

An Evolutionary-Based Adaptive Neuro-Fuzzy Expert System as a Family Counselor before Marriage with the Aim of Divorce Rate Reduction

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ABSTRACT

Due to the growth of divorce rate in developed and developing countries, and with the aim of reducing this phenomenon, an evolutionary-based Adaptive Neuro-Fuzzy Expert System as a family counselor before marriage is developed. The main goal is to combine evolutionary algorithms with fuzzy logic, and inferring nature inspired results for this kind of natural event (divorce). For validating results, a dataset from a human expert (marriage counselor) has been received, which described thoroughly in section IV in details. This dataset has been trained and tested with different Meta-heuristic optimization algorithms like (ACO, DE, PSO and GA) and neural network training methods like (Hybrid and back-propagation). Error factors like (MSE, RMSE, Error Mean and Error STD) will be calculate for each one of these approaches as validation results. Also, classification results with MLP algorithm, made this paper more detailed. Validation processes returned promising results and opened a way to use this kind of counselor expert system in the absence of human expert conditions. Dream to day which all the children grow up with their original parents.

Keywords: *Evolutionary Algorithm, Evolutionary Learning, Fuzzy, Neuro-Fuzzy, Expert System, Marriage Counselor, Divorce*

1. INTRODUCTION

Expert systems have made life easier and better. With the aid of expert systems, human mistakes decrease. Expert systems are demonstrated in section D in details. Nowadays they have a widespread use in different areas. Due to the lack of such a system as marriage counselor, it has been decided to make one. Using this system (as end user), the percentage of successful marriage could be estimated. Also it is possible to prevent unsuccessful marriages happen. Making expert systems using Anfis, has been done before, but not on this subject. As it is clear, the rate of divorce in developed and developing countries is increasing, so making such a system could help to decrease this unpleasant phenomenon.

According to a research in 2012 (United Nations World Demographic Report) [32], for 70 countries, reporting on divorce rate, in which first five were: Russia, Aruba, Belarus, Latvia and Lithuania, with respectively divorce rate of 4.5, 4.4, 4.1, 3.6 and 3.5, of which Iran was at 31th place with divorce rate of 2. Fig1 shows statistical chart of divorce for (year vs number of divorce) and the average age of marriage for (year vs age) in Iran, between 1975-2016. This plot shows that number of divorces is increasing through years. Also Table 1 shows the most important factors in consultation before marriage, taken from human expert (family counselor).

1.1 Fuzzy Logic

Based on Prof Lotf-Ali Asgarzade, founder of fuzzy logic and fuzzy sets [1], as complexity increases, exact sentences lose their meaning, and meaningful sentences their precision. Following this rule, there is a need for converting the absolute results to the results possessing range; The fuzzy hypothesis is also based on this. Considering the similarity of fuzzy concept and probabilities, nevertheless it can never be possible to say that these two concepts are the same. For instance, in crisp problems, we say: "an accident occurred", but in a similar fuzzy case, we say: "how much the damage was", and for instance the intensity of it is shown as between a range of 0 and 1 [2], [3].

Table 1. Most important factors in consultation before marriage

	Variable Name	Range
1	Age Gap	[0 10]
2	Education	[1 5]
3	Economic Similarity	[1 100]
4	Social Similarities	[1 100]
5	Cultural Similarities	[1 100]
6	Social Gap	[1 100]
7	Common Interests	[50 100]
8	Religion Compatibility	[1 100]
9	No of Children from Previous Marriage	[1 5]
10	Desire to Marry	[1 100]
11	Independency	[1 2]
12	Relationship with the Spouse Family	[1 100]
13	Trading in	[0 100]
14	Engagement Time	[1 10]
15	Love	[30 100]
16	Commitment	[40 100]
17	Mental Health	[50 100]
18	The Sense of Having Children	[10 100]
19	Previous Trading	[1 80]
20	Previous Marriage	[1 5]
21	The Proportion of Common Genes	[1 50]
22	Addiction	[1 5]
23	Loyalty	[20 100]
24	Height Ratio	[1 100]
25	Good Income	[1 100]
26	Self Confidence	[40 100]
27	Relation with Non-spouse Before Marriage	[1 10]
28	Spouse Confirmed by Family	[1 10]
29	Divorce in the Family of Grade 1	[1 10]
30	Start Socializing with the Opposite Sex Age	[15 40]

