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Research Paper

# A New Credit Risk System Using Hybrid ELECTRE TRI and NSGA-II Methods

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**Abstract** **ELECTRE TRI is the most applicable and developed outranking based classification method in the field of MCDA. By including a large number of parameters, it provides a huge amount of information on criteria which enriches decision making process, although calculation of these large number of parameters is very time consuming and difficult task. To tackle this problem, this paper proposes a new method called NSGA-ELECTRE, by which the NSGA-II algorithm learns ELECTRE TRI and elicits its parameters through an evolutionary process. The proposed method contributes to the literature by utilizing a pair of conflicting objective functions including Type I errors and Type II errors instead of using a single criterion named "classification accuracy" which used frequently in the related works. The proposed bi-objective method is applied to six known credit risk datasets. The NRGA model is used as a benchmark for validation. Computational results indicate outstanding performance of the NSGA-ELECTRE method.**

**Keywords** *ELECTRE TRI, NSGA-II, Credit risk, NRGA*

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## Introduction

Credit industry has developed rapidly in recent years. Due to high competition in this industry, great number of persons can have access to credit cards without considering their credit conditions on behalf of the bank (Chuang et al., 2009). Reducing the risks of incorrect credit decisions is saving the time, cost and improvement of credit decisions are among the advantages of using credit scoring (Marquez et al.,2012). Traditionally, the banks and credit institutes have used techniques such as discriminate analysis, probity and logic analysis, logistic analysis for credit scoring. Altman (1998) reviewed these techniques widely. Some studies have used machine learning methods (Zekic-Susac et al., 2004; Zhang et al., 2008b). MCDA have come successful in solving problems such as credit scoring, predicting bankruptcy, portfolio management, venture capital investment and country risks (Zopounidis,2013). A rating of companies that includes financial ratios related to credit risk and the probability of bankruptcy is given in the MCDM/A literature(Yurdakul & İç, 2004; Li & Sun, 2010; Doumpos &Zopounidis, 2011; Li et al., 2011; Angilella & Mazzù, 2015; Doumpos et al., 2017). Also, there is comparative and statistical analysis and data-based methods in the credit / bankruptcy risk literature (Doumpos & Zopounidis, 2007; Tsolas, 2015; Mousavi & Ouenniche, 2018; García et al., 2019; Hosaka, 2019; Mahdi et al., 2019; Mai et al., 2019). In addition, several methods are used to evaluate investment strategies for portfolio selection problems, examples include funds selection **(**Garcia-Bernabeu et al., 2016; Ferreira et al., 2018), and venture capital investments (Aouni et al., 2013). Moreover, financial indicators are used in a multi-criteria context also for assessments and creating corporate performance rankings (Deng et al., 2000; García et al., 2010; İç, 2014; Rezaie et al., 2014). Doumpos and Figueira (2019) recently published a sorting analysis of credit ratings for companies based on ELECTRE TRI-nC, an

outranking method. Dincer et al. (2016) considered a hybrid Fuzzy-TOPSIS-AHP approach to assess industry alternatives for portfolio investments from the Borsa Istanbul Stock Exchange 100 Index (BIST 100) in Turkey. ELECTRE family are most developed MCDA models which may use for credit scoring problem. Dompous et Al. (2009) used metaheuristic algorithms of Differential Evolution(DE) to obtain the parameters of ELECTETRI TRI decision making model and implemented their model for several artificial datasets. In the early stages of ELECTRE-based credit scoring, decision makers (DMs) must define their preferential information about criteria as problem parameters. Because of the large amount of parameters, their confusing interpretation in problem context and the imprecise nature of data, obtaining all these parameters simultaneously, especially in large scale problems is very complex and time-consuming. Thus, this paper proposes a method to infer all ELECTRE TRI parameters through a procedure using the assignment examples i.e, previously classified inventory items made by DMs. We use a hybrid NSGA II algorithm which utilizes assignment examples as training data to induce parameters of ELECTRE TRI. Then induced classifier is used to assign unknown data. The target is to find the set of the parameters that minimize Type I errors and Type II errors on each credit risk dataset.

