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A Preprocessing Technique to Investigate the Stability of Multi-Objective Heuristic Ensemble Classifiers

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Extended Abstract

Background and Objectives: According to the random nature of heuristic algorithms, stability analysis of heuristic ensemble classifiers has particular importance.

Methods: The novelty of this paper is using a statistical method consists of Plackett-Burman design, and Taguchi for the first time to specify not only important parameters, but also optimal levels for them. Minitab and Design Expert software programs are utilized to achieve the stability goals of this research.

Results: The proposed approach is useful as a preprocessing method before employing heuristic ensemble classifiers; i.e., first discover optimal levels of important parameters and then apply these parameters to heuristic ensemble classifiers to attain the best results. Another significant difference between this research and previous works related to stability analysis is the definition of the response variable; an average of three criteria of the Pareto front is used as response variable. Finally, to clarify the performance of this method, obtained optimal levels are applied to a typical multi-objective heuristic ensemble classifier, and its results are compared with the results of using empirical values; obtained results indicate improvements in the proposed method.

Conclusion: This approach can analyze more parameters with less computational costs in comparison with previous works. This capability is one of the advantages of the proposed method.

Introduction

Ensemble classification is a popular model applied to improve the performance of individual classifiers and decrease their weaknesses [1]. Ensemble classifier has been welcomed by many researchers; examples of recent research in this area are [2]-[8]. For example, a new selection ensemble method is proposed in [2] to ameliorate the generalization ability and recognition efficiency of the maritime surveillance radar; this technique is based on k-medoids clustering and random reference classifier. A classification algorithm based on MapReduce and ensemble learning for effectively classifying imbalanced large datasets is introduced in [6]. In [8] a novel integration approach of binary classifiers is proposed for multi-class classification; this method can effectively combine information of several binary classifiers into the multi-class classifier.

Heuristic algorithms have high efficiency to solve optimization problems; [9]-[12] are some researches of different fields such as VLSI circuits, clustering and medicine which used heuristic algorithms to solve their problems. Another field, which can use these algorithms, is ensemble classification, in which several important issues can directly affect the performance of the designed ensemble classifier. In this situation, it is often impossible to find the best solution using trial and error, because there is a complex search space with high dimensions. Therefore, considering the capability of efficient probing of these algorithms, heuristic ensemble classifiers are proposed, which are designed by heuristic algorithms [13]. Many types of researches have addressed this field, such as [14]-[18]. For instance, in [14] a novel type of the firefly algorithm is introduced for classifier ensemble reduction; these ensemble classifiers have better performance in comparison with full-sized ensemble classifiers. A novel method for classifier ensemble reduction is presented in [16]; this paper employs feature selection techniques to minimize redundancy in an artificial dataset; this dataset is generated by transforming ensemble predictions into training samples, and classifiers are treated as features. The purpose is to further decrease the size of an ensemble, while improving classification efficiency and accuracy. Also, to select a reduced subset of such artificial features, the global heuristic harmony search is utilized. A novel evolutionary multi-objective ensemble classifier is proposed in [18] for performing feature selection and classification problems. This ensemble can improve the performances of classification of neural network models with a smaller number of input features.

Investigating the stability of these ensembles is an important issue due to the stochastic nature of heuristic algorithms; various answers, obtained in different simulation runs, have a severe dependency on the structural parameters of heuristic algorithms [13]. Despite extensive studies on the various aspects of heuristic ensemble classifiers, the stability of them has been neglected; only a few studies like [13] and [19] have been addressed this issue. In [13] a statistical approach termed two-level factorial design is used to investigate the stability of the heuristic ensemble classifier; in this way, the effects of three structural parameters of the multi-objective algorithm i.e., inflation rate, leader selection pressure and deletion selection pressure on the performance of the designed heuristic ensemble classifier are analyzed.

The stability of the heuristic ensemble classifier is investigating in [19] by using statistical method. For this aim, three regression models (linear, quadratic and cubic) are checked by applying F-test to find better model in each case; in this paper, six parameters of the heuristic algorithm are considered as variables for stability analysis.

The values of structural parameters in heuristic algorithms are usually set by trial and error, which is time-consuming and partly difficult. Considering the significance of stability, the aim of this paper is to provide a method for the optimal setting of the important parameters. The proposed method can be applied as a preprocessing step before employing heuristic ensemble classifiers. In this paper, a heuristic ensemble classifier is designed by using Multi-Objective Inclined Planes Optimization (MOIPO) algorithm to achieve this goal.

