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Using eye-tracking into decision makers evaluation in evolutionary interactive UA-FLP algorithms

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Abstract

Unequal area facility layout problem is an important issue in the design of industrial plants, as well as other fields such as hospitals or schools, among others. While participating in an interactive designing process, the human user is required to evaluate a high number of proposed solutions, which produces them fatigue both mental and physical. In this paper, the use of eye-tracking to estimate user's evaluations from gaze behavior is investigated. The results show that, after a process of training and data taking, it is possible to obtain a good enough estimation of the user's evaluations which is independent of the problem and of the users as well. These promising results advice to use eye-tracking as a substitute for the mouse during users' evaluations.

AQ1

AQ2

Keywords

User ergonomics
User fatigue
Engineering design
UA-FLP
Artificial neural networks

1. Introduction

The plant layout design is a critical issue in industrial manufacturing as well as other fields, like schools, hospitals, and offices, among others. It deals with the arrangement of spaces, machinery, and facilities in order to satisfy certain objectives, as minimizing material handling cost; facilitating supervision and control; integrating man, machines, and support services; workers' safety, adaptability to changing conditions, or waste minimization [43, 48].

The general problem of facility layout planning (FLP) and its variant unequal area facility layout problem (UA-FLP) have been addressed by means of several methods. Initially, the problem was addressed by exact methods, which are useful for finding solutions to problems of reduced size since the problem has been classified as NP-Hard [41]. For example, quadratic assignment problem (QAP) [22, 26, 31], branch and bound [6], integer programming [37], and mixed integer programming [50].

Due to the high computational cost of finding optimal solutions when problems are complex, heuristic methods that find good enough sub-optimal solutions in a reasonable time have been proposed. Firstly, two kinds of algorithms appeared: improvement algorithms and construction algorithms. The first ones start with a solution and try to improve it by interchanging facilities locations, as for example CRAFT [4], but they have the problem that the solutions depend critically on the initial one [7]. The second group obtains the solutions locating successively the facilities in the remaining space until completing a design. Solutions obtained by these algorithms may be far from optimal due to they generate only one layout [27]. Examples of these algorithms are ALDEP [47] and CORELAP [38], among others.

In recent years, meta-heuristic techniques have been extensively used for solving FLPs and, among them, genetic algorithms [2, 19, 23, 35, 44, 49], simulated annealing [5, 36, 42], ant colony optimization [24, 28, 40, 52], tabu search [8, 30, 33, 54], particle swarm optimization [13, 34], and coral reefs optimization [20].

In another way, the possibility of taking into account the subjective preferences of the decision maker (DM) has been suggested with the idea of incorporating subjective qualitative criteria that are difficult to be taken into account in a qualitative fitness function, such as aesthetic aspects, safety reasons, or just the DM's experience [19]. In these approaches, part of the fitness function optimization can be sacrificed to obtain solutions able to fulfill the DM's preferences [18]. While incorporating these new criteria contributes to enrich the quality of the solutions found to be used in the real world, these new kind of approaches have the problem of being very demanding with the DM's attention, since an exhaustive evaluation of solutions is required in each generation or, at least, every few generations of the algorithm [21]. So, a strategy for reducing DM's fatigue is needed as, for example, estimating the evaluation given by the DM from his/her visual behavior.

In that sense, some approaches have been done in order to relate the visual behavior of an expert while he/she is doing a decision-making task. [32], analyzed the visual behavior of financial experts by means of eye-tracking to obtain simple eye metrics in order to determine whether there is a reflection on the decision process or it is just a matter of good luck. In a similar way, [9] used eye-tracking to obtain gaze information while the experts were doing the task of evaluating maps quality, and [51] developed an exemplar-based classifier using the tabu search algorithm to predict decision strategies from user's search behavior. [11] related some uses of gaze analysis in pilots training and selection, and medical diagnosis, among others; [45] used gaze gestures to interact with handheld electronic devices; [25] used eye-tracking to analyze the attention captured by product attributes; and [15], used eye-tracking in a semiautomatic decision-making process obtaining high overall accuracy. [12] used eye-tracking to predict human errors in advance and obtained good enough results; [14], developed a system for designing layout configurations for software-generated interfaces by means of a slicing-tree-based genetic algorithm and using eye-tracking and mouse-tracking to obtain the best configuration; [3], used eye-tracking to determine whether sponsorship's location in posters announcing sports events was really efficient or not, obtaining different results from the previous believing; and [10], integrated the eye-tracking in a decision support center for air traffic control to adapt experts' decisions, concluding that final fixations are worthy to be paid more attention before the decision on routing election. By their part, [29], developed a procedure for feature extraction from eye movement's time series aimed at an age-related classification of humans. In another way, it could be interesting to obtain an estimation of several users evaluations, even when they can interact with the algorithm in different ways [53]. Unfortunately, there is no approach that studies the visual behavior of DMs in UA-FLP in order to reduce human fatigue during evaluation tasks.

In this paper, a relationship between gaze behavior and layouts subjective user evaluation is found. The objective is to break the DMs free from having to do many mouse pulsations during their task of evaluating the solutions showed during an interactive evolutionary algorithm process [18]. In this way, the DMs will be able to center their attention on the main task of evaluating the solutions shown and obtaining a more accurate evaluation. For the best of our knowledge, no alternative has been used yet to mouse pulsations in qualitative evaluation of candidate solutions by the DM, so this would be the main contribution of this paper, releasing him/her of this burdening task of making mouse pulsations and giving him/her the opportunity of concentrating on the evaluation of the solutions.

2. Methods and material

The main objective of this research is to prove whether it is possible to estimate the score assigned by an expert designer (DM) analyzing his/her gaze behavior. To do this, a test strategy has been carried out. Firstly, the genetic algorithm has been arranged in order to obtain the desired set of data. In a normal execution of the algorithm, both optimizing the objective fitness function and fulfilling the DM's subjective requirements must be done simultaneously. Nevertheless, in this case, in which we are only searching for a relationship between gaze behavior and DM evaluation, the weight assigned to the objective fitness function has been set to zero. In other cases, the weights of fitness function and subjective scores must be balanced assigning weights that can be fixed or even dynamic. In the same way, the number of generations of the algorithm between each intervention of the DM can be set to 5, 10, or so on, depending on the size of the problem, but since the objective is obtaining data to analyze the relationship between the scores given by the DMs and their visual behavior, this parameter has been set to one. So, the DM's intervention is required in every generation of the algorithm.

Then, several tests were planned to obtain the required data. The interactive evolutionary algorithm for plant layout design was executed by three expert users (DM1, DM2, and DM3) over four problems taken from the literature: problem 1 (P1: [1]); problem 2 (P2: Slaughterhouse, [46]); problem 3 (P3: Carton Packs, [18]); and problem 4 (P4: Chopped Plastic, [17]). Initially, DM1 realized two preliminary tests over P1 and three over P2. Then, DM2, as well as DM3, conducted three tests over each one of the four problems. The algorithm was executed until obtaining a reasonable number of solutions scored with the maximum score. In this way, Table 1 shows the number of evaluations made by the DMs in each execution of the algorithm, which sum a total of 29 whole tests and a total of 3094 DMs' evaluations.

While realizing the tests, an eye tracker Tobii X2-30 and software Tobii Studio v3.3.0.567 were used.

The general evolutionary process of the genetic algorithm is shown in Fig. 1. Initially, a random population of possible solutions is generated and the classical operators of crossover and mutation are performed on the individuals selected. Then, the DM is required to give a score from 1 to 5, according to his/her subjective preferences, to each one of the nine individuals showed, which are the most representative of the components of the population. Along this process, the DM could be required to evaluate hundreds of plants, which is a very demanding task, not only concerning DM's attention but to his/her posture. Table 1 shows the number of individual solutions that have been required to be evaluated by each one of the DMs for each problem and execution in order to obtain a satisfactory solution.