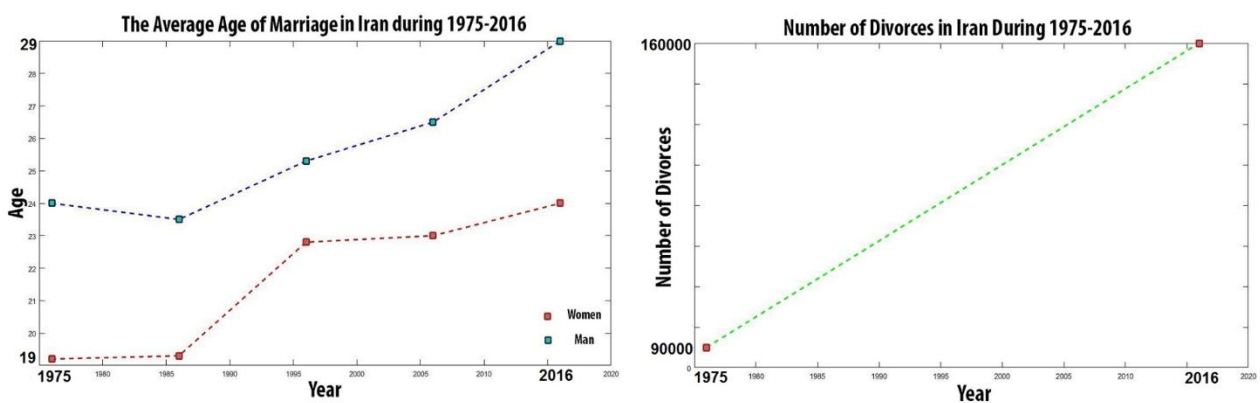


Fig. 1. Statistical chart of divorce and the average age of marriage in Iran between 1975 – 2016 [33]

1.2 Neural Networks

Work on artificial neural networks, commonly referred to as “neural networks,” has been motivated right from its inception by the recognition that the human brain computes in an entirely different way from the conventional digital computer. The brain is a highly complex, nonlinear, and parallel computer (information-processing system). It has the capability to organize its structural constituents, known as neurons, so as to perform certain computations (e.g., pattern recognition, perception, and motor control) many times faster than the fastest digital computer in existence today [14].

Neural networks typically consist of multiple layers or a cube design, and the signal path traverses from the first (input), to the last (output) layer of neural units. Back propagation [15] is the use of forward stimulation to reset weights on the "front" neural units and this is sometimes done in combination with training where the correct result is known. The goal of the neural network is to solve problems in the same way that the human brain would, although several neural networks are more abstract. Modern neural network projects typically work with a few thousand to a few million neural units and millions of connections, which is still several orders of magnitude less complex than the human brain and closer to the computing power of a worm. For more information about neural networks refer to [16]. The optimization methods train the membership function parameters to emulate the training data. The hybrid optimization method is a combination of least-squares and back-propagation gradient descent method.