## Literature Review

Mousseau et al. (2008) developed a simple method based on nonlinear programing to infer weight parameter. Ngo and Mousseau(2002) tried to propose a mathematical model for inferring class boundary parameters. To complete their previous study, Dias (2010) tried to infer the veto parameter based on preference disaggregation and using the linear programing method. Cailloux et al. (2012) proposed a model based on mixed linear programming to infer class parameters i.e., criteria weights, and a veto threshold. Zheng et

al. (2014) proposed a Mixed Integer Linear Programming (MILP) model to infer weight, indifference, and preference based on the ELECTRE TRI technique. Kadziński et al. (2015) developed a mathematical model to infer weight and cutoff (λ) parameters in an urban planning study. Minnetti and Leone (2014) proposed a two-stage procedure for estimation of parameters of the ELECTRE TRI decision-making profiles based on a linear programming problem. Goletsis et al.(2004) proposed a model to disaggregate weight, indifference, and preference parameters of a model based on outranking relations extracted from assignment examples with medical data and symptoms. They conducted data mining operations using the Genetic Algorithm (GA). As Preference disaggregation for MCDA methods is so hard to solve with exact methods metaheuristic algorithms are being used in several studies (Goletsis,2004; Belacel,2007; Al-obeidat et al., 2010,2011; Dompous et al., 2009) which all considered the problem as single objective. In summary, inference, preference disaggregation, and preference learning are techniques that are being used to capture the preferences of experts or DMs in different methods, such as ELECTRE (Mousseau & Slowinski, 1998; Mousseau et al., 2001; Dias & Mousseau, 2006), PROMETHEE (Kadziński & Ciomek, 2016; Lolli et al., 2019), additive models (Jacquet-Lagreze, 1995; Corner & Buchanan, 1997; Aggarwal, 2015; Kadziński et al., 2015), Integral de Choquet (Aggarwal & Fallah Tehrani, 2019), and multi-objective optimization (Duro et al., 2014) using different single objective exact and approximate optimisation methods. Clearly, studies involving multiobjective optimisation approaches is still scare in the literature. Table 1 presents the existing research gap and a summary of previous studies on preference disaggregation with decision making models that are based on outranking relations.

Table 1.
*Research Gap in the Research Background*

| **Papers** | **Inferable Parameters** | | | | | | | **Single/Multi Objective** | **Application** | **Model / Technique** |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Year** | **Profiles** | **w** | **p** | **q** | **v** | $\lambda$ | | **Credit Risk** | |
| | | | | | | | | | Articles on meta-heuristic algorithms | |
| This paper | 2021 | Yes | Yes | Yes | Yes | Yes | Yes | Multi objective | Yes | NSGA |
| [Durot et al.] | 2014 | - | Yes | Yes | Yes | Yes | - | Multi objective | - | MOEA |
| [Al-obeidat et al.] | 2011 | Yes | Yes | Yes | Yes | - | - | Single Objective | Yes | PSO |
| [Al-obeidat et al.] | 2010 | Yes | Yes | Yes | Yes | - | - | Single Objective | - | DE |
| [Belacel et al.] | 2007 | Yes | Yes | Yes | Yes | - | - | Single Objective | - | VNS |
| [Dompous et al.] | 2009 | Yes | Yes | Yes | Yes | Yes | Yes | Single Objective | - | DE |
| [Goletsis et al]. | 2004 | - | Yes | Yes | Yes | - | - | Single Objective | - | GA |
| | | | | | | | | | Articles on classic mathematical models | |
| [De Leon] et al | 2014 | Yes | Yes | Yes | Yes | Yes | Yes | Single Objective | Yes | LP |
| [Kadinzki et al] | 2014 | - | Yes | - | - | - | Yes | Single Objective | Yes | MILP |
| [Zheng et al] | 2014 | - | Yes | Yes | Yes | - | - | Single Objective | Yes | MILP |
| [Cailoux et al] | 2012 | Yes | - | - | - | Yes | - | Single Objective | Yes | LP |
| [Dias et al] | 2004 | - | - | - | - | Yes | - | Single Objective | Yes | LP |
| [Zheng et al] | 2001 | Yes | - | - | - | - | - | Single Objective | Yes | MP |
| [Mousseau et al ] | 2001 | - | Yes | - | - | - | | Single Objective | Yes | LP |
| [Mousseau et al ] | 1998 | Yes | Yes | Yes | Yes | - | Yes | Single Objective | Yes | LP |

In order to cover the research gap, this paper developed a hybrid NSGA-ELECTRE model for credit risk classification problem. One outstanding

advantage of the proposed method in classification of the credit risk is the utilization of ELECTRE TRI method as an outranking approach which considers both qualitative and quantitative criteria in taking decision makers' preferences. In addition, on the contrary of standard data mining models which classify items nominally, the proposed method using ELECTRE TRI has the capability of classification of inventory items in an ordinal way. Figure 1 shows the Flowchart of the proposed classification model.