Fig. 1

General process of the genetic algorithm with human intervention

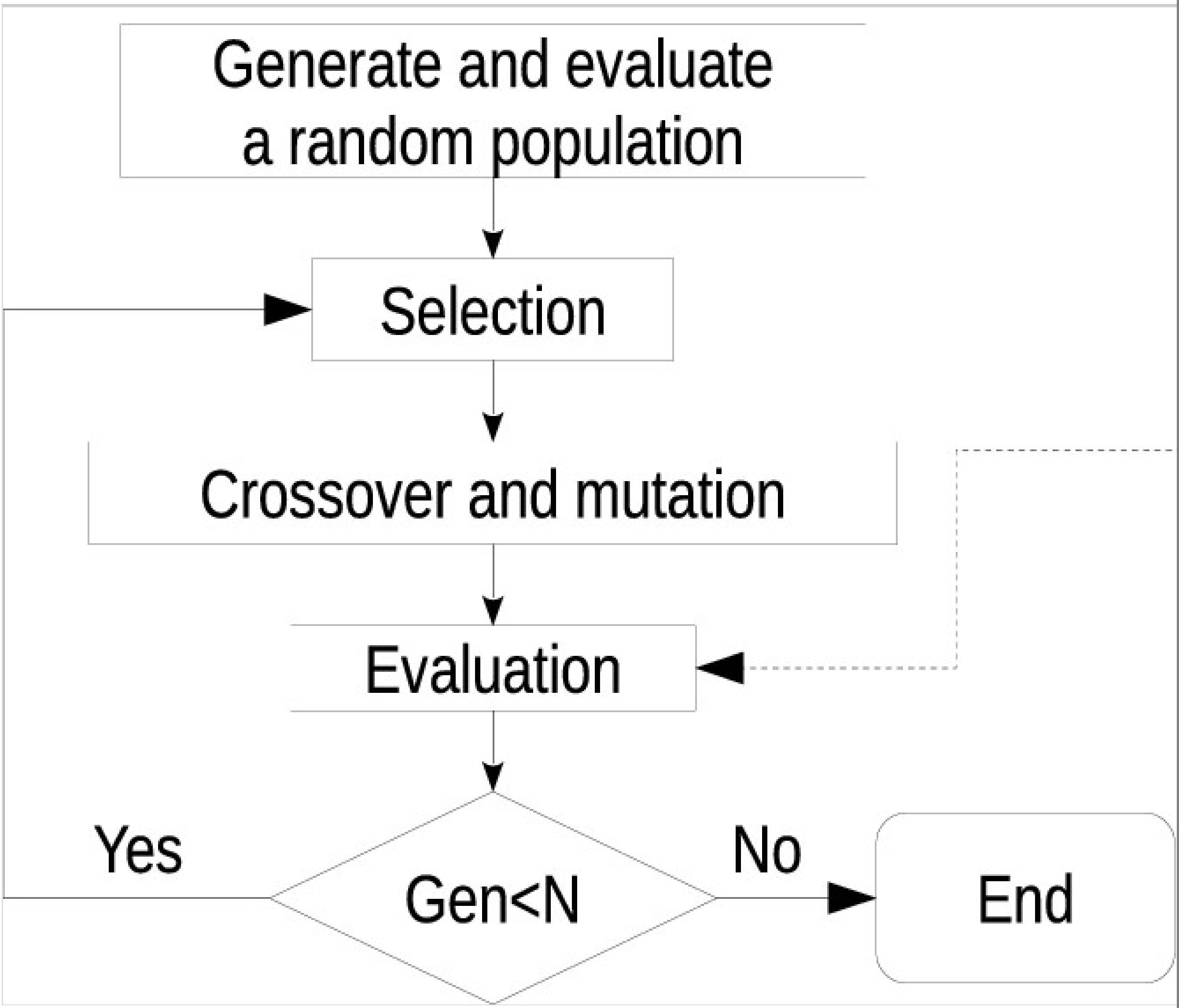


Table 1

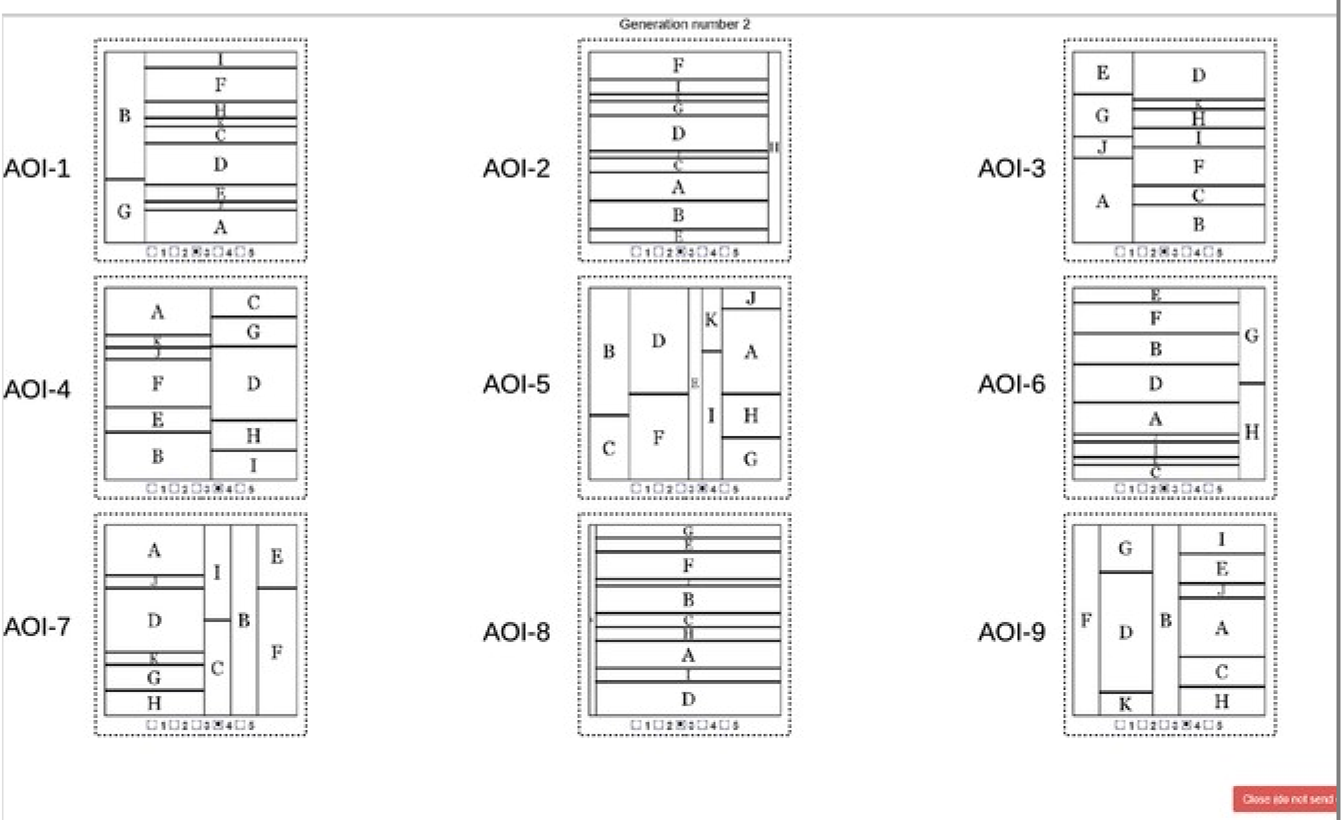
Number of evaluations made by the DMs in each execution of the algorithm

Problem	**P1**			**P2**			**P3**			**P4**		
Execution	1	2	3	1	2	3	1	2	3	1	2	3
DM1	169	166		89	88	83						
DM2	164	170	167	85	84	81	82	84	83	85	85	86
DM3	169	158	173	82	83	74	90	80	83	87	82	82

The screen to be visualized by the DMs during the evaluation process is shown in Fig. 2. In each screen, nine areas of interest (AOI), corresponding to each one of the solutions shown, are defined.