Then, in order to analyze the stability, the impact of 11 parameters of the employed algorithm on the ensemble classifier is investigated. To this end, the Plackett-Burman Screening method is first used to identify the important parameters. Then, important parameters are considered as input variables of the Taguchi method to optimize these parameters. In this paper, Design Expert software and Minitab software are used to implement the Plackett-Burman and Taguchi method, respectively.

The rest of this article is organized as follows: In section 2, the design of the experiment is presented. Section 3 provides a review of the employed optimization algorithm. The method of stability analysis of ensemble classifiers and optimizing important parameters is described in Section 4. Section 5 is for simulation results. Section 6 provides results and discussion. Finally, conclusion is explained in section 7.

Design of Experiments

"Design of Experiments (DoE) is a method of systematically obtaining and organizing knowledge so that it can be used to amend operations in the most efficient manner possible" [20]. DoE includes experiments in which the rate of the change of output response can be observed by making knowledgeable changes in input variables. In fact, the factors are simultaneously experimented to consider the interactions between factors. This method opposes the classic approach, OFAT; i.e., One Factor At a Time where one variable is varied at a time, and all other variables are kept fixed in the experiment.

OFAT experiments often are unqualified, unreliable, and time-consuming and may lead to false optimum conditions for the process. Statistical approaches play a significant role in analyzing and construing the data from engineering experiments. In DoE, intentional changes in the input variables (or factors) are created, and then the variation of the output performance is determined. It's worth noting that each variable influences the response in a special way; some may have strong impacts, some may have medium impacts, and some may have no impacts. Thus the aim of a DoE is to discover which set of factors in a process affect the performance most (screening step) and then specify the best levels for these factors to obtain satisfactory output performance (optimization step) [21].

In this research, Plackett-Burman and Taguchi methods are used for screening and optimization steps of DoE, respectively.

These methods are described in the following.

A. Plackett-Burman Design

Plackett–Burman design is the most common screening approach that screens a large number of factors and specifies important one in a minimal number of runs with a good degree of accuracy. The number of runs needed to check the main effects is multiple of 4 in Plackett–Burman designs instead of 2 as in the case of full factorial design [22].

One of the advantages of Plackett–Burman design is to reduce the amount of observation data; this will be more important when the number of variables is large. For example, for screening 11 factors, 12 observations (runs) are adequate, while a full factorial design would require 211 observations.

In this approach, each factor is investigated at two levels; –1 for the low level and +1 for the high level. The result analysis of this method is described in the section named simulation results.

B. Taguchi Design

As stated before, after identifying the important factors, the optimization step starts. In a traditional optimization method, first, the targets for the output responses are specified, and then the related settings for input variables are performed. In these approaches, factors are investigated one by one in order to determine the best settings to optimize response first, and then the best settings of all factors are collected as the optimal design for the system. But, this procedure cannot vouch that the composed best levels of the factors are the actual optimal design. These combined best settings may not be the optimal response for the system if significant interactions exist among the factors. One-factor-at-a-time optimization approaches are not time efficient. In other words, the one-factor-at-a-time method is not really an optimization approach. New procedures based on the robust design (i.e., Taguchi Method) are more efficient than the traditional one-factor-at-a-time optimization method [23].

Taguchi method is a statistical method proposed by Genichi Taguchi to improve the quality of manufactured goods, and more recently, also applied to engineering [24]. The objective of the Taguchi method is to set the design factors to optimal levels, such that the system response is robust [25]. Taguchi method to DoE is easy to be accepted and applied for users with finite information of statistics; thus it has achieved wide popularity in the engineering and scientific community [26].

Signal to Noise Ratio (SNR) is employed in Taguchi design as the quality specification of choice. SNR is used as a measurable value instead of standard deviation due to the fact that, as the mean reduces, the standard deviation also decreases, and vice versa [26]. The purpose of the SNR is to maximize the signal and minimize the impact of noise. The goal is to gain robustness, and higher SNR leads to greater robustness [27].

Multi-Objective Optimization Algorithms

There are four reasons for popularity of the heuristic algorithms; avoidance from local optima, flexibility, simplicity and having a mechanism without derivation [28]. These methods guarantee a greater probability to reach optimal answers because it utilizes a population to search the problem space [29].

In real applications, there are problems that under specific situations are concurrently confronted with several cost functions [30]. These problems can be solved using multi-objective optimization, in which a set of solutions is defined as optimal solutions. Searching operation in multi-objective heuristic algorithms is accomplished in parallel i.e., a set of agents search the problem space. So, they can find Pareto-optimal solutions with a single simulation run.

