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A Performance Investigation of Different ANFIS Parameters on Screw Withdrawal Strength Virtual Laboratory Tests

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Abstract

Today's computer technology offers large amount usage of virtual environment possibilities to us. By the usage of advanced computer technologies' skills, humankind improved their lifestyles and can easily supply their demands. Certainly, the usage of this technology affects also educational systems and its instruments. Especially, students and researchers can easily get the data from the virtual environment and of course researchers and scientists can share data as well. This study is to investigate the advantages of computer technologies in the field of virtual laboratory usage that is vital part of educational system. In this paper, screw withdrawal strength test was used to point out the usage of virtual laboratory. The method of study based on the testing data of a particleboard screw holding ability, which was obtained under various testing conditions. These testing conditions and the results of tests were used as an input and output data for creating correlations in Adaptive Neuro Fuzzy Inference System (ANFIS). Half of the inputs and outputs were used for training, the others used for virtual testing. All test conditions and results were recorded instantly when the maximum load received for each screw Finally, obtained data were evaluated with the point of average training and testing errors, and mentioned from the place of architecture education.

1. INTRODUCTION

Laboratories are the important components of educational system. It supplies to understand theoretical knowledge by using the advantages of practical elements. Similar words, it is one of the principal ways that students learn how to apply theory. As an example; in science-based courses especially in physic education; many studies show that, it is difficult to teach physical concepts without test methods. [1]

Nevertheless, in some cases -as high equipment costs, limited resources, insufficient expert personal, etc., - physical laboratories could not meet the demands. In laboratory times, students cannot get facility to experiment test equipment and tests by themselves owing to large amount group of student participation or not enough time to attend this activity. [2] So, due to these types of inabilities, the necessity of searching more suitable alternatives will occur.

For last two decades, with the development of computer technologies, the usages of virtual laboratories come into question. Particularly, the reasons that are related with the inabilities for physical laboratories increase the usage of virtual laboratories day by day. Virtual laboratories (simply virtual labs) have been developed to supply many possibilities to the different work fields and industries. This technology supplies to realize the experiments without spending highly physical laboratory costs -cost of materials and labor- and time. It also supplies digital prototyping and simulation solutions without spending much money and many times to produce a prototype.

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In education systems, virtual labs offer many advantages both students and educators. By the usage of it, students can easily understand the coursework with the experience of tests without loss of class time as well as can easily reach the test systems whenever they want thanks to the web. [3]

With the web based virtual labs, students can reach the experimental data in anytime and anyplace. Virtual labs (VL) have been developed any kind of scientific disciplines and software developers or corporations. The virtues of virtual labs have differences in terms of software variety and the creation method of results, which show two-dimensional images or 3D realistic views to simulate a physical lab. [4]

Rauf et al mentioned the importance of using Virtual Labs and Virtual Web Labs applications in software and engineering education, especially in distance education. This study (2019) was emphasized that it is an interactive, arousing curiosity tool where students can access information without physical space and tools, test it, provide easy access, make collective production, and build a faster bridge between teacher and student. [5]

In a (2023) study on virtual lab; 3D virtual physics laboratory was improved to develop cognitive skills in physics experiments for students with learning disabilities. The environment in this VL contains a variety of 3D objects in different colors, created according to criteria tailored for students with special needs. Also, objects were moved using simple physical experiments and responded to falling in different ways in this lab. In the results of working, it was observed that VL and 3D objects and models attracted the attention of students. [6]

In a study of web-based virtual tensile test application with Matlab, it is explained that as an alternative laboratory to real laboratory laboratories, VL applications can be used as support if the physical laboratory is insufficient and portable tools necessary for physical laboratory or conditions are not available. Because it is easier and more understandable for the students involved in the study. Moreover, students preferred the experiments-software in the virtual laboratory compared to the real laboratories. [7]