1.3 Evolutionary Computing

Evolutionary computing is a research area within computer science. As the name suggests, it is a special flavour of computing, which draws inspiration from the process of natural evolution. It is not surprising that some computer scientists have chosen natural evolution as a source of inspiration: the power of evolution in nature is evident in the diverse species that make up our world, each tailored to survive well in its own niche. The fundamental metaphor of evolutionary computing relates this powerful natural evolution to a particular style of problem solving – that of trial-and-error [4]. In artificial intelligence, an evolutionary algorithm (EA) is a subset of evolutionary computation, a generic population-based metaheuristic optimization algorithm. An EA uses mechanisms inspired by biological evolution, such as reproduction, mutation, recombination, and selection. Candidate solutions to the optimization problem play the role of individuals in a population, and the fitness function determines the quality of the solutions. Differential evolution algorithm is one of the popular evolutionary algorithms, which is used here to find best initial cluster centers. Differential Evolution (DE) is a relatively recent heuristic (it was created in the mid-1990s) proposed by Kenneth Price and Rainer Storn [5, 6, 7], which was designed to optimize problems over continuous domains. This approach originated from Kenneth's Price attempts to solve the Tchebycheff Polynomial fitting Problem that had been posed to him by Rainer Storn [8]. Another example is, genetic algorithm (j.holland, k. dejong, 1960) [9], which is a perfect example of them leads initial population to evolution for optimization problems. The operators of this algorithm are inspired of natural genetic changes and natural generation selection. Also Pso [10] which became formulized by Edward and Kennedy in 1995, based on social behavior of animals such fish and birds [11]. In computer science and operations research, the ant colony optimization algorithm (ACO) is a probabilistic technique for solving computational problems which can be reduced to finding good paths through graphs. This algorithm is a member of the ant colony algorithms family, in swarm intelligence methods, and it constitutes some metaheuristic optimizations. Initially proposed by Marco Dorigo in 1992 in his PhD thesis, [12][13] the first algorithm was aiming to search for an optimal path in a graph, based on the behavior of ants seeking a path between their colony and a source of food. The original idea has since diversified to solve a wider class of numerical problems, and as a result, several problems have emerged, drawing on various aspects of the behavior of ants.

1.4 Expert Systems

Expert systems are a special group of software, which are used to aid human experts, or for being as a total or partial alternative for them to be used in the specialized fields. These systems are in fact the early and simpler types of the knowledge base technology, which with gathering, processing and analyzing data are able to infer and resolve problems in the cases, which usually need the knowledge of a human expert in a special field of study. These systems usually store data as facts and rules in the knowledge base, and then using as special inference methods, needed results will be produced. Expert systems have application in a variety of fields; some of them: medicine, accountancy, industry, education, process control, human resources, financial services, archeology, radiography, engineering consultancy in architecture, juridical consultancy etc. In each of these fields, with the aid of experimental systems, more quickly and easily, it is possible to do works such: guidance, processing, classification, consultation, design, recognition, decision-making, analysis, scoring, foretelling, concept-making, detection, justification, learning, management, planning, scheduling and test [17][18].

1.5 Adaptive Neuro fuzzy Inference System (ANFIS)

An adaptive neuro-fuzzy inference system or adaptive network-based fuzzy inference system (ANFIS) is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. The technique was developed in the early 1990s. [10][20] Since it integrates both neural networks and fuzzy logic principles, it has potential to capture the benefits of both in a single framework. Its inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions [21]. Hence, ANFIS is considered to be a universal estimator [22].

2. PRIOR WORKS

In 2017 Hamidreza Saghafi and Milad Arabloo succeeded to make an expert system for estimation of carbon dioxide equilibrium adsorption isotherms using adaptive neuro-fuzzy inference systems (ANFIS) and regression models [23]. Also Kemal Polat and Salih Güneş made an expert system approach based on principal component analysis and adaptive neuro-fuzzy inference system to diagnosis of diabetes disease [24]. Servet Soyguder and Hasan Alli made an expert system for the humidity and temperature control in HVAC systems using ANFIS and optimization with Fuzzy Modeling Approach [25]. In 2009, Melek Acar Boyacioglu and Derya Avcı made An Adaptive Network-Based Fuzzy Inference System (ANFIS) for the prediction of stock market return: The case of the Istanbul Stock Exchange [26].

3. PROPOSED METHOD

In this paper, an evolutionary-based Adaptive Neuro-Fuzzy Expert System as a family counselor before marriage with the aim of reducing divorce rate is proposed. The main goal is to combine evolutionary algorithms with fuzzy logic and inferring nature inspired results for this kind of natural event (divorce). In fact learning process Takes place for (Hybrid, back-propagation, GA, PSO, DE and ACO) learning algorithms, and the results will be compare with each other. Fig2 represents the flowchart of proposed method. Neuro fuzzy network structure for the proposed method is represented in Fig3. Because number of variables were too much (30 variables), for generating fis, FCM[27][28] clustering method is used to decreasing fuzzy rules and output membership functions. As it is clear, there are 30 inputs or neurons or variables and input membership functions. Also there are 9 rules and output membership functions and just one output variable. Membership functions type is Gaussian, as indicated in Fig4. Training fis using hybrid learning and testing train and test data for respective dataset is shown in Figs 5, 6 and 7. Fig8 represents train and test errors for our dataset (ACO learning). These plots are just for ACO learning algorithm and merely for representing proposed method procedure. As Fig8 indicates, train and test errors are close to zero. Fig9 shows 3-D Surface between variable 6 and 24 after train. Also Figs 10 and 11 show Gplotmatrix, Parallel Coordinates Plots and Andrews Plots for five different variables in dataset respectively.