In general, the following points should be considered in multi-objective optimization:

1- The distance from the non-dominated front to the Pareto-optimal front should be minimized. This measure is known as Generational Distance (GD) and is specified in (1) in which n is the number of non-dominated answers and d_i is the Euclidean distance between each of these answers and the nearest solution in the Pareto-optimal front [31]:

$$GD = \frac{\sqrt{\sum_{i=1}^{n} d_i^2}}{n} \tag{1}$$

2- Discovered solutions should have good distribution. For this reason, Spacing (SP) metric [32] was introduced to measure how evenly the members of a Pareto front are distributed. A value of zero for the spacing metric means that all members of the Pareto front are equally spaced. This metric is specified in (2) in which $\bar{d}$ is the mean of all d_i and n is the number of non-dominated answers:

$$SP = \sqrt{\frac{\sum_{i=1}^{n}(\bar{d} - d_i)^2}{n-1}}$$

$$d_i = \min_j \begin{pmatrix} \left|f_1^i(x) - f_1^j(x)\right| + \left|f_2^i(x) - f_2^j(x)\right| \\ + \left|f_3^i(x) - f_3^j(x)\right| \end{pmatrix} \tag{2}$$

$$i, j = 1,2,\dots,n$$

3- Mean Ideal Distance (MID) is used for measuring the closeness between Pareto solution and an ideal point. In a minimization problem, this metric is formulated as (3) in which $f_1^{\,i}$, $f_2^{\,i}$ and $f_3^{\,i}$ denote the first, second and third objective value of the i-th non-dominated solution respectively and n is the number of non-dominated answers:

$$MID = \frac{\sum_{i=1}^{n}\sqrt{f_i^i + f_2^i + f_3^i}}{n} \quad (3)$$

It is obvious that less value of this metric is of interest [33].

The multi-objective algorithm used in this paper is described in the following.

A. Multi-Objective Inclined Planes Optimization (MOIPO) Algorithm

The IPO algorithm is inspired by the dynamic movement of spherical objects along a frictionless inclined surface. These objects tend to reach the lowest points. In this algorithm, the agents are some small balls that explore the problem space to discover optimal solutions. The basic idea of IPO is to impute height to each agent, regarding its objective function. This algorithm is fully explained in [34].

The main structure of the IPO algorithm should be reformed to use it in multi-objective problems. The steps of multi-objective IPO are as follows:

1- Initialize the population, a repository for non-dominated solutions, and evaluation.
2- Separate non-dominated members and store them in the repository.
3- Generate the hypercube of the objective space.
4- Movement of each search agent according to the related equations.
5- Update the IPO parameters.
6- Add non-dominated members of the current population to the repository.
7- Delete dominated members from the repository.
8- Delete additional members if the size of the repository is more than the specified capacity.
9- End if the end conditions are established otherwise go back to step 3.

Stability Analysis of Heuristic Ensemble Classifiers and Optimizing Important Parameters

In this paper, to investigate the stability of heuristic ensemble classifiers, the effect of 11 parameters of the employed heuristic algorithm on a typical heuristic ensemble classifier is investigated. To reach this aim, the Plackett–Burman design is first used for recognizing important parameters. Then, important parameters are considered as input variables of the Taguchi design in order to optimize these parameters. It should be noted that Design Expert and Minitab are used for the implementation of Plackett–Burman design and Taguchi design, respectively.

Ensemble classifier studied in this research is an ensemble designed by MOIPO with the aim of minimizing ensemble size and maximizing the average of accuracy and the average of reliability for classifying Glass dataset. Glass dataset is one of the Benchmark data available at UCI machine learning repository. It has 214 samples, 9 features and 2 classes and can be as a good representative of overlapped data.

One of the main differences of this method with previous works is the definition of the response variable; the response variable is defined as the mean of the three criteria of the Pareto front; these measures are GD, SP, and MID, which introduced in the previous section.

Parameters studied in this research have two levels; low and high. The values of these levels are shown in Table 1. *MaxIt*, *npop*, *Alpha*, *Beta*, and *Gamma* are the number of iterations, population size, inflation rate, leader selection pressure, and deletion selection pressure, respectively.