In a study of Falco et al, it was improved a 3D modelling and simulation methodology for unidirectional composite laminates in a Virtual Test Lab framework. So, a virtual testing toolset has been developed to perform several wood-based test applications according to ASTM. It was built a Graphical User Interface (GUI) of the Virtual Test Lab plug-in in the Abaqus/CAE environment to create a toolset. This virtual test environment revealed that it is a promising computational tool for unidirectional composite laminates under all applied tests. According to the results of the study, it is proposed that standard experimental tests can be reliably simulated in a computational environment, effectively reducing time-consuming and costly physical testing practices. [8]

In this study, screw withdrawal strength test was used to investigate the creation of a virtual lab by using Adaptive Neuro Fuzzy Inference System (ANFIS). This study is aimed to help users on the preferences which research use for ANFIS setting of virtual experiments in future studies as a pre-evaluation tool on which ANFIS combinations serve the best for their use on ANFIS virtual lab tests.

2. METHOD

2.1. Adaptive Neuro Fuzzy Inference System (ANFIS)

Before talking about the ANFIS, it is important to understand the term fuzzy logic that was firstly introduced by Lotfi A. Zadeh in 1965 with a proposal of fuzzy set theory. Fuzzy set was defined by membership degree, which is a range among 0 and 1. In classical set theory, each element will only be an exact member of a set or not. Conversely in Fuzzy Set, membership degree of an element defined a range between 0 (shows non membership) and 1 (defines exact membership of an element). [9] [10] So, fuzzy logic unlike the classical logic that refuses the uncertainty and defends the certainty, asserts that there is nothing in the universe has sharp boundaries. [11]

As Zadeh states, objects with a continuum of grades of membership compose the fuzzy set characterized by a membership (characteristic) function that appoints to each object a grade of membership ranging between zero and one. Also, fuzzy set, consist of notions such as inclusion, union, intersection, complement, relation, convexity, etc., is set up from the characteristics of these notions. Especially, separation theorem for convex fuzzy sets is verified despite of the fuzzy sets be conjoint. [9]

Fuzzy logic as a system has many utilities to deal with the real world's problems [12] [13] which are vague, uncertain, and complex. The rapid growth on the studies of the field in fuzzy logic and fuzzy based systems, artificial intelligence theories and applications has gradually developed. With the development of artificial intelligence, computers and its instruments have improved day by day.

So, today's computer technology offers a wide usage of virtual environment abilities to us with the development of artificial intelligence systems underlying fuzzy logic. In other words, the rapid rise today's technological developments in industrial systems, household electronics, operating systems, robotics, automatic controls, etc. based on the fuzzy logic and fuzzy logic-based systems which behave like human (as an artificial intelligence) and as a controller. [14] [15] [16]

A fuzzy logic-based system has three layers that are fuzzifier, inference engine and defuzzifier. In fuzzifier layer, the crisp inputs converted to fuzzy data using the membership functions. The second layer consisted of two sub sections that are knowledge base and decision-making unit which are jointly referred to inference engine. Knowledge base section consisted of two components that are rule base, which has a few fuzzy rules and database, which defines the membership functions used in fuzzy rules. So, in the inference engine with its all components, fuzzy inference operations are performed.

Despite there are several types of fuzzy inference engines that have been proposed in the literature, there are three types of inference system which are Mamdami, Sugeno (also known as TSK) and Tsukamato are commonly used for applications. In the last section, defuzzifier, converts the fuzzy output of the inference engine to crisp data. [9] [17]

Adaptive neuro fuzzy inference system (ANFIS) was proposed by Jang in 1993, used as an artificial neural network with the combination of fuzzy inference system (FIS). In a FIS, the user predetermines rule structure. Against the human beings and experiments can be described qualitatively by fuzzy if-then rules, modelling a system in fuzzy logic not enough to get the precise quantitative analysis. [17] [18]
In ANFIS system, neural networks used to get learning ability and fuzzy logic used for decision making like human being.