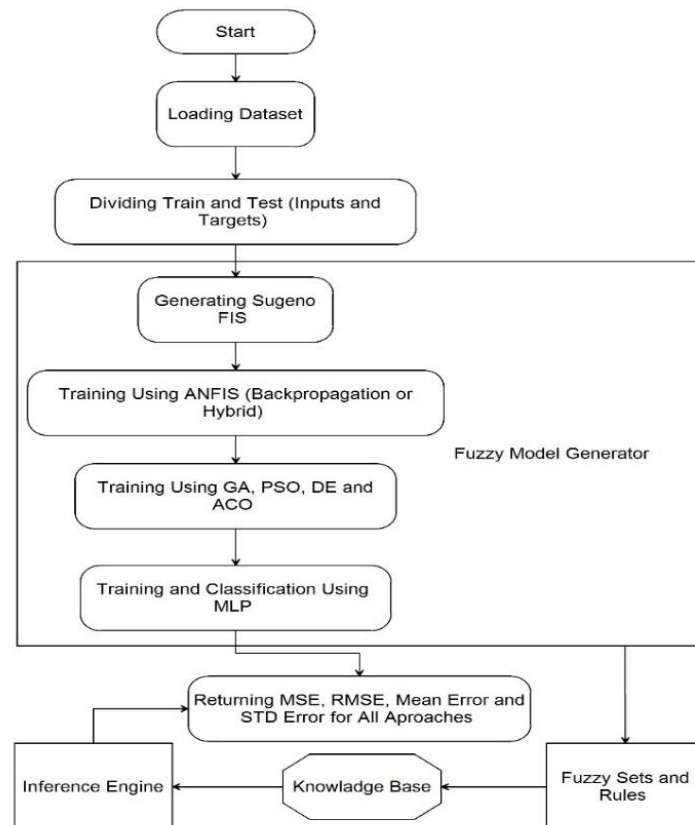


Fig. 2. Flowchart of proposed method

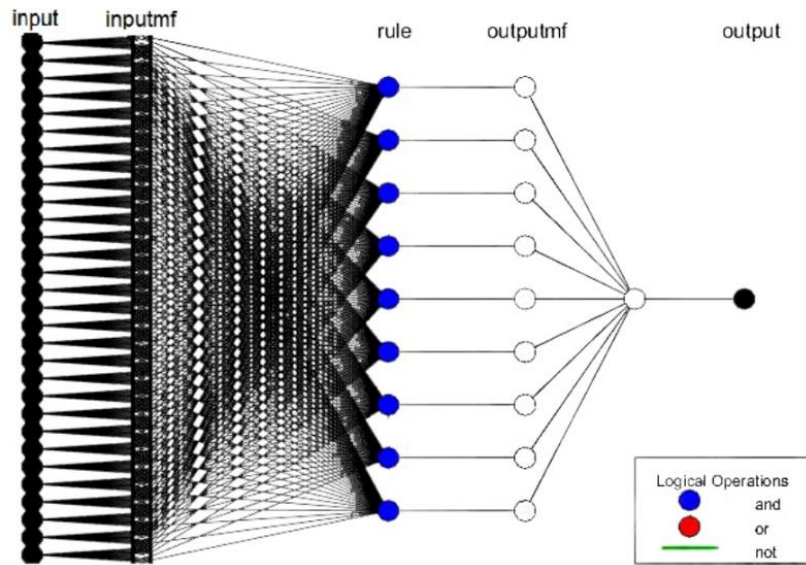


Fig. 3. Neuro fuzzy network structure for the proposed method

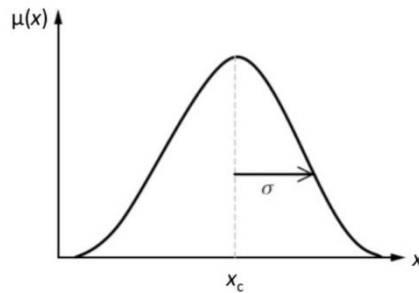


Fig. 4. Gaussian membership function



