System Identification of Model Steel Bridge with Fuzzy Logic

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***Abstract*—Today, civil engineering structures suffer from dynamic effects. Earth on structures have been severely damaged by the earthquake. Thus, there has been loss of life and property. This has particularly affected countries located on active fault lines. Pre- and post-earthquake measures have been developed in world. For these reasons, it is necessary to determine the dynamic performance of structures around the world. There are various methods for determine the dynamic performance. System identification is one of these methods. Mathematical model of the structural system is obtained by system identification method. Fuzzy Logic can be a system identification method. It is known as fuzzy logic, an algorithm for the mathematical projection of the natural, in other words, human intelligence. In this study, steel model bridge was used as test subject. MATLAB software is used. In this study, it is aimed to estimate the output of steel model bridge with fuzzy logic. The output data of the model steel bridge was first obtained on the experimental modal analysis and then the output data obtained with fuzzy logic were compared. As a result of the comparisons, it was observed that a nearly 99% compliance was achieved. In the light of all results, it is seen that fuzzy logic method will be useful in system identification method in civil engineering field.**

***Keywords*—System Identification, Fuzzy Logic, Experimental Modal Analysis, Steel Bridge**

I. INTRODUCTION

Most of structures located in regions prone to earthquake hazards suffer from various types of destruction caused by seismic loads. Under such earthquake occurring [5].There are many studies that take this into account. In the regions of seismic hazards, structures are expected to have vibrations due to seismic loads [15]. In civil engineering field, currently there are many varieties of structural and architectural structures. Such structures can be managed to resist to both static and dynamic loads effectively [16].More work should be done to clarify the performance of structures under seismic loads [13].More researches are being conducted to get required performance of structures under seismic loading, by means of looking at different point of view and directions [14].In recent years, in the world and our country, the determination of the effect of vibrations on structures and structural behavior has become very important [17].Buildings located in seismically active regions are under high risk of severe damages caused by harmful earthquake loads [6].Civil engineering structures are exposed to a variety of natural and artificial effects throughout their lifetime. These effects are the forces that can affect the dynamic characteristics of the structure and thus the service life [18].In all construction systems, damage starts at the material level. As the damage in the system increases, it reaches a value defined as deterioration [19]. Generally forced and ambient vibration methods are used in the purpose of vibration testing of structures [20].The authors pointed out the reasons for their studies. The authors also pointed out that this point should be focused on. This study was carried out considering these negative situations.

System identification (SI) is a modeling process for an unknown system based on a set of input outputs and is used in various engineering fields [8], [9].Subspace system identification is introduced as a powerful black-box system identification tool for structures [21]. The application of the method for supporting excited structures is emphasized in particular. The black- box state- space models derived from the identification of subspace systems are used to estimate the modal properties (i.e. modal damping, modal frequency and mode shapes) of the structures [7], [10].

Depending on the input and output sizes of these systems, in order to obtain a behavioral model, it is necessary to determine and measure the magnitudes affecting the structures. Model identification, system-related, based on physical laws based on the preliminary information and the size of the system (introduction magnitude or input signal) from the system's response to these magnitudes (output magnitude or output signal) It is exploited. Physical laws are defined by differential or algebraic equations. In this way model, not only the relationship between the input and output sizes, but also by determining the model structure are expressed. On the other hand, the lack of any preliminary information about the system or the system is too complex. In case of having, identification methods (such as parametric definition) are used in determining the model of the system. In this case, the model is obtained by using input and output sizes. This technique can be applied by making some preliminary assumptions regarding the choice of system grade, input and output sizes [12].

Stable adaptive controller designs have been one of the most important research topics in recent years as they can produce effective solutions against time-varying system parameters and disturbing effects in the desired system output monitoring problem [11].

The concept of fuzzy logic is at the intersection of mechatronics, artificial intelligence, mathematics, sociology, robotics, medicine and science. Moreover, it is accepted as one of the closest points of human and machine. Thanks to this approach, human experience and various human data are transferred to machines in a way suitable for use by technologies such as artificial intelligence. In other words, the mathematically expressed data, which can be processed by transferring to this computer environment, gives the machines capability. Because in fact, these data are human and verbal data.

Fuzzy logic can also be thought of as a formula that converts one type of encryption into another type of encryption; intermediate values. This formulation is discussed in detail in the method section. In fact, it is also possible to define it as rounded and flexible rather than fuzzy. As an approach, fuzzy logic provides machines with the ability to work in a similar way to human beings, while the starting point is classical logic. It can be said that logic has given such a branch in the modern age after the general development.