With the usage of hybrid learning algorithm and fuzzy if-then rules, ANFIS build the model that maps input to output with the human experiment. So, the usage of ANFIS based on a data set includes a collection of input and output data. With the combination of the advantages of both systems, ANFIS is considered as a universal estimator. Jang mentions that ANFIS is a fuzzy inferences system conducted in the framework of adaptive networks, with the architecture and learning procedure of its foundation. Additionally, ANFIS (proposed by using a hybrid learning procedure) can erect an input-output mapping based on both human knowledge (in the form of fuzzy if-then rules) and stipulated input-output data pairs. [17]

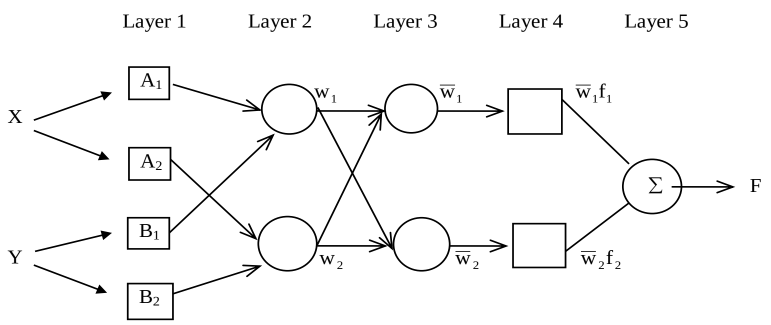

Figure 1. *An ANFIS Architecture with Two Rule Sugeno Type Fuzzy Inference System [17]*

As mentioned before, there are several types of inference engines used in fuzzy logic, but Mamdami and Sugeno are widely used in applications. Sugeno type engine is widely preferential when designing an ANFIS and this type of an ANFIS composed with five layers that are fuzzy layer, product layer, normalized layer, defuzzification layer and total output layer (Fig. 1). In the first layer (fuzzy layer), the relationship between every input is generated as a node with the form of membership functions.

In the second layer (product layer), every node multiplies the incoming signals from the first layer for defining the number of rules, which generated with the Sugeno type fuzzy inference engine. In the third layer (normalized layer), every node accepts all nodes come from the second layer as an input value and calculate the normalized firing level. In the fourth layer (defuzzification layer), the contribution of every rule is computed in each node. In the final layer (total output layer), there is a single node that computes the overall output values of every node in each layer to get the final output of the ANFIS. [17] [18] [19]

2.2. Screw Withdrawal Strength Test

The main components for producing furniture are wood and wood-base products such as particleboard, fiberboards, oriented strand board, etc. Beside this, other materials like glass, metal, leather, natural or artificial stones may also be used for completing furniture's whole design. But another key point to produce furniture is fasteners and their mechanical relations with the materials used for furniture industry.

According to Eckelman, the rational design of furniture needs available methods predicting the holding strength of the fasteners used in its construction to satisfy specified strength and durability requirements. [16] For evaluating properties of wood and wood-base materials, many international standard organizations such as ASTM, DIN, ANSI, BSI, etc. have been defined standard test methods.

So, screw withdrawal strength test is one of the test standards of that defined methods. According to American Society for Testing and Materials (ASTM), the scope of screw holding tests has been expressed as; "Screw-holding tests shall be made on screws threaded into the panel to measure the resistance to screw withdrawal in a plane normal to the face of the panel." [21] Many research show that, both screw and materials' - used for producing furniture- properties are the major factors for defining the screw holding ability.

As an example, if the major diameter of a screw is getting increased, the holding ability gets decreased. In another example, when screw penetration depth is getting increase, the holding ability gets increased too. Additionally, the conditions of wood base materials such as humidity degree, density, fiber structure of material, etc. also affect the screw holding ability that are understood from the literature surveys related with this issue. [22] [23]

2.3. Methodology

An ANFIS-based model, which is used as a powerful artificial intelligence technique in estimation studies and suitable for modeling these and similar tests in virtual environment, has been determined. Defined by the American Society for test Standards (ASTMD3039, ASTMD3410 and ASTMD3518 various testing conditions (density, temperature, moisture, penetration depth, screw torque range, usage of pilot hole)) according to 9Wood's Assemblies of Gates is used for test technics. [22]

