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Fuzzy Logic Methods for Determining the Mechanical Behavior of Masonry Walls

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Abstract

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The mechanical behaviour of the wall, in-situ wall tests and numerical analysis is required along with the material properties. With the support of smart learning techniques, the state of the walls was estimated. This makes it possible to obtain healthy data to support the experiment and modelling. The utilization of mathematical tools like Fuzzy Logic has been demonstrated to be beneficial in resolving intricate engineering issues, without the need to replicate the studied phenomenon, given that the only available information consists of the problem's parameters and desired outcomes. To analyse the wall's behaviour more accurately and quickly, analyses were made using the fuzzy method, one of the smart learning techniques, and compared with the data in the studies in which experimental analysis was applied. The behaviour of the wall, the flexibility and energy capacity were tried to be estimated. In the fuzzy, material parameters and wall load capacities that will affect the properties of the wall are used as inputs. Thirty-five (35) data sets, experiments and modelling data from different studies were taken. Estimation results were compared with empirical results.

Keywords: ductility, energy capacity, fuzzy logic, and masonry wall.

1. Introduction

Unreinforced masonry structures are known for their insufficient seismic per-formance, which has been confirmed through numerous investigations of earth-quake disasters. This inadequate behavior is typically attributed to the unsuitable characteristics displayed by the masonry when subjected to tensile stress. In this regard, unreinforced masonry structures can be enhanced by incorporating verti-cally and horizontally reinforced concrete elements (known as confining ele-ments) to create confined masonry structures. These confined structures offer the advantage of efficiently confining masonry walls and enhancing the structure's' ability to withstand deformation. [1–4].

There are many factors that affect the compressive strength of clay brick mason-ry walls connected by cement mortar. In general, the way masonry responds to compressive loads depends on how the brick and mortar interact. The properties of the materials themselves (bricks and mortar) also change when used in a ma-sonry wall compared to when they are used individually. Additionally, it is im-portant to consider that masonry is a material that has different properties in dif-ferent directions and is highly influenced by construction processes. The wide variety of metrics available, some of which are quantitative (such as brick com-pression resistance) and others more qualitative (such as construction processes), make the construction and design of masonry structures more complex.

The deformability of the wall is influenced by the specific properties of the mor-tar, especially in the joints of the matrix [5-6]. The mechanical properties of the components that compose the walls and joining points were determined through laboratory experiments. Wall models were created. The behavior of the walls was analyzed, and the obtained parameters were utilized in the modeling process for comparisons [7-10]. The fragility of masonry walls is evident when they are ex-posed to compressive stresses. However, under shear stresses, they can exhibit ductile behavior to some extent. Research on the load-displacement behavior of masonry walls under axial load has shown that the compressive strength of the masonry can be estimated using the single-axis compressive strength of the ma-sonry unit, while also considering the compressive strength of the mortar. Further analysis of the district split of the walls revealed that the power level of the wall is low, leading to reduced ductility. To address this issue, the wall distance pro-portion must be carefully designed, and the use of brittle materials should be evaluated. Therefore, it is important to maintain earthquake reliability and ductil-ity through appropriate construction methods [11]. There is evidence that masonry infill walls affect the stiffness and strength of unfilled frame structures. Building designs have often ignored infill walls because their brittle behaviour is unknown. It is recommended to conduct experimental tests and analytical investigations to understand the behaviour of the frame and composite infill walls [12, 13 and 14]. During damage mechanisms, it is also important to conduct extensive tests to determine what caused the corners of the walls to fail. A lateral load acts on an infill wall as a diagonal structure connecting two corners. Masonry structures exhibit limited ductility under shear stresses and brittleness under compression. According to the results of experiments on overload displacement behaviours under axial load in masonry structures, the uniaxial strength of these structures is only determined by their uniaxial strength and the mortar effect is minimal [15-21]. Based on the concept of an excellent plastic curve, Tomazevic (1999) suggests that the durability effect of walls can be explained by considering both inelastic and elastic achievements. This illustrates a reliance on the equal energy dissipation of actual and theoretical stress-strain curves [22]. In a study conducted by Essa et al. (2014), the researchers evaluated the impact of the performance of high strength reinforced concrete beams on the ductility of the infill walls. To achieve this objective, they prepared different types of materials with varying thicknesses and loaded them with filled and non-filled beams [23]. Several parameters were obtained during this count. It was found that the type of scrape-off influences ductility. As a result, the load-bearing walls' behavior could be determined, and it might be possible to devise techniques for repairing the damage [24]. Modeling techniques are often employed to study the behaviors of walls, as ex-perimental work on the walls is not always feasible. Composite models are com-monly used to represent walls in these simulations. However, there are instances where quick judgment is necessary. Recent studies have also incorporated artifi-cial intelligence methods alongside traditional approaches.