Table 1: Low and high levels of parameters

Parameter	Low Level	High Level
MaxIt	200	600
Npop	20	50
C_1	0.1024	12
C_2	0.2399	3.6577
$Shift_1$	1	740
$Shift_2$	80	798.0776
$Scale_1$	0.0036	0.9999
$Scale_2$	0.0034	0.9002
Alpha	0.1000	0.2000
Beta	4	6
Gamma	2	4

It is worth noting that the levels of IPO parameters i.e., c_1, c_2, $shift_1$, $shift_2$, $scale_1$, and $scale_2$ have been extracted according to [34] which is the main reference of IPO algorithm. Also, *Alpha, Beta,* and *Gamma* are the parameters of multi-objective version and their values have been obtained from usual values used in other works like [13] and [19].

Simulation Results

As stated before, the aim of this paper is to find important parameters of the heuristic algorithm (i.e., finding the parameters which influence on the performance of the designed heuristic ensemble classifier) and also find the optimal levels of the important parameters. To achieve this goal, two steps should be done; the first step is the screening step which employs Plackett–Burman approach to identify important parameters from all supposed parameters. The next step is optimization step; in this step, the optimal levels of the significant parameters are found using Taguchi method.

Design Expert software is used for the screening step i.e., Plackett–Burman method.

According to the obtained design matrix in Plackett–Burman method, simulations are performed to complete the response column.

TABLE 2Table 2 shows the values of the design matrix and the response variable from the simulation. In this table, -1 and 1 represent low and high levels for each factor, respectively.

In fact, for different values of the parameters in design matrix, simulation in Matlab is run and the response value is obtained.

After completing the last column of the table, the outputs of this step are obtained by using this matrix; these outputs are reported in the following.

Table 2: Obtained design matrix from plackett–burman method and response variable

Run	*MaxIt*	*npop*	C_1	C_2	$Shift_1$	$Shift_2$	$Scale_1$	$Scale_2$	*Alpha*	*Beta*	*Gamma*	Response
1	1	1	-1	-1	-1	1	-1	1	1	-1	1	29.0813
2	1	-1	1	1	1	-1	-1	-1	1	-1	1	0.8200
3	1	1	-1	1	1	1	-1	-1	-1	1	-1	0.7154
4	-1	-1	-1	1	-1	1	1	-1	1	1	1	8.5715
5	1	-1	1	1	-1	1	1	1	-1	-1	-1	25.2336
6	-1	1	-1	1	1	-1	1	1	1	-1	-1	33.9415
7	-1	1	1	-1	1	1	1	-1	-1	-1	1	18.1211
8	1	1	1	-1	-1	-1	1	-1	1	1	-1	13.5830
9	1	-1	-1	-1	1	-1	1	1	-1	1	1	12.7499
10	-1	1	1	1	-1	-1	-1	1	-1	1	1	16.3629
11	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	2.0088
12	-1	-1	1	-1	1	1	-1	1	1	1	-1	17.4415

One of the outputs is Pareto chart which is presented in the analysis section; this chart indicates the t-value for all the supposed parameters.

This chart is illustrated in Fig. 1. According to this chart, it is clear that the parameters B, G, H, and K have a high contribution in the response; because only these parameters have been able to pass the threshold of t-value.

The parameter J is close to the threshold, but it has not passed it.

Therefore, in order to obtain the results for the analysis of variance, the five mentioned factors are selected.

As stated in the above, the output of the Pareto chart (parameters with high contribution) is used for analysis of variance. The results for the analysis of variance are reported in Table 3.

Table 3: Results for analysis of variance

Parameter	Sum of Squares	Degrees of Freedom	F-value	P-value	R^2	Adjusted R^2	Evaluation
Model	1231.7300	5	21.1300	0.0010	0.9463	0.9015	Suggested
B-npop	168.6600	1	14.4600	0.0089	-	-	Significant
G-$Scale_1$	174.6400	1	14.9800	0.0083	-	-	Significant
H-$Scale_2$	690.0700	1	59.1800	0.0003	-	-	Significant
J-Alpha	66.5300	1	5.7100	0.0541	-	-	Not Significant
K-Beta	131.8300	1	11.3100	0.0152	-	-	Significant