In this study which investigated the usage of virtual laboratory with the adaptive neuro fuzzy inference system (ANFIS), Matlab R2011b with Fuzzy Logic Toolbox was used as software and namely, ANFIS Editor Plug-in in Fuzzy Logic Toolbox was used for the application with Sugeno type FIS engine. As mentioned before, the usage of ANFIS based on a data set, which includes a collection of input, and output data so, in this study, screw withdrawal strength test data, which obtained from Screw Withdrawal Strength in 9Wood's Assemblies titled work the work of Jonathan C. Gates (2009) was used to generate a data set [18] In that work, totally 294 screws were used under various testing conditions. The test conditions include three board densities (low, medium, high), two different temperature and moisture contents (20ºC - %65 RH / 30ºC - %20 RH), two penetration depths (1/2" and 5/8"), three screw torque ranges (weak, standard, over torque) and usage of pilot holes. All test conditions and results were recorded instantly when the maximum load received for each screw.

In data set (Table 1), various test conditions used as an input and the maximum load that were recorded now of rupture used as an output. For the application, half of the data used for training and the others used for testing.

Tablo 1. *An Example of Prepared Data Set Used In ANFIS Editor*

1/2" ASTM - NO PILOT HOLE						
INPUT						OUTPUT
Density	Condition		Screw Pen. Depth	Screw Maj. Diameter	Screw Torque Range	Force
gr/cm3	°C	%RH	Mm	Mm	N-m	N
0,78	20	65	12,7	4,17	2,32	696,15
0,78	20	65	12,7	4,17	3,79	776,21
0,78	20	65	12,7	4,17	6,55	214,85
0,77	20	65	12,7	4,17	2,32	626,75

For the application, thirty-two tests were carried out with different settings, which refer to all the combinations covering in the ANFIS Editor Tool kit to investigate the average errors, which show the best or poor performance and find the optimal combination with the data set used in this work for the evaluation of this kind of a virtual lab. For proposed method, Grid Partition technique is used for generating initial FIS Structure. In the FIS structure specification section, eight different FIS Input Membership Function Types (trimf, trapf, gbellmf, gaussmf, gauss2mf, pimf, dsigmf and psimf) used for input and two different FIS Input Membership Function Types (Constant-Linear) used for output.

For training, two optimization methods that are hybrid (the default parameter which is the mix of least squares method and backpropagation method) and backpropa (backpropagation) used for this study with the optimal number of training epochs that were determined when the test were reached the optimal average training error values.
So, the number of training epochs set 150 for hybrid method with the three input membership function numbers and 50000 for backpropa method with the two input membership function numbers. So, with the combination of all these parameters, thirty-two tests were conducted for investigating the virtual laboratory usage with the available data set in this study.

3. RESULTS

Tables 2-5 below represents the overall results of the study, which obtained by thirty-two different settings in ANFIS Editor Toolbox, depending on the proposed method. As can be seen from the presented this tables, according to average value obtained from the fuzzy table screw withdrawal, values have been combined by changing and keeping constant on the table and obtained some results.

With relevant screw withdrawal, half of the 294 dataset (147) has been used to training, the other half (147) for testing. In the first group of tests (Tests 1-8) ‘constant’ FIS output membership type with ‘hybrid’ optimization method was used. Each of the eight FIS input membership function types, namely trimf, trapf, gbellmf, gaussmf, gauss2mf, pimf, dsigmf, psimf were tested to see different combinations’ performance. For each test five inputs were used with three FIS input membership functions. As stated, above half of the 294 datasets from Gates [22] was used for training each of the ANFIS configurations and the other half is used for testing the optimized ANFIS. Results of the first group (Tests 1-8) are presented on Table 2.

According to the results presented on Table 2, after 150 epochs FIS had optimized error. Best performance among the combinations test number 2 with trapf FIS input membership function type performed consistently with least error for both training and testing with 159,5338 N and 174,6508 N, respectively. Although the testing error difference between test number 2 and the other seven tests were not much significant, training error difference for test number 2 from others were noteworthy.

In the second group of tests (Tests 9-16) 'linear' FIS output membership type with 'hybrid' optimization method was used. Each of the eight FIS input membership function types, namely trimf, trapf, gbellmf, gaussmf, gauss2mf, pimf, dsigmf, psimf were tested to see different combinations' performance. For each test five inputs were used with three FIS input membership functions.