Fig. 5. Training fis using hybrid learning in 20 epoch

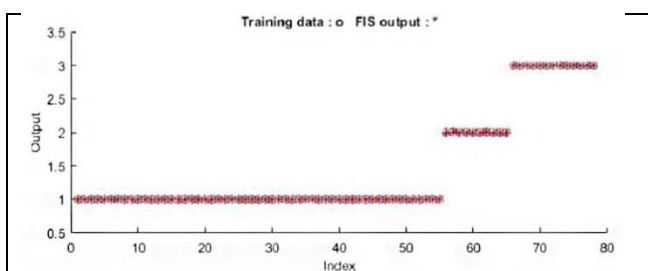


Fig. 6. Testing train data

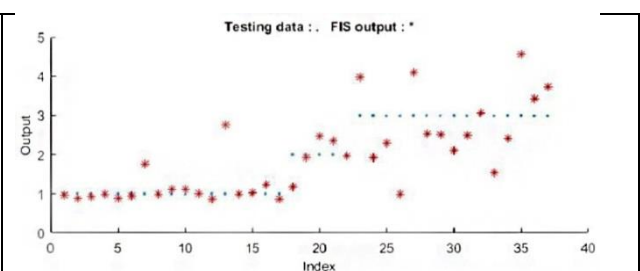


Fig. 7. Testing test dat

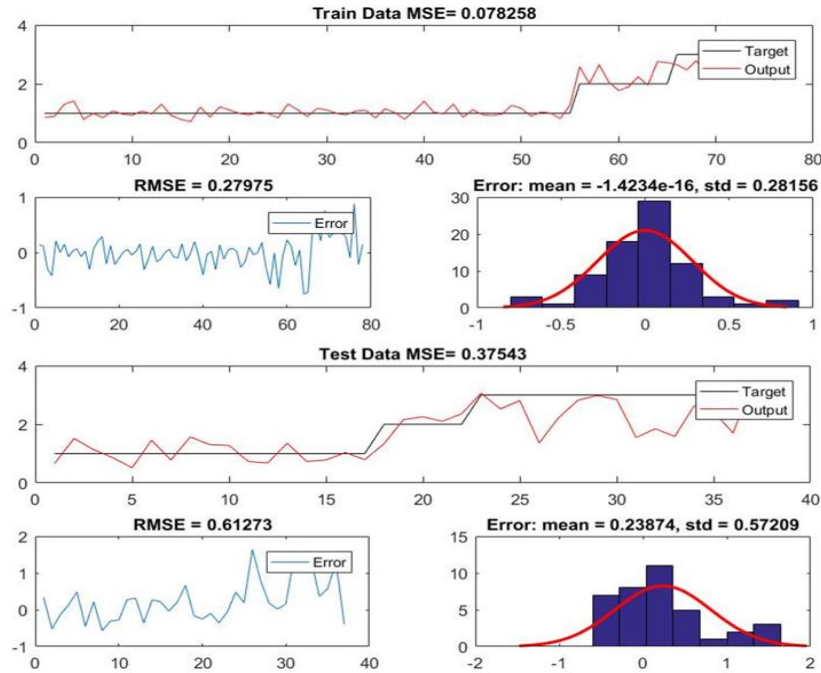


Fig. 8. Train and test errors for our dataset (ACO learning)