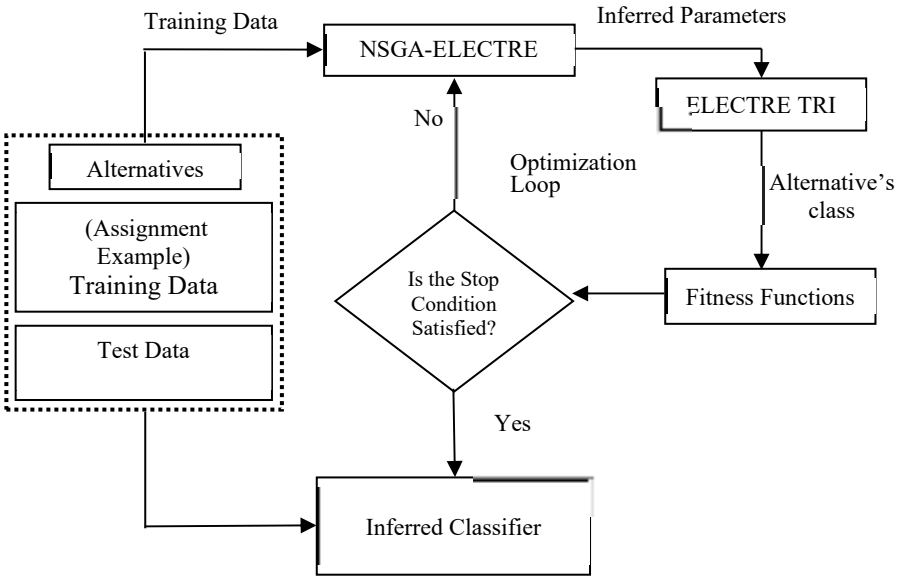


Figure 1.
*Flowchart of the Proposed Method*

## Research Methodology

Different versions of the ELECTRE techniques, which belong to the family of multiple criteria decision making family, have been introduced so far. One of the techniques used for classification of alternatives is the ELECTRE TRI technique that was for the first time introduced by Roy. In this method, alternatives are assigned by DMs to predefined profiles. Classification is achieved by comparing each alternative to profiles representing the boundaries of classes. ELECTRE TRI method, assigns a limited set of alternatives $A_i$ (i=1, 2, … , m) based on n criterion $g_j$ (j = 1,2,…, n), to predefined categories $C_h$ (h=1, 2, …, p) which are bounded by lower and upper limit profiles $b_h$ (h=0, 1, 2, …, p). In this method, the assignment of alternatives to categories results from their comparison with reference profiles ($b_h$) that define the limits of the categories ($C_h$). The implementation of ELECTRE TRI comprises two phases. In the first Phase, Alternatives are firstly compared to the reference profiles (and vice versa) to develop outranking relations (Miracle et al., 2019). The meaning of the outranking relation S, between the alternative $A_i$ and the profile $b_h$ ($A_i$ S $b_h$) is that $A_i$ is at least as good as $b_h$. The validation of the outranking relation "$A_i$ S $b_h$" is based on the concordance and discordance principles. The concordance principle consists in the existence verification of a sufficient majority of criteria in favor of the assertion "$A_i$ S $b_h$", whereas the opposition of the minority of criteria is not enough to preclude it (discordance principle) (Cailoux et al., 2012). In the second phase, outranking relations are employed to assign every alternative to a specific category. In ELECTRE TRI the assignment of an alternative to a specific category does not influence the category, to which another alternative should be assigned. If an alternative $A_i$ outranks lower limit of given category $b_h-1$ i.e. ($A_i$ S $b_h-1$) and simultaneously does not outrank upper limit of the category $b_h$ i.e. ~ ($A_i$ S $b_h$),

the considered alternative $A_i$ is assigned to the considered category ($C_h$). For every couple of alternative Ai and the reference profile $b_h$ the computation of the credibility index σ is required by ELECTRE TRI to validate the outranking relation $A_i$ S $b_h$ ($b_h$ S $A_i$ respectively). For this purpose, the following preference parameters are to be introduced:

