742 | 0.473 | 1.800 |
| Miyazaki  | 0.504 | 1.830 | 0.371 | 1.390 | 0.587 | 2.152 | 0.476 | 1.688 | 0.435 | 1.553 |

Moreover, we perform a Borda counting technique to rank methods as shown in Table 4. Using the LOOCV method, we mention that no method from the five-used SDCP was ranked first overall datasets. Nevertheless, CFRT was rated first in three datasets (the Albrecht, Atkinson, and Kemerer) and the CART method, which is also ranked number one in three datasets: China, Desharnais, and Miyazaki. In contrast, KNN and MLP were ranked first just in COCOMO and ISBSG, respectively, whereas LR may be worst because it was ranked last in three datasets (the Atkinson, COCOMO, and Kemerer). The results indicate that all compared SDCP performed...
better than randomly guessing (positive SA), besides CFRT and CART are among the best (each one is rated first in 3 datasets), but typically no method is the most precise and reliable, and the best regarding its accuracy.

To explain the reached findings, we employed the Wilcoxon test. Table 5 shows the p-values:

- Concerning the Atkinson, china, Desharlains, ISBSG, and Miyazaki datasets: according to p-value, we notice that the difference in performance between CFRT and other methods is not statistically significant. So, the difference in ranks observed in Table 4 between all methods is insignificant in these datasets.
- Regarding the Albrecht dataset: CFRT significantly outperformed MLP, CART, and LR. Also for COCOMO: CFRT significantly outperformed LR, and MLP (p-value=0). The same finding is depicted by Borda counting as shown in Table 4.
- For Kemerer: the difference between CFRT and other techniques is not significant except for LR, where CFRT outperforms it significantly (confirm the results found in Table 4).

3.1. Comparison between CFRT and other SDCP methods

We compared CFRT and other techniques presented in the literature to analyze the accuracy of CFRT in SDCP effectively. We used the techniques reported in articles [44]–[46]. However, these papers used a different version of the dataset and validation methods besides different accuracy measures. Therefore, to make a fair comparison, we make various experimental designs using the same datasets, validation method, and accuracy measures as those used in the comparison papers. Tables 6 and 7 present the comparison results between CFRT and other methods on different used datasets using Pred (25%) and MMRE measures.

### Table 4. The rank of SDCP methods using the Borda counting method

| Method          | Albrecht | Atkinson | China | COCOMO | Desharlains | ISBSG | Miyazaki | Kemerer |
|-----------------|----------|----------|-------|--------|-------------|-------|----------|---------|
| LOOCV CFRT      |          | CART     | KNN   | CART   | MLP         | CART  |          |         |
| LOOCV KNN       |          | LR       | MLPL  | CART   | LR          |      |          |         |
| LOOCV CART      |          | LR       | MLPL  | CFRT   | LR          | CFRT  |          |         |
| LOOCV MLP       |          | LR       | MLPL  | CFRT   | LR          | CFRT  |          |         |

### Table 5. Statistical significance (P-Value)

| Datasets   | LR      | MLP     | CART   | KNN     |
|------------|---------|---------|--------|---------|
| Albrecht   | 0.056   | 0.018   | 0.036  | 0.132   |
| Atkinson   | 0.174   | 0.390   | 0.174  | 0.071   |
| China      | 0.931   | 0.684   | 1.0    | 0.954   |
| COCOMO     | 0.000   | 0.000   | 0.196  | 0.999   |
| Desharlains| 0.853   | 0.343   | 0.414  | 0.546   |
| ISBSG      | 0.999   | 0.999   | 0.990  | 0.857   |
| Kemerer    | 0.027   | 0.299   | 0.165  | 0.511   |
| Miyazaki   | 0.465   | 0.167   | 0.990  | 0.558   |