Artificial Intelligence (AI) refers to the advanced concept of machines being capable of independently performing tasks by utilizing algorithms/models that enable computers and machines to function intelligently. Consequently, AI has been developed at the intersection of various fields, including computer science, cybernetics, information theory, psychology, linguistics, and neurophysiology [25]. All previous research has demonstrated the effectiveness of AI algorithms using traditional methods related to assessment, decision-making, prediction, and optimization. The current survey focuses on these methods as they are applicable to network issues in civil engineering, which is an interdisciplinary field influenced by various global factors that are hard to simulate using calculations in math, physics, and mechanics. Additionally, the effectiveness of AI in solving engineering problems relies on its capability to learn from data inputs and outputs, guaranteeing that the complex relationships between the data are accurately simulated, even when the interdependencies are uncertain, or the physical phenomena are difficult to interpret [26]. Over the years, artificial neural networks (ANNs) and customized Neuro-fuzzy inference systems (ANFIS) have been widely used in civil engineering due to their resilience and high precision. These models have proven successful in various applications, including the evaluation of compressive strength and elastic modulus of different concrete types, as well as the analysis of concrete drying shrinkage and durability [27-36]. The purpose of this report is to determine the compressive strength of a masonry structure made of clay bricks and cement mortar using two numerical techniques: Artificial Neural Networks and Fuzzy Logic, rather than relying on pragmatic models. These techniques address a complex problem by analyzing the input and output data of the system, rather than considering the physical phenomena that served as their inspiration [36-39].

There have been only a few studies that have utilized artificial intelligence technology in the analysis of masonry structures. In one study conducted by Plevris and Asteris [40], they employed an artificial neural network (ANN) to forecast the failure of masonry under biaxial four (4) compression. Their ANN model not only successfully predicted the failure pattern of masonry at a specific θ (angle between the bed joint and horizontal compressive stress), but also identi-fied the three-dimensional failure surface formed by the failure pattern at any θ. Afterwards, Plevris and Asteris [41] proceeded to develop a dimensionless model for predicting masonry surface failure based on ANN. This model can also be applied to other masonry materials with similar geometry and mechanical properties. However, there have been very few studies conducted on the application of artificial intelligence techniques to predict masonry behavior. Zhang et al. [37] conducted a study where they developed a cellular automata model to determine the cracking patterns of vertically loaded masonry structures. In a separate study, Garzón-Roca et al. [38,39] used both artificial neural network (ANN) and fuzzy logic methods to estimate the compressive strength of brick masonry. Another study by Plevris et al. [40] involved the development of an ANN model to analyze the failure surface of masonry under biaxial compressive stress. They aimed to create ANN and ANFIS models that could predict the compressive strength of masonry prisms made of hollow concrete blocks. To achieve this, they compiled and evaluated 102 sets of experimental data from their own experiments and from previously published technical literature. The proposed models were then compared to various empirical techniques to assess their reliability and accuracy [42-45].

The results of this study, which used Fuzzy Logic methods, were subsequently compared with various empirical suggestions to demonstrate their accuracy.

2. Material and Method

2.1. Material

Factory bricks, hollow bricks, clay bricks, pumice, cement mortar, and lime mortar were commonly employed in the research. The mechanical properties of the materials were determined by assessing their compressive strength and bend-ing strength. (Fig 1).

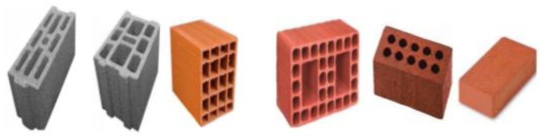


Fig.1 Masonry unit

The table with the data obtained from the studies is presented (Table1) [46-48].