- Criteria weighting vector $W = (w_1, \ldots, w_n)$ with $w_1 + \ldots + w_n = 1$ *and* $, \ldots w_{i0}$
- Profile values including $b_1$ and $b_2$, $with\ g_i(b_2) g_i(b_1)$
- Indifference threshold values $(q_i)$ $with$ $(q_1, \ldots q_i) = 0$
- Preference threshold values $(p_i)$ with $(p_1, \ldots, p_i) q_i$
- Veto threshold values $(v_i)$ with $(v_1, \ldots, v_i) p_i$
- Shear surface (fuzzy comparison) value $\lambda \in [0.5, 1]$

The q and p parameters denote the indifference and preference threshold limits and crease the internal preference information of each criterion. These values reflect the precision of alternative assessment per criterion. In addition, $q_i$ is the largest difference of $b_h$ from an alternative in the j-th criterion [($g_i$(A)-$g_i$($b_h$)], and pi shows the minimum difference of $b_h$ from an alternative in the j-th criterion, which reflects the level of satisfaction with alternative A and profile $b_h$ for the $g_i$ criterion. There are two situations for assessing and acknowledging the outranking relation (S) in this condition: consistency and inconsistency situations. If the outranking relation is true the values of most criteria are in the desired utility range in the consistency situation, but in the inconsistency situation the values exceed the range. Figure 2 shows ordered classes and reference profiles under every criterion j.

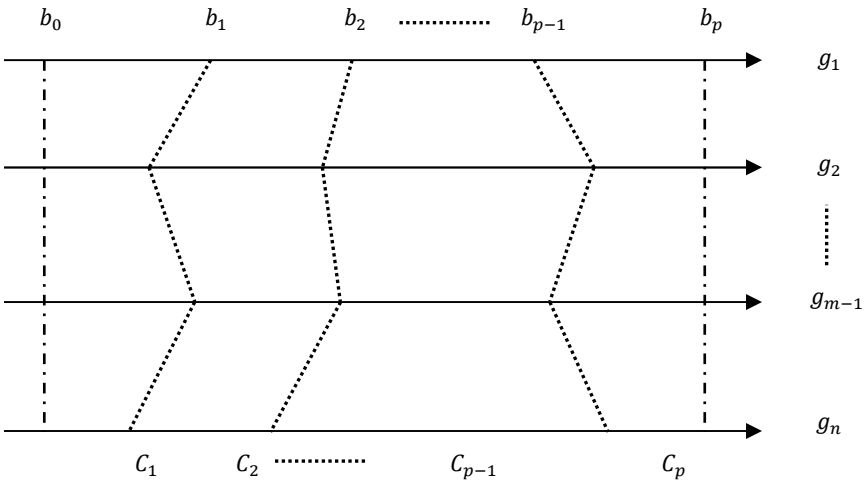


Figure 2.
*Ordered Classes and Reference Profiles under Every Criterion j*

Two other parameters are also involved in establishing of outranking relations $W_i$ (which stands for the weight of the criteria) and $V_i$ (which is the veto threshold or the threshold of rejecting characteristics involved in the formation of outranking relations). $V_i$ is the minimum difference between $g_{i(bh)}$ and $g_{i(a)}$ and rejects the $a_{Sbh}$ relation. Therefore, if the distance between the $b_h$ profile and A in the $i_{th}$ criterion exceeds $V_i$, then the aforementioned criterion vetoes the above relation.

In the ELECTRE TRI classification method, the above parameters form the model input along with the alternatives. The output of this model includes alternatives classified based on the predefined profiles. Figure 3 depicts the input and output of the ELECTRE TRI technique. Since the process of calculating the above parameters is complicated and time-consuming, after obtaining the assignment examples from the DMs, which form the classified examples of alternatives in the A, B, and C classes, this problem is changed

into a learning model to be able to infer the problem parameters. Figure 1 presents the research, conceptual model. As seen, the input to this model is training data, which is the previously tested experience of DMs with inventory classification. In other words, to overcome the challenge of the inventory classification problem, which is classification of big data, it is necessary to use a random sample of items classified by experts to allow for inferring parameters. This sample is referred to as the assignment example. In the next stage, throughout the process of the research proposed model, which is called NSGA-ELECTRE, the basic parameters of ELECTRE TRI are inferred from assignment examples. The model's fitness function shows the number of accurately classified inventories based on the technique used in the ELECTRE TRI method compared with actual classifications of assignment examples. The stop condition is completion of iterations defined in the algorithm parameters. In the end, the ELECTRE TRI model and parameters inferred as the learning process output are used for classification of test data. In the following, the ELECTRE TRI classification technique is introduced briefly. Moreover, to solve the credit risk classification problem, a model based on the NSGA-II is proposed. In this research, to optimize the ELECTRE TRI model's parameters the extended PSO algorithm is developed. In this research, we optimize parameters by combining a multi-criteria decision making technique based on outranking relations using the evolutionary NSGA-II. Parameters of the NSGA-II model are determined as follows.

