FUZZY LOGIC APPLICATIONS IN CIVIL ENGINNERING

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(The Licence Number of Publicator: 2014/31220)
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E mail: iksadyayinevi@gmail.com
www.iksadyayinevi.com
It is responsibility of the author to abide by the publishing ethics rules.
Iksad Publications – 2022©
ISBN: 978-625-6380-29-5
Cover Design: İbrahim KAYA
December/ 2022
Ankara / Turkey
Size = 16 x 24 cm

PREFACE

Civil engineering, the first branch of engineering in the world, has been an indispensable part of life with the beginning of humanity. Civil engineering is all about people. it operates to develop and improve the services and facilities that common people use in their daily lives. Today, the rapidly changing technology and demographic developments are experiencing, and the importance of civil engineering is gradually increasing. Our world is constantly growing and developing. However, it also has negative aspects. Infrastructure problems caused by unplanned urbanization and rapid population growth are growing. New construction projects are needed. This shows the importance of the projects of competent people such as civil engineers. Therefore, it will be a supporter of life with its infrastructure and superstructure activities both today and in the future.

Today, computer technology is constantly evolving. Thanks to this emerging technology, it is possible to apply different and complex mathematical models. Artificial intelligence methods; It provides effective solutions in many design and analysis. Fuzzy logic method, which is one of these models, provides a starting point for important applications in artificial intelligence. There is much debate in the literature regarding the benefits and harms of these models. However, the positive aspects are much more. All these developments in computer technology attract the attention of civil engineers who do theoretical and practical studies. However, fuzzy logic model is widely used in civil engineering studies as in almost every field. In this study, after the introduction of the model, the studies on fuzzy logic modeling in different disciplines of civil engineering are evaluated.

I hope the study will contribute to my colleagues and enthusiasts….

Dr. Naci BÜYÜKKARACIĞAN
Konya- 2022

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INTRODUCTION

Civil engineering is a disipline of engineering that brings together all kinds of structures that people need with different materials and designs, plans, builds and supervises, that is, transforms thought into action. Civil engineering means civilization.

The civil engineer takes an active role in the zoning and construction activities carried out to make a settlement livable. they all work. The main fields of activity of civil engineering are wherever people are. For example, the planning and design of buildings built for shelter, work and production, transportation and water structures. (railway, highway, port, bridge, hydraulic dam, power plant, factory, industrial plant, treatment plant, etc. At the same time, all these The development, production and control of materials used in buildings are also within the scope of civil engineering. Civil engineering will continue to perform construction activities necessary for life as long as human history continues.

Regardless of their field, civil engineers have the same responsibilities. First of all, it is among the responsibilities of civil engineers to plan the work to be done and to determine at what date and at which stage it will be. In addition, it is one of the duties of the civil engineer to determine the legal responsibilities of the project to be built and to ensure the progress of the project in accordance with these.

The Civil engineer is also responsible for enforcing the occupational health and safety rules at the construction site he is responsible for. Researching the environmental impacts of the project, developing solutions to prevent damage to the environment and ensuring communication between workers and bosses are among the responsibilities.

Competition conditions brought about by globalization and technological developments also affect sectors related to consumer goods such as real estate, banking and white goods. In this respect, civil engineers working for consumers should have a wide range of knowledge from cost accounting to geology. Civil engineering is a person who not only performs technical services, but also performs administrative activities. Construction businesses are important in this

respect. At the same time, the primary purpose of establishment of enterprises is to continue their existence (Karasioğlu, 2022).

A successful civil engineer should be able to expose and solve engineering problems. This can be achieved with a good level of mathematics and physics knowledge. When work-related problems arise on the site or in the office, civil engineers are often the go-to person for a solution. Because the work they have done is from the design and implementation of my big projects that require a lot of responsibility. With these aspects, civil engineers can lead a team of professionals from different professions, not only in the fields of planning and construction, but also in gaining the trust of their officials in the relevant fields.

As stated before, the applications of civil engineering are based on mathematics and physical sciences. Examining, taking into account past experiences and developing methods that will enable the material to be used more efficiently, protecting and observing the living environment, providing industry and transportation facilities to the use of humanity in safety are the fields of activity of the civil engineer. The problems created by the changing conditions need to be revealed, described and resolved. Civil engineering calculations is a engineering disipline that can apply modern methods based on analytical calculation.

Especially since the 1990s, in the calculations of civil engineering, besides the classical methods, artificial intelligence techniques have found a solid place for themselves. These techniques give more suitable results especially for optimization. The crazy development of computer technology has made it possible to make especially complex mathematical models in a short time. The use of artificial intelligence techniques in the field of engineering has expanded. Because according to this model, the results are more suitable than other classical methods.

Artificial intelligence is designed according to the human mindset. It can be defined as trying to perform computer operations by understanding and reasoning among similar thoughts similar to the human thinking system. That is, it is a way of thinking of a pre-programmed software. We can make a different definition of artificial intelligence as a computer with the capabilities of the same human

intelligence. We can list these abilities as learning, reasoning, understanding and drawing conclusions. Artificial intelligence was first introduced to the literature by McCulloch and Pitts (Kaya, 2001).

Our age is witnessing a rapid development and change in every aspect. Every day we come across developed variants of the products used or new products. The development in transportation and communication technologies brings about the rapid spread of these products (Altınışık, 2013). Increasing and changing demands affect technological developments and especially computer technology. The fuzzy logic method is one of the most widely used artificial intelligence techniques in the solution of civil engineering problems. In addition, artificial neural networks, expert systems and genetic algorithms are also used in some construction areas. (Tayfun and Yurtçu, 2006).

The construction industry is a living industry. With this aspect, it has to follow information technologies, computer software and developing innovations as in sectors such as education, health and logistics. Because of the changing economic and technological conditions, limited resources such as materials, labor, machinery and financial budget used in the construction sector should be used as effectively and efficiently as possible. For this reason, the use of computer-aided innovations in the construction industry has become mandatory.

Artificial neural networks is preferred to determine the relationships and connection degrees between all parameters in the examined system. Qualified personnel, materials and time are required in the implementation of applications such as experimental studies required to obtain some information before civil engineering applications, and such parameters directly affect the economy and environmental order. When the method of determining the necessary parameters using artificial intelligence models is chosen, the majority of such requirements will be met and it provides significant time and economic savings.

It is a great advantage that fuzzy logic is close to human thinking, and applications are fast and cost-effective. However, the biggest disadvantage is that the rules used in fuzzy logic require expert experience and membership degrees can be found by the method of knowledge based on expert opinion. In addition, developing fuzzy logic

modeling studies are progressing rapidly to eliminate this disadvantage. This method, which has a wide application network, is widely used in studies that will facilitate human life. With this aspect, it has become a method used in all disciplines of civil engineering.

In this study, it is aimed to introduce the usage areas of fuzzy logic modeling in civil engineering. For this purpose, after explaining other artificial intelligence techniques, the theoretical principles and application principles of the fuzzy logic model have been revealed. Then, in the light of the studies up to the present, the applications of the civil engineering discipline in the sub-fields were evaluated.

1. ARTIFICIAL INTELLIGENCE

Artificial intelligence, in short, is the name given to the ability of a computer or computer-controlled robot to perform tasks usually associated with intelligent beings. Artificial intelligence makes it possible for machines to learn from experience, adapt to new inputs, and perform human-like tasks (Nabiyev, 2012).

With the emergence of strong artificial intelligence, it has been argued that machines (robots) cannot distinguish between good and bad because they do not have emotions. Besides, it is true that man cannot do it alone, he acts by combining irrational functions, and machines can do that too. Artificial intelligence studies focus on this issue. With recent studies, "old-style" artificial intelligence systems using rule-based approaches are also being abandoned (Button, 2017).

The theoretical basis of artificial intelligence is based on four elements. These:

1. Thinking like a human

2. Thinking wisely

3. To act humanely

4. Acting wisely

Artificial intelligence studies are also used for purposes such as determination, calculation and grouping to explain activities in different areas of daily life. Artificial intelligence logic is based on the ability to learn. A person cannot do a job without learning. For this reason, it is necessary for the artificial intelligence to learn the job to be modeled beforehand. However, artificial intelligence that completes a successful learning procedure is to realize what it has learned in the most accurate way very quickly (Öztürk and Şahin, 2018).

Artificial intelligence Technologies use neural networks, expert systems, artificial fuzzy logic, machine learning and genetic algorithms. Artificial intelligence can successfully simulate the events in nature by studying (learning) living things. Algorithms like ant colony, particle swarm and artificial bee are used as artificial intelligence optimization techniques. "In general, artificial intelligence is the transfer of human

intelligence, physiological and neurological structure such as the nervous system, gene structure and natural events to computers and software by modeling.

1.1. Expert System

Expert System is a software prpgramme that models the thinking and decision-making processes that can be done by an expert on a particular subject. Experts use their knowledge and experience when solving problems. It is important for expert systems to have a knowledge base and an inference mechanism. Having this architectural feature is its superiority compared to other decision support systems. (Buchanan and Shortliffe, 1984).

Many expert systems have been created with LISP and PROLOG artificial intelligence programming languages. Artificial intelligence languages perform by using data base and inference mechanism. This data base and mechanism consists of descriptive and symbolic rules and relationships.

In expert systems, IF-THEN rules are generally used with frames in information representation. Probability theory is used to make inferences under uncertainty. Expert systems have four basic elements: knowledge foundation, knowledge base, inference mechanism and user interface (Figure 1).

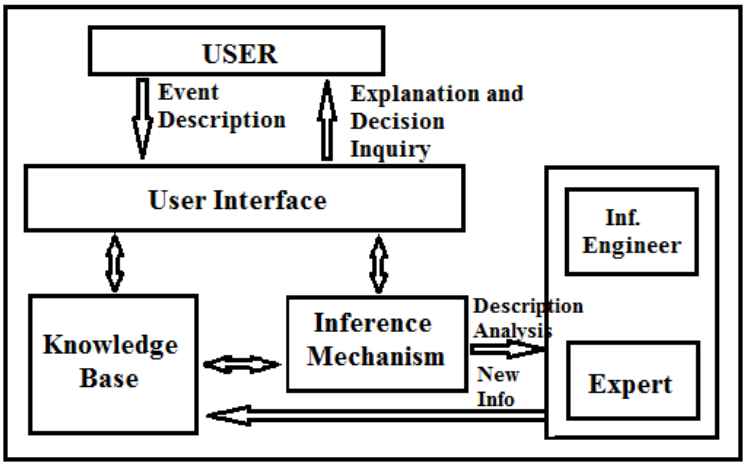

Figure 1. Expert Systems

Strengths of expert systems (Sell, 1985):

1. Expanding expertise

2. cost reductions

3. Increasing quality

4. They are based on logical cause-effect relationships

5. Ability to work with uncertain data and rules

6. Being able to explain when questioned

7. Being able to produce suggestions

8. They are reliable

9. Their use in education

10. They can store institutional information.

Barriers to expert system development and weaknesses of expert system (Sell, 1985):

1. Lack of sufficient specialist knowledge

2. Difficulty obtaining information from experts

3. Experts themselves do not know cause-effect relationships

4. Differences of opinion and terminology among experts on the same subject

The inability of expert systems to renew themselves by learning

6. Expert systems remain static and limited while experts can be creative

7. High development cost.

Well Known Expert Systems, Dendral (Determination of molecular structures), Mycin (a system for the treatment of bacteriological and meningitic diseases in the field of medicine),

Prospector (In mineral exploration studies). Recently, expert system shells have been used to refresh expert systems. Structurally, an expert system needs a database. This database consists of facts accepted by the majority or agreed by experts.

Expert systems have been used mostly for simple applications and have been successful in some fields. However, there are still many problems and weak points that expert systems cannot overcome.

In addition, human reviews are seen as more expensive than the expert system. Expert systems work faster than humans. Expert systems enable quality improvement by giving consistent and appropriate advice and reducing the error rate. Many expert systems are used to detect faulty processes and make recommendations for repair. Significant reduction in deterioration times is possible with the use of expert systems. Likewise, expert systems provide flexibility in production and service delivery.

There are cases where people depend on expensive devices for monitoring and control. However, the same tasks as expert systems can be performed with cheaper devices. Some people work in dangerous environments. Expert systems allow people to stay out of dangerous environments. The expert system is reliable. The expert system is inquisitive, constantly checking all the details carefully.

Expert systems respond very quickly, especially since a large part of the given data needs to be reviewed. In the case of working with incomplete and imprecise information, expert systems work with imprecise information similar to humans.

Training can be provided by using the explanatory feature of the expert system as a teaching device. Problem solving ability: Expert systems increase problem solving abilities by allowing experts to integrate their judgments. Since these systems process information symbolically rather than numerically, it is compatible with the decision-making styles of many managers. Expert systems are performmed to analysis complex problems that exceed human capabilities (Giarratono and Riley., 1994).

If the system contains a lot of information, that is, if the subject is comprehensive, it may be necessary to use too many rules and too

many parameters. This is quite problematic and makes operation difficult. Complexity prevents the establishment of an expert system. In addition, if the information used in the system is not healthy, expert systems are not useful. Civil engineering applications are quite extensive. This situation will slow down the operation of the expert system.

Expert systems have been used in civil engineering, especially in building information modeling studies, in the rapid determination of earthquake damage, in construction cost analysis, in the selection of spillway and energy breaker structure type, in the intelligent control transportation networks, and in the analysis of construction materials supply chain applications slope stability problem. Especially Expert systems create a great potential in structural engineering education as well as in structural design and analysis. Structural engineering education is usually done in parts, in the form of building material, strength and usability analysis of structural systems, sizing of structural elements and design of integrated structural systems.

However, it should not be forgotten that complete and accurate information in the field of civil engineering has not been reached yet. So it is very difficult to find complete and accurate information. Even if the system works with insufficient and conflicting information, this would be too risky. The query methods used in the information gathering stage for the system may be more complicated than the expert system itself and may require an examination outside the system. In this case, expert systems alone are not sufficient. Most civil engineering problems have time-varying properties. Trying to solve such time-varying problems with expert systems is risky. In this case, too, the laws of change must be known and used. Otherwise, the information used may become inaccurate or irrelevant in the next step (Krowdiy and Wee, 1993).