Tablo 2. *Results of the 'constant' FIS Output Membership Type with 'hybrid' Optimization Method*

TEST	FIS	INPUT			OUTPUT		DATASET		TRAINING		ERROR	
Test Number	Fuzzy Inference System (FIS) Type	Input Number	Fuzzy Inference System (FIS) Input Membership Function Numbers	Fuzzy Inference System (FIS) Input Membership Function Type	Output Number	Fuzzy Inference System (FIS) Output Membership Function Type	Training Data Number	Testing Data Number	Optimization Method	Fuzzy Inference System (FIS) Error Optimized Epoch	Average Training Error (N)	Average Testing Error (N)
1	Grid Part.	5	3	trimf	1	constant	147	147	hybrid	150	176,1323	211,506
2	Grid Part.	5	3	trapf	1	constant	147	147	hybrid	150	159,5338	174,6508
3	Grid Part.	5	3	gbellmf	1	constant	147	147	hybrid	150	170,7864	243,15
4	Grid Part.	5	3	gaussmf	1	constant	147	147	hybrid	150	170,8588	525,6247
5	Grid Part.	5	3	gauss2mf	1	constant	147	147	hybrid	150	173,5609	1381,34
6	Grid Part.	5	3	pimf	1	constant	147	147	hybrid	150	173,7883	343,5699
7	Grid Part.	5	3	dsigmf	1	constant	147	147	hybrid	150	172,6517	487,5512
8	Grid Part.	5	3	psimf	1	constant	147	147	hybrid	150	172,6517	487,5552

As stated, below again half of the 294 datasets from Gates [22] was used for training each of the ANFIS configurations and the other half is used for testing the optimized ANFIS. Results of the second group (Tests 9-16) are presented on Table 3. According to the results presented on Table 3, like the first group of tests, after 150 epochs FIS had optimized error. However, best performance among the combinations on training and testing was not consistent. While test number 13 with gauss2mf FIS input membership function type showed the least error with 129,5081, which was better than each test on group one, the testing error of test 13 was not satisfactory. Test number 9 with trimf FIS input membership function type showed the second-best training performance with 130,8174 N and best performance on testing with 206,5132 N, which was by far worse than each test on group one.

Tablo 3. *Results of the 'linear' FIS Output Membership Type with 'hybrid' Optimization Method*

TEST	FIS	INPUT			OUTPUT		DATASET		TRAINING		ERROR	
Test Number	Fuzzy Inference System (FIS) Type	Input Number	Fuzzy Inference System (FIS) Input Membership Function Numbers	Fuzzy Inference System (FIS) Input Membership Function Type	Output Number	Fuzzy Inference System (FIS) Output Membership Function Type	Training Data Number	Testing Data Number	Optimization Method	Fuzzy Inference System (FIS) Error Optimized Epoch	Average Training Error (N)	Average Testing Error (N)
9	Grid Part.	5	3	trimf	1	linear	147	147	hybrid	150	130,8174	206,5132
10	Grid Part.	5	3	trapf	1	linear	147	147	hybrid	150	134,0916	310,4051
11	Grid Part.	5	3	gbellmf	1	linear	147	147	hybrid	150	134,3158	245,3595
12	Grid Part.	5	3	gaussmf	1	linear	147	147	hybrid	150	130,3386	1096,543
13	Grid Part.	5	3	gauss2mf	1	linear	147	147	hybrid	150	129,5081	335,0368
14	Grid Part.	5	3	pimf	1	linear	147	147	hybrid	150	132,9657	328,4507
15	Grid Part.	5	3	dsigmf	1	linear	147	147	hybrid	150	131,8466	4136,001
16	Grid Part.	5	3	psimf	1	linear	147	147	hybrid	150	131,8465	4136,32

In the third group of tests (Tests 17-24) again 'constant' FIS output membership type was used but this time with 'backpropa' optimization method. Each of the eight FIS input membership function types, namely trimf, trapf, gbellmf, gaussmf, gauss2mf, pimf, dsigmf, psimf were tested to see different combinations' performance. For each test five inputs were used with two FIS input membership functions.