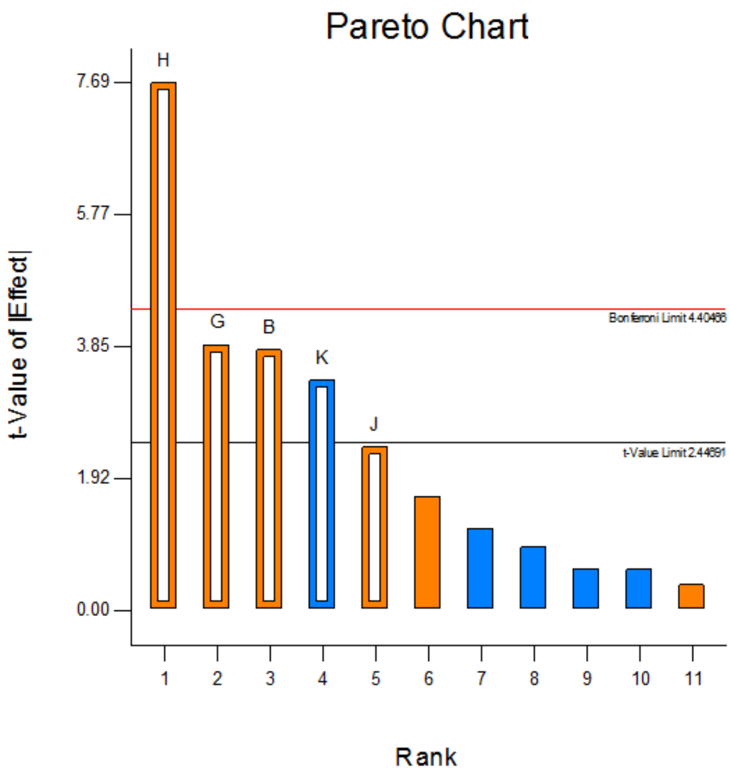

Fig. 1: Pareto chart; the output of Design Expert Software.

Regarding the values of R^2 and adjusted R^2 in the

Table 3, it can be concluded that this model i.e., linear is suitable.

Also, obtained p-values indicate that four parameters i.e., *npop*, *Scale*$_1$, *Scale*$_2$, and *Beta* are significant. (Level of significance is 0.05)

Now, we know that linear model is specified as a suitable model.

Another outcome of the Plackett–Burman method is the estimated coefficients for each parameter to complete the equation of the model. So, this model can be determined by (4):

$$\begin{aligned} y &= 14.89 + 3.74899 \times npop + 3.81489 \times Scale_1 \\ &+ 7.58324 \times Scale_2 + 2.35459 \times Alpha \\ &- 3.31451 \times Beta \end{aligned} \tag{4}$$

Besides the analysis of variance, checking the normality of the data or the residuals is one of the assumptions for the efficiency of the model. In this way, data may need to be transformed (in terms of being normal). To clarify this, the Box-Cox plot, another output of the method, should be checked. If blue and green lines situate near each other and both of them place between red lines, no transform is needed. The Box-Cox plot is shown in Fig. 2. According to the above description and also the report of the plot (left side of the plot), no transform is needed.

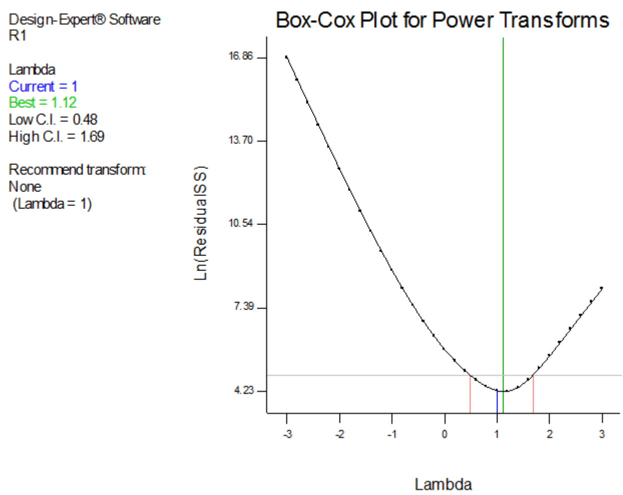

Fig. 2: Box-Cox plot.

Up to now, important parameters are determined by using Plackett–Burman design.

The next step is to optimize these parameters. Taguchi design is used for this step and is implemented in Minitab software. In this method, L12 design is selected considering the number of parameters and related levels. Table 4 indicates the Taguchi design matrix and response in which 1 and 2 demonstrate the low level and high level, respectively. It should be noted that the column of response is obtained by using the related values of parameters in the simulation run in Matlab.

Table 4: Taguchi design matrix and related responses

Run	*npop*	$Scale_1$	$Scale_2$	*Beta*	Response
1	1	1	1	1	2.9060
2	1	1	1	1	1.0439
3	1	1	2	2	19.9259
4	1	2	1	2	6.8677
5	1	2	2	1	1.2943
6	1	2	2	2	17.5981
7	2	1	2	2	16.5677
8	2	1	2	1	2.2139
9	2	1	1	2	12.4842
10	2	2	2	1	6.6250
11	2	2	1	2	1.6371
12	2	2	1	1	9.7931

The following figures, i.e., main effects plot for mean and main effects plot for signal-to-noise ratios, are the outputs of the Taguchi analysis.