1.2. Machine Learning

Machine learning is a software algorithm that uses data from the same problem to model a problem. The basis of the method is based on technology that enables computers to learn. Examples are used to predict the connection of the inputs and outputs of events. The theoretical basis of the model is established according to the principle

of the most efficient operation of the model and the algorithm. There are many machine learning methods available. Some of them are Logistic regression analysis, Bayes classifier, k-means algorithm, decision trees, k-nearest neighbor algorithm, support vector machines and neural networks. Some of these methods have very good prediction, some clustering and some classification abilities (Zhou, 2021).

Learning strategies consist of three elements: supervised, unsupervised and reinforcement. The aim in supervised learning is to obtain the output closest to the target values by giving the target values to the model-input relationship. The system is an unsupervised learning system as it relies only on the relationship between input values without target values. Clustering is done by grouping values close to each other. In the reinforcement learning method, a criterion is used that evaluates the output against the given input (Tripathy et al., 2016). In Figure 2, the workin2011g principles of machine learning are diagrammed in detail.

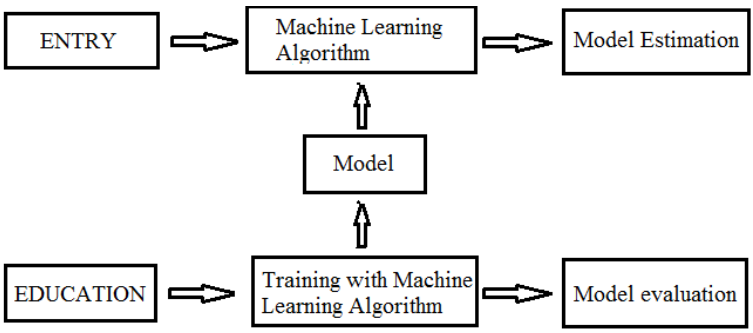

Figure 2. Mechanism of Machine learning

Machine learning model can be used in estimating compressive strength, in calculating the safety coefficient of retaining structures, in estimating the consistency class of soils, in determining lake or stream level changes, in stream flow estimation, in estimating moments of column-beam joints, in building damage analysis, in determining the crack model in concrete bridges, in concrete mix. and is used to determine their strength.

1.3. Genetic Algorithms

This optimization model, which was first introduced to the literature by John Holland, is actually a stochastic search method based on natural selection. Genetic algorithm, inspired by the rule of living the best in nature, is a search method used to find specific data from a dataset. Different from traditional optimization methods, genetic algorithms do not use the parameter set but its coded form. Genetic algorithms that work according to probability rules only need an objective function. They solve the solution in a much shorter time by actively searching the entire solution space (Goldberg, 1989).

Genetic algorithms fall under evolutionary computing, which is the fastest developing model of artificial intelligence. How genetic algorithms search is explained by the concept of subsequence. Subsequences are theoretical constructs used to explain the behavior of genetic algorithms.

The genetic algorithm uses natural selection operators. Examples of these are crossover, mutation and first generation solution sequences (Papadrakis and Lagaros, 1994).

In the genetic algorithm, independent parameters must be encoded within the chromosomes. Each individual in the stack is encoded in binary or as an integer. Genetic algorithms work with very general principles as seen in the flowchart in Figure 3.

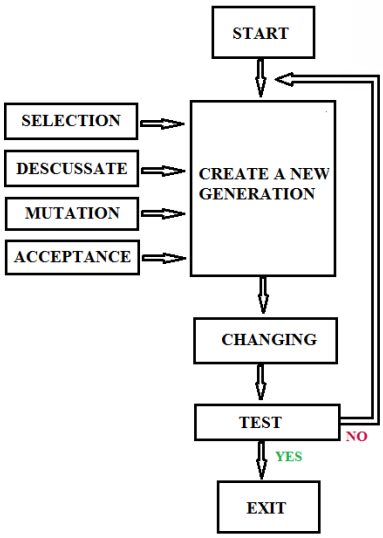

Figure 3. Mechanism of Genetic algorithm

For the solution of the problem, the fitness function f(x) is found for the data of the random sample chromosomes consisting of n chromosomes. Finding a new population is essential. Finding a new population is essential. For this purpose, the processes are repeated until the result is obtained. The process steps are as follows:

1. Selection: In this step, two parental chromosomes are selected according to f(x) where the one with the highest fitness has a high chance of being selected.

2. Crossover: The generation of a new individual by the parents' probability of a crossover. If no crossover is applied, individuals will be exact copies of their ancestors.

3. Mutation: The degradation of generations is prevented by changing the values of some chromosome genes.

4. Addition: It is ensured that the new individual participates in the new population.

5. Modification: Using the new population formed in re-running the algorithm,

6. Test: If the result is satisfactory, the algorithm is terminated and the final population is presented as the solution.

7.Cycle: Returning to step 2.

A genetic algorithm usually does between 50 and 500 iterations. GA is a stochastic search method. GA is probabilistic, not deterministic, that is, it obeys Randomization techniques. Since they are looking for solutions at more than one point at the same time, they are algorithms that work in parallel by their nature.

A one-point approach is sufficient for solving the problem in classical optimization techniques. However, as we mentioned at the beginning, the genetic algorithm scans the solution space with an infinite number of points. That is, there is no need for any special form to model a problem in genetic algorithms. Since the genetic algorithm is included in the dynamic programming class, it constitutes a very suitable structure for complex problem types and creates a very effective solution space for solving the problem.

Genetic algorithm gives very suitable results for discontinuity problems. It can also be used effectively in the shape and weight optimization of cage and frame elements. Besides all these positive aspects, genetic algorithm technique has some disadvantages. When the genetic algorithm searches on limited quantities, there may be some selection errors in the results. In addition, if the chromosome length and mutation processes are not taken into account during the selection of the population size, the solution time becomes longer and the program may enter a vicious circle.

Genetic algorithms are preffered in the fields of simulation, automatic programming and information systems, optimization, mechanical learning, economic and social system models, and business and economics. In addition, Evolutionary Algorithms are used to find the dimensions of each column and slab in the building and calculate the design and best cost for slab concrete, realizing the most efficient design of plane steel frames. Straight truss systems are used to optimize the roof trusses under different loads, to calculate the effects of earthquake and building load, to analyze the shear stability, to estimate the optimum solution in environmental structure design, and in the optimum budget. design in the repair of structures, optimization of

materials used in water treatment, solution of dynamic and statistical problems in water resources systems, modeling of river flows.

1.4. Artificial neural networks (ANN)

An Artificial Neural Network is a network of interconnected artificial neurons, where each neuron corresponds to a computing unit. This network is actually a computer that can output new information by obtaining it. The system is based on nodes interacting with each other and sharing information. This method is particularly successful in nonlinear control (Narendra & Parthasarathy, 1990).

The human brain structure has been the basic model for artificial neural networks. Just as with humans, the principles of performing perception and control tasks apply. Perceptual actions and control activities are necessary human activities. The human brain, which is accepted as a model, has an essential motor structure for thinking, recognizing, speaking, hearing and physical movements (Abraham, 2005).

The method is also used in material analysis, medical analysis, management organization studies, optical character transport, fingerprint recognition, optical character transport, optimum route determination, data mining and quality control (Öztemel, 2003).

The field of artificial intelligence was first heard at a conference held at Dartmouth College in 1956 (Lewis, 2014). Since 1970, although few researchers have continued their studies, the success of solving the XOR problem has increased the interest in artificial neural networks. Since the 1980s, they have become systems used in daily life studies with the support of hardware technology.

The human brain structure has a complex system composed of many interconnected nerve cells (Figure 4a). Artificial neurons are the basic processing elements of neural networks. A simple Neuron model consists of the effects of synapses, link weights in modulated input signals. Here, the nonlinear property of neurons is represented by a transfer function.

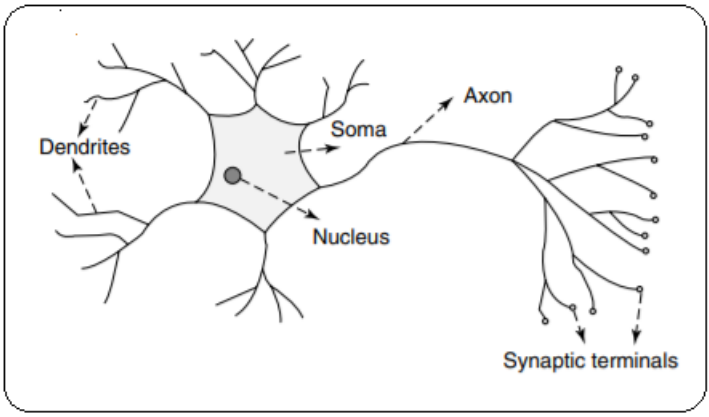

Figure 4a. Sturucture of Mammalian neuron

The ability of an artificial neuron to do its learning is achieved by applying a learning algorithm determined according to its weights (Bishop, 1995).

The working principle of the artificial neural network is shown in Figure 4b.

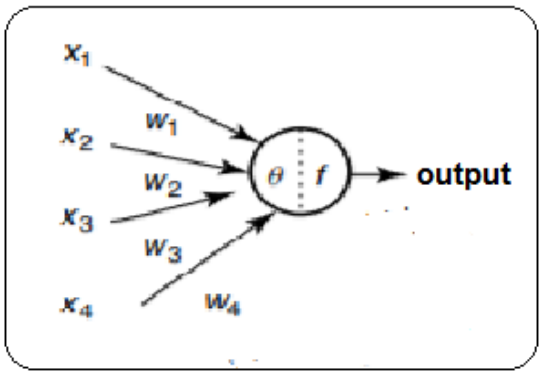

Figure 4b. Artificial neuron

The process steps are as follows:

1-) Determining the set and entering the input vector (input) into the system
2-) Prediction of output value
3-) Determining the error between the output value and the requested value

4-) Analysis of neural network weight to ensure minimum errors
5-) Repeating the process until the errors are within the confidence limit.

The basic structure of artificial neural networks consists of data processing networks connected in parallel with each other. This network consists of unidirectionally connected transaction members (Figure 4c).

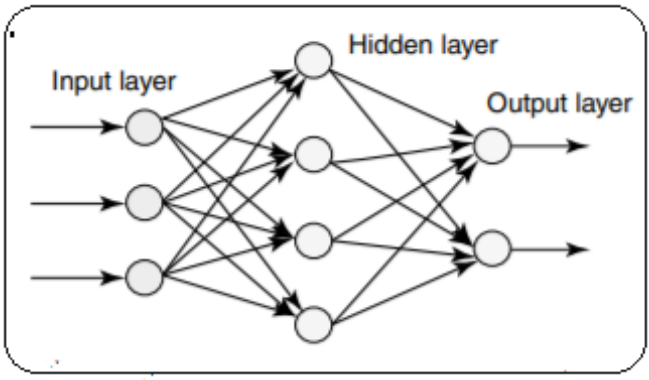

Figure 4c. Multilayered artificial neural network

As mentioned before, the artificial neural network system is designed in a way similar to the functioning of the human brain. It has the ability to design its behavior according to environmental influences, similar to the human brain. In order to achieve this, the inputs and outputs can be uploaded to the system and programmed to produce different scores. In fact, the internal structure of the system is quite sotisfied. The target element is only one, but can be duplicated at any time. The program equations are not known when examining the data set to calculate the target element.

In analysis, the data score entered into the system is very important. If the optimum number of data is exceeded, there is no learning but memorization. Generally, 4/5 of the data is used for training artificial neural networks and the rest is used for testing (Özbayrak, 2019).

The success of ANN in computation and data processing comes from its structure, learning ability and drawing conclusions. The generalization feature is the ability of ANN to give appropriate

reactions to inputs that are not encountered in the education or learning process. Due to this feature, ANN can successfully solve sophisticated problems. Cell is the basic processing element of ANN. This element is not linear. ANN with nonlinear cells is also naturally nonlinear. The nonlinearity feature also gave the ANN the ability to easily solve nonlinear problems.

It is necessary for the learning process for the ANN to exhibit the desired behavior and be designed in accordance with its target. This is only possible with correct cell connections and appropriate weight values. The complex structure of ANN does not allow predetermination of connections and weights. ANN must first be done by using problem training examples in order to perform the learning process. Then, the generalization process is started. In other words, the problem that ANN learned after the training should produce the target response for the test samples that it did not see during the training. During the analysis, different situations may be encountered. For example, ANN may return correct characters for garbled characters. Similarly, the trained ANN model can give the same response to the input signals that it did not encounter during the training process. ANN can adapt the element weights to the variations in the problem in the process. The trained ANN can be retrained if there is a change in the problem. If there is a continuous variation in the problem, the training continues simultaneously. These features increase the analysis power of ANN considerably. With this aspect, ANN is successfully used in areas such as continuously changing samples recognition, system fault diagnosis and system control (Ergezer et al., 2003).

Modeling of artificial neural networks is easier than other systems due to the easy availability of simulators used in their calculations. In modeling, it makes the learning function a simulator. Another advantage of ANN is that a trained network can reach correct results with incomplete and erroneous data. Classical computer systems are very sensitive to errors that may occur in the system. The slightest error that may occur in the system may lead to inability to reach the result or to a major error in the results. However, damage to one or more neurons in the artificial neural network does not affect the system as much as it does in traditional computing technologies.

In addition, another feature of model is that it is capable of learning and adapting to new environments during the use of the

network outside of education. Thus, since all the processing elements in the neural network work simultaneously, they produce fast solutions in the application process. In the ANN studies conducted to date, there is no acceptance of the required properties of the data used in artificial neural network training. All kinds of data can be used for training provided that it is encoded with numbers. This is an important advantage that artificial neural network technology has over multidimensional statistical methods based on some assumptions (Schalkof, 1997).