- Maximum number of iterations: considered to be 200.
- Population size: considered to be 50.
- Selection: The Roulette Wheel Strategy is used for selecting the parents.
- Crossover Operator: This study uses the single-point crossover operator. In addition, the crossover probability, i.e. a ratio of parents on which the crossover operator acts, is considered to be 1.

- Mutation Operator: The uniform mutation operator is used to develop the given algorithm. This operator first acts on all parameters, and then randomly on some parameters. The mutation probability takes the probability of change in each gene, which is considered to be equal to 0.1. The mutation rate, which reflects a ratio of parents on which the mutation operator acts, is considered to be equal to 0.8.
- Fitness Function: In this study, both Type I errors and Type II errors are used as classification performance evaluation criteria. .

$$f_1: \text{Min } FP_{rate}(w_j, r_k, , q_j, p_j, v_j, \lambda)$$
$$f_2: \text{Min } FN_{rate}(w_j, r_k, , q_j, p_j, v_j, \lambda)$$

In addition, the general form of the optimization problem is written as follows for credit classification with binary classes.

$$Max\ CA(w_i, b_i, q_i, p_i, v_i, \lambda)$$
$$St.: \sum w_i = 1$$
$$b_{i+1} \geq b_i$$
$$v_i \geq p_i \geq q_i \geq 0$$
$$0.5 < \lambda < 1;$$
$$i = 1, .., n$$

To handle poor chromosomes, penalty strategy is employed and violation from constrains of Equation 3.6 is determined by Equation 3.7:

$$R_j = \text{Max}(q_j - p_j, 0)$$
$$\bar{R} = \frac{1}{m}\sum\left(\frac{R_j}{u_j - l_j}\right)$$
$$S_j = \text{Max}(v_j - p_j, 0)$$
$$\bar{S} = \frac{1}{m}\sum\left(\frac{S_j}{u_j - l_j}\right)$$

Where, $u_j$ and $l_j$ are up and low bounds of each criterion and m is the total number of criteria. The penalty values for both objective functions are determined through cumulative function (Equation 3.8).

$$(x) = \begin{cases} f(x) & x \in \text{feasible region} \\ f(x) + \frac{1}{2}(\bar{R} + \bar{S}) & x \notin \text{feasible region} \end{cases}$$

chromosome representation and generation of initial population:
Regarding the variables of decision which are parameters of ELCETERTRI consider the structure of chromosomes as:
$\text{Solution} = (w_1, \dots w_m, r_1, r_2 \dots r_{b-1}, q_1, \dots, q_m, p_1, \dots, p_m, v_1, \dots, v_m, \lambda)$
In all metaheuristic algorithms, it is very important that the initial population cover the solution space adequately. To produce the initial population, the range of weight vector (W) is considered (1,n). for weight of each of the criterion, a value with the uniform distribution probability is produced. Then, to ensure that the sum of weights is 1, they are normalized. For p, q and v parameters, the search space is limited between the minimum and maximum of each alternative in each criterion and random values are produced with uniform probability distribution. The profiles are also determined in maximum and minimum range of alternatives values in each criterion and sort them from small to big. To produce $\lambda$ parameter this process is done in [0.5,1] through producing random numbers from uniform distribution. The whole procedure explaining the classification stages for NSGA-ELECTRE model is shown in figure 3. After production population initialization, optimization is done in consecutive iterations. After implementing the stages of optimization, the optimized parameters and test data are delivered to ELCETERE TRI for classification.