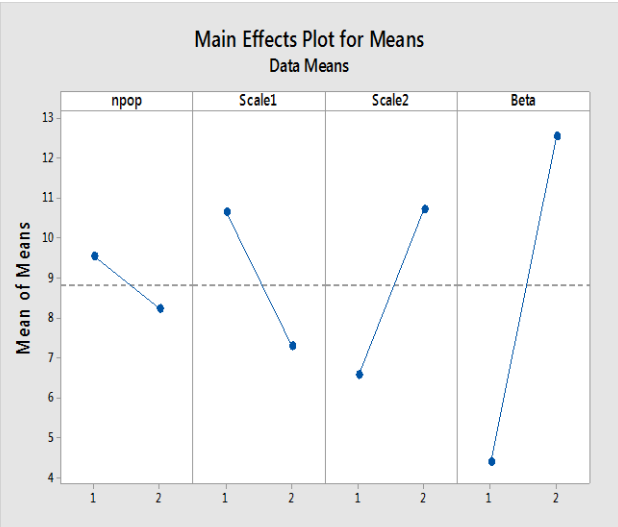

Fig. 3: Main effects plot for means.

According to

Fig. 3 and in order to achieve the optimal solution, *npop*, and $Scale_1$ should be at a high level and $Scale_2$, and *Beta* should be at a low level.

These answers are definitive if they match the main effects plot for signal-to-noise ratios. This plot is shown in Fig. 4.

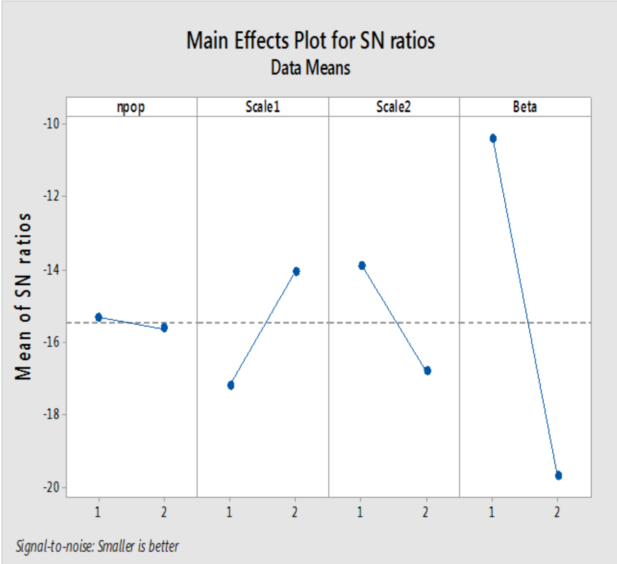

Fig. 4: Main effects plot for signal-to-noise ratios.

Due to the above figure, the results for $Scale_1$, $Scale_2$ and *Beta* parameters are consistent with

Fig. 3; the maximum amount of signal-to-noise ratio occurs when $Scale_1$ is at a high level, and $Scale_2$ and *Beta* are at a low level.

But two obtained plots for *npop* do not match because the maximum amount of signal-to-noise ratio happens when this parameter is at a low level. So, the optimal levels for $Scale_1$, $Scale_2$ and *Beta* are the high level of them which are 0.9999, 0.9002 and 6, respectively.

In order to evaluate the performance of the proposed ensemble classifier with optimal levels of parameters, simulations have been done in two modes, i.e., optimal levels mode and empirical values mode. Obtained results are reported in Table 5.

Optimal values used in this part are the high levels of $Scale_1$, $Scale_2$ and *Beta*. Empirical values, which used in the second mode, are as the following:

npop: 20
MaxIt: 200
C_1: 0.7184
C_2: 2.7613
$Shift_1$: 72.4684
$Shift_2$: 188.5077
$Scale_1$: 0.035
$Scale_2$: 0.8245
Alpha: 0.1
Beta: 4
Gamma: 2

Table 5: Obtained comparative results of objective functions in two different modes of parameters values

Data	First Mode (Optimal levels of parameters)			Second Mode (Empirical values of parameters)		
	Ensemble Size	Average of Accuracy	Average of Reliability	Ensemble Size	Average of Accuracy	Average of Reliability
Glass	13	23	20	**8**	29	11
	96.75	**98.07**	97.43	94.48	96.41	94.85
	95.46	96.75	**97.43**	93.87	94.48	94.85

In the above Table, reported values in the columns of ensemble size, average of accuracy, and average of reliability are related to the points of the Pareto front with the best ensemble size, the best average of accuracy, and the best average of reliability. In addition, the values of the first, second, and third rows indicate ensemble size, an average of accuracy, and an average of reliability related to each point of the Pareto front, respectively.