Despite all the advantages of artificial neural networks, there are also many negative aspects. First of all, artificial neural networks are not sufficient for solving problems that require precise data for modeling and require precise results. In addition, they are not efficient in solving wide-ranging problems. As it is known, civil engineering problems are very comprehensive and complex, and solutions change according to changing conditions. Solving the problem requires using one of the multiple solutions that must be distinguished under different conditions. In this case, artificial neural networks cannot be successful.

Artificial neural networks are not successful in solving problems that require classification. Due to the scarcity of input and output units in artificial neurons, classification processes are performed successfully with classical natural methods without much difficulty. On the other hand, sensations such as sight and hearing are natural classification processes that occur instantly, and those working in artificial neural networks have not yet reached a conclusion. Artificial neural networks cannot be used successfully in solving problems where experience is an important factor. For example, the information that an inexperienced person will give to the system while training the networks may be incomplete or incomplete. Success depends on the quality of the information used for education. For the solution of a problem, the exact number of neurons to be assigned to this problem is not known.

There is no mechanism in the literature that adjusts the required number of neurons and the number of connections between them. It is known from applications made with artificial neural networks that problems arise in their deficiency or excess. It cannot be used optimally in situations that require arithmetic operations and conditional propositions. Error explanations are not at the desired level. (Tuzcuoğlu, 2003).

Today, artificial neural networks are used in many fields. It is used in production planning, classification of blood analysis, brain modeling studies, quality control, fingerprint recognition, automatic vehicle inspection, credit card fraud detection, optimum route determination for intelligent vehicles and robots, estimation of the lifetime of mechanical parts, voice recognition, inspection, Examples are meteorological interpretation, electrical signal recognition, handwriting recognition, identification and treatment of diseases, classification of radar and sonar signals, and filtering of spam mails.

ANN models are used in calculations in many different engineering branches. Calculations of river flow, evaporation, sediment transport, precipitation estimations, estimation of traffic accidents and casualties, modeling of energy consumption on highways, estimation of compressive strength of concrete or cement mortars, damage assessment of structures after earthquake, determination of grain size in the ground and calculation of carrying capacity, construction site management used in organizational optimization.

2. FUZZY LOGIC

The Aristotelian Logic used in the scientific world contains only 0 and 1 relations (open/closed). However, in Aristotelian logic, there is no near-hot, cold, or near-small-large. For brief information purposes, the weather temperature can only be given as cold and hot. However, there are also gray people, medium height individuals and warm weather in daily life (Taheri, 2013). In this respect, Aristotelian logic is not sufficient to explain the events that occur in daily life. Fuzzy logic is widely used in problems that cannot be explained on the basis of Aristotelian Logic and because the parameters that are not taken into account in line with the 0-1 logic cause significant result changes in the equation, and because concepts such as "warm" are placed in the equation instead of just "cold" or just "hot".

Fuzzy logic entered the scientific world with the publication of Lotfi A. Zadeh's articles in 1965 (Zadeh, 1965). Artificial intelligence, probability theory, genetic algorithms (Holland, 1975) and artificial neural networks (Werbos, 1994) are used in the theoretical structure and functioning of the fuzzy logic model. In fuzzy logic, besides the possibility of events, the degree of possibility is calculated (Bush, 1996).

Fuzzy logic was initially viewed with suspicion, especially by researchers working on probability calculus. Therefore, its recognition and acceptance was slow until it was used by Japanese engineers who were practitioners. Fuzzy Logic, Assilian and Mamdan in 1975, was used in the control system of a steam engine, while it was used in the control of large and complex systems in the 1980s. In the same period, slow progress was achieved in theory and practice, as few scientists preferred to study fuzzy logic. As it has just been stated, the contribution of Japanese engineers to the advancement of fuzzy logic is great. Sugeno can be given as an example. In those years, the compatibility of the fuzzy logic model with new technological structures enabled it to be used especially in process control. In 1983, the control of a self-parking car was provided with fuzzy logic. The automatic brake control of the Sendai subway, which started in 1981 and was completed in 1987, was carried out with fuzzy logic. With this project, Japanese Hitachi company engineers Yasunobu and Miyomoto

put forward the most advanced subway control system of that period (Sugeno, 1985).

Fuzzy logic is preferred in computers used to reflect human thought in the inadequacy of classical logic. Fuzzy sets and their subsets form the basis of the fuzzy logic model. In the classical logic model, it is yes/no for an item to be a member of a set. That is, it is either a member or not of the relevant set. As it is known, general inferences can be made with symbolic logic rules and propositions that refer to both concrete and abstract facts.

These inferences are made at the beginning of the study by clarifying the ambiguities in the concepts and terms and giving them certainty. In the fuzzy logic model, ideal results are obtained by making use of symbolic logic, idealized terms and concepts. This situation contradicts the ordinary world. Because most of the events or phenomena that occur in the real world are blurry and uncertain. For this, Fuzzy control rules are determined. Afterwards, the blurring and sharpening operations are performed. (Ödük, 2019).

The scope of application areas of Fuzzy Control is wide. With the use of these applications, an economical control system is formed. Fuzzy Logic is a mathematical model that is used in daily life and provides interpretation of human behavior. With this aspect, fuzzy logic is used in many parts of human life. In fuzzy logic, membership can be assigned to intermediate values. For example, high, medium and low values. Moreover; It can be given with even more intermediate values such as very low, medium and very high. Fuzzy sets form the basis of fuzzy systems (Ödük, 2020).

The inconsistency of the third and the existence of the principle of non-contradiction are the most important elements of fuzzy logic. It is possible in fuzzy logic for a significance to be both true and false at the same time. This situation shows the similarity of fuzzy logic with real life. The uncertainty between being in an event or not being in an event creates a blur. One of the situations where fuzzy logic is perfectly appropriate is when it takes people's opinions into account when there is not enough information in very complex events. At the same time, fuzzy logic requires human understanding and judgment. Uncertainty is an important source of information in daily life, even if it is not

numerical. it is possible to use such information sources in the explanation of events, in fuzzy logic.

Communication between people is established by talking in daily life. With fuzzy logic, it is possible to model verbal ambiguities in people's speech. For this, these uncertainties are included in the analysis. If such information exists in this system, it is important to determine how it can be used in analysis. In fuzzy logic, an event is approximated and the model is controlled by simple mathematical equations.

Certain tolerance ranges of the inferences to be made in the fuzzy logic model are predetermined. However, when determining the tolerance range, excessive accuracy entails both high costs and problem solving. The successful solving of a problem depends on the selection of the most appropriate method with the appropriate numerical and verbal data collected. Fuzzy logic is very successful in the analysis of verbal data as well as numerical data.

The fuzzy logic approach includes interlocking, ambiguous statements instead of sharp statements. Due to this feature, it can make precise calculations in fuzzy logic. In order to analyze any situation of information systems, the rule set consisting of data and expert opinions is uploaded to the computer. Mathematical expression of verbal rules created in the form "If this is so and if this is so, do this". ... It is found by associating fuzzy sets with each other. Input engine is called this processing in fuzzy decision making process.

As mentioned before, there are two situations in which an element is a member of the set in a classical set. Belonging to the cluster (1) or not (0). In Fuzzy Logic, an element's belonging to that set ranges from 0 to 1. In other words, while there is a membership value of (0) or (1) in the classical set, there are values ranging from (0-1) in fuzzy logic. From this point of view, we can think of fuzzy logic as an extended classical set. Each element in the fuzzy set has a membership degree. The membership degree of the elements takes a value in the range of [0,1], which is determined by expert opinion.

If we explain the subject concretely, any temperature value can be warmer or colder than the temperature accepted in the classical set. Each temperature state in the fuzzy set is given a membership degree.

That is, each element has a membership degree in the cluster it belongs to (Ödük, 2020). As is known, the truth value of a proposition consists of a set of {0,1} values in binary logic. As explained above, in fuzzy logic, the truth value is chosen from the set of [0,1] ⊆ R numbers" (Ros 1995).

In Fuzzy Logic, the degree of occurrence of events is more important than the probability of them happening. Probability and fuzziness are models that differ from each other in terms of both meaning and mathematical structure. Probability is used to determine whether an event will occur or not. Fuzziness is used to determine the extent of occurrence of an event and the measure of occurrence of a proposition.

In order to explain the selected event with fuzzy logic, it is necessary to determine the boundaries of the inferences to be obtained as a result of the analysis at the beginning. This maximum sensitivity, in addition to reducing high costs, also sheds light on the explanation of very complex events. (Şen, 2009).

In summary, the main purpose of the logical logic model is to calculate the correctness value of a new proposition found with the help of the accepted proposition. Proposition is a concept that expresses certainty as true/false. If the proposition is true or false because of this truth or falsehood, the numerical value it receives is called the truth value. In the model, propositions are an expression of certainty.

Verbal expression is the concept that allows a decision to be accepted as right or wrong. With this decision, the boundary condition of the set is determined. When an object satisfies the boundary condition, it is assumed to be a member of the set. If an object does not belong to the related cluster, it is understood that the boundary condition for the object is not met.

It is not always true that fuzzy logic controllers are more costly and less reliable because they need more information about the process and sensors. The reason fuzzy logic controllers outperform conventional controllers is because a non-linear controller is used. However, most likely a nonlinear controller cannot be made with a small performance processor, similar to a fuzzy controller.

Expert knowledge is of great importance in determining the rules used in fuzzy control. There is no single recommended method for determining membership functions in the literature. The most suitable function that fits the model can only be determined by testing different functions. This method requires a long process. From this point of view, the response of the system cannot be predicted since stability analysis of the supervised system cannot be made.

Determining the set of fuzzy rules is the first step in fuzzy system analysis. The writing of the rules is carried out by taking the opinion of the experts related to the event in question. The fuzzy control diagram is expressed in Figure 5.

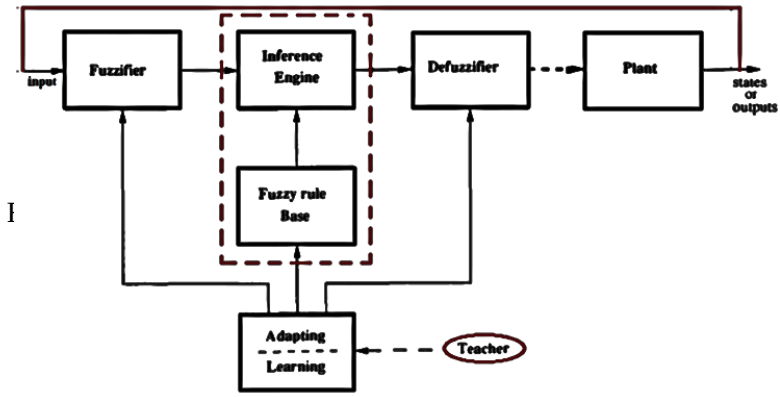

Figure 5. Fuzzy Control Block Diagram

Input: Input data has information about numerical or verbal inputs that must be given to the system.

Fuzzification: It is the first step of modeling with fuzzy logic. The exact values are converted to fuzzy values. It is the processor to which membership degrees are assigned. Numerical data is converted into verbal data. In fuzzification, it is the determination of elements with a membership degree between (0-1). For this, the numerical degrees of the membership are converted into fuzzy system symbols. Fuzzy values transformed into fuzzy symbols get membership degrees according to their membership functions. The process of converting a value to a fuzzy value is given in Figure 6.

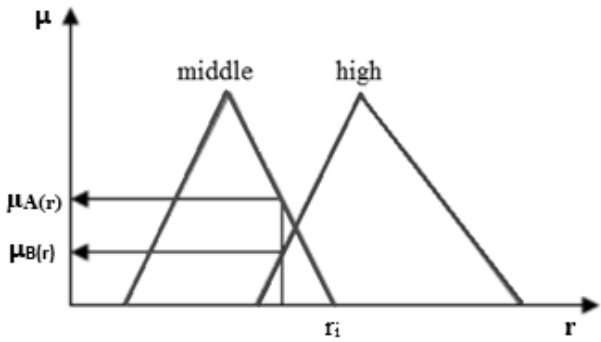

Figure 6. Fuzzfication Process

Fuzzy Rule Base and Database: It is the name given to the section that connects the input data, which can be written as an IF-THEN, to the output data. In the rules writing process, the rules for all connections between input and output data are constructed. Linking all of the mentioned inputs and outputs together forms. (Figure 7., Ödük, 2020).

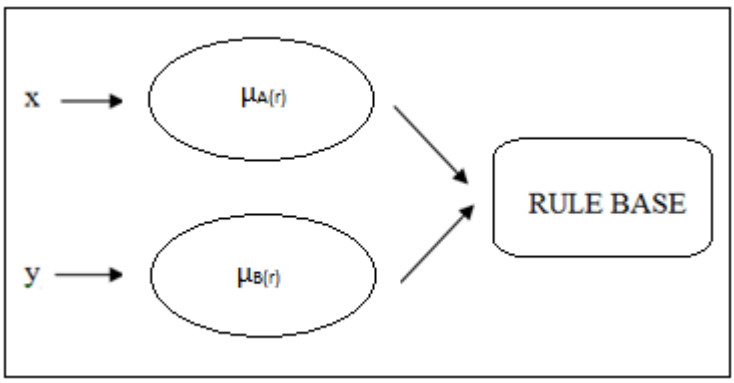

Figure 7. The IF-THEN Prosses

Fuzzy Inference Engine Mechanism: This mechanism sends all input and output relationships to the fuzzy rule base and makes it act as output. Output shapes of inputs are determined in this mechanism. In this mechanism, the ties of the input and output fuzzy values are summed in the fuzzy rule base. In this mechanism that works as a fuzzy inference compiler, it is the gathering place of the rules that set the movement of the system with an output.

This mechanism is accepted as the most important and main part in the application of fuzzy logic method. In this section, the fuzzy logic

application uses fuzzy concepts for human-like decision making and inference. Necessary controls are made after the conclusion of the inferences.

There are two kinds of inference rules in fuzzy logic. These are Generalized Modus Ponens, GMP and Back Chain Rule. Direct reflection and use of past examples in GMP; In GMT, there is direct thought and comparison.