Table 1. Mechanical strengths of materials

Code	Flexure Strength Brick	Flexure Strength Mortar	Compressive Strength Brick	Compressive Strength Mortar
A2	0.3	2.12	6.38	12.5
A3	0.3	2.12	6.38	12.5
A4	0.3	2.59	6.38	4.59
A5	0.3	2.59	6.38	4.59
A7	0.4	2.12	6.11	12.5
A8	0.4	2.12	6.11	12.5
A9	0.4	2.12	6.11	12.5
A11	0.4	2.59	6.11	4.59
A12	0.4	2.59	6.11	4.59
A13	0.8	2.12	6.05	12.5
A14	0.8	2.12	6.05	12.5
A15	0.8	2.12	6.05	12.5
A17	0.8	2.59	6.05	4.59
A19	0.5	2.12	2.63	12.5
A20	0.5	2.12	2.63	12.5
A22	0.5	2.59	2.63	4.59
A23	0.5	2.59	2.63	4.59
A24	0.5	2.59	2.63	4.59
B1	3	3	10.3	7.2
B2	4	4	8.8	7.1
B3	3.4	3.4	7.5	6

B4	3.3	3.3	7.8	5.7
B5	4	4	8.5	7.3
B6	3.3	3.3	7.9	5.2
C1	1.32	1.32	2.37	2.37
C2	1.32	1.32	2.37	2.37
D2	2	2	10.5	10.5
D3	2	2	11.5	11.5

Sample models of the walls were established in the studies, and experiments were conducted (Figure 2-3). To analyze and compare the conditions of these test walls, simulations were conducted. It was determined that the results of the experiment and the fuzzy logic were compared, and these results showed similarity.

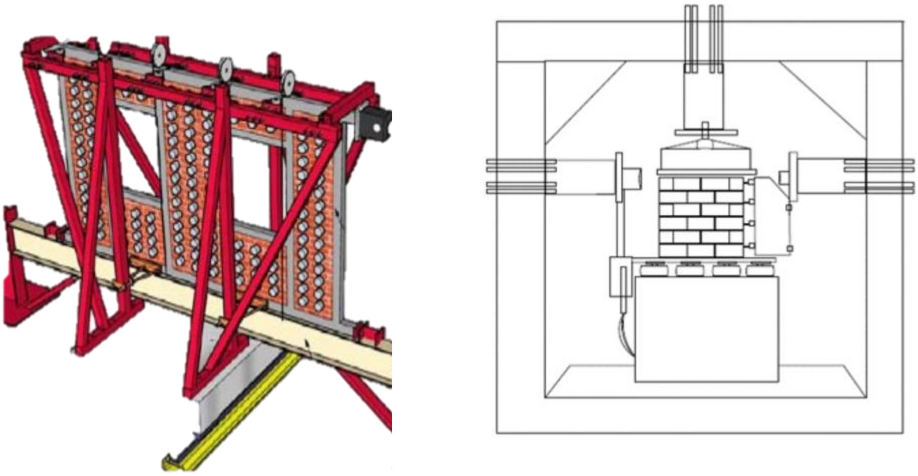


Fig.2 Experimental of Walls Set

It was discovered that the mechanical properties of the materials used in wall production have an impact on the ductility and energy capacity of the walls. As a result, the data obtained from these studies were utilized in this study.