Fig. 2

Screen of individuals evaluation with areas of interest identification



During the genetic algorithm evolutionary process, a number of gaze parameters have been recorded simultaneously with DMs evaluation. Concretely, the selected parameters were:

1. *Time to First Fixation (TFF)* The time that the DM takes to fix his/her attention for the first time in the AOI object of study. Lowest TFF indicates elements that first catch the attention.

2. *Total Fixation Duration (TFD)* The total time that the DM has put his/her attention on a particular AOI, just in only one time or several times. Greater values denote more difficulty or more interest.

3. *Fixation Count (FC)* Number of times the DM has fixed the gaze on an AOI. In a similar way that TFD greater values denote more difficulty or more interest.

4. *Total Visit Duration (TVD)* The total time the DM has looked at a particular AOI.

5. *Visit Count (VC)* The number of times the DM has looked at a particular AOI.

Thus, each time a DM finishes the evaluation of an AOI, six data are recorded: TFF, TFD, FC, TVD, VC, and the evaluation given to the particular solution represented in the AOI (integer from 1 to 5). The hypothesis presented here is that it is possible to infer the evaluation given by the DM from the values of the five gaze parameters without the necessity of his/her explicit expression. So, ten mouse clicks (nine for the evaluation of the solutions and one to close the screen and pass to the next step of the algorithm) could be substituted by just one click. To do that, several artificial neural networks (ANN) have been implemented searching for the possible relationship between gaze parameters and DM's evaluation. The chosen ANN type was the multilayer feed-forward ANN with Levenberg-Marquardt as an optimization method for training the network since it is both simple and accurate [16, 39]. The percentage of data used for training was always 70%, while the remaining 15% was used for validation and test. Initially, a particular ANN has been set for each problem, DM and execution. In a second phase, we wondered if every single DM has the same gaze behavior for all the executions of the same problem or, in other words, if the gaze behavior of the DMs is independent of the execution in each problem. The subsequent question is whether every single DM has the same gaze behavior for all the problems or if the gaze behavior of the DM is independent of the problem. Finally, the last question would be if the gaze behavior of the three DMs are the same, what could allow to establish an unique relationship between the gaze parameters and the user evaluation independently of the DMs and the problem.

3. Data analysis

3.1. Preliminary tests

In the initial phase of the study, the DM1 was required to do some preliminary tests over problems P1 and P2. Concretely, two executions were performed over P1, and three over P2. An ANN was set out with the following configuration (Fig. 3): input data, the five columns with TFF, TFD, FC, TVD, and VC; target data, the column with DM1's evaluation for each solution shown; number of hidden layers (sigmoid), 1; number of output layers (linear), 1. To measure the goodness of the adjustment between target data and output data, four metrics were used: (1) root mean square root (RMSE); (2) mean absolute error (MAE); (3) mean bias error (MBE); and (4) correlation coefficient (R). The results of the five tests carried out by DM1 are shown in Table 2. Figure 4 shows the distribution of errors (output—target).