The database, rule base, and rule analyzer are the entities that form the fuzzy controllers basis. Fuzzy controllers are a rule-based system. Here, rules established according to the IF-THEN system, types of membership functions and limit values can be found. Rule-based inference system the internal structure of a can be shown schematically as in Figure 8. The basis of fuzzy controller, database, rule analyzer and rule base form the fuzzy controllers basis. Fuzzy controllers are a rule-based system. Here, rules established according to the IF-THEN system, types of membership functions and limit values can be found. A rule-based inference system internal structure of can be shown schematically as in Figure 8.

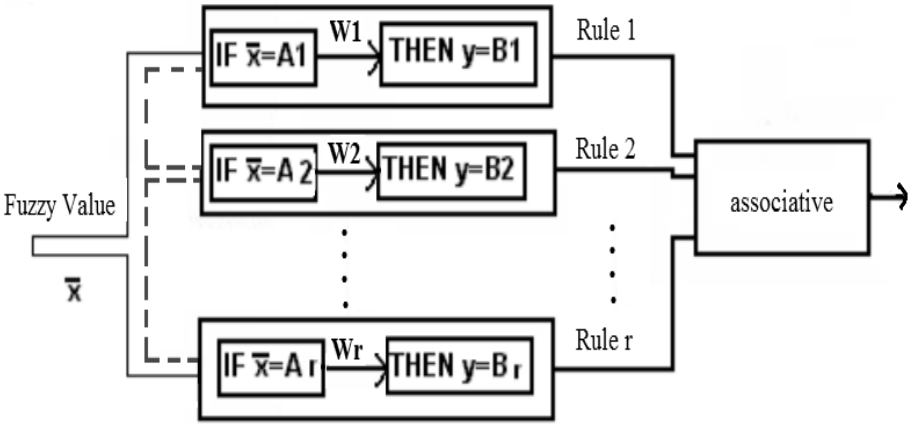

Figure 8. Sturucture of Fuzzy Rule - Based Inference System

2.1. Determination of Membership Degree

Fuzzy sets can be expressed with membership functions. Membership functions give the weight of each object in a set. This degree of gravity can be from 0 to 1. The part of the subset where the

items with membership degrees equal to 1 are collected is called the Core of that subset.

Here μ(x)=1. In contrast, the range containing all the elements of a set is called the support of that set. Each underlying item has more or less degrees of membership (between 0 and 1). The mathematical expression for this is 0<μ(x)<1. The parts formed by the elements whose membership degrees are not equal to 1 or 0 are called the boundary regions of the membership functio

Formula 1 shows elements A_1, A_2, A_3, A_4 and A_5. Since it belongs to the set x, it shows that the member membership degrees are equal to 1 (Şen, 2011).

$$x=\{A_1,A_2,A_3,A_4,A_5\}\ ;\ m_{A1}=m_{A2}=m_{A3}=m_{A4}=m_{A5}=1.0 \quad (1)$$

In clusters, the membership degree value take different between [0-1]. Each of the real numbers on the horizontal axis corresponds to the membership degrees, that can take different between [0-1] on the other axis (Figure 9 Şen, 2010).

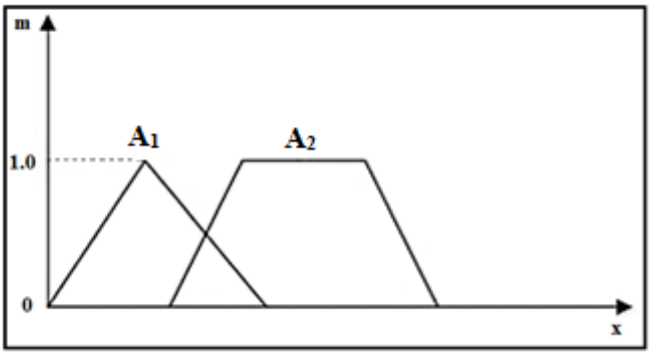

Figure 9. Degrees of membership in fuzzy sets

The elements in a classical set "x" are specified as x= {x_1, x_2, x_3.., x_n }. The elements in a fuzzy set "x", together with their membership degrees;

$$X=\{\frac{m(x_1)}{x_1}+\frac{m(x_2)}{x_2}+\frac{m(x_3)}{x_3}+\ldots+\frac{m(x_n)}{x_n}\} \quad (2)$$

m(xi), the degree of membership and xi the element value. In conditions where a fuzzy set reveals continuity, (3) (Şen, 2010).

$$X=\{\int \frac{m(x)}{x}\} \quad (3)$$

Membership functions are determined by the expert. The subsets of the sample according to the weather conditions given by Şen (2011) as an example for the membership function can be explained with Figure 10.

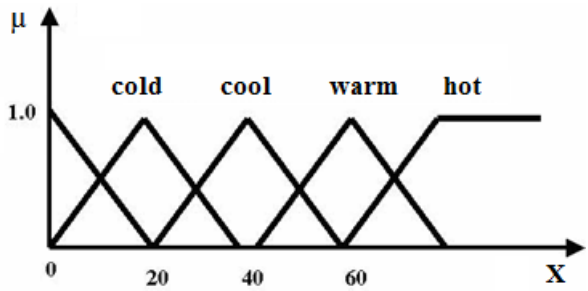

Figure 10. Example of Temperature fuzzy subsets (Şen, 2010)

Function forms may change according to experts' opinion. There aredifferent forms of membership functions in fuzzy models.

In most applications, the membership function is in a simple form as given in Figure 11. Membership functions basic forms (triangle, trapezoid, quadratic, gaussian, bell curve) are shown in Figure 11. In fuzzy logic theory, expressing the boundaries of the region and verbal expression of the membership weights of the sensor information can only be achieved by determining the appropriate membership functions. Functions have no shape and number limitations. (Ödük, 2021).

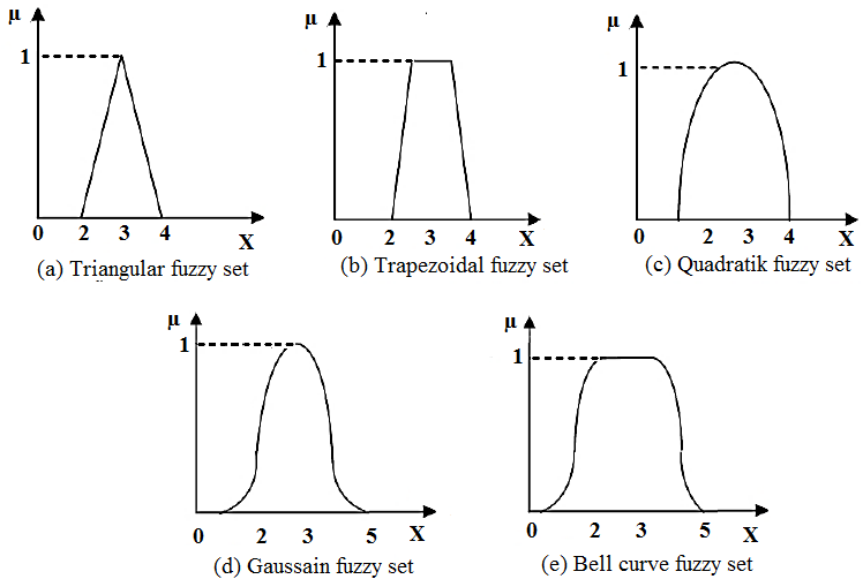

Figure 11. Membership functions Forms

In systems based on fuzzy logic, the triangle membership function is mostly preferred in the expression of output and input parameters. The trapezoidal membership function is also used to indicate both output and input variables. The Gaussian membership function can be customized with parameters {c, σ}. It can be used to express the output and input variables for the systems to be controlled (Elmas, 2003; Jang et al., 1997).

Preferred inference methods in fuzzy systems:,

a. Mamdani Inference
b. Sugeno Inference

There are also Tsukamoto inference and Larsen inference methods.

a. Mamdani Inference: This method is the most preferred inference method in fuzzy. The main reasons for choosing the Mamdani inference are that it is easy to design and more interpretable.

It was named Mamdani because it was first designed by İbrahim Mamdani in 1975. In his study, he created a set of verbal control rules by taking advantage of expert opinions. He provided the control of the steam engine and boiler system with the model.

In this inference, inputs and outputs consist of fuzzy values. The rules that determine the membership values are determined according to the input values. The specified values are passed to the max or min operator according to the rules and/or element connectors. The choice of max or min operator depends on the rule facts and/or state. If the fact in the rule is related to 'and', membership values are given to the min operator. Similarly; If the fact in the rule is related to 'or', membership values are transferred to the max operator.

These operators rotate the minimum value and the largest selected among the assigned values.

According to the Mamdani inference method; The determined fitness values are transformed to the max or min operator for triggered rules and the obtained values are matched with the linguistic values of the result value given in the rules (Figure 12).

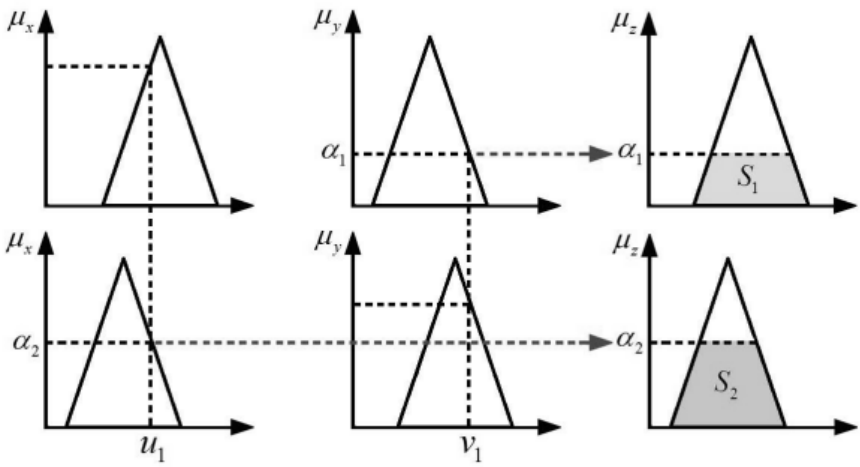

Figure 12. Structure of the Mamdani fuzzy inference method

Finally, in the Mamdani deduction; The areas cut by the obtained membership values on the result sets are calculated. These areas are summed and the total area value found is then scaled from fuzzy values to values in the desired range using defuzzification methods.

In the Mamdani inference method process, the membership levels obtained as a result of the fuzzification unit operations and the output membership function are correlated by using the minimum relation operator information. The fuzzy logic model provides more useful and

easier modeling than classical logic, especially in modeling problems that do not contain exact numerical values. The advantages of the Mamdani method are that it can be designed easily and that it is highly parallel to human behavior.

b. Sugeno Inference: This inference method gives suitable results especially in control problems. Because of this feature, it is preferred in this type of analysis. The difference from the Mamdani inference system is the form of output value. Fuzzy values are produced in Mamadi system. But in Sugeno inference, the output value is a function. As a result, it is as simple as calculating the mean from defuzzification operations in Sugeno inference.

In the Mamdani method, we saw that the output value is defined as a fuzzy set as well as the input values. In Sugeno, on the other hand, while the inputs can be in the fuzzy set form and output should be defined as a function, usually polynomial (Figure 13).

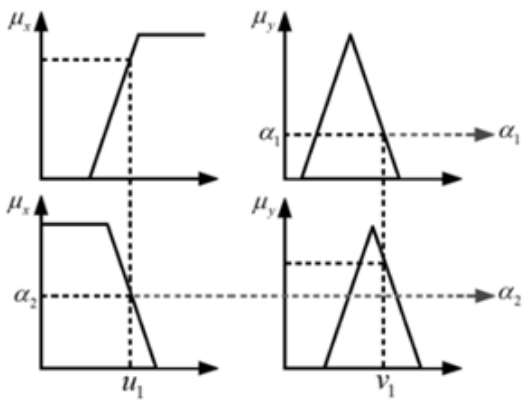

Figure 13. Structure of Takagi-Sugeno fuzzy inference method

According to Sugeno inference system, levels of the membership from the fuzzification unit can be related with the polynomial output membership functions (Jang, 1997). The Sugeno inference system, on the other hand, is very suitable for mathematical analysis and calculation and gives numerically precise results (Takagi and Sugeno, 1985).

The biggest advantage of the Sugeno inference system is its computational convenience. Besides, it works well with adaptive

techniques. Another positive aspect of the method is that it is suitable for mathematical analysis. However, the system is not compatible with human intuition. In the implementation of the system, there is an increase in the number of inputs and subsets. Therefore, it makes it difficult to train the data. Parallel to this, the number of final parameters determined to find the result also increase

Defuzzification Module: It is the mechanism by which fuzzy inference results are converted into digital outputs. It is the opposite of blurring. Defuzzification is applied to both input and output data. The fuzzy set emerges as a result of the inference process. Because fuzzy sets do not exist in the ordinary world. Therefore, the fuzzy value can be converted to real value.

Clarification methods commonly used in the literature are as follows:

a. Clarification with Center of Gravity Method

The exact value of BMD can be found by calculating the following equations.

Discrete domain can be calculated by (4);

$$u = \frac{\sum_{i=1}^{1} u_i . \mu_{out} u(u_i)}{\sum_{i=1}^{1} \mu_{out} u(u_i)} \tag{4}$$

and continuous domain;

$$u^* = \frac{\int u . \mu_{out} u(u)\, du}{\int \mu_{out} u(u)\, du} \tag{5}$$

can be calculated. Here, u_i represets i. membership function and μ_{out} $u(u_i)$ means i. is the degree of membership function.

The center of the region under the combined membership functions is determined by this method.

Defuzzification by Weighted Average of Centers

This method is applied to output sets with symmetric membership functions. The fuzzy output data can be found from the combination of the dedicated A_1 and A_2 fuzzy output sets. The approximate value of the center of gravity can be found using the weighted average of the centers of the implied output sets x_1 and x_2. The values of the centers of the implied output sets having the same form.