Step1: Read Data
Step2: Define Initial Parameters of GA ; /*N: population size,
MG: maximum generation,
Nc: Number of Crossover Operation
Nm: Number of Mutation Operation*/
Step3: Divide Data into 5 Folds
For each Fold Do
Put current fold in test's group and put another folds in train group
Step4: Generate $P_0$ ; /∗ Initial population ∗/
t=0 ;
Do Non-Dominate Sorting for each solution
Calculate Crowding Distance for each solution
Step5: GA Loop
While not Termination Criterion ($P_t$) Do
Evaluate($P_t$) ;
Step 5-1: Select Parents by Binary Tournament Selection and Save Parents in $G^1_t$
Step5-2: Do Crossover
For j=1 to Nc Do
Crossover $G^1_t$ (j) and $G^1_t$ (j+1) by Single_Point Strategy
End For
Save offspring in $P'_t$
Evaluate($P'_t$)
Step 5-3 : Select α%*Nm numbers of $P_t$ by Random , save in $M^1_t$
Step 5-4 : Do Mutation on $M^1_t$ by Uniform Strategy Type 1, Save offspring in $P''_t$
Step 5-5 : Select $(1-\alpha)$%*Nm numbers of $P_t$ by Random, save in $M^2_t$

Step 5-6 : Do Mutation on $M^2_t$ by Uniform Strategy Type 2, Save offspring in $P'''_t$
Step 5-7: integrate population ($P_t$) and offspring ($P'_t$, $P''_t$, $P'''_t$)
Step 5-8: Do Non-Dominate Sorting for each solution
Step 5-9:Calculate Crowding Distance for each solution
Step 5-10: Sort individuals based on their Crowding Distance and Rank respectively and Choose first N individuals ($P_{t+1}$)
Step 5-11: Do Non-Dominate Sorting for each solution
Step 5-12:Calculate Crowding Distance for each solution
t = t + 1 ;
End While
Step 6: save final Pareto
End For
Step 7: Output

Figure 3.
*Pseudo Code_NSGA*

## Findings

NSGA ELECTRE is applied to each dataset through the K-fold method. Since there is not a global measure for estimation of the algorithm performance, the mean of the 5-fold measures is used for estimation of the algorithm performance. The following six real datasets were used in credit classification in the proposed method: credit data of Australia, Germany, Japan, Iran, Poland, and the USA; Poland's dataset included recorded two-year data and the US dataset corresponded a shortened database used by the San Diego University, Californian, and Fair Isaac Corporation (Marquez et al., 2012). Table 4.12 presents a summary of the main properties of these datasets.

Table 2.
*Properties of Datasets Used in the Second Method*

| | **Dataset** | **# alternatives** | **# measures** | **# defaults** | **# non-defaults** |
|---|---|---|---|---|---|
| Dataset 1 | Australia | 690 | 14 | 307 | 383 |
| Dataset 2 | Germany | 1000 | 24 | 700 | 300 |
| Dataset 3 | Japan | 690 | 15 | 296 | 357 |
| Dataset 4 | Iran | 1000 | 27 | 950 | 50 |
| Dataset 5 | Poland | 240 | 30 | 128 | 112 |
| Dataset 6 | USA | 2435 | 38 | 1836 | 599 |

Performance evaluation measures of the multi-objective metaheuristic algorithms obtained from five runs of NSGA-ELECTRE in each dataset, are separately presented in this table. It is worth noting that, for the MID criterion, the value of the first front in each run is recorded.

Convergence with Pareto-optimal solutions and creation of density and diversity among obtained solutions are two major goals of every multi-objective evolutionary algorithm. However, since these two objectives are contradictory, there is no absolute criterion capable of making decision about the performance of algorithms by itself. If such criterion was accessible, we could claim the superiority of an algorithm over the other ones. Since no benchmark was found from literature review to compare with the proposed method (NSGA ELECTRE), the NRGA was once implemented and then NSGA ELECTRE and NRGA ELECTRE algorithms are compared in terms of the following criteria to validate the results:

- Number of Solutions (NOS)

The algorithm capable of providing more non-dominated solutions in Pareto-archive is more efficient in presenting the real Pareto-optimal level and providing decision-makers with more number of options.

- *Mean Ideal Distance (MID)*

It is used to measure the approximation to real Pareto-optimal level

- *Coverage Set*

The coverage set criterion C (A, B) computes the ratio of solutions in Set B that are poorly dominated by some solutions in Set A

- *Spacing*

This criterion, which is among the density measurement criterion, computes the approximate distance of consecutive solutions

- *Maximum Spread*

It measures the length of the space diagonal created by final non-dominated solutions in the objective space

- *CPU Time*

This measure shows the time required by an algorithm to obtain relative Pareto. The more this measure is smaller, the more it is useful.

The coverage function for Pareto values obtained from NSGA-ELECTRE and NRGA-ELECTRE, applied to all datasets. The Pareto fronts obtained from applying these two algorithms to the second dataset in are presented in figure 4. According to this diagram, it seems that the selected Pareto front of NSGA-ELECTRE covers the selected Pareto front of NRGA-ELECTRE.

