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An Improved Fuzzy Classification System for Financial Credit Decision using Multi-Objective Evolutionary Optimization

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Abstract*: In fuzzy classification system, accuracy has been gained at the cost of interpretability and vice versa. This situation is known as Interpretability-Accuracy Trade-off. To handle this trade-off between accuracy and interpretability the evolutionary algorithms (EAs) are often used to optimize the performance of the fuzzy classification system. From the last two decades, several multi-objective evolutionary systems have been designed and successfully implemented in several fields for finding multiple solutions at a single run. In Financial Decision making concerning Credit Allocation, Classification is a significant component to obtain credit scores and predict bankruptcy. A fuzzy classification system for the financial credit decision has been designed and find out the Accuracy and Interpretability parameters for applying various MOEAs to get the pareto optimal solution resulting in to improvement in the performance of the proposed system. The proposed model implemented on standard benchmark financial credit allocation datasets i.e., German Credit Approval system available from the UCI repository of machine learning databases (http://archive.ics.uci.edu/ml) and using the open source tool MOEA framework (http://www.moeaframework.org). The experimental analysis highlights that the NSGA-III works efficiently for financial credit approval system and improves the performance by making a balanced trade-off between accuracy and interpretability.

Index Terms*: Fuzzy Classifier; I-A Trade-off, Evolutionary Algorithm; Fuzzy rules; Multi-Objective, MOEA, etc

I. INTRODUCTION

The single objective evolutionary algorithm gives the only single optimal solution. In general, most of the real-world problems do not realize the single optimal solution based on the single objective functions. A computer system with less architecture may consume less power, but the performance might be not acceptable [1,2]. In this case, a computer system has a single objective to consume less power.

To achieve high performance with less power consumption, require more than one objective function. Also, a credit approval system needs more than one objective function that covers different parameters such as the status of existing accounts, present employment, income status and more [3].

In such a case, the evolutionary algorithm is suited because it poses a set of solutions simultaneously. To find an optimal solution by using more than one object function, the multi-objective evolutionary algorithm has been designed [4]. The multi-objective evolutionary algorithm uses the non dominated set of populations sorting and sharing mechanism.

Nowadays, most of the real-world problems required multi-objective evolutionary technique to achieve an optimal solution in a single execution. To do this several multi-objective evolutionary algorithms have been designed to give more than one Pareto optimal solutions. The only difference is the assignment of fitness value. Some of the algorithms used different selection technique to select a population set. But one of the main issues of which one is best for which type of problems. In this way, several comparative studies have been conducted by eminent scholars. But one of the main issues related to past comparative study is to none of the surveys mention that of which one is good for which type of problems and in terms of performance analysis. In this article, a comparative analysis of different MOEAs has been conducted on a benchmark data set that is extracted from the UCI repository and also analyzes the performance of different MOEAs. This study also helps in further improvement of MOEAs.

II. MULTI-OBJECTIVE EVOLUTIONARY ALGORITHMS (MOEAS)

The prime objective of the design of the fuzzy system is to gain a high degree of accuracy and interpretability, but its nature is opposite, i.e., if the accuracy is high, then interpretability is relatively low and vice-versa. To handle the trade-off between accuracy and interpretability, the multi-objective optimization [5-9] has been used.

Such kind of optimization having Evolutionary based multi comprises merger of any one of the methods like evolutionary based programming [10], genetic programming [11], genetic rules [12], and evolution methods [13] to handle issues of many objectives.

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Fig 1. shows the standard process of an MOEA.

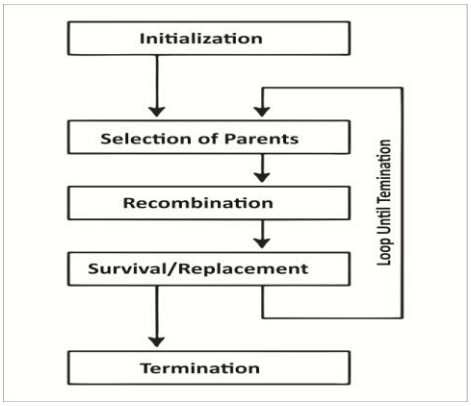


Fig 1: Process of MOEA

The multi-objective evolutionary algorithms are classified into two generations. In the first generation the MOGA [14], NSGA [15] and NPGA [16] has been designed having a choice of fitness sharing and niching associated with Pareto rank. In the second generation, the SPEA [1], SPEA2 [17], PAES [18-20], NSGA-II [21], NPGA2 [22], PESA [23] and PESA-II [24] has been designed to cover different perspective and makes a balance between accuracy and interpretability.