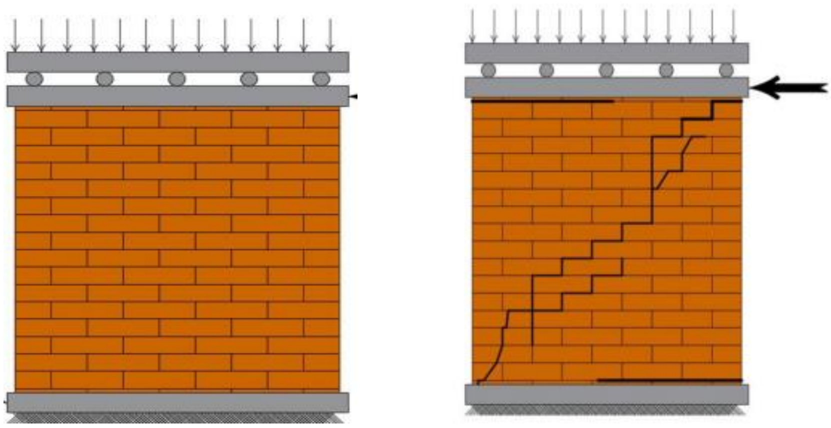


Fig 3. Before-After Experimental System

The data obtained depending on the experiment data of the walls are given in the table. Thirty- five (35) sample wall works were selected. These walls are coded as follows (Table 2)

Table 2. Walls of Experimental Results

Code	Horizontal Load	Δu	Δy	Ductility	Energy Capacity
A1	92.53	34.12	28.15	1.21	2325.41
A2	107.16	29.81	22.85	1.30	1722.03
A3	95.44	32.67	17.7	1.85	1824.57
A4	42.02	35.96	23.61	1.52	786.72
A5	49.07	24.99	12.08	2.07	703.11
A6	42.96	52.27	30.7	1.70	1263.54
A7	43.39	31.08	23.73	1.31	756.31
A8	52.51	22.18	17.85	1.24	565.14
A9	44.47	21.87	14.73	1.49	527.72
A10	26.21	18.77	16.37	1.15	306.2
A11	40.57	13.41	11.88	1.29	244.89
A12	34.41	34.43	17.18	2.00	500.43
A13	18.93	22.65	17.8	1.27	295.81
A14	51.27	30.56	9.89	3.09	1169.9
A15	35.77	24.51	15.2	1.61	553.26
A16	12.08	21.93	10.56	2.08	186.83
A17	14.41	25.6	9.43	2.71	270.66
A18	12.42	23.05	8.47	2.72	206.73
A19	46.21	36.21	22.95	1.58	1127.48
A20	96.06	28.15	21.47	1.31	1400.33
A21	53.58	21.79	10.3	2.12	471.375
A22	36.4	21.76	11.83	1.84	441.02
A23	46.69	22.95	14.55	1.57	557.16
A24	43.92	12.65	6.78	1.86	334.93
B1	84.2	8	1.8	4.44	597.82
B2	95.2	7.4	1.6	4.63	628.32
B3	52.4	21.7	2.2	9.86	1079.44
B4	75.3	14.3	1.5	9.53	1020.31
B5	63.8	15.3	1.6	9.56	925.1
B6	94.1	20.9	4.6	4.54	1750.26
C1	35.3	12	2.5	4.80	379.47
C2	63.4	11.9	1.2	9.92	716.42
D1	40	4	0.8	5.00	144
D2	42	3.7	0.8	4.63	138.6
D3	70	3.9	0.6	6.50	252

2.2. Method

Sufficient data has been collected at the start of fuzzy Logic modeling to define the parameters of the models (Table 3-4). This data is obtained from the experiments being conducted and from previous studies.

Table 3 Training Data Test

	Flexure Strength	Flexure Strength	Compressive Strength	Compressive Strength	Ductility	Energy Capacity
	Brick	**Mortar**	**Brick**	**Mortar**	**Wall**	**Wall**
A2	0.3	2.12	6.38	12.5	1.30	1722.03
A7	0.4	2.12	6.11	12.5	1.31	756.31
A11	0.4	2.59	6.11	4.59	1.29	244.89
A17	0.8	2.59	6.05	4.59	2.71	270.66
A19	0.5	2.12	2.63	12.5	1.58	1127.48
A22	0.5	2.59	2.63	4.59	1.84	441.02
D2	2	2	10.5	10.5	4.63	138.6