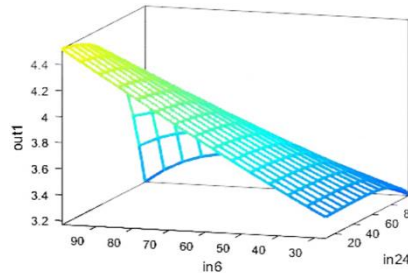


Fig. 9. Surface between variable 6 and 24 after train

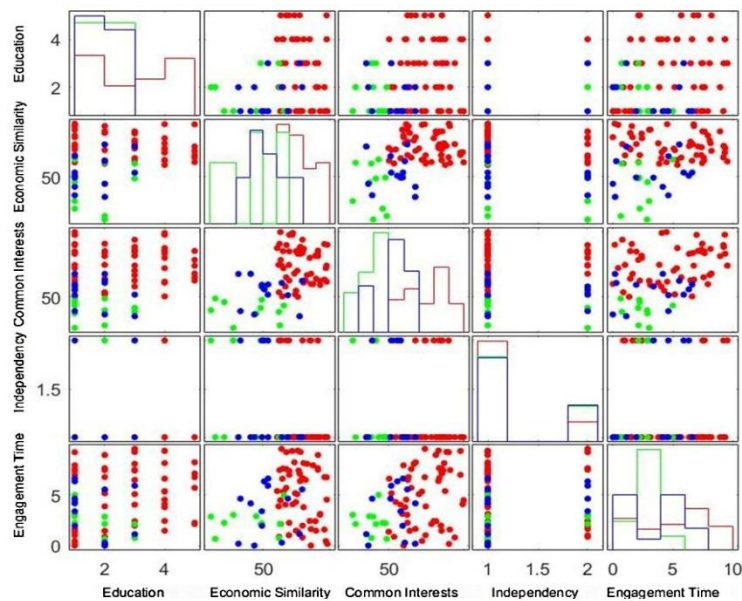


Fig. 10. Gplotmatrix for five different variables in dataset

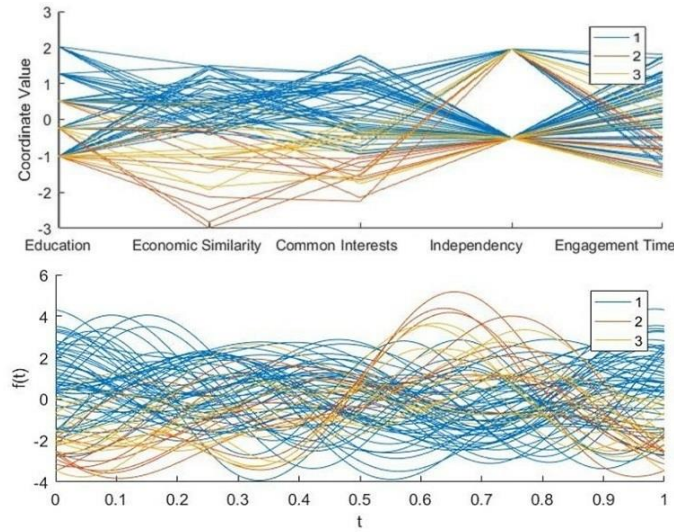


Fig. 11. Parallel Coordinates Plots and Andrews Plots for five different variables in dataset

4. VALIDATIONS AND RESULTS

Results are acquired from a dataset, collected during 5 years from 115 subjects. Next, 30 of most important consultation factors selected as features or variables. There are three classes in the dataset (Get marry, Do not marry, Divorce). 72 subjects as Get marry class, 14 subjects as Do not marry class and 27 subjects as Divorce class are collected. This dataset is achieved from human expert (marriage counselor). Fig 12 represents our neural network structure for MLP classification. Table 2 and Table 3 indicate calculated errors such (MSE [29], RMSE [30], Mean Error [31] and STD Error [31]) for different learning algorithms which has been used (Train and Test). Dataset splitted into 70% train data and 30% test data; number of hidden neurons are 10. Table 4 represents evolutionary learning algorithms parameters. Fig 13 shows confusion matrix for training, testing, validation and all data with MLP classification algorithm. This dataset has been classified with three classes which indicating 97% accuracy. Minimizing cross-entropy is almost zero. Finally Fig14 and Fig15 show Performance and Error histogram plot for MLP classification algorithm on our dataset. MSE and RMSE formulas are shown in f (1) and f (2).

The Mean Squared Error (MSE) or Mean Squared Deviation (MSD) of an estimator (of a procedure for estimating an unobserved quantity) measures the average of the squares of the errors or deviations—that is, the difference between the estimator and what is estimated.