To achieve the diversified set of Pareto optimal solution, the **eMOEA** has been designed [29,30]. In this algorithm, the search space has been divided into many grids, and every grid maintains the diversity of the Pareto front and has only one solution in each grid box.

A. Multi-Objective Genetic Algorithm (MOGA)

MOGA is a variation of Goldberg's method designed by Fonesca and Fleming (1993) [14]. In this algorithm, the rank of the individual population corresponds to the total number of chromosomes present in the population that is dominated and all non-dominated populations are ranked 1. This method penalizes the dominated population due to population density. To assign the fitness, first sort the populations, according to their rank, after that assign the fitness based on their rank from best to worst. After that find the average fitness value of same ranked population and grouped in the same. Such type of blocked fitness assignment produces immense selection pressure as a result of premature convergence. To improve the performance of MOGA, the neural network concepts are hybridized [25].

B. Non-dominated Sorting Genetic Algorithm (NSGA)

It is an extension of the traditional genetic algorithm for multi-objective function optimizations. The primary objective of this algorithm is to consider a set of objective functions and find multiple Pareto solutions at a single run. Instead of an evolutionary process, the NSGA [15] includes the selection, crossover and mutation process of GA. The initial population is in the nature of hierarchy. In this algorithm, first populations are ranked based on Pareto dominance. After that, All non-dominance data are classified into non-dominance categories and assign the fitness value, i.e., proportional to the population size. After that single point crossover and mutation has been performed. After that, these sets of populations are classified and ignored. Further, the next level of population data is used. This process will continue until all the population is classified. This algorithm takes only one generation data at a time for classification, so that it takes more computation time than others. The lack of elitism may affect the performance of the GA and the solution also.

To overcome these limitations, Deb et. al. (2002) [21] improved the NSGAs and named **NSGA-II**. The NSGA-II reduces the time, complexity and increases the performance of the GA. First, it creates a population of individuals with ranks and sort the population data according to their non-dominant level and generate new offspring and combined with the parents. After that niching has been conducted with the help of crowded distance of each participant. Further, it has been improved with the help of e-dominance and enhance the random search from the diverse set of Pareto optimal solutions [31], known as **eNSGA-II**. Above discussed NSGA approaches, considers only two objectives problems. To consider a number of problems, the **NSGA-III** has been designed [32].

C. Niched-Pareto Genetic Algorithm (NPGA)

This algorithm works on the concept of the tournament selection method. Horn et. al 1993,1994) [16, 26] proposed the NPGA by using the concept of tournament selection method based on Pareto dominance. In NSGA, the populations set is in the hierarchy in nature and consider only one set of the population at a time this may take more time to classify the population. In NPGA, the two individuals are selected randomly from the population, and if anyone is dominated, then another one will win and classified. If both of them are either dominated or non-dominated, then the fitness sharing [27] is used to decide the winner.

Erickson et al. (2001) [22] designed an improved version of NPGA called NPGA2.

NPGA suffers with some ties case when both of the individuals are either dominated or non dominated. To resolve the tie situation, NPGA2 uses a Pareto ranking with tournament selection. And also continuously updated fitness sharing concept [28] has been used in NPGA2, to share the fitness value. Instead of current generation populations, the partially filled next generation population has been used for classification.

D. Strength Pareto Evolutionary Algorithm (SPEA)

In MOGAs the selection of populations and assigning fitness value take a considerable amount of time and in many cases convergence is premature. To overcome this limitation Zitzler and Thiele (1999) [1] designed SPEA. This algorithm tries to integrate different MOEAs (Multi-Objective Evolutionary Algorithm). In this way, the author used an archive of external non-dominated population sets. The non-dominated population set is archived at each generation in the external non-dominated archive. Instead of rank, the strength of the external non-dominated individuals has been computed as per the MOGAs, and it is proportional to a total number of the non-dominated set of elements of each set. The fitness value is depending on the strength of the external non-dominated factors that dominate it. The effectiveness of this depends on the size of the external non-dominated solutions set. The size of the external non-dominated solutions affects the selection process; if its size grows too large, then the selection pressure might be very less. However, it penalizes searching.

To avoid this, the author used a pruning technique to restrict the size of the external non-dominated solution under the defined threshold.

To improve the efficiency of SPEA, the**SPEA2** has been designed by Zitzler et. al (2001) [17]. The main predecessor of the SPEA2 is (i) The fitness assignment in SPEA depends on the size of the external non-dominated solutions, to improve this, the author considers the total number of elements that dominate and the number of elements which dominated by the element. (ii) Searching in SPEA is too complex, to improve this author used nearest neighbor destiny estimation technique. (iii) In SPEA, the limit of the archive is not fixed that penalize the searching process, to overcome this, the author enhance the archive storage capacity that guarantees to ensure the optimal solutions.