Bridges are a must among transportation structures. Indispensable in our lives. Secure bridge design is therefore very important. Further periodic maintenance is also very important, rather than the initial design. Therefore, the current status of the bridges needs to be determined quite accurately. However, correct diagnosis and correct periodic maintenance and retrofitting can be performed. It is also known that bridges are highly exposed to dynamic loads. System identification of bridges is of high importance for all these reasons. In this study, the acceleration response (output acceleration) of a steel bridge sample was investigated experimentally and by fuzzy logic method.

In this study, it is aimed to examine an example of fuzzy logic method which is an innovative and modern method.

II. METHODOLOGY

Fuzzy logic is a form of logic that assumes that there can be any real number between 0 and 1, including both the accuracy values of the variables. It is used to address the concept of partial truth in which the value of truth can vary between completely true or completely false. On the other hand, in Boolean logic, the accuracy values of the variables can only be an integer 0 or 1. The term fuzzy logic was introduced by Lotfi Zadeh in 1965 with the suggestion of fuzzy set theory. Fuzzy logic theory has been used in many fields since the 1920s.Fuzzy logic is based on the observation that individuals make decisions based on inaccurate and non-quantitative information. Fuzzy models or sets are a mathematical way of representing uncertainty and uncertain information (fuzzy term). These models are capable of recognizing, representing, using, interpreting and using uncertain and uncertain data and information. Fuzzy logic is applied in many fields from control theory to artificial intelligence. Classical logic allows only true or false results. However, there are also variable response propositions. In such cases, the spectrum in which the actual sampled responses are mapped emerges as a result of incorrect or partial information. Both degrees of accuracy and probabilities are between 0 and 1 and therefore may seem similar at first glance, but fuzzy logic uses accuracy degrees as a mathematical uncertainty model, while probability is a mathematical model of neglect. Basic applications can characterize various sub-ranges of a continuous variable. For example, the acceleration measurement for the control of structures may have several separate membership functions that define the specific acceleration ranges required to accurately control the dampers. Each function maps the same acceleration value to an accuracy value in the range 0 to 1. These accuracy values can then be used to determine how the dampers should be controlled. While variables in mathematics often take numeric values, in fuzzy logic applications, non-numeric values are often used to facilitate the expression of rules and phenomena. A linguistic variable, such as structure types, can accept values such as old and new. Natural languages do not always contain sufficient value terms to express a fuzzy value scale. It is common practice to replace linguistic values with adjectives or adverbs. For example, you can use quiet and a slightly words to create additional values, quite old or slightly new. Fuzzification operations can match mathematical input values with fuzzy membership functions. And de-fuzzification operations can be used to map the fuzzy output membership function to a "crisp" output value which can then be used for decision or control purposes.

Process;

1. Fuzzify all input values into fuzzy membership functions.
2. Execute all applicable rules in the rule base to compute the fuzzy output functions.
3. De-fuzzify the fuzzy output functions to get "crisp" output values.

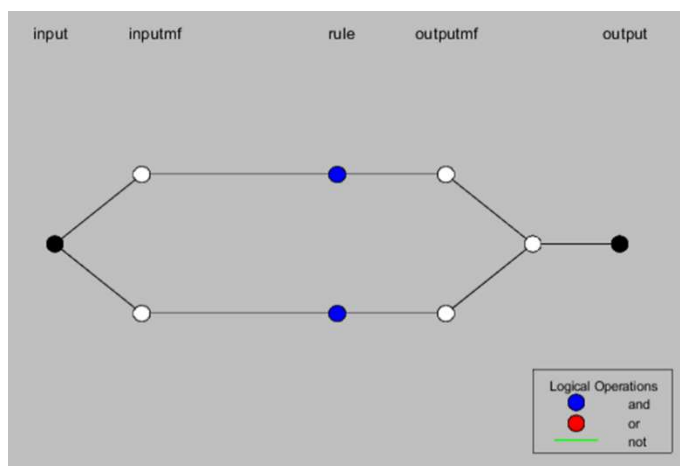

Fig 1. Anfis Model

Sugeno Fuzzy Inference Systems

Sugeno fuzzy inference also referred to as Takagi-Sugeno-Kang fuzzy inference, uses singleton output membership functions that are either constant or a linear function of the input values. The defuzzification process for a Sugeno system is more computationally effective compared to that of a Mamdani system, since it uses a weighted average or weighted sum of a few data points rather than calculate a centroid of a two-dimensional area. [22].