Half of the 294 datasets from Gates (2009) were used for training each of the ANFIS configurations and the other half is used for testing the optimized ANFIS. Results of the third group (Tests 17-24) are presented on Table 4.

According to the results presented on Table 4, the FIS was optimized only after 50000 epochs, which took much longer time comparing the first two groups, which were saturated after 150 epochs. This time best performance among the combinations test number 17 with trimf FIS input membership function type performed consistently with least error for both training and testing with 358,7764 N for both. When compared to the first two groups even the best results of test number 17 were by far worse. Considering this fact with 50000 epochs, which took much longer time, it can be stated that 'constant' FIS output membership type was used but this time with 'backpropa' optimization method is not an option for these tests.

Tablo 4. *Results of the 'constant' FIS Output Membership Type with 'backpropa' Optimization Method*

TEST	FIS	INPUT			OUTPUT		DATASET		TRAINING		ERROR	
Test Number	Fuzzy Inference System (FIS) Type	Input Number	Fuzzy Inference System (FIS) Input Membership Function Numbers	Fuzzy Inference System (FIS) Input Membership Function Type	Output Number	Fuzzy Inference System (FIS) Output Membership Function Type	Training Data Number	Testing Data Number	Optimization Method	Fuzzy Inference System (FIS) Error Optimized Epoch	Average Training Error (N)	Average Testing Error (N)
17	Grid Part.	5	2	trimf	1	constant	147	147	backpropa	50000	358,7764	358,7764
18	Grid Part.	5	2	trapf	1	constant	147	147	backpropa	50000	433,0068	433,0017
19	Grid Part.	5	2	gbellmf	1	constant	147	147	backpropa	50000	459,3985	459,3973
20	Grid Part.	5	2	gaussmf	1	constant	147	147	backpropa	50000	409,8461	409,846
21	Grid Part.	5	2	gauss2mf	1	constant	147	147	backpropa	50000	436,1096	436,1045
22	Grid Part.	5	2	pimf	1	constant	147	147	backpropa	50000	431,3501	431,3451
23	Grid Part.	5	2	dsigmf	1	constant	147	147	backpropa	50000	435,0846	435,0796
24	Grid Part.	5	2	psimf	1	constant	147	147	backpropa	50000	431,3374	431,3323

In the last group of tests (Tests 25-32) 'linear' FIS output membership type was with 'backpropa' optimization method. Each of the eight FIS input membership function types, namely trimf, trapf, gbellmf, gaussmf, gauss2mf, pimf, dsigmf, psimf were tested to see different combinations' performance. For each test five inputs were used with two FIS input membership functions. Half of the 294 datasets from Gates [22] were used for training each of the ANFIS configurations and the other half is used for testing the optimized ANFIS. Results of the third group (Tests 25-32) are presented on Table 5.

Tablo 5. *Results of the 'linear' FIS Output Membership Type with 'backpropa' Optimization Method*

TEST	FIS	INPUT			OUTPUT		DATASET		TRAINING		ERROR	
Test Number	Fuzzy Inference System (FIS) Type	Input Number	Fuzzy Inference System (FIS) Input Membership Function Numbers	Fuzzy Inference System (FIS) Input Membership Function Type	Output Number	Fuzzy Inference System (FIS) Output Membership Function Type	Training Data Number	Testing Data Number	Optimization Method	Fuzzy Inference System (FIS) Error Optimized Epoch	Average Training Error (N)	Average Testing Error (N)
25	Grid Part.	5	2	trimf	1	linear	147	147	backpropa	15000	167,9503	167,9498
26	Grid Part.	5	2	trapf	1	linear	147	147	backpropa	15000	219,6123	219,607
27	Grid Part.	5	2	gbellmf	1	linear	147	147	backpropa	15000	175,0248	168,7474
28	Grid Part.	5	2	gaussmf	1	linear	147	147	backpropa	15000	182,2851	170,8686
29	Grid Part.	5	2	gauss2mf	1	linear	147	147	backpropa	15000	175,4552	168,6323
30	Grid Part.	5	2	pimf	1	linear	147	147	backpropa	15000	**165,2545**	**159,0245**
31	Grid Part.	5	2	dsigmf	1	linear	147	147	backpropa	15000	175,3376	169,8328
32	Grid Part.	5	2	psimf	1	linear	147	147	backpropa	15000	175,1072	170,3702

According to the results presented on Table 5, the FIS was optimized again only after 50000 epochs, which took much longer time comparing the first two groups, which were saturated after 150 epochs. This time best performance among the combinations test number 30 with pimf FIS input membership function type performed consistently with least error for both training and testing with 165,2545 N and 159,0245 N, respectively.