E. Pareto Archived Evolution Strategy (PAES)

Corne et. al (2000) [23] use the concept of archived non-dominated solutions and proposed a new algorithm named PAES that used the grid-based approach for selection. This algorithm used 1+1 strategy (that means one parent generates only one offspring) with the archived non-dominated solutions set. After mutation, each individual is compared with the archived non-dominated solutions set. This algorithm uses a novel approach to maintain diversity by the crowding procedure. In crowding procedure, space is divided, and the placement of the solution is based on their objective value. This algorithm provides a grid-based placement of solution. The grid-based system increases the efficiency of searching and reduces computation complexity.

F. Pareto Envelope-based Selection Algorithm (PESA)

Corne et al(2000) [23] designed a new algorithm called PESA. In this algorithm, the population size has been divided into two parts (i) internal population: size is very less and directly used in classification and (ii) external population: size is bigger than internal. To maintain, the selection diversity, a hyper-grid phenotype space has been used with the application of crowding technique. This crowding technique is used to access the population from the external archived solution of non dominated populations.

In PESA, the selection of the population forms a hyper grid that takes high computation time. To reduce the computation time, the region-based selection from the hype box is used and designed an improved version of PESA is called PESA-II by [24]. This algorithm uses the Pareto ranking in selecting from a hyper box. This hyper box-based selection with Pareto ranking reduces the computation cost. Summary of different MOEAs with respect to fitness sharing and representations is given at Table-I.

Table-I : Summary of different MOEAs with respect to fitness sharing and representations.

MOEAs	Fitness	Sharing	Representation
MOGA	Linear Interpolation	α_{share}	{0, 1}
NSGA	Dummy Fitness	Genotype α_{share}	{0,1} or Real Number
NSGA-II	Crowding	Phenotype	{0,1} or Real Number
NPGA	Tournament Selection	Phenotype fitness	{0,1} or Real Number
NPGA-II	Rank Dominance	Continuously update Fitness	{0,1} or Real Number
SPEA	Strength value	Phenotype real number	{0, 1}
SPEA2	Strength value	Density function	{0,1} or Real Number
PAES	One to one grid	Hyperbox	{0,1} or Real Number
PESA	Pareto ranking	Hyperbox	{0, 1}
PESA-II	Region based	Hyperbox	{0, 1}

III. MULTI-OBJECTIVE FORMULATION AND EVALUATION OF FINANCIAL CREDIT SYSTEM

In this section, our main objective is to define the multi-objective formulation and evaluation of the financial credit allocation system with the help of prominent MOEAs algorithms such as NSGA-II, NSGA-III, SPEA2, eMOEA, and eNSGA-II. To do this, we have considered the German financial credit allocation system data set downloaded from machine learning repository (http://archive.ics.uci.edu/ml). Description of Dataset is given in Table II.

Table-II: Dataset description of German Financial Credit System

SN	Characteristic	Value
1	Type	Classification
2	Number of Attributes	20 (7 Numerical, 13 Categorical)
3	Number of Instances	1000
4	Attribute Characteristic	Integer

First, we have classified the data using Wang and Mendel model and Strong Fuzzy Partition (SFP) with the help of GUAJE Tool.

Our previous research considers two different classification systems one is based on the fuzzy decision tree and another one is Wang and Mendel classification method and highlights that the Wang and Mendel model outperform in the financial credit allocation system.

The proposed system, achieving higher accuracy at the cost of very low and negligible interpretability. The result of the Wang and Mendel classification system for German Credit allocation system is shown in Table III.

Table-III: Classification and performance measure of the German Credit allocation system (Total Instances = 1000)

	Class 1	Class 2
TP (True Positive)	699	300
FP (False Positive)	0	1
TN(True Negative)	300	699
FN (False Negative)	1	0
In error cases	1	0
Accuracy	99.9%	
Precision	0.999	
Recall	0.999	
F-measures	0.999	

Mean Square Classification Error	0.072

To know the interpretability of the proposed model, we have considered Nauck Index, Number of Rules (NRL), Total Rule Length (TRL), Average Rule Length (ARL) and Accumulated Rule Complexity (ARC). The interpretability for the dataset is shown in Table IV.