Fig. 3

Artificial neural network configuration

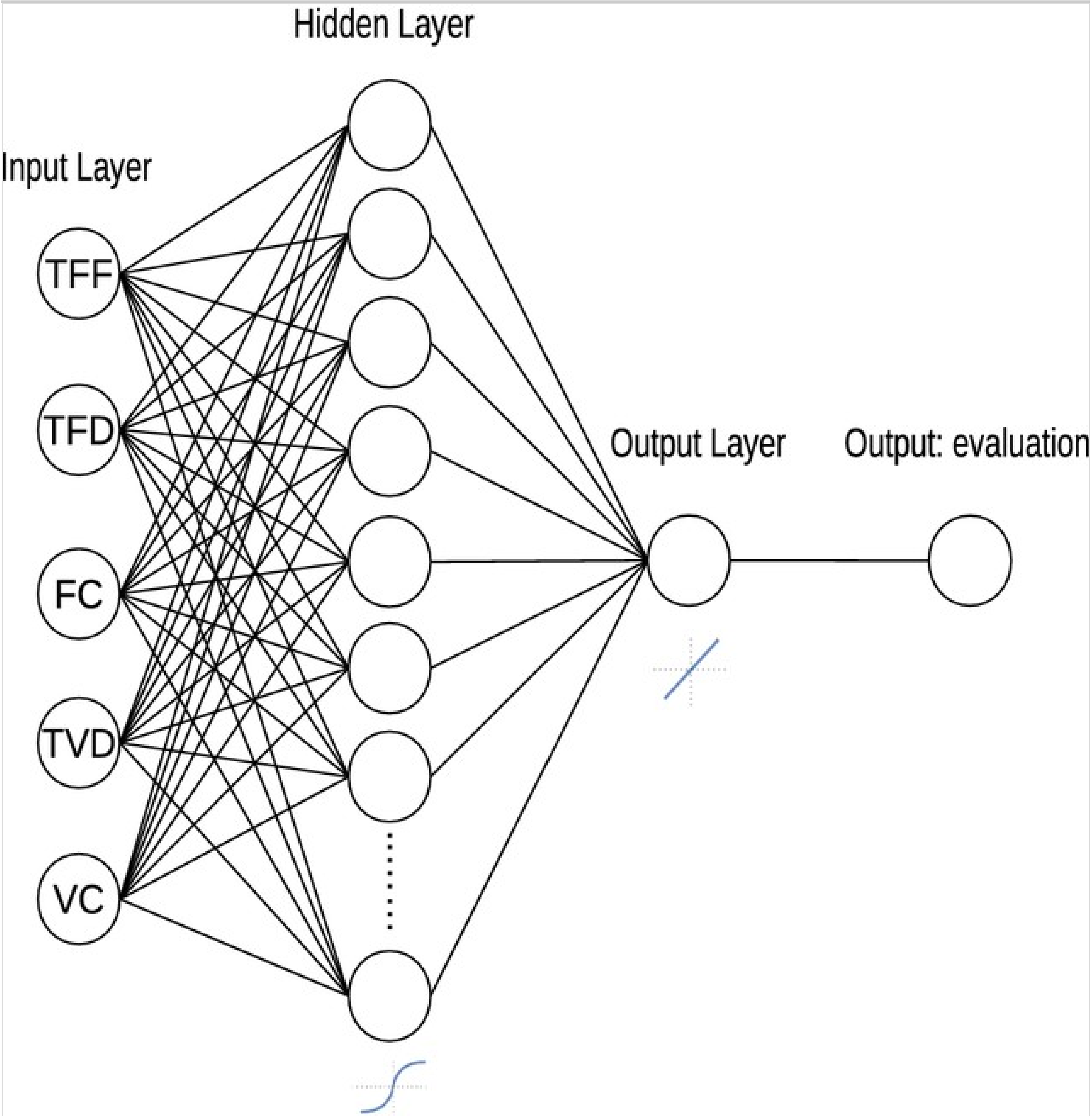


Table 2

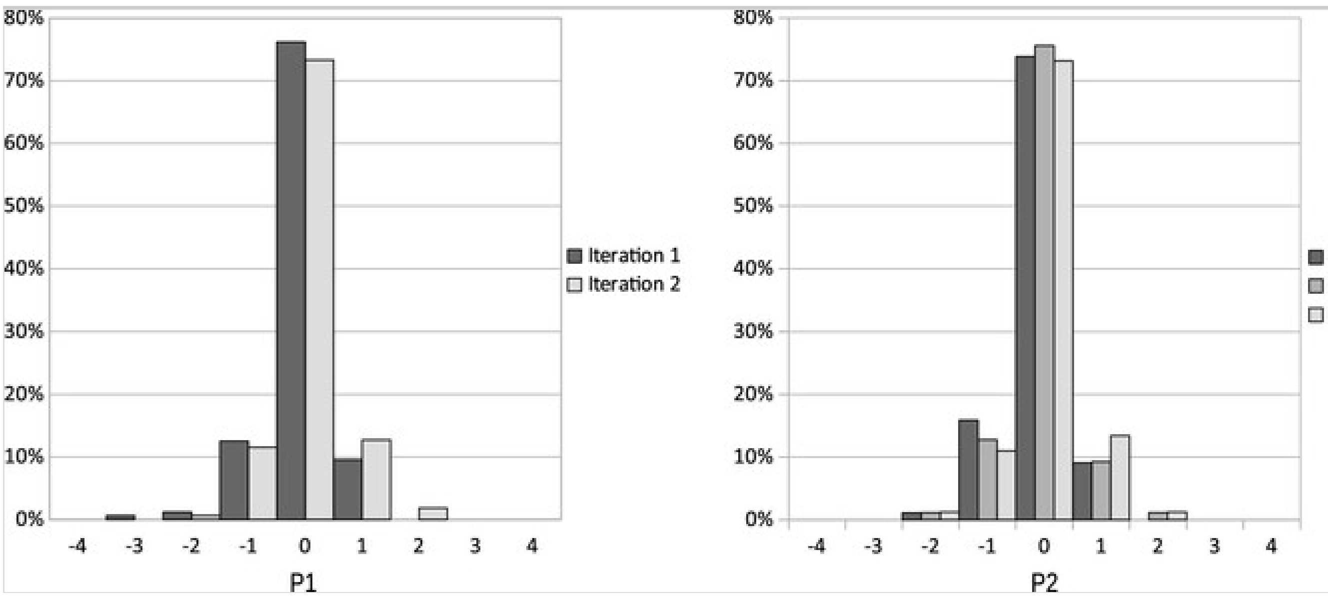
Metrics obtained in each problem and execution by DM1

Problem	**P1**		**P2**		
Execution	1	2	1	2	3
RMSE	0.55	0.53	0.53	0.53	0.53
MAE	0.35	0.38	0.36	0.36	0.36
MBE	− 0.11	0.02	− 0.03	− 0.05	0.04

Problem	P1		P2		
R	0.72	0.72	0.78	0.76	0.80

Fig. 4

Distribution of errors (output-target) in DM1 executions



The results obtained in these first essays were really promising. All the values of the metrics calculated over target and output data were very acceptable. For example, MAE values showed the mean absolute error was under 0.38 in all cases, while looking at Fig. 4, it can be observed that in most cases, the error is 0; and in the rest, it is between $+1$ and -1. Only in very few cases, the error is greater than $+1$ or -1, which is perfectly acceptable for the application in which these data will be used.

Then, a χ^2 independence test was carried out to determine whether the results of the estimations of DM1's evaluation were independent of the execution, as Fig. 4 suggests. The results show that the estimated data are independent of the execution in both problems ($\chi^2(5) = 0.03, p = 0.99999, \alpha = 0.05$ in P1; and $\chi^2(8) = 0.03, p = 1; \alpha = 0.05$ in P2). So, new ANNs were set combining the data of all the executions for each problem. Results obtained with combined data can be seen in Table 3 and Fig. 5. As expected, the performance of estimated data in combined executions is similar to the ones obtained in individual executions, which could suggest that it is not necessary to do a high number of repetitions to train the neural network.