You can change a Mamdani system into a Sugeno system using the convert to Sugeno function. The resulting Sugeno system has constant output membership functions that correspond to the centroids of the Mamdani output membership functions.

Each rule in a Sugeno system operates as shown in the following diagram, which shows a two input system with input values *x* and *y*.

Sugeno fuzzy inference systems is given figure 2.

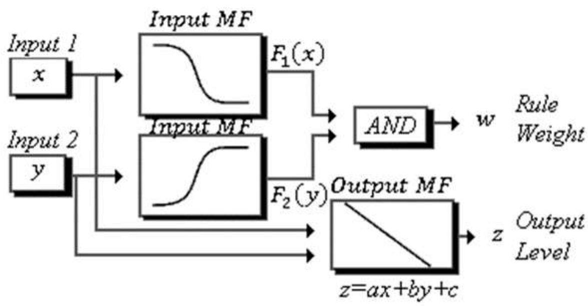

Fig. 2. Sugeno Fuzzy Inference Systems

Each rule generates two values:

z_i −Rule output level, which is either a constant value or a linear function of the input values:

$$z_i = a_i x + b_i y + c_i \quad (1)$$

Here, *x* and *y* are the values of *input 1* and *input 2*, respectively, and a_i , b_i , and c_i are constant coefficients. For a zero-order Sugeno system, Z_i is a constant (*a = b = 0*).

w_i −Rule weight strength derived from the rule antecedent

$$w_i = AndMethod(F_1(x), F_2(y))$$

Here, $F_1(\ldots)$ and $F_2(\ldots)$are the membership functions for *inputs 1* and *2*, respectively.

The output of each rule is the weighted output level, which is the product of $w_i$andz_i.

The easiest way to visualize first-order Sugeno systems (*a* and *b* are nonzero) is to think of each rule as describing the location of a moving singleton. That is, the singleton output spikes can move around in a linear fashion within the output space, depending on the input values. The rule firing strength then defines the size of the singleton spike.

The final output of the system is the weighted average over all rule outputs:

$$Final\ Output = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i} (2)$$

Where *N* is the number of rules.

The following figure shows the fuzzy inference process for a Sugeno system.

III. DESCRIPTION OF MODEL STEEL BRIDGE

The bridge model has a deformed belt geometry. Steel was used as the material in the bridge model. The legs tilted inward along the long axis of the deck provided console operation of the end portions of the deck. The legs have a 45-degree bending. The profiles along the axis of the deck are made of box profile with a thickness of 2.5cm. Round lattices with a thickness of 2 cm are used in trusses. In the Diagonal and Cross Connection elements, iron elements of 10mm and 12mm in diameter are used.In this study, 6.10 m span, 1,88 m high steel model bridge was used. The model steel bridge given in fig 3.

Fig 3. Model steel bridge

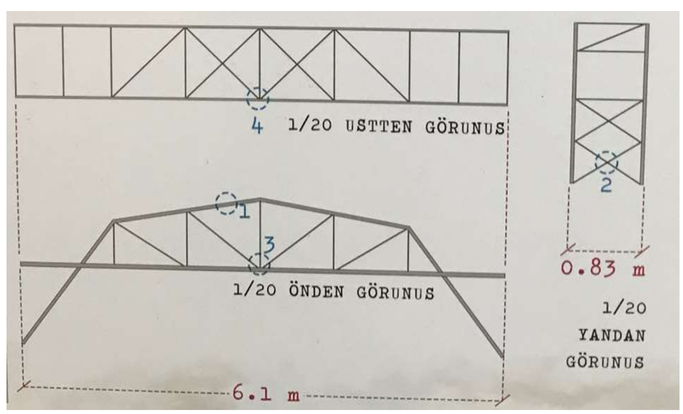

Fig 4. Model steel bridge geometric information

The model steel bridge geometric information given in fig 4. The data acquisition units and accelerometers used for measurement are also shown in fig 5.

Fig 5. Datalogger and accelerometers

TESTBOX 2010 was used as the data collection device used in experimental measurements.

Experimental outputs were taken by accelerometers on model steel bridge. Experimental inputs were taken by ground seismometer. Experimental measurements are shown in Figure 3.

IV. ANALYSIS RESULTS

The input values for the model steel bridge experimental measurements are as in figure 6.The input acceleration values were measured from ground level seismometer.