Table-IV: Interpretability of the German credit allocation system

Parameters	Value
Nauck's Index	0
NRL	1371
TRL	25871
ARL	18.87
ARC	1433.189
Interpretability Index	0.001

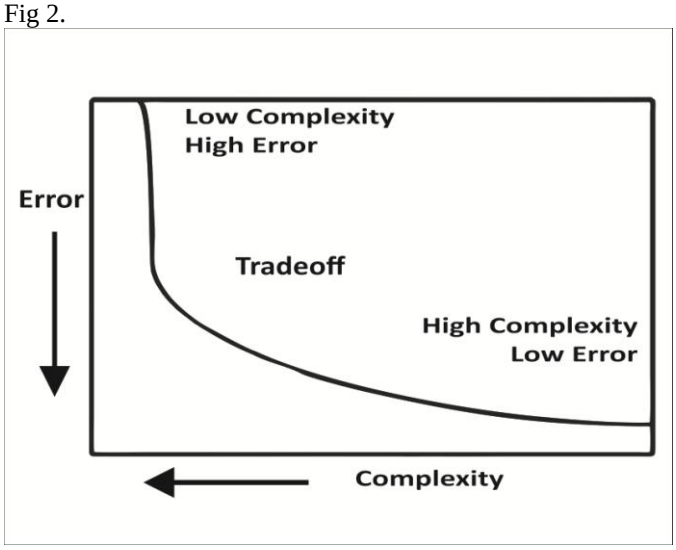
Here it can be seen that the interpretability of data-based models is very low and selected the maximum number of rules. The interpretability of the system is assessed in terms of NRL, TRL, ARL, AFR (Average Fired Rule). On the other hand, accuracy is measured in terms of the percentage of correctly classified customers having good credit classification. This has been tested with a selection of the different number of rules and results of interpretability and accuracy on different values of the number of rules are given in Table V.

Table-V: Result of accuracy and interpretability with the different value of NRL

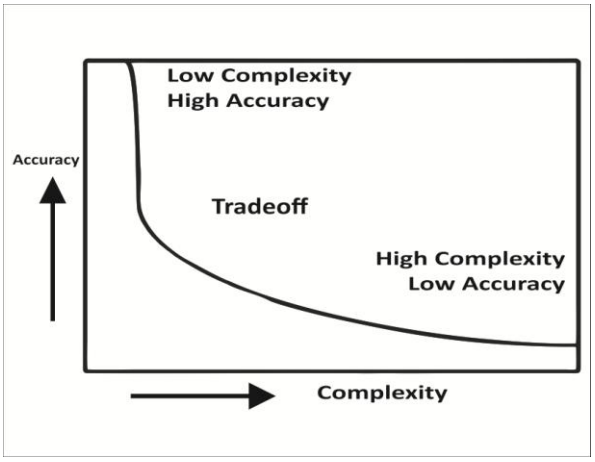
	Interpretability Parameters				Accuracy Parameter
SN	**NRL**	**TRL**	**ARL**	**AFR**	**% of Correctly Classified Clients**
1	200	6000	20	52.54	40.0
2	400	8000	20	54.54	40.4
3	500	10000	20	68.27	50.3
4	600	12000	20	72.76	60.3
5	700	14000	20	77.28	70.4
6	800	16000	20	91.63	80.4
7	850	17000	20	108.3	85.5
8	900	18000	20	108.93	90.5
9	996	19920	20	116.05	99.9

Accuracy defines as the number of correctly classified customer and Interpretability depends on the number of rules, total rule length, and average rule length. Error and complexity depend on the mean square error, and root mean square error. But here it seems that when we consider more number of rules, then we get high accuracy but require more computation time.

To achieve the trade-off between accuracy and interpretability, the multi-objective evolutionary technique is required, that minimizes error and complexity and maximizes accuracy and interpretability of fuzzy system as shown in Fig 2.



a: Error and complexity of a fuzzy system



b: Accuracy and complexity of a fuzzy system

Fig 2: Error and accuracy with complexity of fuzzy system.

To get the balanced trade-off between accuracy and interpretability, we have designed a multi-objective evaluation system with the following formulations:

OB1(x) = Percentage error in Correctly Classified Clients (PECC)

OB2(x) = Number of Rules (NOR)

OB3(x) =Total Rule Length (TRL)

Formulation – Minimize NOR and Minimize PECC is defined as below functions:

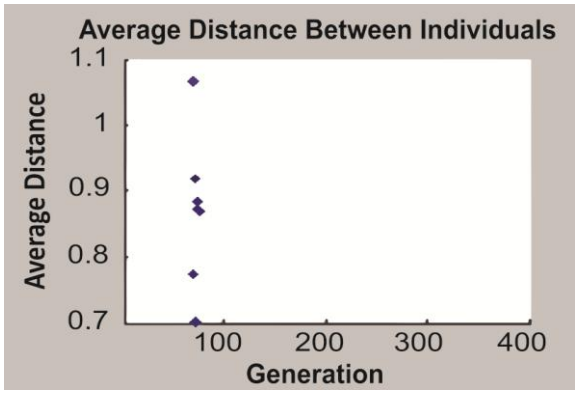
fun1(s) =OB1(s)-w1.OB2(s)

fun2(s)=OB1(s)-w2.OB3(s)