When compared to the first three groups the testing result of test 30 (159,0245 N) was the best, even better than the result of the test number 2 (174,6508 N).

4. DISCUSSION

Virtual labs are very recent subjects on many fields [24][25][26][27] but it is much rare to find examples which are mostly limited to recent studies on material tests. [28][29][30][31][32][33][34] Due to rare studies in literature on virtual labs using fuzzy neural networks and systems [35][36][37][38] numerous tests have been made while FIS Error optimized epoch is determined. In Total thirty-two tests, along five input number and one output number, sixteen hybrid optimization methods for learning and sixteen backpropa optimization methods to test have been defined to ANFIS with grid part type for Fuzzy Inference System (FIS) which is like Hasim and Mohd Aras [37] and Elmas and Akcayol [39]. Learning has been taken place using three different error optimized epoch values.

While training has been realized at a higher epoch value using backpropa for optimization method, this value has been much declined the hybrid method is used. The highest average errors for training and testing obtained from the test number 17 which is the combination of backpropa optimization method with 50000 Epoch value in training, trimf Membership Function Type with two Input Membership Functions number in Input value and constant Membership Function Type in Output value.

However, epoch value for training is low to 15000 from 50000 and obtained a lower margin of error for testing although the test number thirty is used combination of backpropa optimization method with two input FIS membership functions number, PIMF Membership Function Type and linear Membership Function Type in Output value. Moreover, test number 13 has given the closest value to true with the result having a minimum margin of error learning in virtue of collaboration of hybrid optimization method with 150 epoch value in training, gauss2mf Membership Function Type and three Input Membership Functions number in Input value. These results confirm the former findings of authors. [37] [40] [41] [42]

Nevertheless, different output membership function type has changed the results of test number two and number nine having the same characteristics as hybrid optimization method with 150 epoch value, tramph

Membership Function Type and three Input Membership Functions number in Input value. Although the same membership function combinations result on contrary with Hasim and Mohd Aras [37] most of the other combinations showed much better performances. Only few results performed worse than Hasim and Mohd Aras [37], except the constant FIS output membership function types combined with bacpropa optimization method which is obviously not a usable alternative.

While the test number 2 used Constant membership function type in output has given an average margin of error in both of test end learning, the test number 9 used linear type has a higher margin of result only for testing. So, in this table using two different optimization methods; it has been seen that linear membership function type has an effect in the direction of reducing the margin of error by decreasing epoch value.

Hybrid Optimization method have been perfected by reaching saturation at 50000 error optimized epoch with three input membership function numbers, but backpropa method have reached this situation at 150 error optimized epoch with two membership function numbers. It has been seen that the sensitivity of the system has been lost in the lower values and system has been swollen in the higher values. In these tests made with hybrid and backpropa optimization methods, between 1 and 16 tests have reached saturation and yielded results much faster, although between 17 and 32 ones have taken longer time as expected from the former results on Logar [35], Hasin and Mohd Aras [37] and Iliadis et al. [41].

According to the Tables 2-5, combinations on tests numbers 13, 2 and 30 respectively have had better results in training. However, combinations on tests numbers 30, 2 and 9 respectively have given better results in testing. Combination on test number 17 has given the worst result both training and testing. Because of the change on four input variables, the results are so different through test numbers 2 and 17.
While the combination of hybrid method, 150 epoch value, three membership function number and trapf membership function type has supplied test number two being the best, the concept of backpropa method, 50000 epoch value, 2 membership function number and trimpf membership function type has made combination on test number 17 the worst. The most optimal results have showed at combinations on test numbers 2 and 30. Combination on test number 2 has given again the fastest optimal result when time is important in test. While both combinations perform better than Kubat and Kiraz [38] and Hasim and Mohd Aras [37]; yet, if time is not important, combination on test number 30 has given an optimal result more sensitive with low error over test number 2.