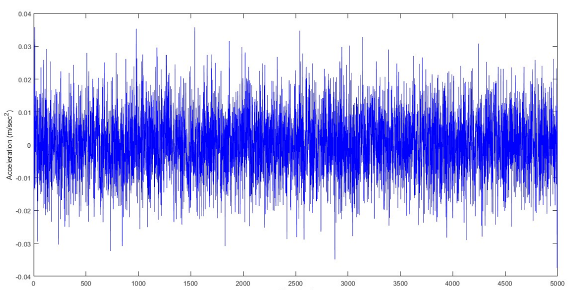

Fig 6. İnput

The output values for the model steel bridge of experimental measurements are as in figure 7.The output acceleration values are taken from the model steel bridge top point by means of accelerometers.

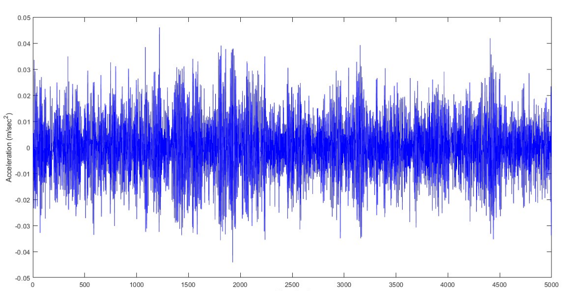

Fig 7. Output

The membership function plots of input variables used in the training are shown in fig 8.

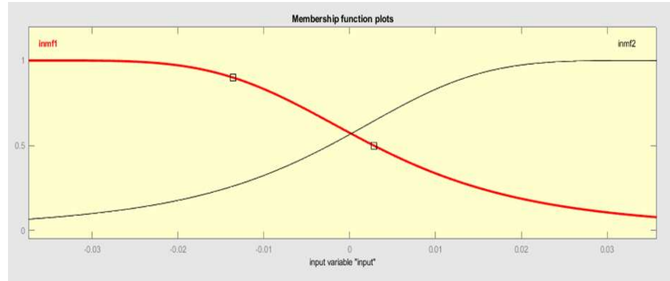

Fig 8. Membership functions of input

The Checking data shown in fig 9

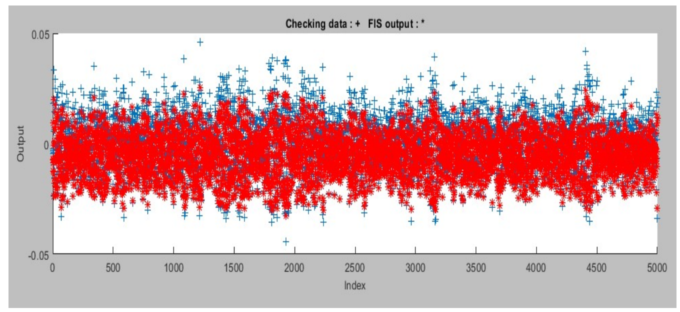

Fig 9. Checking data

The Training data shown in fig 10.

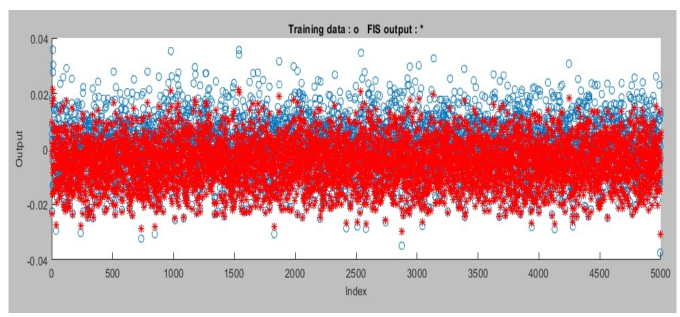

Fig 10. Training data

Matlab software and Testlab software were used to obtain the data.

The output data obtained from model steel bridge on accelometer should be compared with the output data obtained with fuzzy logic. For this purpose, figure 7 and figure 10 were compared and the output data obtained were examined.

When the obtained data is examined, the concordance between the trained output and the measured output is clearly seen. When the peak points are taken into consideration, the acceleration graph obtained in both cases is similar to each other.

V. CONCLUSIONS

In order to predict the output data without attempting any experiments were constructed models in fuzzy logic methods.

The models were trained with input and output data. Using only input data in trained model steel bridge was predicted. The values are very closer to the experimental results obtained from training and testing for fuzzy logic models.

As a result, model steel bridge's output data can be predicted using fuzzy logic models without attempting any experiments in a quite short period of time with tiny error rates. These conclusions have shown that fuzzy logic are practicable methods for predicting model steel bridge's output data.

Fuzzy logic can give time and labor practicality to system identification method. It can also provide a modern perspective.

In the light of this information, it can be said that fuzzy logic method can be used for system identification of other civil engineering structures.

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