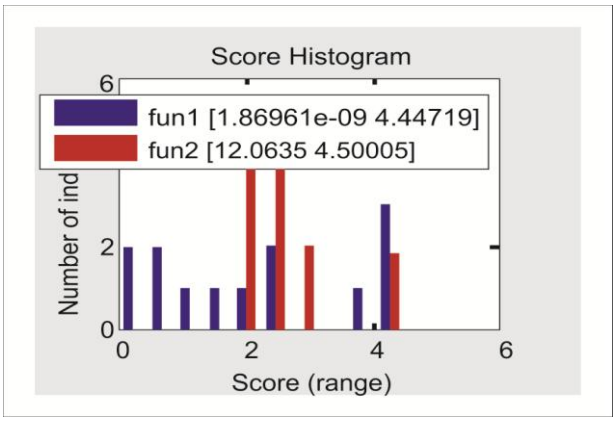
IV. RESULTS AND DISCUSSION

The non-dominated solution along with the Pareto front as per

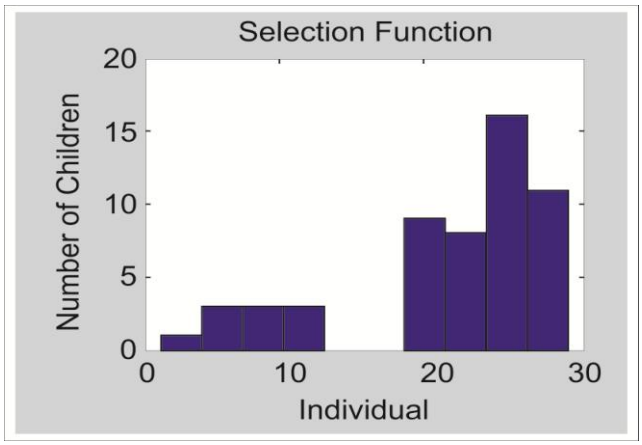
the above formulation is generated using the MATLAB tool is shown in fig 3 (a-d).



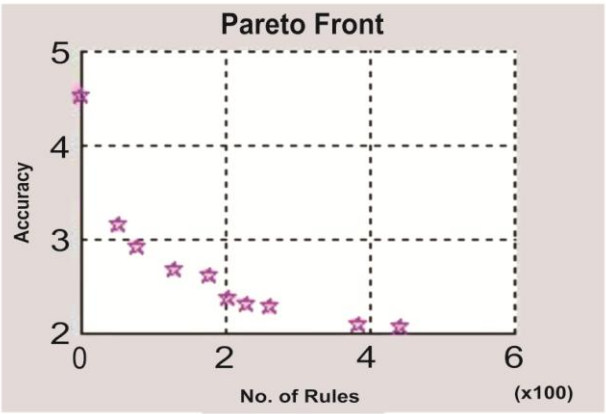
a: Average distance between individuals



a: Histogram of above formulation on the given data.



b: Selection Function of the model



c: Pareto front of the given dataset with the defined formulation

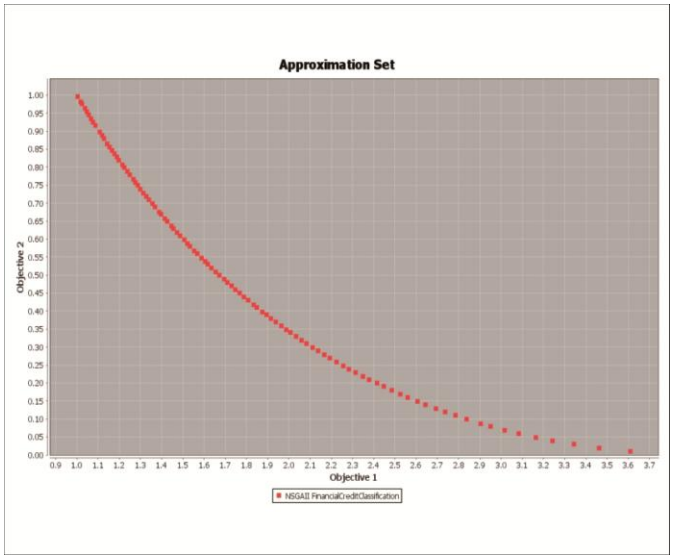
Fig 3: Results of the designed system with defined formulations using GA.

When running MOEAs on a MOP, the MOEA outputs an approximation of the Pareto optimal set and Pareto front. The approximation of the Pareto front, called the approximation set, can be used to measure the quality of an MOEA on a particular problem with the help of generational distance (GD) and inverted generational distance (IGD). Where GD refers to the average distance from every solution in the approximation set to the nearest solution in the reference set and IGD is the inverse of GD.