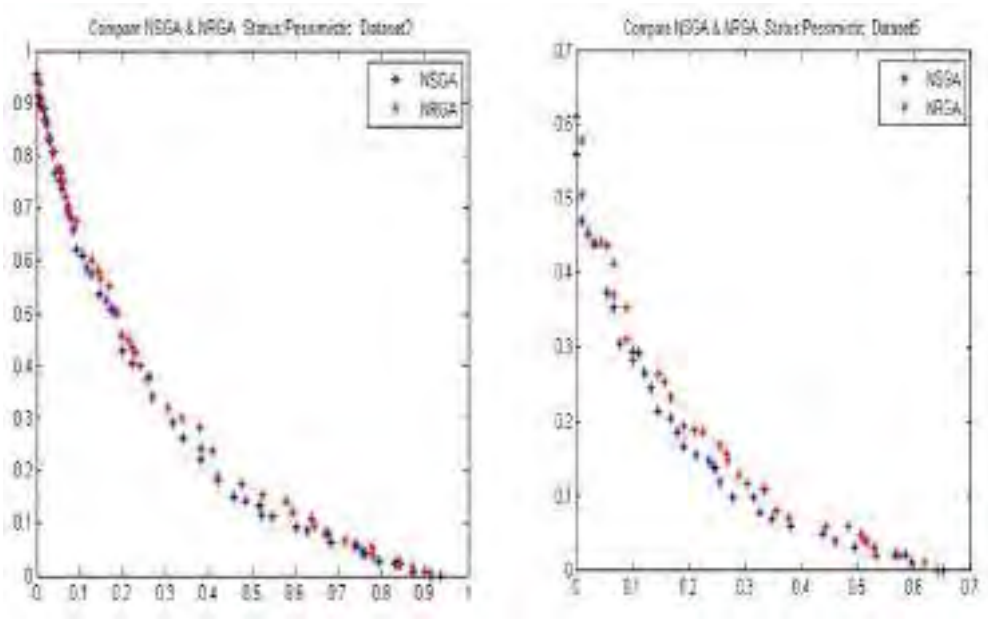


Figure 4.
*Comparison of Pareto Fronts of These Two Algorithms in the Second and Fifth Datasets*

Table 3 shows the mean value of results from running of these two algorithms. The mean of each row was computed and presented along with the coverage values.

Table 3.

*Comparison of These Two Algorithm*

| Dataset | NSGA-ELECTRE | | | | | |
|---|---|---|---|---|---|---|
| | **MID** | **Spacing** | **Spread** | **NOS** | **CPU Time** | **Coverage** |
| 1 | 0.44401 | 0.014331 | 1.127975 | 34.4 | 2775.323 | 0.6429 |
| 2 | 0.681321 | 0.016238 | 1.352823 | 46.4 | 4087.615 | 0.6727 |
| 3 | 0.451829 | 0.014137 | 1.167253 | 29.8 | 2692.961 | 0.3171 |
| 4 | 0.549709 | 0.019405 | 1.239658 | 39.8 | 4195.103 | 0.7059 |
| 5 | 0.419614 | 0.012058 | 0.910219 | 42.8 | 1225.373 | 0.8936 |
| 6 | 0.553006 | 0.013145 | 1.302425 | 41 | 10370.74 | 0.6604 |
| Average | 0.516582 | 0.014886 | 1.183392 | 39.03 | 4224.52 | 0.6487 |

| | NRGA-ELECTRE | | | | | |
|---|---|---|---|---|---|---|
| **Dataset** | **MID** | **Spacing** | **Spread** | **NOS** | **CPU Time** | **Coverage** |
| 1 | 0.430213 | 0.014189 | 1.123947 | 25.4 | 2858.404 | 0.3889 |
| 2 | 0.66114 | 0.018488 | 1.342205 | 24.6 | 4123.55 | 0.1404 |
| 3 | 0.449783 | 0.013345 | 1.188715 | 35.6 | 2737.051 | 0.5686 |
| 4 | 0.590591 | 0.015984 | 1.257927 | 21.6 | 4264.179 | 0.1698 |
| 5 | 0.450035 | 0.01261 | 0.969751 | 33.4 | 1215.129 | 0.1373 |
| 6 | 0.565758 | 0.013778 | 1.302161 | 33.2 | 10439.65 | 0.0794 |
| Average | 0.524587 | 0.014732 | 1.197451 | 28.9 | 4272.994 | 0.2474 |

Based on the mean values in the last row of Table 3, it seems that NSGA-ELECTRE performs better than NRGA-ELECTRE given CPU Time, NOS, MID, and Coverage measures. There is a slight difference between the two algorithms given the spacing measure. With respect to the spread measure, it seems that the NRGA-ELECTRE performed better than the NSGA-ELECTRE. Due to high coverage of NSGA-ELECTRE on NRGA-ELECTRE, higher spread value seems probable.