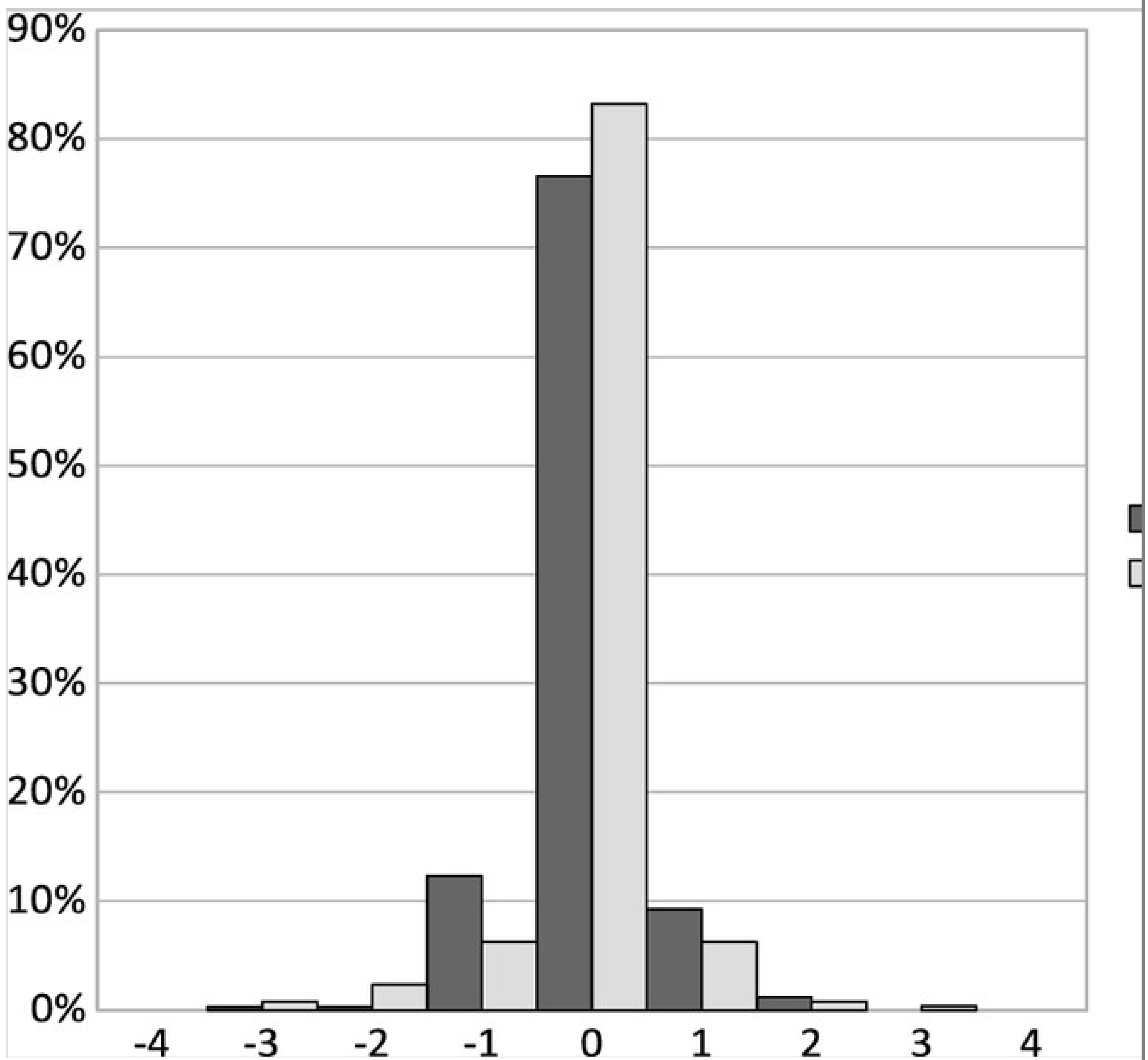
Table 3

Metrics for combined data of DM1 in P1 and P2

	RMSE	**MAE**	**MBE**	***R***
P1	0.50	0.33	− 0.01	0.76
P2	0.67	0.29	− 0.04	0.69

Fig. 5

Distribution of errors in DM1 combined executions for P1 and P2



Equally, it is still possible to make one more question: if the results of the estimation of the DM1's evaluation are independent of the problem. If the answer to this question was affirmative, only one execution would be necessary to obtain the estimated values. So, a new χ^2 test was carried out in order to determine whether the results of DM1's evaluations are independent of the problem. This test was carried out comparing the combined data of all the individual executions for P1 and for P2 with the result that the estimated data are independent of the problem too ($\chi^2(6) = 0.05, p = 1, \alpha = 0.05$). The values of the four metrics for the combined result and errors are shown, respectively, in Table 4 and Fig. 6.

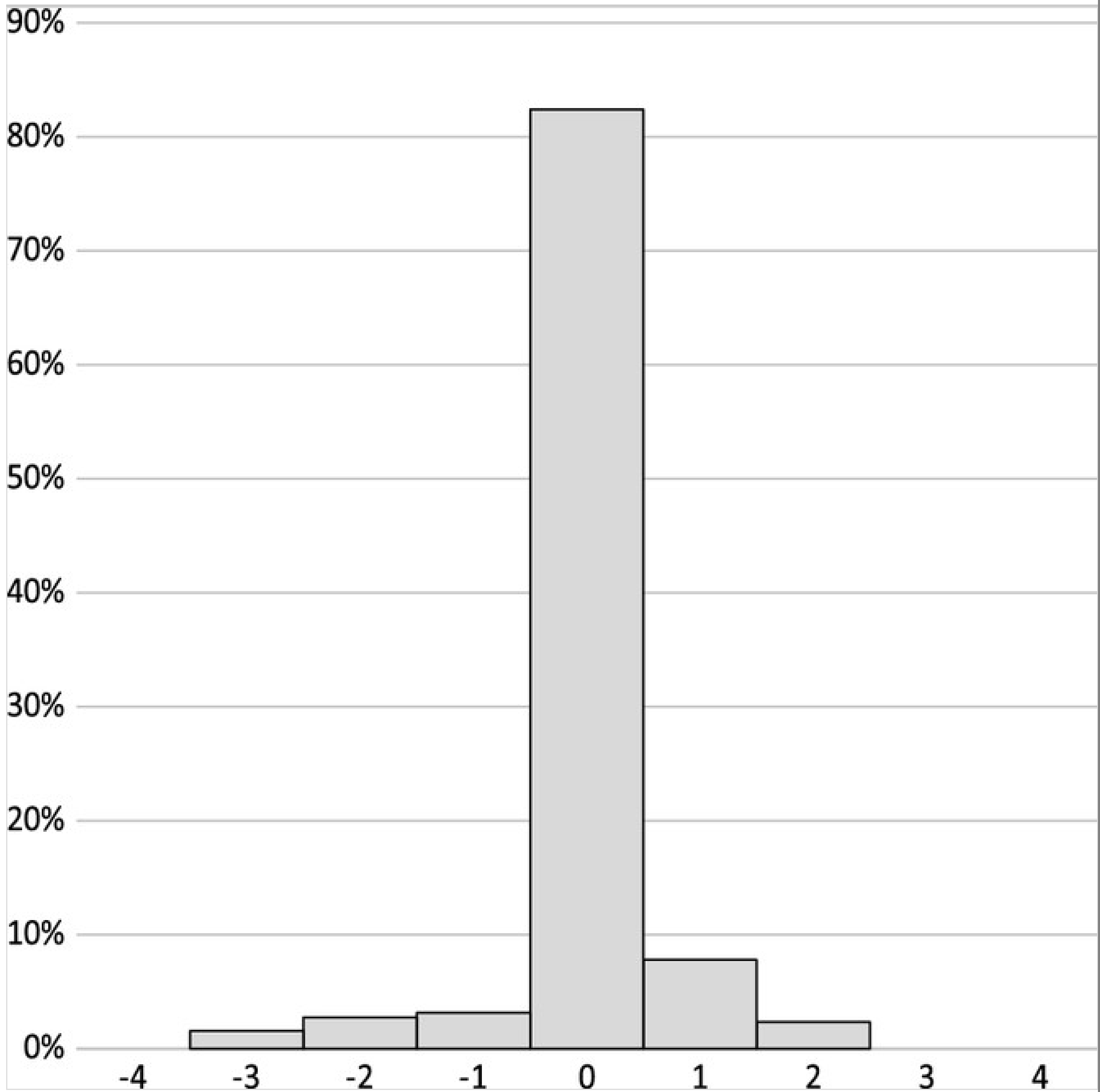
Table 4

Metrics for combined data of DM1

RMSE	MAE	MBE	*R*
0.66	0.35	0.05	0.71

Fig. 6

Distribution of errors for combined data of DM1



3.2. Data analysis for DM2 and DM3 tests

Once seen the results obtained by DM1, it is appropriate to analyze the results obtained by the other two DMs following the same guidelines, with the results shown in Table 5 and Figs. 7 and 8.

Table 5

Metrics obtained in each problem and execution by DM2 and DM3

		RMSE	MAE	MBE	*R*	RMSE	MAE	MBE	*R*

		RMSE	MAE	MBE	*R*	RMSE	MAE	MBE	*R*
DM2		P1				P2			
	Execution 1	0.57	0.23	− 0.03	0.81	0.48	0.25	− 0.11	0.85
	Execution 2	0.80	0.49	0.09	0.72	0.52	0.37	0.03	0.71
	Execution 3	0.65	0.48	0.28	0.78	0.54	0.38	− 0.03	0.71
		P3				P4			
	Execution 1	0.54	0.35	0.11	0.74	0.57	0.35	− 0.02	0.71
	Execution 2	0.53	0.39	− 0.17	0.76	0.59	0.35	0.00	0.71
	Execution 3	0.51	0.34	0.03	0.71	0.52	0.37	0.02	0.81
		P1				P2			
DM3	Execution 1	0.48	0.29	0.01	0.74	0.56	0.39	0.03	0.81
	Execution 2	0.59	0.39	0.01	0.68	0.49	0.33	0.03	0.77
	Execution 3	0.47	0.37	− 0.05	0.78	0.57	0.35	− 0.08	0.71
		P3				P4			
	Execution 1	0.54	0.32	0.02	0.72	0.51	0.37	− 0.11	0.76
	Execution 2	0.41	0.27	− 0.06	0.77	0.72	0.44	0.16	0.71
	Execution 3	0.47	0.34	0.05	0.80	0.56	0.37	0.02	0.73