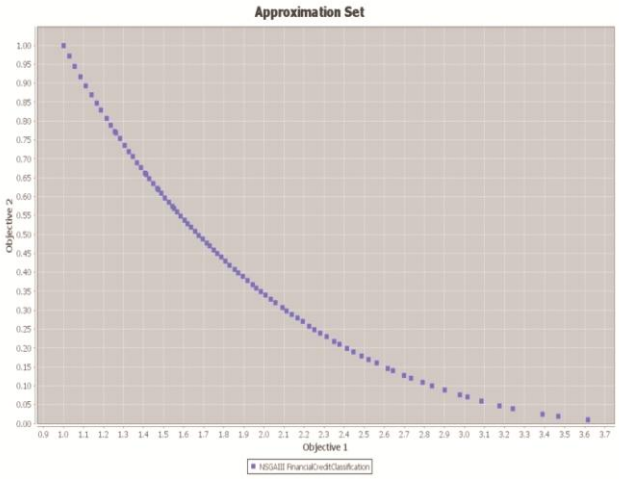
It is the average distance from every solution in the reference set to the nearest solution in the approximation set.

Further, an open source MOEA framework (downloaded from http://www.moeaframework.org) has been used to design and implement the optimization problem for financial credit classification. To evaluate the performance and generate the Pareto optimal solution, we have used different MOEAs like NSGA-II, NSGA-III, SPEA-2, eMOEA, eNSGAII, to achieve our objective Minimise NOR (objective 1) which means maximization of Interpretability and Minimise Error PECC (objective 2) leads to maximization of Accuracy. The Pareto fronts generated by the different MOEAs are shown in Fig 4(a-e) and the generational distance of all solutions of different MOEAs is shown in Fig 5(a-e).

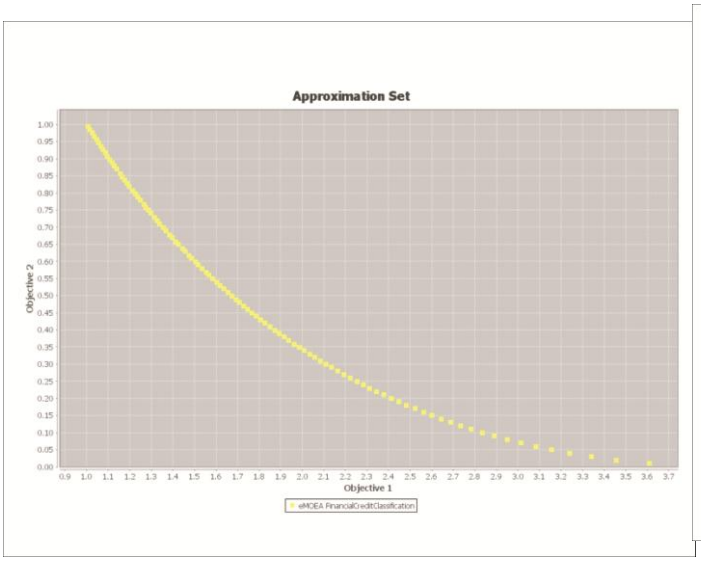
Paretofronts



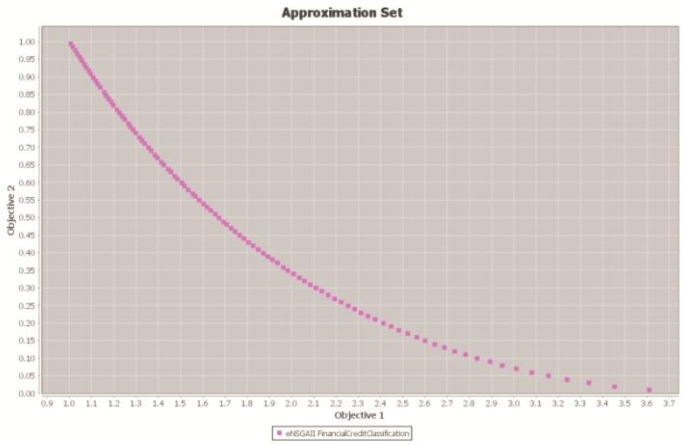
a: Pareto front with formulation using NSGA-II