Due to these results, when using optimal levels of parameters, the average of accuracy and the average of reliability have been improved. Only ensemble size has a better amount in the empirical mode, but in this situation, the values for two other objective functions are better with optimal levels of parameters. It should be noted that low differences in two modes relate to the fact that empirical values are extracted with trial and error to achieve the best results, and they are available from previous works. However, this process is time-consuming and has no guarantee to get optimal levels of parameters.

On the other hand, in general, these empirical values are not available.

Results and Discussion

One of the advantages of the proposed approach in comparison with previous works is that more parameters can be analyzed with less computational costs; checking the impact of these 11 parameters by the approaches of [13] or [19] is very complicated and time-consuming. Also, the proposed approach of this paper can optimize the value of the important parameters but the other works cannot do this. However, Plackett–Burman method unlike [13] and [19] don't consider the interactions and only main effects are studied in this method.

Conclusion

One of the important issues in the field of heuristic ensemble classifiers is the stability of these classifiers.

This topic is important due to the random nature of the heuristic algorithms. This paper has reviewed this issue with a statistical perspective; in addition to evaluating stability, important and effective parameters are detected.

Also, by using the Taguchi design in Minitab software, it is possible to determine the optimal levels for important parameters. Using these optimal levels will make the output better than the empirical mode. It should be noted that empirical values are obtained using the trial and error method. Using new methods of stability investigation is one of the suggestions for the future works.

Author Contributions

Z.K. Pourtaheri performed the simulations, interpreted the results and wrote all parts of the manuscript.

Conflict of Interest

The author declares that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy have been completely observed by the authors.

Abbreviations

MOIPO	Multi-Objective Inclined Planes Optimization
DoE	Design of Experiments
OFAT	One Factor At a Time
SNR	Signal to Noise Ratio
GD	Generational Distance
SP	Spacing metric
MID	Mean Ideal Distance
IPO	Inclined Planes Optimization

References

[1] M. Hosni, I. Abnane, A. Idri, J. M. C. de Gea, J. L. F. Alemán, "Reviewing ensemble classification methods in breast cancer," Computer Methods and Programs in Biomedicine, 177: 89-112, 2019.

[2] X. Fan, S. Hu, J. He, "A dynamic selection ensemble method for target recognition based on clustering and randomized reference classifier," International Journal of Machine Learning and Cybernetics, 10(3): 515-525, 2019.

[3] H. Zhang, H. He, W. Zhang, "Classifier selection and clustering with fuzzy assignment in ensemble model for credit scoring," Neurocomputing, 316: 210-221, 2018.

[4] P. Sidhu, M. P. S. Bhatia, "A novel online ensemble approach to handle concept drifting data streams: diversified dynamic weighted majority, " International Journal of Machine Learning and Cybernetics, 9(1): 37-61, 2018.

[5] R. Kianzad, H. Montazery Kordy, "Automatic sleep stages detection based on EEG signals using combination of classifiers," Journal of Electrical and Computer Engineering Innovations, 1(2): 99-105, 2013.

[6] J. Zhai, S. Zhang, C. Wang, "The classification of imbalanced large data sets based on MapReduce and ensemble of ELM classifiers," International Journal of Machine Learning and Cybernetics, 8(3): 1009-1017, 2017.

[7] V. S. Costa, A. D. S. Farias, B. Bedregal, R.H. Santiago, A. M. D. P. Canuto, "Combining multiple algorithms in classifier ensembles using generalized mixture functions," Neurocomputing, 313: 402-414, 2018.

[8] T. Takenouchi, S. Ishii, "Binary classifiers ensemble based on Bregman divergence for multi-class classification," Neurocomputing, 273: 424-434, 2018.

[9] M. R. Esmaeili, S. H. Zahiri, S. M. Razavi, "A framework for high-level synthesis of VLSI circuits using a modified moth-flame optimization algorithm," Journal of Electrical and Computer Engineering Innovations, 7(1): 93-110, 2019.

[10] I. Behravan, S. H. Zahiri, S. M. Razavi, R. Trasarti, "Clustering a big mobility dataset using an automatic swarm intelligence-based clustering method," Journal of Electrical and Computer Engineering Innovations, 6(2):2 43-262, 2018.