Fig. 7

Distribution of errors in DM2 executions

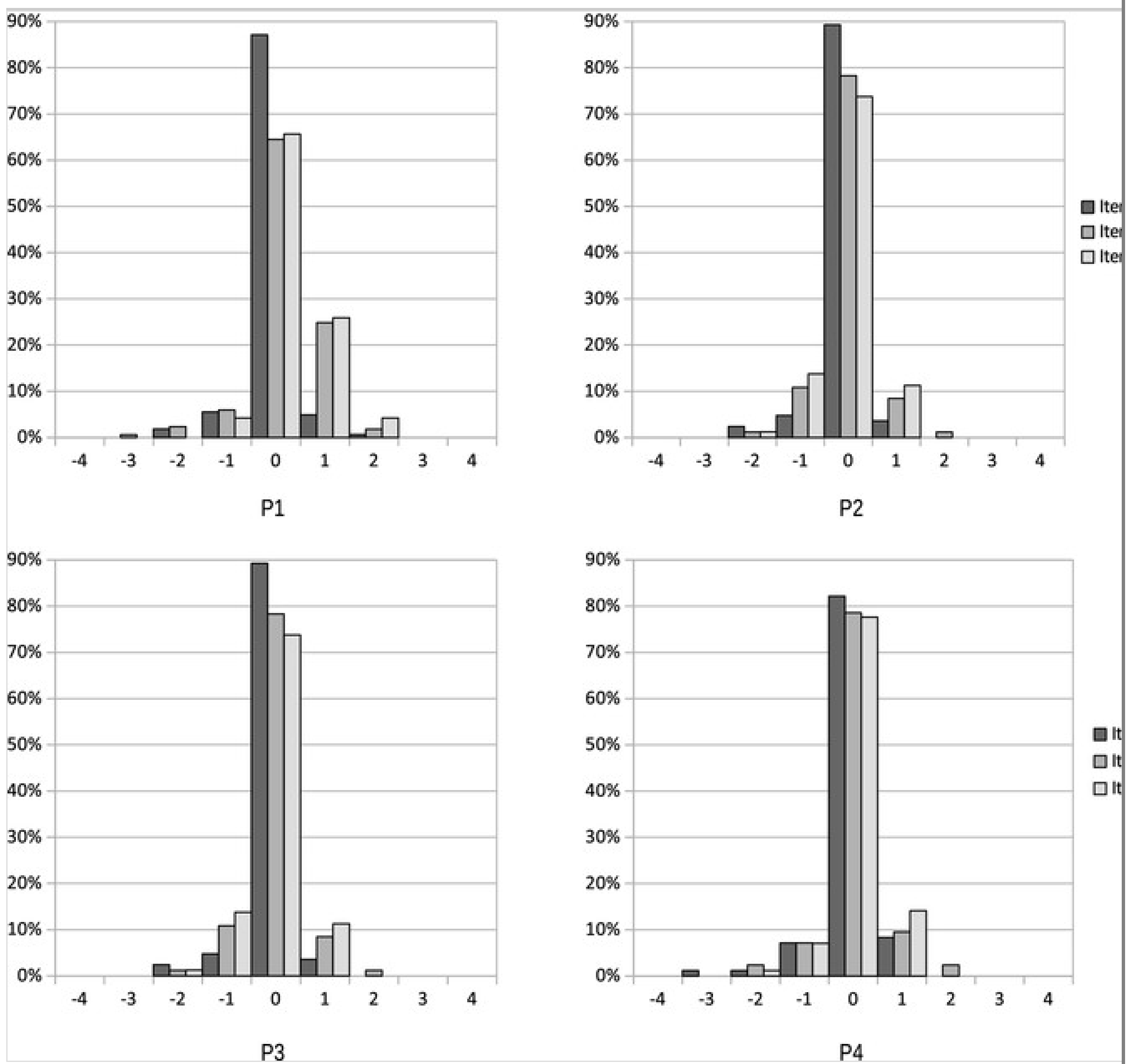
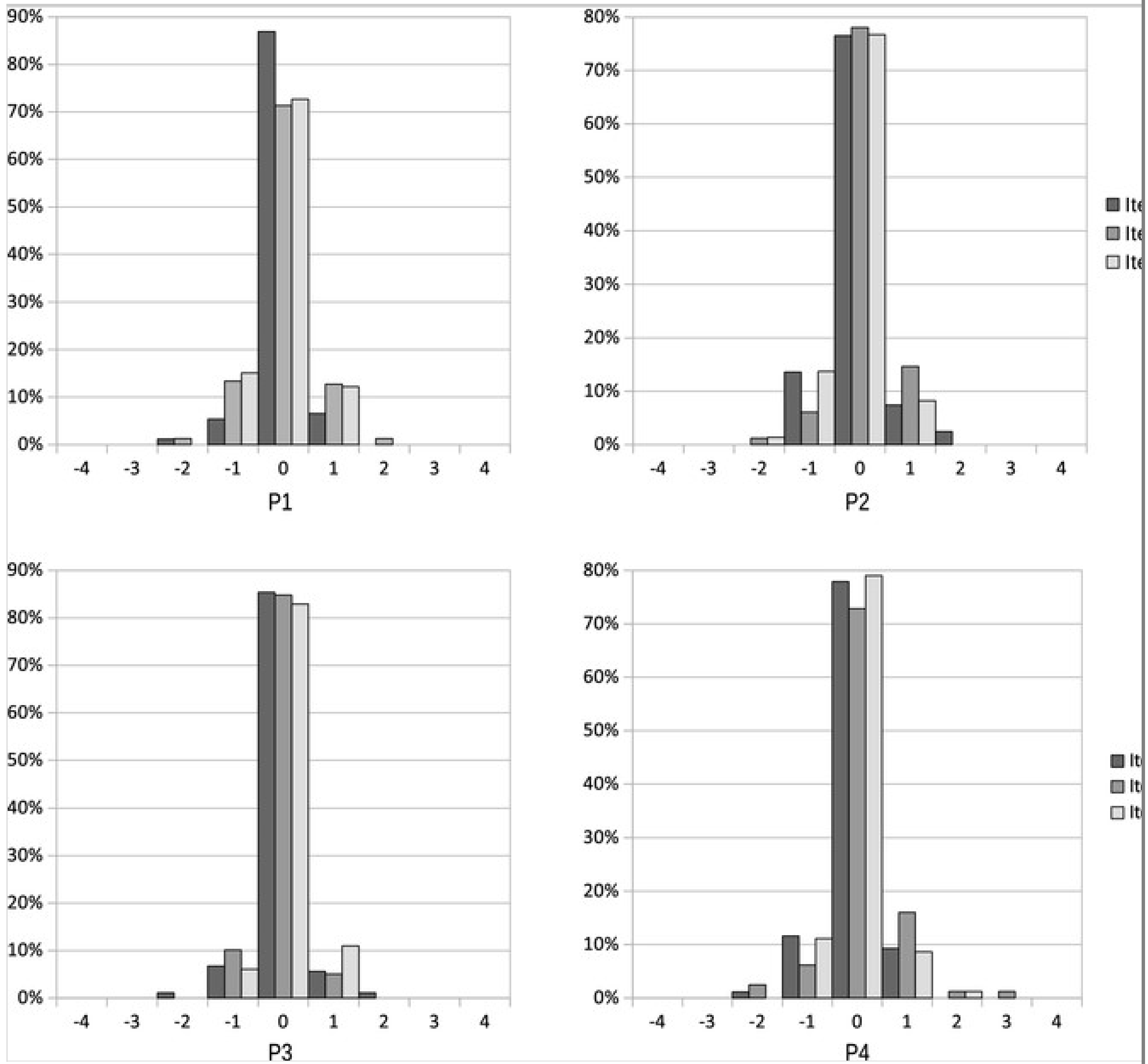


Fig. 8

Distribution of errors in DM3 executions



AQ3

Following the procedure performed with DM1 executions, χ^2 tests were conducted to determine whether there is a dependence of the results with the execution of each problem or not. The results of these tests are shown in Table 6. In all cases, there exists clear independence of results from the execution, so a new ANN was set out with the combined data for each problem and DM. Table 7 shows the metrics obtained for combined data for each problem and DM2 and DM3, while Fig. 9 shows the error's distributions in the combined executions of DM1 and DM2 for the four problems. These data suggest again that the visual behaviors of DMs during evaluation could be independent of the problem. When carried out a new χ^2 test to determine the veracity of this hypothesis ($\alpha = 0.05$), the obtained data were as follows: (1) DM2, $\chi^2(18) = 0.00$; $p = 1$; and (2) DM3, $\chi^2(15) = 0.08$; $p = 1$, which confirms that the results are independent of the problem too. So, it is possible to obtain good results with fewer tests in real laboratory conditions. Results of the new estimations combining all data for DM1 and DM2, respectively, are shown in Table 8 and Fig. 10.