Table 4 Testing Data Set

	Flexure Strength	Flexure Strength	Compressive Strength	Compressive Strength	Ductility	Energy Capacity
Code	**Brick**	**Mortar**	**Brick**	**Mortar**	**Wall**	**Wall**
A1	0.3	2.12	6.38	12.5	1.21	2325.41
A3	0.3	2.12	6.38	12.5	1.85	1824.57
A4	0.3	2.59	6.38	4.59	1.52	786.72
A5	0.3	2.59	6.38	4.59	2.07	703.11
A6	0.3	2.59	6.38	4.59	1.70	1263.54
A8	0.4	2.12	6.11	12.5	1.24	565.14
A9	0.4	2.12	6.11	12.5	1.49	527.72
A10	0.4	2.59	6.11	4.59	1.15	306.20
A12	0.4	2.59	6.11	4.59	2.00	500.43
A13	0.8	2.12	6.05	12.5	1.27	295.81
A14	0.8	2.12	6.05	12.5	3.09	1169.90
A15	0.8	2.12	6.05	12.5	1.61	553.26
A16	0.8	2.59	6.05	4.59	2.08	186.83
A18	0.8	2.59	6.05	4.59	2.72	206.73
A20	0.5	2.12	2.63	12.5	1.31	1400.33
A21	0.5	2.12	2.63	12.5	2.12	471.38
A23	0.5	2.59	2.63	4.59	1.57	557.16
A24	0.5	2.59	2.63	4.59	1.86	334.93
B1	3	3	10.3	7.2	4.44	597.82
B2	4	4	8.8	7.1	4.63	628.32
B3	3.4	3.4	7.5	6	9.86	1079.44
B4	3.3	3.3	7.8	5.7	9.53	1020.32
B5	4	4	8.5	7.3	9.56	925.10
B6	3.3	3.3	7.9	5.2	4.54	1750.26
C1	1.32	1.32	2.37	2.37	4.80	379.48
C2	1.32	1.32	2.37	2.37	9.92	716.42
D1	2	2	10.5	10.5	5.00	144.00
D3	2	2	11.5	11.5	6.50	252.00

2. 2. 1. Fuzzy Logic The fuzzy Logic theory, proposed by Zadeh [50], is a mathematical application that enables its use in uncertain environments. Unlike classic logic, which categorizes items as either belonging (1) or not belonging (0) to a set, fuzzy Logic considers a blurred pattern as a set that does not have a clearly defined limit [51]. This set may only contain basic information with a partial membership rating (a number between 0 and 1). In 1985, Sugano [52] conducted a study on a fuzzy deduction technique, which showed that the out-come of the if-then rules can be linear or constant. A fundamental rule in Sugano's fuzzy model takes the form: "If input 1 = x and input 2 = y, then output is z = ax + by + c." For each rule, the resulting output zi is weighted by the firing strength wi of the rule [50]. Therefore, the final output (ofinal) of the technique is the average of all control outputs, which are balanced and estimated as shown in figure 4.

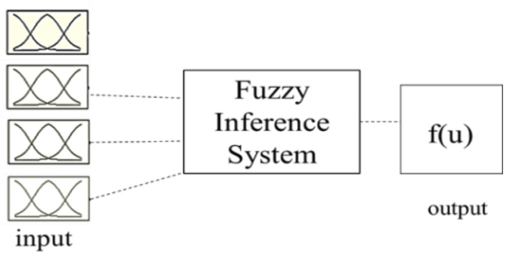


Fig. 4 Back propagation training fuzzy logic.

2.2.2. Fuzzy Logic and Set Data

In order to increase the size of the training-testing database, 35 test data sets were compiled from published information, specifically representing the test results for 35 prisms (as shown in Table 3-4). For the implementation of Fuzzy Logic, the MATLAB Fuzzy Logic Toolbox [51] was utilized to create a fuzzy deduction system. This system can be employed to determine the ductility and energy capacity of a masonry structure (f), provided that the compressive strengths of its bricks and mortar, as well as its flexure strength, are already known. This toolbox includes a membership function, the if-then rules, and the weight wi. These elements define the fuzzy inference system and establish the connections between a set of inputs and the output. In this section, a hierarchical evaluation was first established, which divided the factors that influence the health of the masonry structure into four layers. Based on the hierarchical model, the judgment matrix of each level was determined using expert experience and the characteristics of masonry structures. The weight coefficient vectors were then calculated based on the judgment matrix. The process of fuzzy logic is depicted in figure 5.