### Table 6. The values of Pred(25%) over all datasets

| Réf         | Methods      | Validation technique | ALBRECHT | CHINA | COCOMO | DESHARNAIS | ISBSG | KEMER | MIYAZAKI |
|-------------|--------------|----------------------|----------|-------|--------|------------|-------|-------|----------|
| [3]         | LR           | LOOCV                | 33       | 76    | 10     | 30         | 13    | 13    | 25       |
|             | SVR-PLOY     | LOOCV                | 21       | 93    | 27     | 25         | 40    | 40    | 23       |
|             | SVR-RBF      | LOOCV                | 42       | 90    | 31     | 34         | 53    | 53    | 46       |
| [3]         | MLP          | LOOCV                | 46       | 86    | 13     | 32         | 13    | 13    | 33       |
|             | MSP          | LOOCV                | 25       | 79    | 32     | 32         | 2     | 2     | 10       |
|             | CA           | LOOCV                | 33       | 38    | 26     | 36         | 33    | 33    | 31       |
|             | FA           | LOOCV                | 45       | 38    | 46     | 26         | 47    | 47    | 42       |
| [4]         | SVR_BFE      | LOOCV                | 42.857   | 83.333| 36.842 | 39.13      | 31.111| 20    | 28.571   |
|             | SVR_Boruta   | LOOCV                | 28.571   | 75.333| 34.211 | 34.783     | 24.444| 0     | 42.857   |
|             | CFRT (our    | LOOCV                | 42.857   | 81.333| 36.842 | 30.435     | 31.111| 20    | 42.857   |
|             | proposed     | model                |         |       |        |            |       |       |         |
| [5]         | RF           | 30% holdout           | 42.86    | 51.31 | 43.48  | 33.33      | 66.67 | 66.67 | 93.66   |
|             | RT           | 30% holdout           | 28.57    | 15.79 | 43.48  | 26.67      |       |       |         |
|             | CFRT (our    | 30% holdout           | 50       | 50    | 60.5   | 50         | 39.1  |       |         |

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As shown in Table 6, the proposed CFRT model outperformed all the twelve compared techniques (LR, MLP, M5P, CA, FA, RF, RT, SVR, SVR-PLOY, SVR-RBF, SVR_BFE, and SVR_Boruta) in four datasets: Albrecht, COCOMO, Desharnais, and ISBSG using LOOCV and 30 fold cross-validation techniques. While in the Kemerer dataset, CFRT outperformed 9 out of 12 techniques except (RF, SVR_RBF, and FA). Concerning the Miyazaki dataset, CFRT outperformed 8 out of 12 techniques except (SVR_RBF, FA, SVR_Boruta, and SVR).

| Réf | Methods | Validation technique | ALBRECHT | CHINA | COCOMO | DESHARNAIS | ISBSG | KEMERER | MIYAZAKI |
|-----|---------|----------------------|----------|-------|--------|------------|-------|---------|----------|
| [5] | RF      | 30% holdout          | 0.73     | 0.97  | 0.42   | 1.17       | 0.57  | LOOCV   | 1.458    |
|     | RT      | 30% holdout          | 0.97     | 2.74  | 0.52   | 3.71       |        |         |          |
|     | CFRT (our proposed model) | 30% holdout | 0.394 | 0.394 | 0.844 | 0.570 | 1.458 |         | 0.593    |
| [4] | SVR_BFE | LOOCV                | 0.548    | 0.17  | 1.242  | 0.462      | 1.092 | 1.334   | 1.367    |
|     | SVR_Boruta | LOOCV                | 0.566    | 0.242 | 1.524  | 0.457      | 1.559 | 1.671   | 0.527    |
|     | SVR     | LOOCV                | 0.583    | 0.187 | 1.375  | 0.467      | 1.478 | 1.235   | 0.553    |
|     | CFRT (our proposed model) | LOOCV | 0.782 | 0.782 | 1.020 | 0.677 | 0.684 | 2.05    | 0.593    |

According to MMRE values (Table 7), CFRT outperformed RT in Albrecht, COCOMO, and ISBSG. Also, it outperformed RF in Albrecht, COCOMO, with similar MMRE in Desharnais, ISBSG, and Kemerer. In addition, CFRT outperformed SVR, SVR_Boruta, and SVR_BFE in COCOMO Kemerer, while in Miyazaki, it outperformed SVR_BFE only. Finally, we conclude from these comparison results that CFRT is a promising and competitive technique to the others existing in the literature, so it can effectively be used for SDCP purposes.