There is still one more matter to be addressed. Once proved that the relationship between DMs' gaze behavior and the scores assigned to the problem solutions are independent of the problem, the final question is whether we need to do tests with several DMs or if is it enough with just one of them. To investigate this possibility, a last χ^2 test was carried out with the result of $\chi^2(12) = 0.09, p = 1, \alpha = 0.05$. Finally, it can be said that it would have been enough with just one execution in one problem with one DM to obtain a valid estimation rule. Anyway, Table 9 and Fig. 11 show metrics and errors distribution for combined data for all tests.

Table 6

Results of χ^2 tests for each problem and DM ($\alpha = 0.05$)

	χ^2	**d.f.**	***p***
DM2			
P1	0.26	10	1
P2	0.13	8	1
P3	0.19	8	1
P4	0.10	10	1
DM3			
P1	0.13	8	1
P2	0.13	8	1
P3	0.09	8	1
P4	0.11	10	1

Table 7

Metrics for combined data of DM2 and DM3

	RMSE	MAE	MBE	***R***
DM2				
P1	0.72	0.39	0.12	0.70
P2	0.56	0.35	0.10	0.74
P3	0.59	0.36	− 0.05	0.69
P4	0.54	0.34	0.01	0.79
DM3				
P1	0.72	0.34	− 0.09	0.70
P2	0.50	0.25	− 0.01	0.80
P3	0.64	0.34	− 0.08	0.68
P4	0.59	0.37	− 0.06	0.72