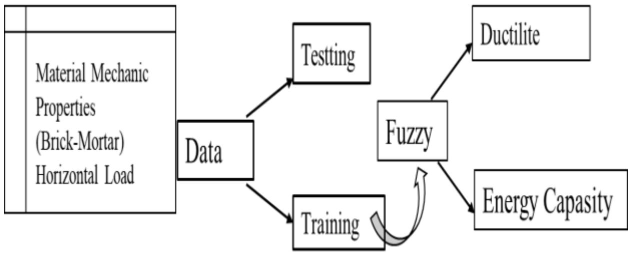
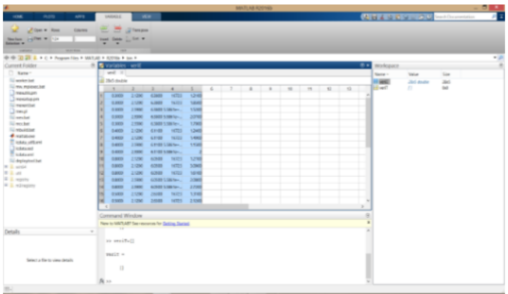
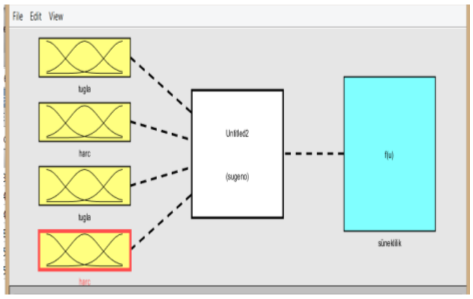


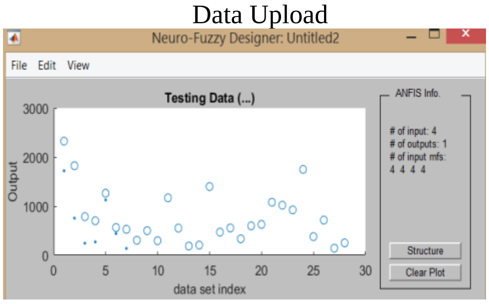
Fig. 5 Fuzzy Logic process

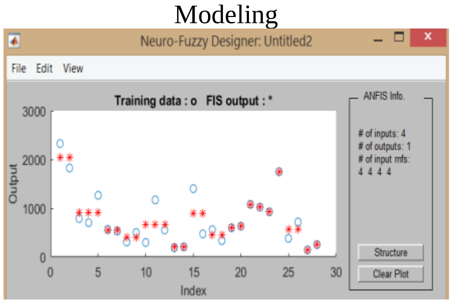
The evaluation matrix was determined using the grey method. Consequently, the comprehensive rating vector for each layer factor was calculated using fuzzy linear transformation, which involves the weight coefficients vector and the evaluation matrix. Figure 6 depicts the study upload system.





Data Upload Modeling





Testing and Training Data Training Data and FIS out-put

Fig. 6 Fuzzy Logic Study System and Upload Data

3. Finding and Results

After allocating 7 out of 35 data for training, the data underwent training. The preceding section provides a detailed explanation of how the model operates. A comparison was made between the data obtained from the fuzzy model and the actual data. The graphs generated using the acquired data demonstrate that an accurate prediction was made using fuzzy logic. The objective of the research was to obtain information regarding the ductility and energy capacities of the walls. By adding the horizontal loading, according to the material strengths, the displacement of the wall at the point where it first started to flow and the final displacement under loading were also estimated to support the study. In Figure 6 and 7 the study was observed to be demonstrable. Looking at the R^2 coefficients, which was obtained as 0.93-0.95 (figure 6-7).