5. CONCLUSION

This study investigated virtual lab for screw withdrawal strength test by using Adaptive Neuro Fuzzy Inference System (ANFIS). This framework, Matlab R2011b with Fuzzy Logic Toolbox was used as software and namely, ANFIS Editor Plug-in in Fuzzy Logic Toolbox was used for the application with Sugeno type FIS engine. An ANFIS data set was used based on inputs and outputs. Also, screw withdrawal strength test data was obtained. Totally 294 screws were tested under various testing conditions (density, temperature, moisture, penetration depth, screw torque range, usage of pilot hole) according to 9Wood’s Assemblies of Gates [22].

All test conditions and results were recorded instantly when the maximum load received for each screw. According to the findings of 32 tests, the combination of test number 17 should never be used due to bad result on both training and testing. On the other hand, combinations on test number 2 can be preferred because of having best result. Thus, users will choose the combination most suitable for their virtual lab tests easier and in less time without requiring physical testing before implementation and a long and troublesome process which will be spent for these tests thanks to virtual screw withdrawal strength test.
Also, virtual laboratory tests in architecture education offer numerous benefits, including increased accessibility, cost-effectiveness, safety, enhanced visualization, scalability, flexibility, and collaboration. By leveraging technology, these virtual experiences provide students with valuable hands-on learning opportunities that complement traditional classroom instruction and better prepare them for real-world architectural challenges. The contributions of the virtual laboratory to architecture and design education can be grouped under the following topics;

Accessibility: Virtual laboratory tests allow students to access and perform experiments from anywhere, at any time. This accessibility is particularly beneficial for students who may not have access to physical laboratories or expensive equipment. It eliminates geographical limitations and enables students to engage in hands-on learning experiences remotely.

Cost-effectiveness: Setting up and maintaining physical laboratories can be expensive. Virtual laboratory tests significantly reduce the costs associated with purchasing and maintaining equipment, as well as the need for physical space. This cost-effectiveness makes architecture education more affordable and accessible to a wider range of students.

Safety: Architecture involves experimentation with various materials and processes, some of which may pose safety risks. Virtual laboratory tests provide a safe environment for students to explore and experiment without the potential hazards associated with physical materials. It allows students to learn and make mistakes without the risk of injury or damage.

Enhanced Visualization: Virtual laboratory tests often incorporate advanced computer graphics and simulations, allowing students to visualize architectural concepts in a more interactive and engaging manner. Students can explore three-dimensional models, manipulate parameters, and observe real-time visual feedback, which enhances their understanding of complex architectural principles.

Scalability and Replicability: Virtual laboratory tests can be easily scaled up to accommodate a larger number of students simultaneously. It allows educational institutions to offer architecture courses to a greater number of students without constraints imposed by physical infrastructure limitations. Additionally, virtual experiments can be replicated and repeated, enabling students to reinforce their learning and conduct multiple iterations of experiments for deeper understanding.

Flexibility and Customization: Virtual laboratory tests provide flexibility in terms of experiment design and customization. Instructors can tailor experiments to align with specific learning objectives, adjust parameters, and simulate different scenarios. This flexibility enables students to explore a wider range of architectural concepts and experiment with various design possibilities.

Collaboration and Feedback: Virtual laboratory tests often incorporate collaborative features, allowing students to work together on experiments, share insights, and provide feedback to their peers. This collaborative environment fosters teamwork and enhances communication and problem-solving skills, which are crucial in architectural practice. [5][6][7][8][43][44][45][46]

Overall, this study would be able to help sector and education in interior design and architecture at further studies. Next studies can be done with larger database to improve sensitivity on results with different screw and strength specs. Also, under favor of this study, all design elements having numeric data and creating interior space such as furniture by researching previous could contribute to design, implementation, and revision projects. In addition, this paper includes results that have the potential to create current and interdisciplinary discussions.

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