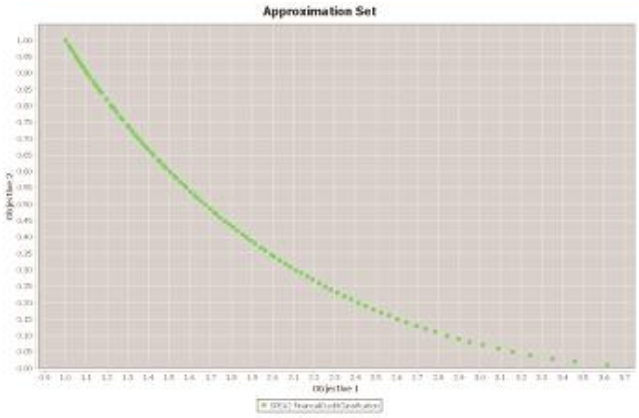
b: Pareto front with formulation using NSGA-III



c: Pareto front with formulation using eMOEA



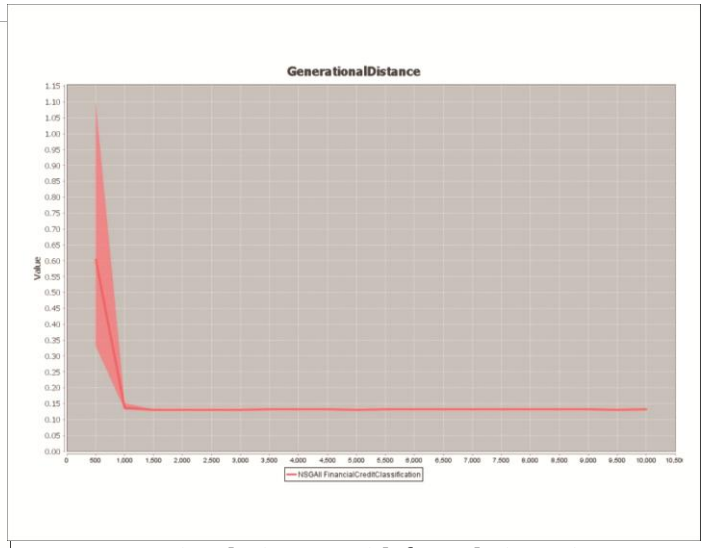
b: Pareto front with formulation using eNSGA-II



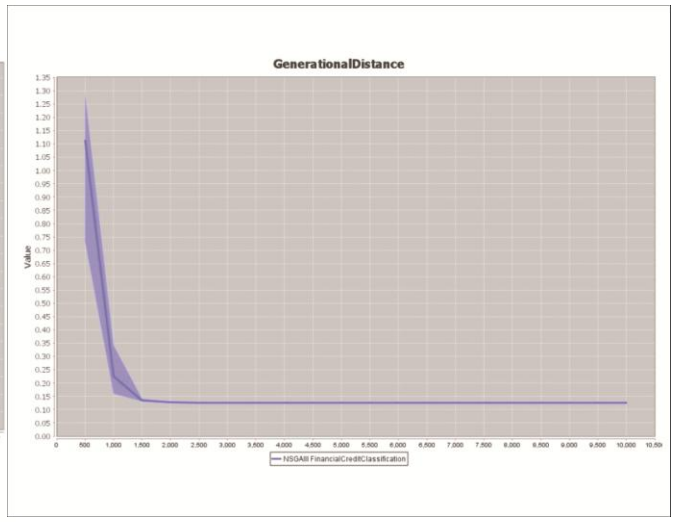
e: Pareto front with formulation using SPEA-2

Fig 4: Pareto front with formulation using different MOEAs.

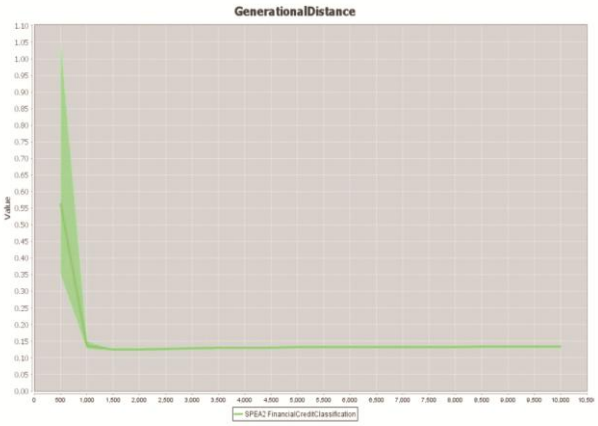
Generational Distances



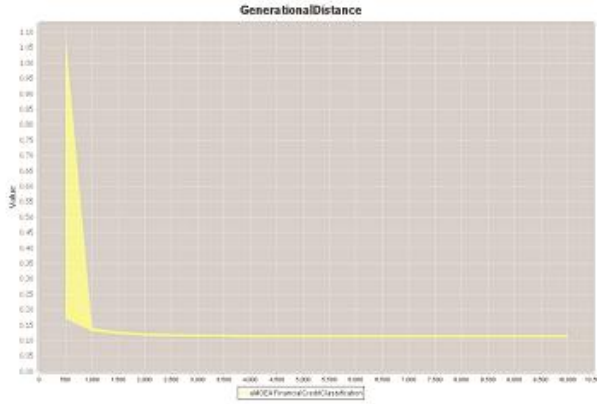
a: Generational Distance with formulation using NSGA-II