### 3.2. Threats to validity

The findings of this study are not definitive, and they are also subject to some criticism. Mainly, they are related to the internal and external threats to validity. Which are detailed as follows:

#### 3.2.1. Internal validity

The 10-fold cross-validation used in the grid search to select the best hyperparameters may threaten the resulting conclusions of this paper even though many studies use the same cross-validation [29] and the grid search method for parameter selection [14], [33]. This can have a significant impact on the obtained results. Additionally, the chosen validation method may be perceived as another threat. However, in this study, we surmount it using the LOOCV method, which is considered a stable method (even if the experimentation is repeated, the same results are produced), contrary to other validation methods [47]. Another reason behind the use of LOOCV is its behavior of producing reduced bias and a more significant variance of predictions [48]. Moreover, we limited this study to handle just numeric features, not categorical ones. Therefore, taking into account, categorical features remain, since many popular software databases include categorical attributes.

#### 3.2.2. External validity

In this study, we deal with the following two external validity issues: the first is about the probability of generalizing the empirical results, while the second concerns the experimental design. The chosen datasets have the following characteristics: They differ in their sizes and the number of features, they include projects from several domains, the data (projects) originated from distinct organizations, and they were gathered at various periods. Therefore, the used datasets allow us to make a suitable conclusion thanks to their typical characteristics and number (eight datasets).

### 4. CONCLUSION

This paper proposes a new method of FRTs: the CFRT. The comparison is made with four SDCP methods, notably LR, MLP, KNN, and CART employing eight datasets and the LOOCV method. Firstly, we assessed the performance of the five SDCP methods using the SA measure. After that, we calculated the effect size to verify that the estimations were not generated by chance. Furthermore, due to the insufficiency of the SA criterion to make any conclusion concerning the accuracy of the compared techniques, we used
some reliable criteria to perform the Borda counting method that enables us to rank the SDCP methods according to their accuracy, and finally to validate and make a justification of the attained findings we perform a statistical Wilcoxon test.

We intend from this comparative study to answer the three previously asked questions: i) ReQu1: Does the CFRT technique perform better than the four techniques according to the SA measure using LOOCV? Using LOOCV and according to SA values, no specific method performed better than the others over whole datasets. ii) ReQu2: Does the CFRT present the most precise technique compared to the four SDCP methods by using LOOCV? We mention that no method from the five-used SDCP was rated one over all datasets. However, CFRT and CART are among the best (each one is rated first in 3 datasets) and iii) ReQu3: Does CFRT significantly outperform the other SDCP methods according to the statistical test? The performance of CFRT compared to the other techniques differs depending on the dataset and the SDCP method employed.

In summary, affirming that a specific method performs better in any context is a problematic issue, considering that distinct findings were obtained when changing the context of estimation, such as distinct scenarios of evaluations, distinct datasets, and distinct SDCP methods. However, according to the performed analysis, CFRT is among the best. It is rated first in 3 datasets according to four accuracy measures: MAE, MBRE, MBRE, and LSD. Also, according to the Pred(25%) values, the proposed CFRT model outperformed all the twelve compared techniques (LR, MLP, M5P, CA, FA, RF, RT, SVR, SVR-PLOY, SVR-RBE, SVR_BFE, and SVR_Boruta) in four datasets: Albrecht, COCOMO, Desharnais, and ISBSG using LOOCV and 30 fold cross-validation techniques. Therefore, CFRT remains a promising SDCP method. Regarding future work, the proposed model of "CFRT" can be optimized using an optimization algorithm such as an "optimized artificial immune network (Opt-aintet)" to have an improved model, which will then be applied for SDCP concerns, and more specifically for agile projects.

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