Fig. 9

Distribution of errors in DM2 and DM3 combined executions

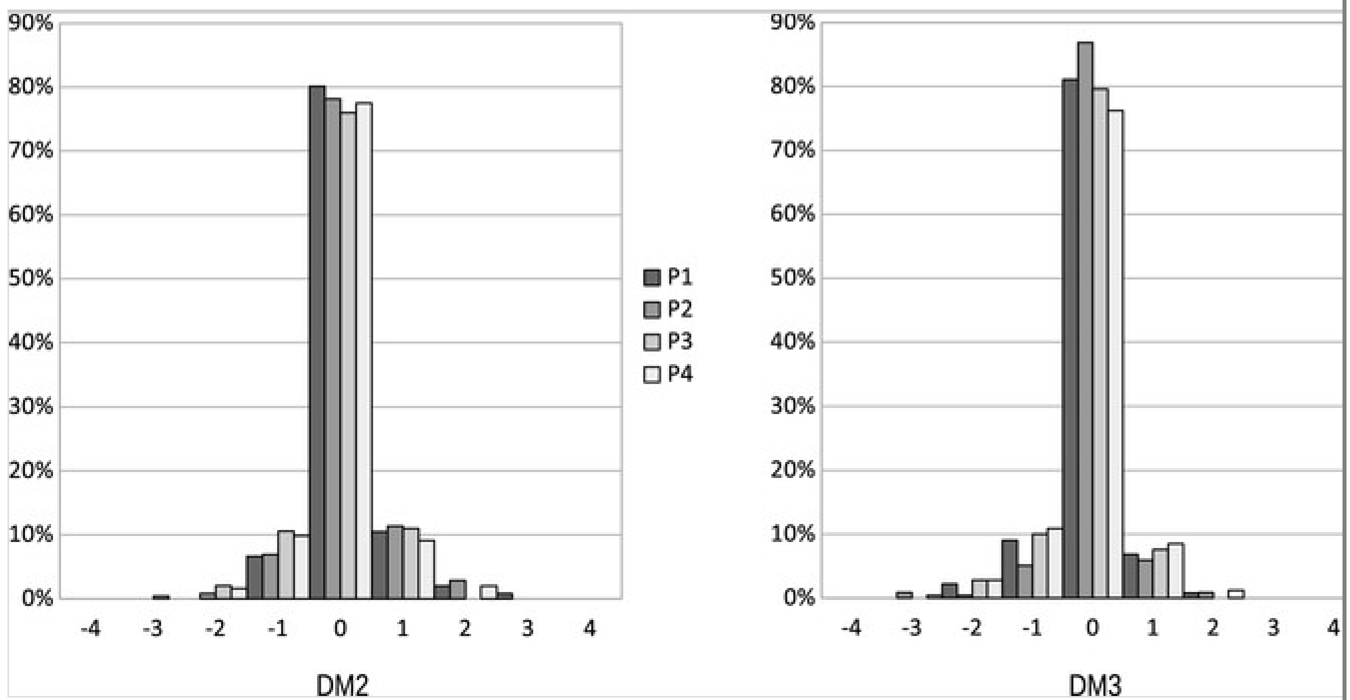


Table 8

Metrics for combined data of the four problems of DM2 y DM3

	RMSE	MAE	MBE	*R*
DM2	0.59	0.36	− 0.01	0.78
DM3	0.61	0.36	0.02	0.75

Fig. 10

Distribution of errors for combined data of DM2 and DM3

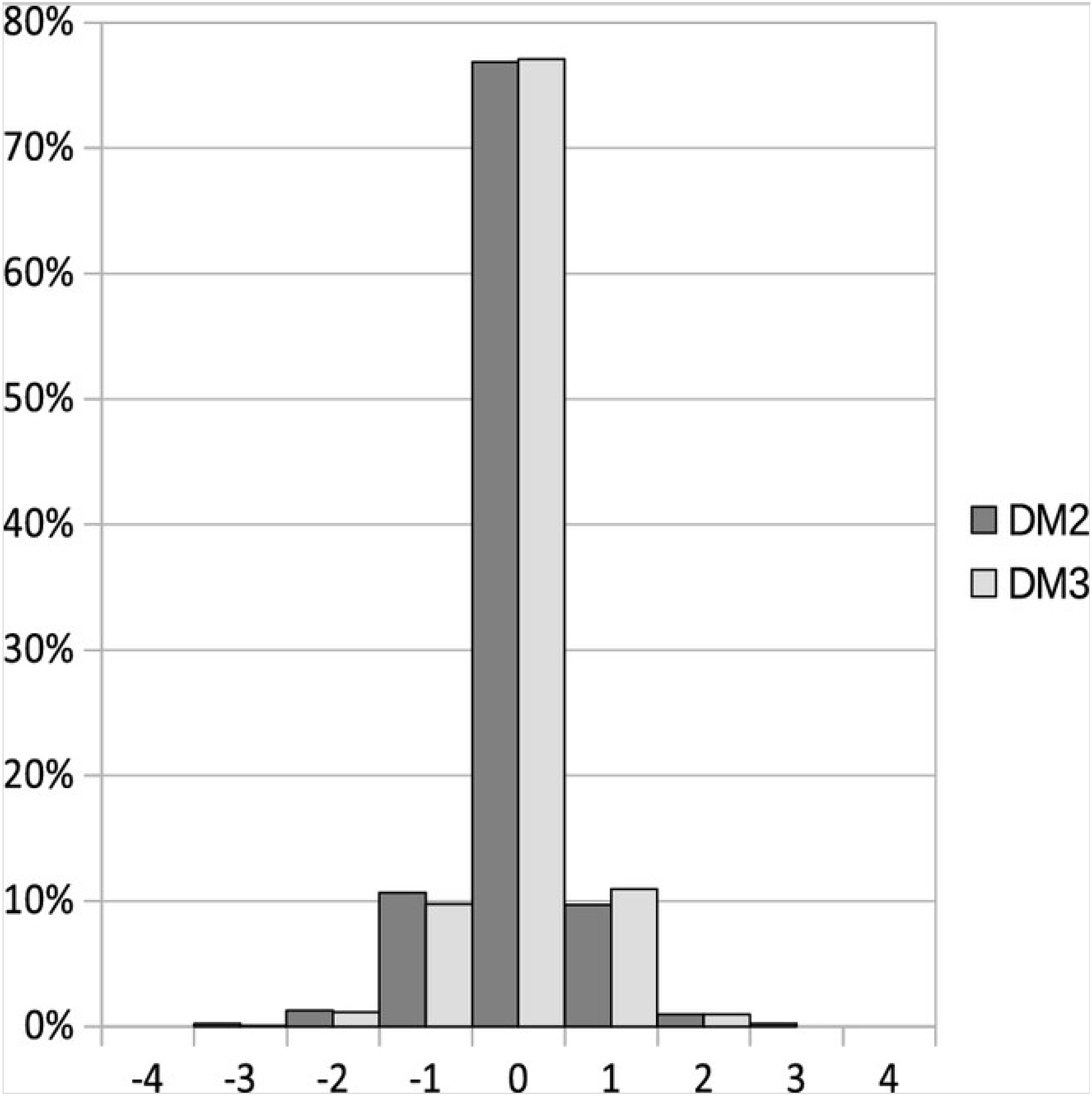


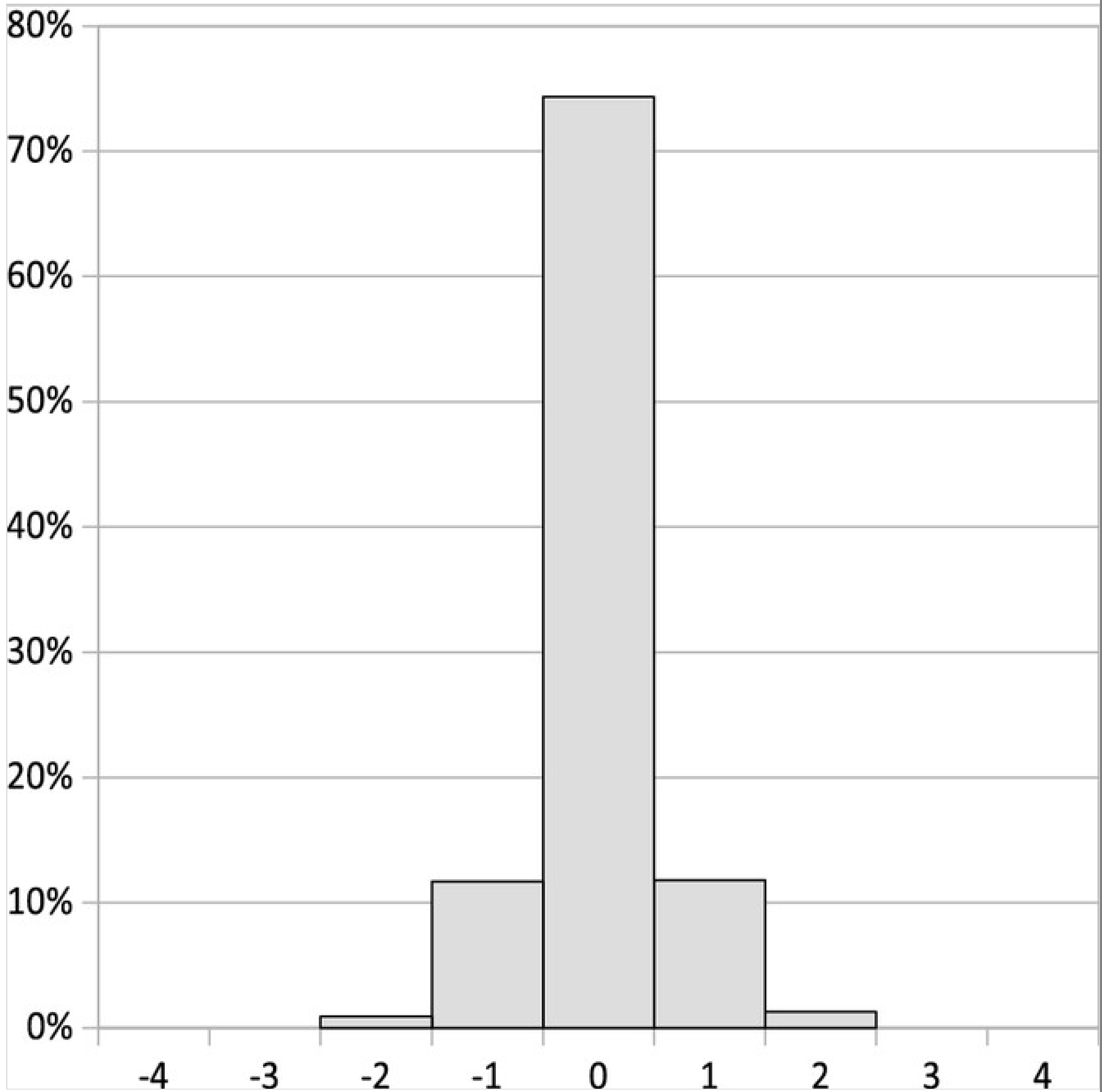
Table 9

Metrics for combined data of whole data combination

RMSE	MAE	MBE	*R*
0.55	0.39	0.00	0.79

Fig. 11

Distribution of errors for whole data combination



4. Conclusions

The problem of facilities allocation in industrial or other kinds of installations with certain restrictions is classified as an NP-Hard problem in which a correct disposition of facilities could help to save money, energy, and resources in general. Many kinds of algorithms have been proposed to approach the problem, but evolutionary algorithms have been the most widely used recently and, among them, interactive evolutionary algorithms have been proposed to take into account, not only the objective minimization of a fitness function but the subjective preferences of an expert DM. In such approaches, the DM is required to evaluate a great number of solutions in a repetitive and very tiring way. In this paper, the application of ANN to assist the DM in the process of evaluating the solutions has been proposed. To do this, a set of tests has been carried out recording the DMs' gaze behavior while they evaluated the solutions in real conditions and obtaining a whole set of evaluations estimated data using ANNs. The main findings of the tests and the process of estimating scores are: (a) it is possible to estimate the scores given by the DMs by using ANN and taking five metrics of the gaze as the starting point (TFF, TFC, FC, TVD, VC); (b) the metrics obtained during 29 different tests carried out by three different experts over four problems (with a total of 3094 evaluations) showed a good fitting between measured and estimated values; (c) the estimation of the scores given by the DMs is independent of the problem, the execution, and even of the person who makes the evaluation task, so a single initial test is needed to obtain the relation between the evaluation and the gaze metrics.

Nevertheless, more detailed research has to be done to use eye-tracking as a substitute for clicking repetitively the mouse. In the same way, a more detailed analysis could be carried out to determine the weight of every one of the gaze parameters on the DMs score, to simplify the computing process eliminating those least representatives. Finally, a complete analysis of the commercial catalog of eye-trackers must be done shortly to determine what are the minimum precision required to cheapen the equipment cost.

Publisher's Note

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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