Figure 5 presents the convergence of NSGA-ELECTRE algorithm through plotting MID commutated over different generations and is equal to the objective function diagram by time in single-objective algorithms.

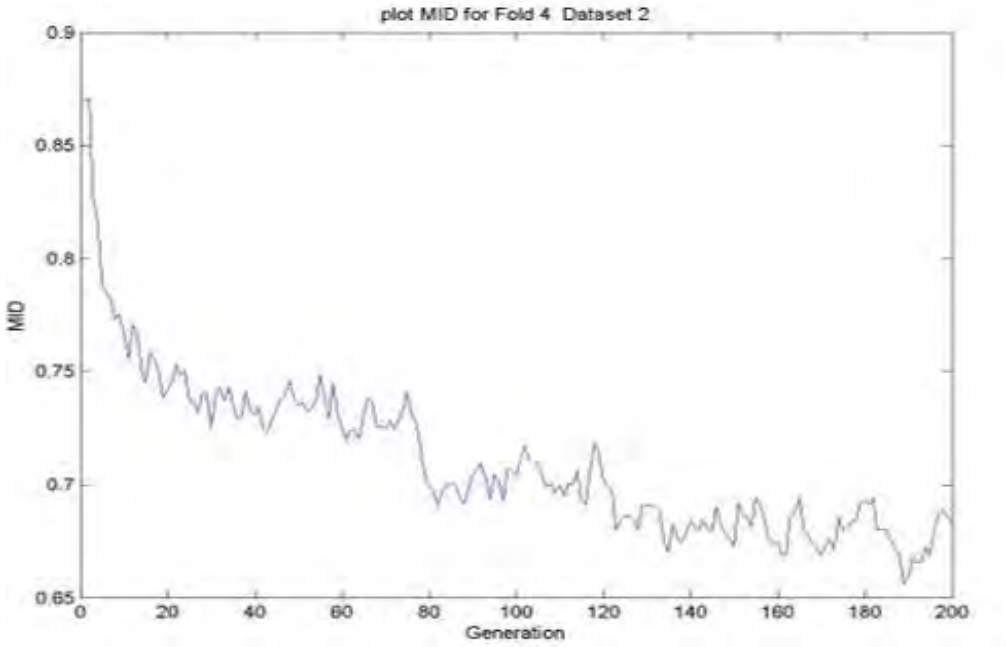


Figure 5.
*NSGA-ELECTRE Multi-Objective Convergence Diagram for the Second Dataset*

In this diagram, each point reflects the MID value of the first front of its corresponding generation and shows that appropriate performance of the algorithm results in gradual decrease in diagram's inclination over successive generations. In other words, the first front of the generations reaches closer to optimal Pareto. In this study, MATLAB was used for programing the proposed metaheuristic methods, using a laptop with 3 GHz Processor and 4GB RAM.

## Conclusion

This paper proposes a new classification approach based on outranking relations to validate credit clients. In this approach, the NSGA-II inferred all ELECTRE TRI parameters for each criterion and class. As a result, more detailed information about the measures, greater flexibility and classification optimization are achieved. In this approach, there is no need for criteria normalization. In contrast to exact methods, it can infer all parameters in large scale real problems with acceptable accuracy during a reasonable time. In addition, two metrics, i.e. the first- and second-type errors that measure the prediction error in each class were used because credit datasets are imbalanced and thus a single metric cannot reflect the classification quality. The proposed method was applied to six credit datasets and the results showed its efficiency. Currently, there is a growing interest among researchers in the field of machine learning toward preference modeling and decision-making. Similarly, MCDA researchers are greatly interested in using progresses made in machine learning. The road ahead focuses mainly on discovering new ways for combination of these two fields. The use of other conflicting classification metrics to form a many-objectives optimization problem, also generalization proposed approach to other outranking relations based methods are recommended.

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