[11] S. Roostaee, H. R. Ghaffary, "Diagnosis of heart disease based on meta heuristic algorithms and clustering methods," Journal of Electrical and Computer Engineering Innovations, 4(2): 105-110, 2016.

[12] M. Hasanluo, F. Soleimanian Gharehchopogh, "Software cost estimation by a new hybrid model of particle swarm optimization and k-nearest neighbor algorithms," Journal of Electrical and Computer Engineering Innovations, 4(1): 49-55, 2016.

[13] Z. K. Pourtaheri, S. H. Zahiri, S. M. Razavi, "Stability investigation of multi-objective heuristic ensemble classifiers," International Journal of Machine Learning and Cybernetics, 10(5): 1109-1121, 2019.

[14] L. Zhang, W. Srisukkham, S. C. Neoh, C. P. Lim, D. Pandit, "Classifier ensemble reduction using a modified firefly algorithm: An empirical evaluation," Expert Systems with Applications, 93: 395-422, 2018.

[15] A. Rahman, B. Verma, "Ensemble classifier generation using non-uniform layered clustering and genetic algorithm," Knowledge-Based Systems, 43: 30–42, 2013.

[16] R. Diao, F. Chao, T. Peng, N. Snooke, Q. Shen, "Feature selection inspired classifier ensemble reduction," IEEE Transactions on Cybernetics, 44(8): 1259-1268, 2014.

[17] P. Shunmugapriya, S. Kanmani, "Optimization of stacking ensemble configurations through artificial bee colony algorithm," Swarm and Evolutionary Computation, 12: 24–32, Oct. 2013.

[18] C. J. Tan, C. P. Lim, Y. N. Cheah, "A multi-objective evolutionary algorithm-based ensemble optimizer for feature selection and classification with neural network models," Neurocomputing, 125: 217–228, 2014.

[19] Z. K. Pourtaheri, S. H. Zahiri, S. M. Razavi, "Design and stability analysis of multi-objective ensemble classifiers," Electronic Letters on Computer Vision and Image Analysis, 15(3): 32-47, 2016.

[20] L. Condra, Reliability improvement with design of experiment, CRC Press,: 8, 2001.

[21] J. Antony, Design of experiments for engineers and scientists, Elsevier,:1-2, 2014.

[22] R. L. Plackett, J. P. Burman, "The design of optimum multifactorial experiments," Biometrika, 33(4): 305-325, 1946.

[23] T. Mori, Taguchi methods: benefits, impacts, mathematics, statistics, and applications, ASME Press,:36, 2011.

[24] J. L. Rosa, A. Robin, M. B. Silva, C. A. Baldan, M. P. Peres, "Electrodeposition of copper on titanium wires: Taguchi experimental design approach," Journal of Materials Processing Technology, 209(3): 1181-1188, 2009.

[25] M. S. Phadke, Quality engineering using robust design, Prentice-Hall PTR, New Jersey, 1995.

[26] S. K. Karna, R. Sahai, "An overview on Taguchi method," International Journal of Engineering and Mathematical Sciences, 1(1): 1-7, 2012.

[27] R. K. Roy, Design of experiments using the Taguchi approach: 16 steps to product and process improvement, John Wiley & Sons, 2001.

[28] S. Mirjalili, S. M. Mirjalili, A. Lewis, "Grey wolf optimizer," Advances in Engineering Software, 69: 46-61, 2014.

[29] S. J. Nanda, G. Panda, "A survey on nature inspired metaheuristic algorithms for partitional clustering," Swarm and Evolutionary Computation, 16: 1–18, 2014.

[30] N. Sayyadi Shahraki, S. H. Zahiri, "Low-area/low-power CMOS op-amps design based on total optimality index using reinforcement learning approach," Journal of Electrical and Computer Engineering Innovations, 6(2): 193-208, 2018.

[31] D. A. Van Veldhuizen, G. B. Lamont, "Evolutionary computation and convergence to a pareto front," presented at the Genetic Programming Conference: 221-228, 1998.

[32] J. R. Schott, "Fault tolerant design using single and multicriteria genetic algorithm optimization," MS thesis, Massachusetts Institute of Technology, Cambridge, 1995.

[33] M. Arjmand, A. A. Najafi, "Solving a multi-mode bi-objective resource investment problem using meta-heuristic algorithms," Advanced Computational Techniques in Electromagnetics, 1(1): 41-58, 2015.

[34] M. H. Mozaffari, H. Abdy, and S. H. Zahiri, "IPO: an inclined planes system optimization algorithm," Computing and Informatics, 35(1): 222-240, 2016.

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