It is preferred because it is easy to calculate the output and does not need improvement. Its value can be estimated using direct implied output sets (Akpolat, 2000).

w_n represent the certainty degree of the relevant rule.

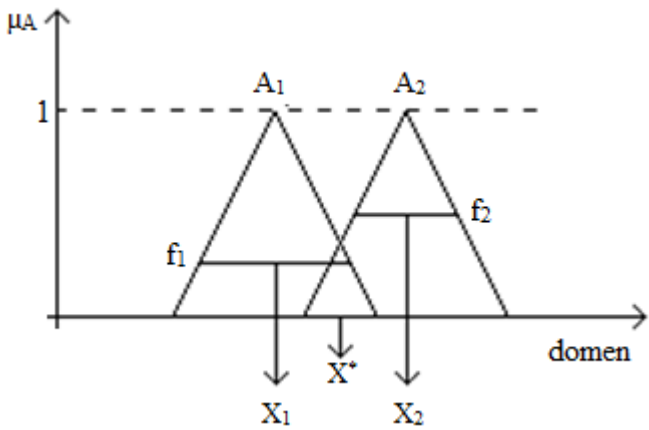

Figure 14. Weighted Average of Centers Method4

b. Clarification by Calculating the Center of the Largest Region on the Domen

In this method, when there are at least two convex fuzzy subsets in the output fuzzy set, the centroid with the largest area in the convex fuzzy set is used in the defuzzification process (Figure 15). The formulation of the system is shown in (6).

$$z^* = \frac{\int u_{ebC}(z) z dz}{\int u_{ebC}(z) dz} \tag{6}$$

$u_{ebC}(z)$ represents the sub-region dominated

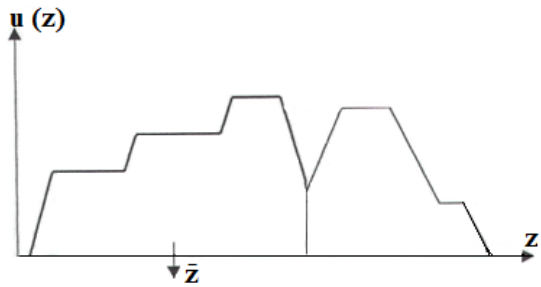

Figure 15. Defuzzification by Calculating the Center of the Largest Region on the Domen

c. Average of Maximums Defuzzification Method

The control motion is estimated by process mean of the points on chosen area where all membership function represents maximum degree of membership. (7) is used for finding area (z).

$$z^{*}=\frac{a+b}{2} \tag{7}$$

It is determinated by using the fuzzy output sets)Figure 16). It is calculated by (8)

$$z^{*}=\frac{a+b}{2}=\frac{6+7}{2}=6.5\text{m} \tag{8}$$

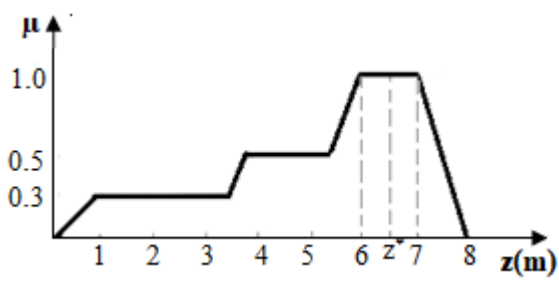

Figure 16. Defuzzification by Maximum Membership Function Average Method

The advantages of the fuzzy logic method::

- It provides simple suggestions for the control of complex and ill-defined systems that are unpredictable, change over time, as in daily life.

- The mathematical principles on which it is based are easy to understand.
- It is easier to analyze nonlinear, time-varying and uncertain systems, which are difficult to solve.
- Expert can define his own experiences in the system as rules for solution
- It can be easily applied to systems/problems in many areas.
- Operations can be made with missing data.
- When the system is too complex to be explained with a simple mathematical model, fuzzy logic can produce easier and cheaper solutions than conventional logic.

Disadvantages of the fuzzy logic method:

- Fuzzy control rules are determined based on expert experience.- Requires a lot of data usage to solve the problem.
- Certain rules cannot be followed in the selection of the membership functions used.
- The more complex the problem, the more difficult it is to identify control sets and membership functions. This increases the resolution time.

Fuzzy control is appropriate when a simple mathematical modeling system cannot be expressed, processes with highly nonlinearity are controlled, and systems with memory limits. In addition, It is not recommended to use fuzzy control if traditional control approaches give satisfactory results, an easily solvable mathematical model is available, and the hardware to be used supports traditional control strategies (Büyükkarcığan, 2022).

The first academic fuzzy logic application in the literature was a steam engine by Ebrahim Mamdani in 1973. In 1980, fuzzy logic modeling of the kiln control of a cement factory in Denmark was the first commercial application. Cameras produced using fuzzy logic give a clearer image even than those with autofocus. In addition, fuzzy logic, computer, machinery, construction, environment, electricity, electronics, agriculture, food, chemistry, biomedical, geology, and mechatronics, applied mathematics, natural sciences, medical research, economics, management, political science and psychology, public It is used by policy analysts, business analysts and law.

Applications of fuzzy logic in concrete areas: power systems, medical diagnosis and treatment plans, subway systems, facial pattern recognition, air conditioning systems, electrical appliances, anti-slip braking systems, information-based systems for multi-purpose optimization, transmission systems, weather forecasts, product pricing , stock trading, models for project risk assessment. There are examples of successful applications in many different fields such as fuzzy logic, industrial automation, image processing, control systems, robotics, optimization, energy engineering and consumer electronics.

Some of the studies in fields differnet from civil Engineering include urban development modeling (Liu and Phinn, 2003), creating and applying the decision model in economy management (Ouyang, 2022), Computing and Construction Fields (Akyol et al., 2009), evaulation of renewable energy systems (Suganthi et al., 2015), microelectronic Design (Baturone et al., 2018), medical expert systems (Awotunde et al., 2014; Korenevskiy, 2015; Öduk, 2021, Kaur and Singh 2022), Investigation of concrete strengths produced with different cement mixtures by fuzzy logic method (Büyükkaracığan et al., 2011),

pavement rehabilitation and maintenance prioritization of urban roads (Moazami et al., 2011), work accident and occupational diseases risk management (Nunes et al., 2012), food and beverage processes (Birle et al., 2013), landslide susceptibility analysis (Pradhan, 2010), social sustainability performance evaluation of automotive component manufacturing organization (Rajak and Vinodh, 2015) , biomedical informatics analysis (Patel et al., 2013), predicting roof fall rate in (Ghasemi and Ataei, 2013), analyiss of a security control lane (Kierzkowski and Kisiel, 2017), control of the heating system (Kobersi et al., 2013), bankruptcy risk assessment (Gim and Whalen, 1999), planning and decision making (Lootsma, 2013), Thirty criteria based leanness assessment (Vinodh and Vimal) , 2012), energy management modeling (Roumila et al., 2017), supply chain performance management nad measuring practices (Ganga and Carpinetti, 2011; Kozarevic, and Puska, 2018), evaulation of education system (Mago and Sandhu, 2013), churn prediction on education data (Supangat et al., 2021), academic performance analysis (Yadav and Singh, 2011; Aziz and Hashem, 2019; Ramírez-Coronel et al., 2020), justice applications (Turcoane, 2012; Cooper and Ternes, 2013; Hussaini, 2022), fire

support planning (Pereira, 1999), greenhouse automation (Ödük and Allaverdi, 2009), lift system control of high-rise buildings (Ödük et al., 2011), agricultural practices (Ödük, 2020; Puska et al., 2021; Paul et al., 2021).

2.2. Adaptive network-based fuzzy inference system (ANFIS)

ANFIS is a well-known ANN method whose methodology is designed according to the Sugeno fuzzy inference system. It is designed for modeling nonlinear functions. Due to its methodology, ANFIS can benefit from both fuzzy inference methods and neural network methods. Insufficient information input and comprehension problems in other models were effective in the development of the ANFIS model. Understanding the knowledge learned in neural networks is difficult. Understandable verbal expressions in fuzzy logic make it easier to understand the information learned with neural networks. In this respect, a more understandable flow of information can be provided between the system and the user (Büyükkaracığan, 2013)..

As mentioned before, the ANFIS model uses a hybrid learning algorithm as well as a sugeno type fuzzy inference system. The elements that make up the model are adaptive networks, directly connected nodes. In the system, a node corresponds to each processing unit. The relationship between the nodes indicates an indeterminate correlation among themselves. The adaptability feature is valid for both all nodes and some of them.

The ability of ANFIS to create rules can be achieved by benefiting from expert opinions. Expert opinions are used to predict many problems in artificial neural networks. Since the expert opinion conveys his experience, better results can be obtained from the mean squares of error (MSE) criterion. At the start of the fuzzy system, the system is blurred with the Anfis 1 or Anfis 2 commands. Entering parameters for learning is done by determining score of iterations and determining error tolerance. The learning process can be started by using ANFIS commands and the process is stopped when the tolerance is reached. The transaction must be verified with independent data. The schematic structure of the ANFIS model is shown in Figure 17.

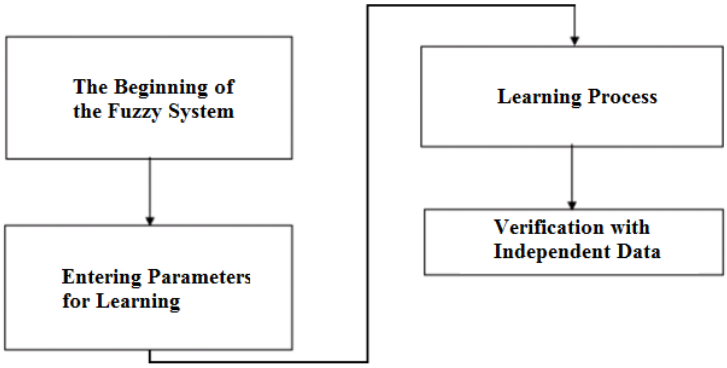

Figure 17. Flowchart of ANFIS model

The functioning of the layers in the ANFIS structure are input layer, blur layer, rule layer, normalization layer, rinse layer and total layer respectively (Gemici et al., 2013). The inference system of the ANFIS system is shown in figure 18.

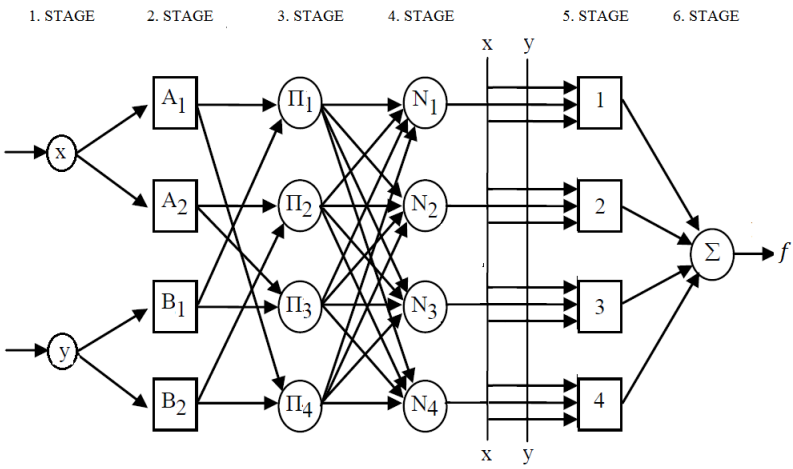

Figure 18.ANFIS extraction system

Exampe

In order to give an application example of ANFIS, a summary of the work done by the author himself and presented at a congress in 2021 is given (Büyükkaracığan, 2021).

In this study, daily flow data values of Çarşamba Stream.-Sorkun Flow Observation Station No. D16A115 were used. This station is on Çarşamba Stream in Konya Basin. The code of the observation station

for the 84 km2 watershed area is 1150 m. In the calculations, meteorological observation station data in Seydişehir and Hadim were used as precipitation data. C_t; Since the value is mountainous terrain was taken 1.2. h_a = 525.3 mm. K value was taken as 0.208. 10 years of river flows were analyzed (Büyükkaracığan, 2020).

Fuzzy logic modeling has been carried out with the ANFIS plugin in MATLAB program. In the ANFIS model, the types of input and output membership functions that give an acceptable error value with the trial-and-error method for each input combination and the number of membership functions are determined. 70% of the data set was taken as a training and the remaining 30% was taken as a test. Input values are current values one, two and three days ago, while output value is current value. During the training of the network, 3 sub-sets were used. Different forms of membership functions were also tried, and the most appropriate form of membership function was found to be triangular. The most successful forecast was the forecast for the day before. Here, the login membership functions gaussmf, gauss2mf, trimf, trapmf functions are used. Values between 1-3 are tried for each login function as the number of membership functions. Constant (Cons.) And linear functions are used as output membership function. The first 50% of the data set was trained as a block and the following part was tested as a block.

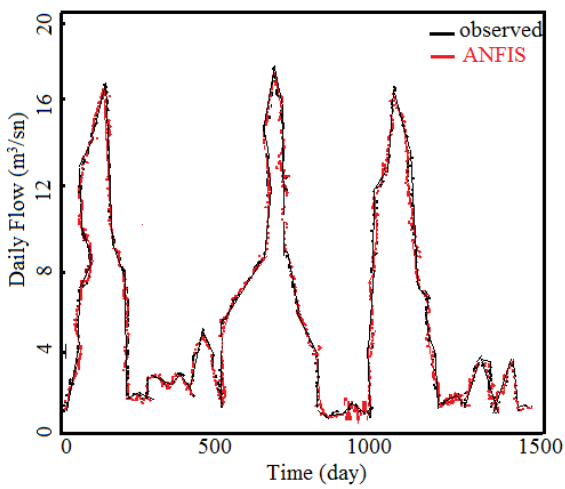

Figure 19. ANFIS Prediction-Observation Time Series

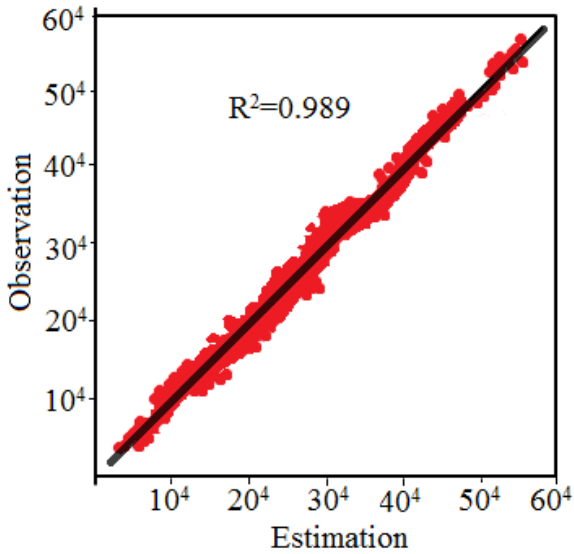

Fig. 20. Results of ANFIS Method

Since the internal dependency is very strong in daily flow data, all models made using one and / or two days and / or previous values have made very good predictions. As can be seen from Figure 4 and Figure 5, modeling with ANFIS has given good results.