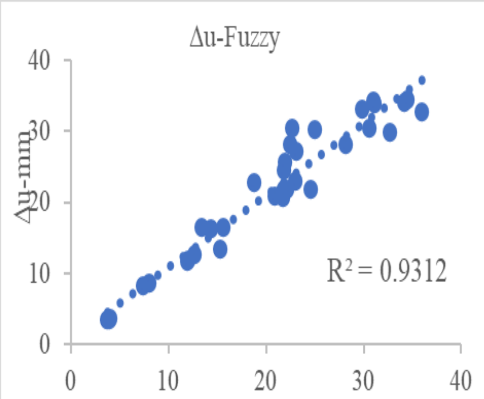


Fig 6. Du- Fuzzy Logic Dat

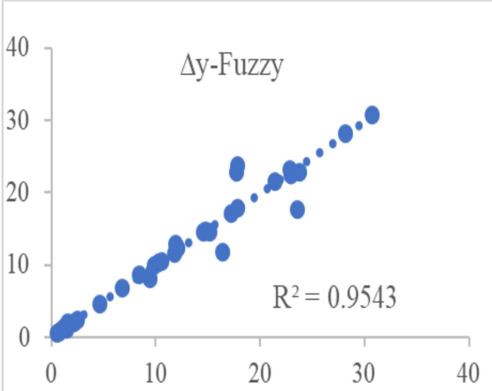


Fig. 7 Dy-Fuzzy Logic Data

The ductility and energy capacity of the wall are important for interpreting its behavior. The main objective of the study was to analyses the conditions of the walls using intelligent techniques. The figure 8 and 9 values and have obtained in show that the study is supported by fuzzy logic. R^2 values were obtained as 0.99 to 0.97.

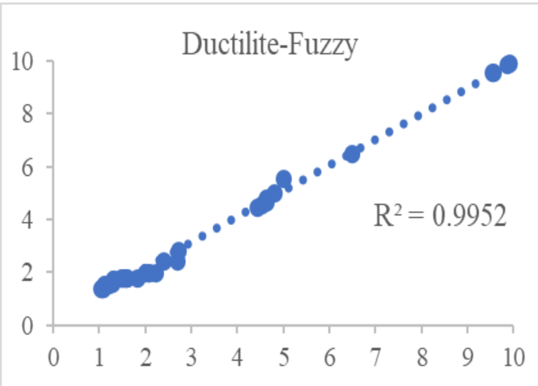


Fig. 8 Ductility- Fuzzy Logic Data

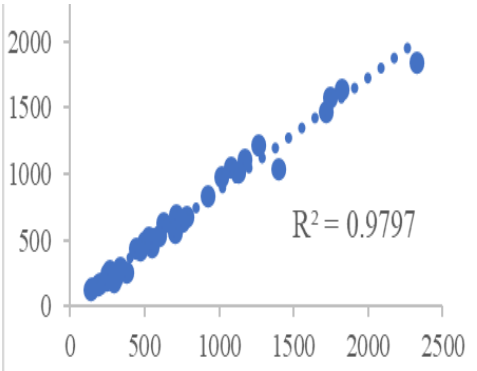


Fig 9 Energy Capacity- Fuzzy Logic

Experiment and model values were modeled by fuzzy logic. What's more, the results are charted to be healthy. To compare the Values, here, they are compared with the RSM technique. The results from the RSM are given in the table of 5. In both estimation methods, results close to the real values were obtained. When the R coefficients are compared according to the obtained data, it has been determined that the values are very close. R values were obtained above 0.9

Table 5. Experimental, RSM and Fuzzy Logic Compared

Run no.[a]	**Independent variables**				**Dependent variables**					
	Compressive Strenght		**Flexure Strenght**		**Ductilite**			**Energy Capacity**		
	Brick	**Mortar**	**Brick**	**Mortar**	**Experimental**	**RSM**	**Fuzzy**	**Experimental**	**RSM**	**Fuzzy**
1	0.3	2.12	6.38	12.5	1.21	1.50	1.53	1550	1520.8	1463.0
2	0.3	2.12	6.38	12.5	1.30	1.50	1.71	1722.03	1520.8	1577.0
3	0.3	2.12	6.38	12.5	1.85	1.50	1.76	1824.5	1520.8	1642
4	0.3	2.59	6.38	4.59	1.52	1.76	1.76	786.72	940.59	679
5	0.3	2.59	6.38	4.59	2.07	1.76	1.99	703.11	940.5	562
6	0.3	2.59	6.38	4.59	1.70	1.76	1.76	1263.54	940.5	1220
7	0.4	2.12	6.11	12.5	1.31	1.20	1.71	756.31	849.55	562.0
8	0.4	2.12	6.11	12.5	1.24	1.20	1.57	565.14	849.5	628.0
9	0.4	2.12	6.11	12.5	1.49	1.20	1.76	527.72	849.5	538.0
10	0.4	2.59	6.11	4.59	1.15	1.56	1.53	306.2	331.7	189.0
11	0.4	2.59	6.11	4.59	1.29	1.56	1.57	244.8	331.7	271.0
12	0.4	2.59	6.11	4.59	2.00	1.56	1.99	500.4	331.7	224