If (Y^{\wedge}) is a vector of n predictions, and Y is the vector of observed values corresponding to the inputs to the function which generated the predictions, then the MSE of the predictor can be estimated by:

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i^{\wedge} - Y_i)^2 \quad (1)$$

The root-mean-square deviation (RMSD) or root-mean-square error (RMSE) is a frequently used measure of the differences between values (sample and population values) predicted by a model or an estimator and the values actually observed. The RMSD represents the sample standard deviation of the differences between predicted values and observed values. The RMSD of predicted values y_t^{\wedge} for times t of a regression's dependent variable y_t is computed for n different predictions as the square root of the mean of the squares of the deviations:

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (y_t^{\wedge} - y_t)^2}{n}} \quad (2)$$

Or simply RMSE is sqrt of (MSE). Mean Error and STD Error are mean and standard deviation of train and test error. Train and test errors are subtraction of targets from output in dataset.

Table 2. (MSE, RMSE, Mean Error and STD Error) for different learning algorithms (train)

TRAIN	MSE	RMSE	Mean Error	STD Error
Hybrid	0.022	0.015	-0.023	0.045
Back Propagation	0.092	0.303	-0.213	0.217
GA	0.055	0.236	-0.003	0.238
PSO	0.007	0.085	-0.0003	0.085
DE	0.078	0.279	-0.0011	0.281
ACO	0.071	0.274	-0.0019	0.290

Table 3. (MSE, RMSE, Mean Error and STD Error) for different learning algorithms (test)

TEST	MSE	RMSE	Mean Error	STD Error
Hybrid	0.291	0.437	0.075	0.437
Back Propagation	0.201	0.448	-0.001	0.454
GA	0.293	0.541	0.212	0.505
PSO	0.349	0.590	0.305	0.512
DE	0.375	0.612	0.238	0.572
ACO	0.380	0.610	0.241	0.569

Table 4. Evolutionary learning algorithms parameters

PARAMETERS	GA	PSO	DE	ACO
Number of Decision Variables	910	910	910	910
Size of Decision Variables Matrix	[1,910]	[1,910]	[1,910]	[1,910]
Lower Bound of Variables	-10	-10	-10	-10
Upper Bound of Variables	10	10	10	10
Maximum Number of Iterations	500	1000	200	200
Population Size	100	40	20	30
Crossover Percentage	0.7	-	0.1	-
Number of Offsprings (Parnets)	70	-	-	-
Mutation Percentage	0.5	-	-	-
Number of Mutants	50	-	-	-
Mutation Rate	0.1	0.2	0.2	0.3
Selection Pressure	8	-	-	-
Inertia Weight	-	1	-	-
Inertia Weight Damping Ratio	-	0.99	-	-
Personal Learning Coefficient	-	1	-	-
Global Learning Coefficient	-	2	-	-
Lower Bound of Scaling Factor	-	-	0.2	-
Upper Bound of Scaling Factor	-	-	0.8	-
Sample Size	-	-	-	60
Intensification Factor (Selection Pressure)	-	-	-	0.4
Deviation-Distance Ratio	-	-	-	1