It is used simply in modeling with fuzzy logic, modeling of all natural phenomena without requiring any pretreatment. They can be used frequently as developable methods for researchers working in the field of hydrology (Altunkaynak and Başakın, 2018). As a result, ANFIS fuzzy logic method applications have been shown to perform successfully in current prediction.

2.3. Applications in MATLAB Simulink Environment

Matlab software is a computer software for numerical calculation, data analysis and display, and interactive algorithm development. MATLAB is a program that prepares the infrastructure for the user to easily calculate very complex matrices. At the same time, a wide variety of algorithms are implemented with the use of this program. It is possible to create user interfaces depending on the user's demand. It enables to draw functions and data which are essential especially in engineering applications. These interfaces are written in other

languages such as C, C++, Java and Fortran. MATLAB implementation of fuzzy logic method is explained using functions registered in "Fuzzy Logic Toolbox".

The toolbox also contains scripts and tools with graphical interfaces that can be used by developed software interfaces. In this way, they can develop fuzzy inference systems and communicate with other software interfaces. The Matlab program supports script files that can host a series of Matlab commands called "m-files" in the same file in order of operation and run them with a single command. However, m files can also be used to call one or more functions that can output an output.

For example, the "genfis2" function can be performed to create a fuzzy inference model. The fuzzy function creates the relevant Sugeno type fuzzy inference infrastructure by finding the rule bases to model the data behavior of available data set with the subtractive clustering method. For this purpose, it first uses the "subclust" function is used for determinning the number of rules. Then, it creates the rules to be used in the model with the least squares estimation method.

An interface called fuzzy inference should be used. The interface in question consists of 5 sub-interfaces: FIS Editor, Membership Function Editor, Rule Editor, Rule Viewer and Surface Viewer. During the modeling phase, the FIS Editor opens. Structure, memberships and rules are defined in this interface. Rules and surfaces can be followed according to the entered inputs (Figure 21).

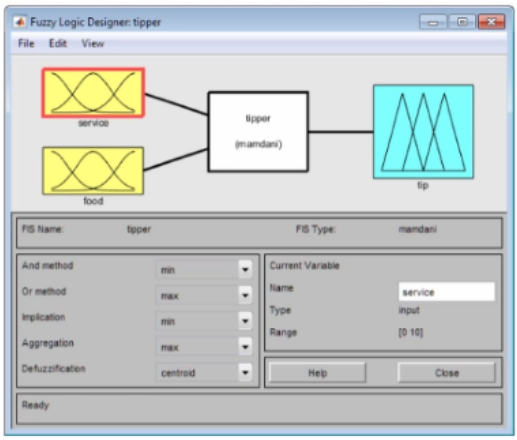

Figure 21. Fuzyy Logic Designer Tipper

With Fuzyy Logic Designer App, the system's input / output numbers and variables and their names are entered. Here, the membership function form is defined for each variable membership. There are 11 predefined shapes in the system. Besides, users can also create them privately.

After the membership functions are created, the rules that will determine the behavior can be created with the Rule Editor Tipper and can be corrected later (Figure 22).

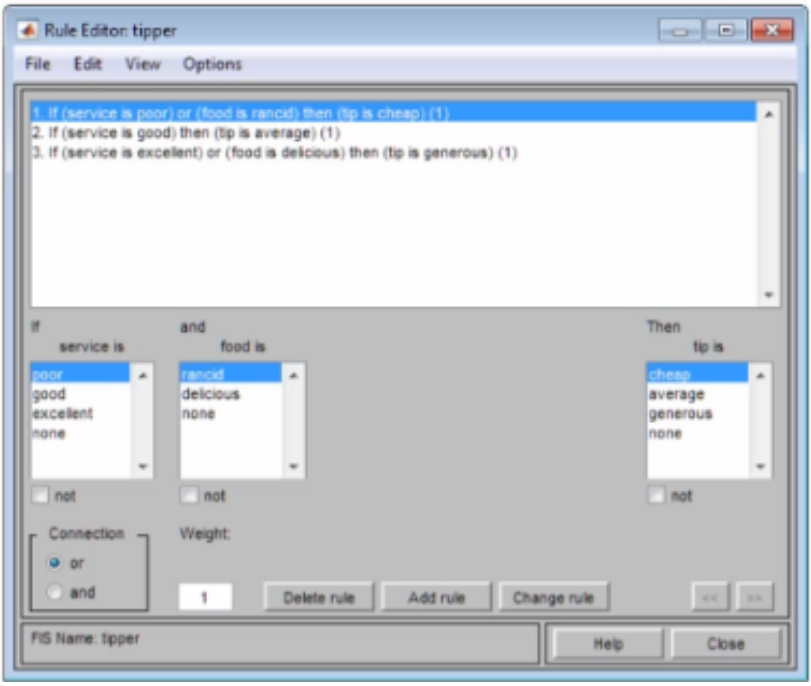

Figure 22. Rule Editor Tipper

With the help of the Editor, AND/OR relations can be established between the relations. The established rules can be changed and additions can be made.

After the rule definitions are completed, it’s possible to find our which rule is active with Rule Viewer (Figure 23).

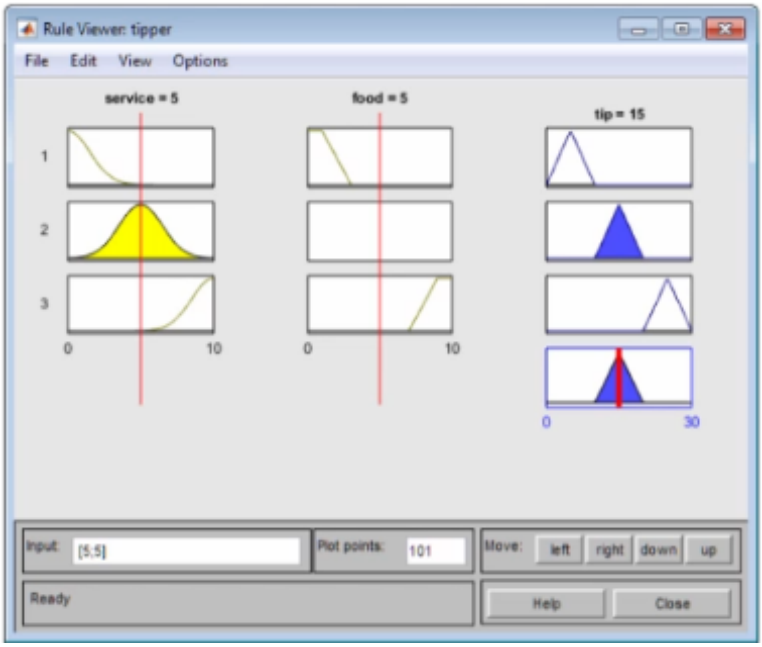

Figure 23. Rule Viewer Tipper

For the realization of all these applications, it can be realized by transferring the algorithms previously created in the simulink block to MATLAB.

2.4.Applications of Fuzzy Logic PD Controller in MATLAB Fuzzy Logic Toolbox Environment

In the Matlab environment, Fuzzy Logic Toolbox is opened by typing “fuzzy” on the command line. Input and output variables are determined and named (Figure 24).

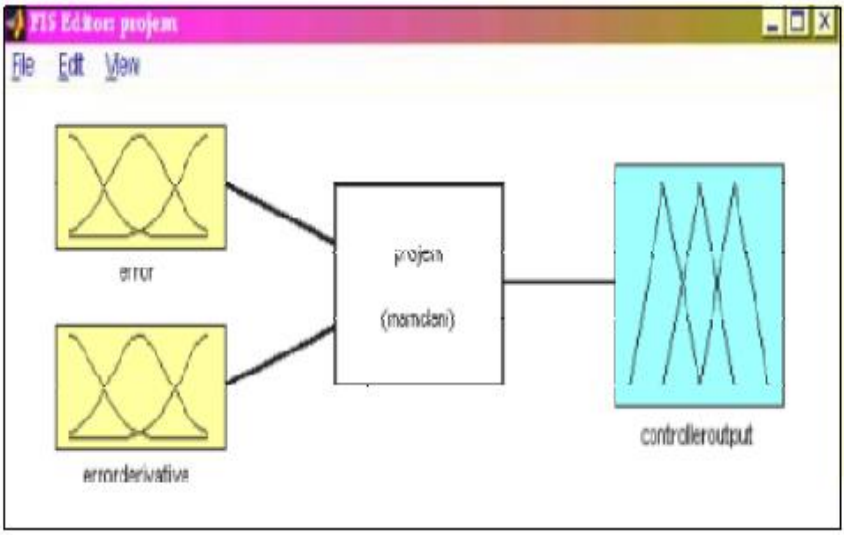

Figure 24. Fuzzy logic input and output variables

The membership function must be defined for each entry registered in the system. One of the membership functions used in the system is selected. The creation of membership functions in the FIS environment is selected as follows. PD Controller Output Values should be considered while creating these membership functions. In the FIS environment, double-clicking on the error variable opens the Membership Function Editor (Figure 25).

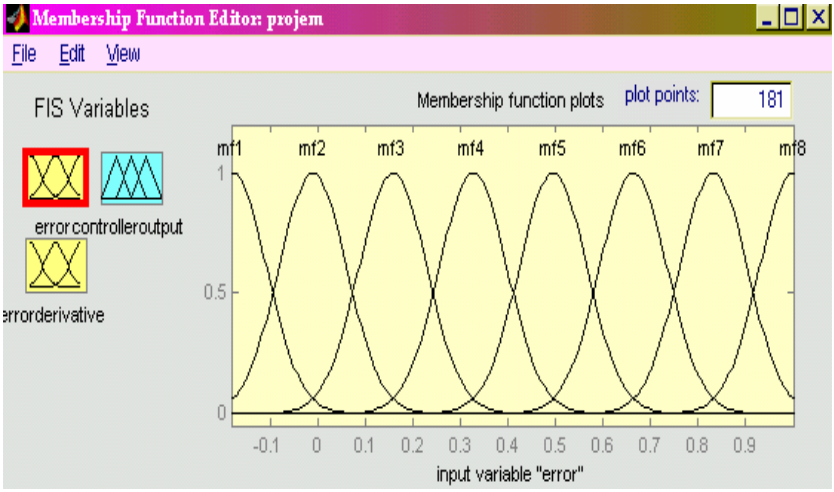

Figure 25. Membership Function editor and error

Membership Function Editor is accessed by double-clicking on the error derivative variable in the FIS environment (Figure 26).

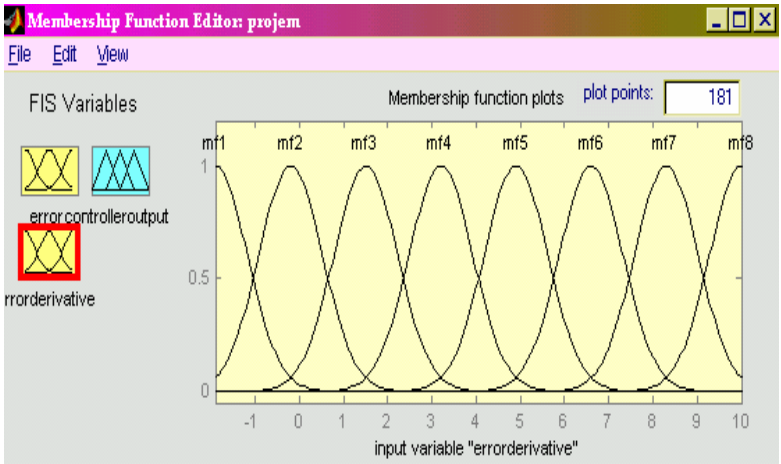

Figure 26. FIS editor and derivative of error

Similarly, in the FIS environment, double-clicking on the controller output variable opens the Membership Function Editor (Figure 27).

In order to observe the clarified output values, and to obtain numerically how the change in the input parameters affect the output parameter, again from the View option, the Rules tab should be selected and checked.

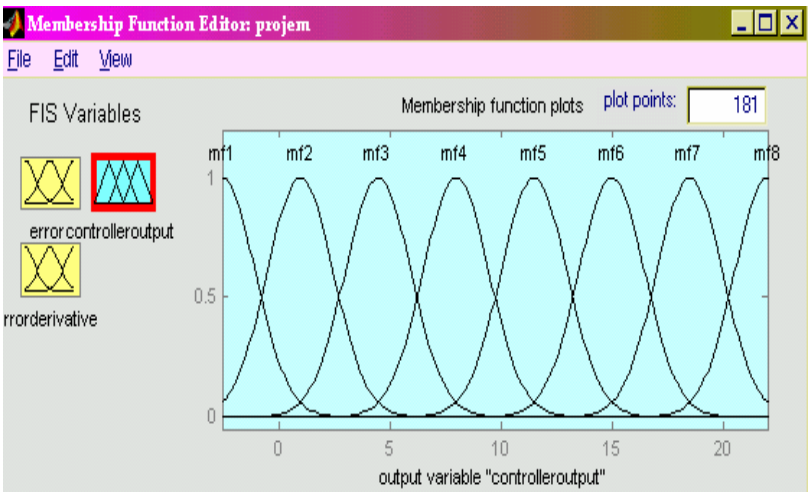

Figure 27. FIS editor and controller output

Rules are used to determine the relationship between input and output values. Fuzzy logic rules are prepared according to the traditional PD controller structure and are only required for design. PD Controller Output Values are matched according to certain time intervals and the matching according to the membership function which these values belong can be carried to the FIS rules.