13	0.8	2.12	6.05	12.5	1.27	1.62	1.57	295.8	412.7	294
14	0.8	2.12	6.05	12.5	2.03	1.62	1.99	569	412.7	441
15	0.8	2.12	6.05	12.5	1.61	1.62	1.76	553.2	412.76	253
16	0.8	2.59	6.05	4.59	2.08	2.53	1.99	186.8	231.1	172
17	0.8	2.59	6.05	4.59	2.71	2.53	2.4	270.6	231.1	247
18	0.8	2.59	6.05	4.59	2.72	2.53	2.8	206.7	231.1	201
19	0.5	2.12	2.63	12.5	1.58	1.65	1.76	1127.4	1166.3	1012
20	0.5	2.12	2.63	12.5	1.31	1.65	1.71	1400.3	1166.3	1115
21	0.5	2.12	2.63	12.5	2.12	1.65	1.99	997	1166.3	1047
22	0.5	2.59	2.63	4.59	1.84	1.81	1.76	441.02	439.3	487
23	0.5	2.59	2.63	4.59	1.57	1.81	1.76	557.16	439.3	517
24	0.5	2.59	2.63	4.59	1.86	1.81	1.76	334.9	439.38	426
25	3	3	10.3	7.2	4.75	4.78	5	597	597.78	602
26	4	4	8.8	7.1	4.63	4.70	4.63	2112	2207.6	1839
27	3.4	3.4	7.5	6	10.65	10.71	9.91	1079.4	1212.8	1220
28	3.3	3.3	7.8	5.7	7.89	7.92	7.94	1020.3	999.53	833
29	4	4	8.5	7.3	9.56	9.70	9.56	264	156.30	162
30	3.3	3.3	7.9	5.2	5.28	5.39	5.55	1347	1273.0	1042
31	1.32	1.32	2.37	2.37	7.36	7.37	7.34	379.4	551.09	448
32	1.32	1.32	2.37	2.37	7.36	7.37	7.34	716.4	551.09	512
33	2	2	10.5	10.5	5.00	4.79	5.55	144	124.02	140
34	2	2	10.5	10.5	4.63	4.79	4.81	138.6	124.02	125
35	2	2	11.5	11.5	6.50	6.44	6.5	1038	1084.2	980

4. Conclusions

In this study, the researchers utilized the numerical procedure of fuzzy logic to determine the compressive strength and tension of masonry prisms. They gathered a reliable database of published experimental results, from which they randomly selected 35 samples for instructional purposes.
The remaining 28 samples were then used to test the suggested modeling. The research resulted in the subsequent outcome, which shows that the Fuzzy Logic modeling trained by the algorithm in the hidden layer performs well in predicting commodities. The projected significance is important in relation to experimental consequences for both the training and testing sets in the formulated models.
The Fuzzy Logic model, which utilized bell-shaped participation functions, displayed a high level of accuracy. Additionally, the performance indices indicated that the Fuzzy Logic model slightly outperformed the RSM model. The comparison revealed that, on average, the empirical methods underestimated ductility and energy capacity by around 10.
On the other hand, the predicted results obtained from the models developed in this study closely align with experimental values. Generally, the proposed Fuzzy Logic models exhibit great applicability and reliability in predicting the ductility and energy capacity of various masonry prisms.
The estimation of ductility's energy has been found to be more accurate compared to its capacity. According to the study, selecting material properties allows for estimating the mechanical behaviors of the wall.
In subsequent research, various mechanical strengths can be examined, or empirical formulas can be created to describe the behaviors of the wall. Experimental data is open to further increases and experimentation with various methods in smart learning techniques.

Contribution of Researchers

All researchers have contributed equally to writing this paper.

Conflicts of Interest

The authors declare no conflict of interest.

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