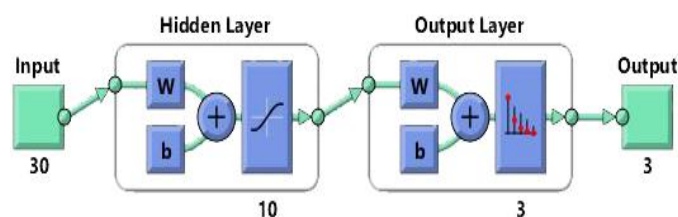


Fig. 12. Neural network structure for MLP classification

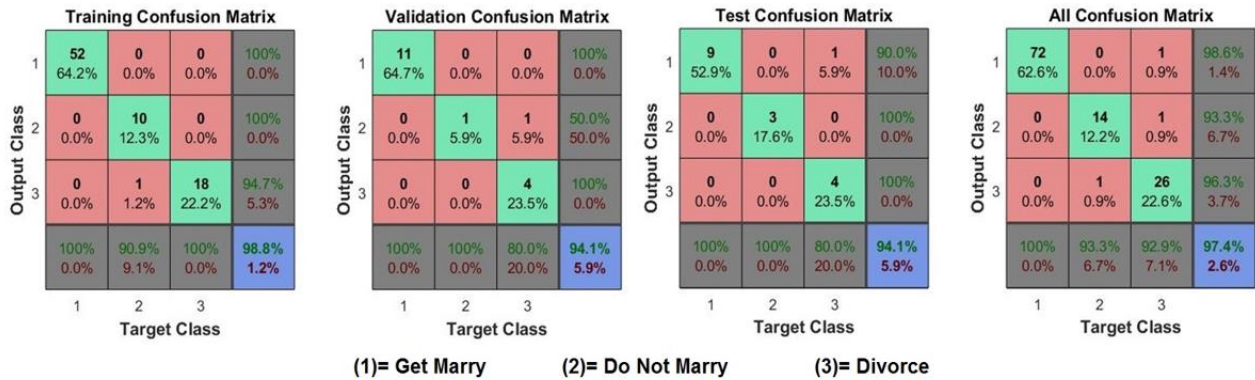


Fig. 13. Confusion matrixes for training, validation, testing and all data with MLP classification algorithm

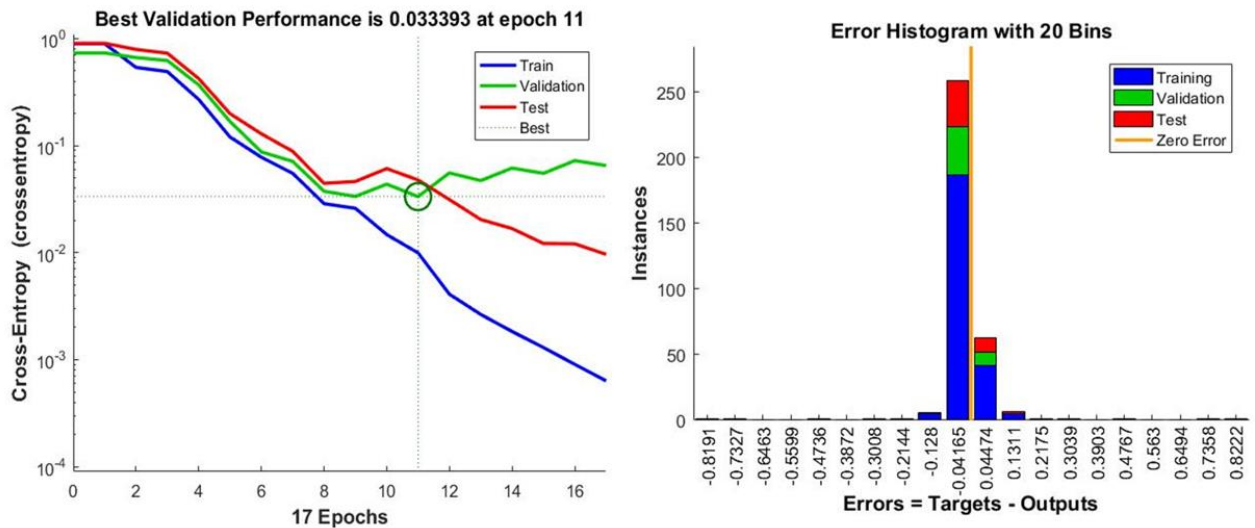


Fig. 14. Performance plot for MLP classification algorithm – **Fig. 15.** Error histogram plot for MLP classification algorithm

5. CONCLUSION AND SUGGESTION

Using evolutionary algorithms as learning algorithm, and combining them with fuzzy logic produces extraordinary results, which resulting in not only being able to compete with neural network learning algorithms, but also sometimes being better. These kind of evolutionary learning algorithms worked well on our acquired dataset and returned satisfactory and promising results. The goal was combining artificial intelligence techniques with a social event like “marring and divorce” and making an expert system as marriage counselor, helping to reduce divorce rate around the world. It is suggested to combine other evolutionary algorithms -as learning algorithms- with fuzzy logic to achieve different and maybe better results.

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