In the FIS environment, the Rule Editor, which is accessed by opening the Edit menu on the FIS editor and selecting the Rule Editor, opens.

The AND (and) fuzzy operator is used when writing rules. The interpretation of the rules as a result of using this operator can be seen with the help of Rule Viewer. Rule Viewer can be opened by opening the View menu on the FIS editor and selecting Rule Viewer.

3. FUZZY LOGIC CIVIL ENGINEERING APPLICATIONS

Civil engineering is basic engineering branche that took place with the existence of humanity. Civil engineering interests include buildings, industrial structures, roads, bridges, canals, dams, airports, sewer systems, pipelines, structural components, management of structures. A civil engineer is a technical staff member who is responsible for the study of all these structures, then planning, calculating and drawing the project, supervising its construction and operation after completion. The first applications in the history of engineering were carried out by civil engineers.

Structural engineering is a department that performs static and dynamic analysis of all kinds of structures. It can be said that it is the basic branch of civil engineering. Because no matter what branch they work in, civil engineers need to train themselves in static, dynamic, reinforced concrete and steel construction. Structural engineers also study the mechanical interactions between the structure and the ground on which the structure sits. Structural engineer is the person responsible for the design of structures with sufficient rigidity and in an economical way. It is responsible for determining the forces and stresses that may occur with the static analysis of the structures and making calculations accordingly. In structural engineering, sub-disciplines such as wind engineering and earthquake engineering have emerged according to the fields they deal with (Narayanan and Beeby, 2017).

The structural mechanics branch undertakes the studies related to strength, that is fundamental and important subjects. Deformation, displacement and stress of any structure, also sizing building sizing elements are other study areas of this department. It studies the behavior of rigid and deformable bodies.

Building materials engineering department is responsible of the building material to be constructed at every period of the construction. Concrete, cement, steel, wood, plastic etc. used in the building. It provides services in the production, development and quality control of building materials. Subjects such as material technique, deterioration of materials, rusting are also the subjects covered by this department. In addition, this branch also takes part in forensic engineering and structural damage analysis.

Earthquake Engineering is a science related to the identification of earthquake source, reduction of earthquake risks, and design of earthquake resistant structures. Earthquake engineer, on the other hand, is a person who analyzes the earthquake behavior of soils, structures and systems and examines the properties of ground motion. In terms of civil engineering, earthquake resistant building design is at the forefront. The fact that our country is located in an earthquake zone and painful experiences have increased the sensitivity to earthquakes. For this reason, the importance of this branch of engineering, which is a increasing sub-branch of structural engineering.

Construction management calculates all the costs required for the construction of a building and is responsible for making the plan and schedule, selecting materials and providing equipment. The main purpose here is to do the best quality work with the least cost. It is the planning, execution and supervision of a construction project, ensuring that it is completed within the specified time, budget and quality.

transportation engineering is the department that is responsible for all infrastructure, superstructure and ground survey studies required for land, air and water transportation, and the same studies for railway and sea transportation. In addition to these, urban traffic planning is one of the responsibilities of this branch. In this respect, transportation engineering is a branch related to transporting people and goods in an efficient, safe and environmentally friendly way. The main subject of transportation engineering is transportation structures. These structures are highway, port, railway, airport. The transportation engineer also monitors all business activities related to public transportation, their infrastructure. These activities include design, construction, control and maintenance. The working areas of engineers in this branch are design of transportation structures, transportation planning, intelligent transportation system, traffic engineering, infrastructure management and pavement engineering.

Highway engineers are the branch of engineering responsible for the planning, construction and control of highways and the regulation of traffic flows. In a broader sense, the highway engineer is responsible for making the passages of river structures, ditches, tunnels, water, electricity and telephone installations on the road route and observing the natural compaction, to pour soil on the settlements, to pour crushed

stone and asphalt to cover the road, to make drainage channels on the road sides, etc. performs tasks and procedures.

Bridge engineers deal with bridges that are built to allow pedestrians and vehicles to cross valleys, rivers, roads and other obstacles. Engineers are responsible for bridge site detection, planing, design, construction, repair and inspection activities.

Railway engineering is sub-branch of transportation engineering concerned with the planning, design, building, controlling and operation of the railway system. A railway engineer, on the other hand, is a person who uses tools, equipment and equipment effectively, examines the construction site in accordance with occupational health and safety, environmental legislation and the quality requirements of the profession, to determine the railway route and to construct bridges and culverts. Tunnel and retaining walls, railway length and width calculations, repair of damaged rails, maintenance and repair of bridges and tunnels.

Hydraulic engineering is a branch of science that studies water forces, precipitation, behavior of surface waters, water structures, ports, coastal structures and water resources. Hydraulic Engineers are those who deal with the planning, design and operation of dams and ponds, water supply and distribution, environmental sanitation facilities, port facilities and marine structures. Water resources engineering, on the other hand, is a branch related to the collection and management of water.

Geotechnical engineering is a branch of enginnering responsible for the determination of the structure of the ground on which the structure will be placed, the strength of the ground and its bearing capacity, and research activities. After these studies, it conducts research on all activities related to placing the building on the ground in an economical and safe manner.

Tunnel engineering is a sub-branch of science which conducts research on the planning, design, building and operation of tunnel projects by determining the scope and scale. Tunnel engineer, on the other hand, is responsible for providing a safe working environment at the Tunnel project site, controlling the work done, arranging areas such as occupational safety and quality control.

Fuzzy logic finds a wide application area in civil engineering in parallel with the developments in other branches over time. The best application areas of the fuzzy set concept in the field of civil engineering have come to fore in construction business studies because verbal expressions can fit into a mathematical model.

Civil engineering projects take place under a wide variety of uncertainties. As a result of the uncertainties and risks caused by both the structures of the projects and the environmental effects, there are difficulties in determining the activity durations during the work program construction phase. At the same time, one of the best solutions for such uncertainties in water resources engineering and transportation engineering, which is affected by many random variables, is fuzzy logic approach.

In order to make fuzzy logic modeling, first of all it is necessary to blur the input and output data. In the most general definition, fuzzification is the expression of numerical data and linguistic expressions as fuzzy membership functions. The second stage is the creation of fuzzy rule bases. A fuzzy rule base is created with the rules written in the IF-THEN type connects the inputs in the database to the outputs. The mechanism, which includes the collection of operations that gather the relations established on the basis of the fuzzy rule and ensure that the system behaves with a single output, is the fuzzy inference collection. In this engine, the inferences of all the rules are gathered together and it is determined according to the inputs, it is estimated what type of output can be obtained from the system. In the clarification process, which is the last stage of modeling with fuzzy logic, the fuzzy information is converted into definite results. That is, defuzzification is the re-digitization of blurred data.

The application principles of fuzzy logic method in different disciplines of civil engineering are given at this stage.

3.1. Principles of Applying Fuzzy Logic in Different Disciplines

Information about the process flows of fuzzy logic applications in different civil engineering fields is given in this section,. The mentioned process steps are selected from the applications in the

literature and the appropriate ones are given. Different field, practical and tangible success were determined as selection criteria.

a. Determination of Concrete Compressive Strength

As input to the fuzzy logic method created to estimate the compressive strength of concrete samples; Membership functions are created for age, area, breaking load parameters. Membership functions of the compressive strength selected as output are determined. These models can be determined separately for cube and cylindrical samples. Example rules:

- If (age 7) and (area cylinder) and (fracture load is normal) it is (cylinder mf7)
- If (age 14) and (cylinder area) and (breaking load is bad) it is (cylinder mf5).
- If (age 21) and (cylinder area) and (breaking load is good) it is (cylinder mf6).

After modeling, the validity of the model is tested by using the calculation results. Based on the inputs in the explanation screen, the concrete compressive strength is calculated with the model. The compressive strengths obtained as a result of the test should be compared.

b. Determination of bearing capacity moments of reinforced concrete beams

The numerical data of the created fuzzy logic model; beam width, beam height, characteristic compressive strength and reinforcement ratio between maximum and minimum reinforcement ratio and a coefficient k with a value between 0 and 1 are considered as variable parameters. The only output of the model is designed as the beam bearing moment. It is necessary for the developed fuzzy logic model to be able to address more general analyzes and for all beam section geometries in this study, common fuzzy sets should be defined for the reinforcement ratios that do not exceed the min.- max. limits stipulated by regulations. In order for the fuzzy logic algorithm to experience the problem, fuzzy sets of the four variable parameters mentioned above are created.

For example, for the Beam width parameter, the fuzzy set is 200,250, 300; fuzzy set 300, 400, 500, 600 for the beam height parameter; fuzzy set 20, 30, 40, 50 for characteristic compressive strength parameter; For a k coefficient variable parameter that takes between (0 – 1), the fuzzy set can be taken as 0, 0.25, 0.50, 0.75, 1.00. The fuzzy set value selection may vary according to the expert's opinion. Accordingly, fuzzy sets of four variable parameters are preferably formed using the triangular membership function. Classical reinforced concrete calculations of the values corresponding to membership 1 of the fuzzy sets of variable parameters are performed in order to form fuzzy sets for the bearing moment output. At the end of different beam solution, different outputs are obtained. For this reason, a different fuzzy set is created for the bearing power moment output. The clarified outputs should be compared with the compressive strengths obtained as a result of the test.

c. Determination of Modulus of Elasticity of Concretes

First of all, the range of compressive strengths is determined in the developed fuzzy model. After determining the membership functions for the concrete compressive strength, the linear equations for elasticity modulus and the rule base, modulus elasticity modulus is calculated for a given fc value. Rules are created. An example rule is given below.

If fc is too low, then y_1= -138.5xfc+11170
If fc is medium low, then y_2= -634.2xfc+36510
If fc is low then y_3= -1137xfc+89840
If fc is normal, then y_4= -295.3 xfc+66530
If fc is high then y_5=302.3xfc+201110
If fc is medium high then y_6=433.1xfc+3901

Membership functions are then determined (preferably gaussian or triangular). For each rule, the so-called trigger degrees wi's are calculated. The yi values are calculated from the linear equations in the result sections of the rule, and the resultant elasticity modulus is calculated with the mean formula.

d. Rapid Detection of Earthquake Damages of Structures

Damages occurring in any structure under the effect of earthquake can be grouped under certain headings.

Damages caused by considering each building element and the structure in general, Plaster cracks, infill wall damage, frame damage, shear damage in columns, Compression fracture in columns, column-beam joint damage, beam damage, slanted tension cracks in beams, damage on shear walls. . For all the necessary parameters, fuzzy membership will be made (if the concrete quality is bad and the carrier system is ignorance or the curtain carriers are insufficient) In a rule chain, the bad concrete quality will be taken into account with a membership degree, and again considering the standards, the curtain carriers being insufficient will be taken into account. fuzzy memberships will be determined for their status) and evaluated in expert system inference. Otherwise, expressions such as less too no should partially many will be able to express different ranges. There are many factors that increase the damage in a structure due to an earthquake.

This the age of the building, the intensity of the strongest earthquake in the region within the last 5, 10, 15, 20 and 50 years distance from active faults, the average of the number and intensities of earthquakes in the last 10, 20 years, Liquefaction risk, Earthquake region, Local soil class, floor number, floor heights, building behavior coefficient (R), structural system, workmanship quality, Structural defects (Soft floor, short column, band window, irregularity in plan, discontinuity in vertical rigid elements, Strong beam-weak column etc.), Building importance coefficient, The purpose of use of the building (housing, hospital, school, etcF.) importance factor, Previous renovation, repair status, addition or reduction status in the building outside the project, average annual humidity of the region, control of sections, amount of openings in the building, dilatation status, zoning status, type of floor and floor system in floors, type of partition wall, maximum opening amount. The appropriate ones are selected for input parameters. In study output parameter is the damage status after a possible earthquake (scenario). Defined rules are included in the inference by taking into account the regulation values and other known immutable facts and calculating fuzzy membership values for some parameters. Some of the parameters are treated as fuzzy rules. It is

recommended to join the sizes in the form of triangular or trapezoidal membership degrees.

Another approach to damage detection is to obtain the permanent displacement score between floors by fuzzy logic. The damage determined depending on magnitude for the permanent displacement between the floors in a building is considered as the permanent displacement score (KP) between the floors. KP is the value ranging from 0 to 10. Considering that the sum of the scores other than the system damage score can be maximum 20 in the calculation of the total damage score, KP, which can reach a maximum of 10 points, has a great effect on the total score. KP is taken as the fuzzy input variable. inter-floor displacement score membership values (0 points (less) for KP ≤ 0.0015; 2.00 points (moderate) for 0.0015 < KP ≤ 0.0050; 5.00 (high) points for 0.0050 < KP ≤ 0.0200 and 10.00 points for KP > 0.0200 (extreme)). As the fuzzy output variable, the score corresponding to the interstory displacement score is taken into account. It is recommended to choose trapezoidal membership functions for under and over named membership functions, and triangular membership function for others.

e. Setting a Strategy in the Construction Sector

Inputs for the fuzzy logic method in strategy determination for the management of construction companies or in a organization of the construction site can be selected as the three main headings obtained as a result of factor analysis, strength, opportunity evaluation and effects from threats. As the output, the objectives of the companies in determining the strategy are used. Opportunity evaluation capabilities of companies and strengths as weak, medium, strong; The situations of being affected by threats are expressed with 3 fuzzy linguistic terms as low, medium and high. Entries are graded from 0 to 100. When determining the membership functions of the inputs, it is recommended to use questionnaires to determine which numerical range linguistic terms fall into.