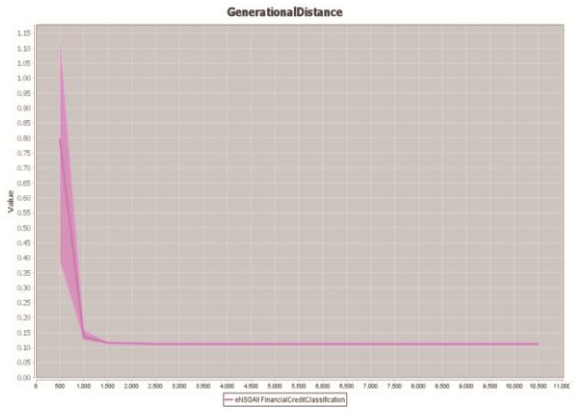
b: Generational Distance with formulation using NSGA-III



c: Generational Distance with formulation using SPEA-2



d: Generational Distance with formulation using eMOEA



d: Generational Distance with formulation using eNSGA-II

Fig 5: Generational Distance with formulation using different MOEAs.

Finally, the cumulated generational distance and inverted generational distance has been analysed statistically for all MOEAs and shown in Table VI.

Table-VI: Performance of the different MOEAs in terms of GD and IGD.

Algorithm	Generational Distance	Inverted Generational Distance
NSGA II	1.129E-1	1.310E0
NSGA III	1.121E-1	1.310E0
SPEA2	1.127E-1	1.310E0
eMOEA	1.123E-1	1.310E0
eNSGA II	1.123E-1	1.310E0

The above table VI shows the measures of generational distance which is average distance from every solution in the approximation set to the nearest solution in the reference set, hence it may be concluded that the NSGA III gives the optimal solution with average generational distance. Further we have computed the accuracy and interpretability of given model based on Table V and VI. The computational results state that after implementation of MOEA with two different objective functions such as Minimization of number of rules(Maximization of Interpretability) and Minimization of percentage error in correctly classified customer (Maximization of Accuracy), our proposed fuzzy classification system for financial credit decision based on Wang and Mendel model gives a balanced trade-off between interpretability and accuracy with the help of multi objective optimization using NSGA-III. Results of accuracy and interpretability of model with all above discussed MOEAs are shown in Table VII. After implementation of NSGA-III, the model gives 74.76% accuracy and interpretability index value is 0.4627. Based on this result, we can conclude that the NSGA-III is more suited in case of financial credit allocation system and gives a better trade-off between accuracy and interpretability. This research limited to the selection of a number of objectives that is only two, but it requires more number of objectives to make closer with accuracy and interpretability. Further research will address this issue.

Table-VII: Accuracy and interpretability measures of used MOEAs

Algorithm	Accuracy	Interpretability Index
NSGA II	81.1%	0.023
NSGA III	74.76%	0.4627
SPEA2	87.23%	0.1
eMOEA	60.34%	0.002
eNSGA II	58.37%	0.18

From Table VII, it can be seen that SPEA2 gives highest accuracy but has very less interpretability index value. As similar to the SPEA2, the NSGA-II gives accuracy above of 81% but relatively their interpretability index value is very less.

However, the NSGA-III gives the average accuracy as well as acceptable interpretability index value as compared to the accuracy and interpretability derived from the fuzzy system without optimization. From above discussion, we can conclude that the NSGA-III can be used for improving the performance of financial credit allocation system in terms of accuracy and interpretability.

V. CONCLUSION AND FUTURE SCOPE

The evolutionary multi objective algorithms are being deployed in the development of fuzzy systems to achieve the trade-off between accuracy and interpretability. To avoid bankruptcy in case of financial credit allocation system, it requires an improved fuzzy classification system that mange the trade-off between interpretability and accuracy.

The main focus of the authors to design a new improved fuzzy classification system in terms of performance using MOEAs that manages the trade-off between accuracy and interpretability. In this article, the author designed a new fuzzy classification system with two objective optimization i.e accuracy and interpretability. The proposed fuzzy classification system has been implemented on a benchmark dataset of German financial credit allocation system and tests the performance of the given MOEAs formulation on five standard MOEAs with the help of an open source tool named "MOEA framework." The experimental result highlights that the NSGA-III outperforms the German financial credit allocation system, and the authors recommended NSGA-III for optimization of the performance of financial credit allocation system as it gives a balanced interpretability and accuracy measures. The current research considers only two objectives accuracy and interpretability; In future authors would like to develop a model using more number of objectives to improve the performance of the proposed system.

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