Opportunity evaluation membership grades, weak, medium, strong; membership degrees of strength are determined as weak, medium, strong, and membership degrees of being affected by threats are determined as low, medium, high. It is recommended to use the triangle membership function. The targets of the companies are used as

output. 4 linguistic terms are chosen as targets: customer satisfaction, process optimization, risk minimization and profit maximization.

f. Urban Transformation Applications

Generally used data collection tools are tests, interviews, questionnaires, observations and documents. While fuzzy logic translates verbal expression into mathematical language, it is necessary to ensure compatibility with the mathematical language by using correct verbal expressions within the framework of the established logic. Verbal statements should include the requests of the flat owners and the proposals of the contractors. The program should be designed with the logic of mediation, in which each of them will gain from the result, in order to bring the interlocutors together in common interests with benefit-cost analysis (F-M). Additional cost expenses to be incurred by meeting the existing demands of the floor owners by the contractor may be undertaken by the contractor if the cost to be met brings a benefit such as the contractor's preference as well as the benefit provided to the floor owners.

In the same way, in order not to lose a reliable contractor, flat owners can also give up certain demands. During the development of the program, the demands and offers of the interlocutors were evaluated and the issues that were important for the parties were determined in advance.

While designing the program, many criteria are eliminated and there are 3 main and 3 sub-criteria that will lead to the result quickly. These are the input parameters. The main criteria are determined as sharing of property gains, building features, eviction-delivery process. While the membership degrees are being determined, the variable ranges between 0 and 1 have increased and the highest verbal variable “indispensable” gets closer to 1, while the lowest variable “nomatter” gets closer to zero. This reduces the blurriness and makes the software more understandable and easier to use for the flat owners. While determining membership functions of verbal variables, the shape of the fuzzy set is chosen as trapezoidal.

g. Time – Cost – Quality Optimization in Construction Project

With the fuzzy logic analysis method, the target for time - cost - quality optimization study of a construction project, 3-way (Time - Cost - Quality) optimization and management decisions are planned based on mathematical data. Parameters can be determined for the application work by creating a general work flow diagram of the building project. For this, activity information including the processes from excavation to the completed state of the exterior, roof and flat screeds of the project should be collected. According to this; After determining the general work flow diagram activities, such as excavation, reinforced concrete, steel fabrications, facade cladding, screed manufacturing, wall manufacturing, joinery manufacturing, the definitions of the activities are made with the project manager and the site supervisor and the alternative methods of activities are listed. Excavation (Using a 40 Ton Excavator, Using a 50 Ton Excavator, Using JCB, reinforced concrete (Manufacturing on site, ready mixed concrete), Steel fabrications (using mobile cranes, using tower cranes), facade cladding (using H type scaffolding, using suspended scaffolding), screed Input parameters and membership degrees are determined in the form of constructions (machine screed, manual screed), joinery manufactures (one-stage assembly, two-stage assembly). The activities are connected to each other in the general work flow diagram with the manager and the site supervisor.The Time Values are determined according to the alternative methods.The time value data collected during the sample productions in the construction site were used to determine the time values, and for the methods that did not produce samples, the experiences of the sub-contractors working in the project and the project managers were used. benefit it is. In the determination of cost values, the evaluation is made on the proposals given by the companies for the methods. For the methods that do not have a bid, bids are collected from the companies and the most suitable bid is evaluated. Finally, a table of cost values (output parameters) is created according to alternative methods.

h. Modeling of Contribution in International Construction Projects

In the fuzzy logic model; There are five input data and one output data. Related factors of employer, project, firm, contract, tender

process, economic, risk and environment groups are chosen for the input parameters of the model. The output parameter is the estimated contribution amount as a percentage over the total construction cost.

In the survey study; input data is graded in the range of 1-5. According to this scale, one value is rated as very low, two values as low, three values as moderate, four values as high and five values as very high. In the fuzzification of the input data of the model study, five levels can be also considered and similarly, the input data is blurred with very low, low, medium, high, very high clusters. Another important point to be considered in the assignment; It is the membership functions assignment of the same membership functions for the input group, taking into account the evaluation of the participants on the same scale in the survey study for all inputs. Triangle membership functions created for factor groups are determined.

As an example, an example of randomly selected from the different rules developed is as follows:

1) IF “Employer Factors” is low and “Project Factors” is very low and “Company Factors” is low and “Tender Process - Contract Factors” is very low and “Economic Environment – Risk Factors” is hıgh, then “Contribution” is very low.
2) IF “Employer Factors” is hıgh and “Project Factors” is very low and “Company Factors” is very low, and “Tender Process - Contract Factors” is low and “Economic Environment – Risk Factors” is high, then “Contribution” is low.

The model suitability can be checked by comparing the estimated contribution margin values with the developed fuzzy logic model with the survey data.

i. Dam fullness level detection

While determining the membership degrees, first of all, SCADA data should be normalized by dividing the largest values among each other. Membership degrees are obtained by normalization. The occupancy values of the dam are determined as data training data between certain years, and the data between the following years as test data.

The square mean error values of ANFIS functions are obtained by processing the training dataset with different ANFIS functions (for example: pimf, rapmf, gbellmf, dsigmf, trimf, gaussmf, gauss2mf, psigmf) and the selected method (for example: hybrid and feedback (backpropa)). Training, control data and fuzzy rule are used for linear and non-linear parameter parameters. By using the lowest KOH value (Hybrid gaussmf), the training data is uploaded to the ANFIS system by using the Dam Occupancy values in the education.txt (Notepad) and the CBD is created again. The test phase is created by integrating the test.txt (Notepad) data into the system. In the test phase, the training data and the estimated values made by fuzzy model are compared. The distributions of observation values and prediction values corresponding to the input values are displayed in the graphic area of the ANFIS editor window. The control of the model is checked by observing the overlap between the observed values and the predicted values.

j. Detection of Evaporation

Membership functions can be created for determinning the amount of evaporation. The input parameters of temperature, humidity, wind speed, atmospheric pressure, sunshine intensity and sunshine duration obtained from a station. Evaporation amount is selected as output. The data belonging to a certain period of the data of the station are used in training period for models, and the remaining data is taken to test phase of the models. The preference here is to use the first 3/4 of the total data year in the training phase. The remaining (1/4) in the testing phase is performed. It first uses a back sepread sepread of all parameters, then a method of combination back propagation for the membership function involved with the input parameters, and the least squares method of the corresponding parameters involved with the output membership functions. It is recommended to use the Gaussian membership function.

k. Estimation of the amount of solids in rivers

First, the maximum and minimum values for the dependent and independent variables are determined. Afterwards, the number and shape of membership functions are estimated. The parameters used for design the shape and structure of the membership functions are calculated. It is recommended to choose fuzzy sets as triangles. 75% of all data should be used for training and 25% for testing. The variation

range for turbidity and flow rate is determined as input parameters. The output parameter is sediment. Base and ceiling values are created based on fuzzy logic and membership functions. Rules produced for membership functions created according to fuzzy logic in the Matlab program are shown. Analyzes are made according to these rules and the results are interpreted.

l. Drought Analysis

In the sample rule base created in the study, precipitation, temperature, relative humidity and sunshine duration are used as input parameters, while drought and humidity are determined as output parameters. In addition, analysis can be performed using only oil values. Using the standardized precipitation index method, 3-, 6-, 9-, and 12-month SPI values can be obtained and forecast models for these time periods can be created. Models with different delay values are installed. These models are the single-input model using the value one month earlier (t-1) from the time series values, the two-input model using the values one and two months ago (t-1, t-2) together as input, and the one, two and three months ago model. It is a three-input model in which values (t-1, t-2, t-3) are chosen for inputs. The month (t) in all models is used as output. In these models, the aim is to calculate the possible SPI value one month later. Simulations are performed by considering the month in it as the value one month later. In each model, 75% of the input. Output data are split into two groups as training and 25% as testing.

It would be appropriate to choose the Gaussian membership function from the fuzzy set functions. Although the increase in the number of fuzzy subsets decreases the error in the training set, the error value increases in the test part. It can be interpreted that the established model loses its ability to generalize and learns too much. The optimal number of subsets is determined. After the modeling, scatter graphs are drawn and the success of the models is obtained visually.

m. Traffic Safety Modeling

For this modeling, the sum of the estimated number of accidents in a year on a highway section should be calculated. This sum includes the annual average daily traffic volume on a highway segment (ts/day), length of the highway segment), location of the highway segment (0 in

chosen city, lane width; average lane width, shoulder width (ft) for two different travel directions; Average shoulder width for two different travel directions, roadside hazard ratio (values from 1 to 7) and density of connection roads in the highway section are affected. While creating the fuzzy base model, these data are taken exactly to test the result. The basic model created with fuzzy logic rules consists of at least five inputs and one output from the mentioned parameters. The values and data used in determining the membership functions are the values in the guideline report. Function ranges are the values obtained by trial studies. The variables in the base model consist of two fuzzy subsets. As the number of fuzzy subsets increases, the precision of the result increases. However, the data and results of the guide model are taken into account for testing base model. Consistency with the results of the guide model is obtained as a result of the variables having two fuzzy subsets.

Annual average daily traffic; Since it is the most important variable used in the model, the function range is taken in multiple values. In terms of the ease of writing and displaying the fuzzy rules, the annual average daily traffic should be included in the model in piecewise intervals. There is continuity in the model prepared for these intervals of the annual average daily traffic. Strip width and shoulder width are divided into two fuzzy subsets, 'narrow' and 'wide'. Roadside hazard ratio; The impact of the road environment on road safety on interurban undivided highways is graded from (good) to (bad). The number of access roads in the unit road segment can be divided into two fuzzy subsets 'few' and 'more'. Connection road density is taken as the number of connection roads with a value of 1 for one km of highway section. The number of accidents of the base model is determined as the output of the estimated total number of accidents in a year. Thus, the accident number output is divided into nine fuzzy subsets. It is recommended to use the Gaussian membership function.

n. Determining Traffic Light Duration at Signalized Intersections

In the modeling for a single branch of a signalized intersection, there is a correlation between the average speed of the vehicles on that intersection arm and the number of vehicles passing through that intersection arm per hour, the green light duration that gives the right of

passage to the relevant vehicle group at the traffic light at the end of the intersection.

Exists. traffic flow; It consists of three parameters expressed as speed, traffic density and flow rate. current ratio; It is found by multiplying speed and traffic density. The priority among these parameters is the average value of the speed. The speed expression uses a constant operating speed by defining a single speed value. The ratio of the vehicles traveling on a certain road section to the length of that road is called the density, and the hourly value of the vehicles passing in a certain time is called the flow rate. The inverse ratio between the traffic volume and the average speed continues until the average speed value corresponding to the maximum flow rate. This value is also the point where it reaches the traffic capacity value. The lower and upper values approaching this point are the points where the current reaches the delays. From all these graphics; The result is that the increase in traffic density and traffic volume reduces the average speed of traffic considerably. Accordingly, the green light duration can be selected as the output parameter while taking the input parameter, average speed, and traffic volume. Membership degrees are slow, medium, fast for average speed; low, medium and high for traffic volume; The green light duration can be set in seconds, 20, 40, 80, 100, 120. The matrix of the rules created for the entered functions is determined. It is recommended to use triangle or Gaussian membership functions in calculations.

o. Port Planning

The most important input parameters in determining the length of the port berth are the number of ships arriving, ship sizes and the characteristics of the handling equipment. The length of the port berth varies according to the number of ships arriving at the port, their lengths, the occupancy rate of the ship, how the cargo is loaded, the number of cranes that can operate on the ship and the characteristics of the handling equipment. One of the factors affecting the length of the ship berth is the length of the ship. This size, defined between 100 m and 300 m, can be divided into 3 fuzzy subsets. (These dimensions may vary according to the working area). These are the subsets 'short', 'medium', 'long'. Another factor affecting the length of the ship berth is the number of ships arriving at the port. The monthly number of ships arriving at the port is divided into 3 fuzzy subsets as smal', Medium and

large. Accordingly, the membership function (triangle) is determined. The third factor affecting the size of the ship's berth is the characteristics of the handling equipment. Hourly container handling capacity is divided into 3 fuzzy subsets as 'small', 'medium' and 'large'. The output of this model, the port berth length, is divided into 4 fuzzy subsets as small, medium, large and very large. The monthly average used berth lengths found with the established fuzzy model are divided by the port berth length and the monthly average usage rates are obtained and compared with the actual usage rates.

p.Traffic Signal Control Applications

The number of arriving vehicles and the queue length are chosen for the input parameters for the fuzzy model, and the green time extension amount is taken as the output parameter. The fuzzy logic controller is controlled based on the rule base prepared according to the input and output parameters. For evaulation the performance of the established algorithm, simulation models are created and the fuzzy logic controller is compared with the traffic excited control system in terms of delay times. A different point of view in signaling modeling is a phase selector based on fuzzy logic for traffic control. In this system, three inputs are used: tail length at green light, tail length at red light, and circuit length. The output is the phase variability.

r. Vehicle-tracking modeling

As input parameters, Speed (too little, desired level, too much), desired speed (too little, desired level, too much), distance (too close, close, medium, far, too far), Speed difference (positive, zero) , negative) is selected. The output parameter is acceleration (slow down, slow down, slow down a little, stay the same, speed up a little, speed up, speed up a lot), Lane change (slow down too much, slow down, slow down a little, stay the same, speed up a little, speed up, speed up a little). Triangle function is recommended.

Estimating the vertical flow profiles of a stream at any point. Data sets containing measurements of current velocity profiles, meteorological conditions and water levels should be used in the creation of the model. The predictions performed by the fuzzy logic model are made based on the velocity vector and depth estimated by the measurements. In fuzzy logic models, it is necessary to write a

separate rule base for each output. For this purpose, a separate model is established for each output, since it is practically equivalent to a separate model. Models including water level difference and wind speeds are compared by modeling surface flow velocity components in the same direction as wind speed, and models established with atmospheric pressure and water level difference at intermediate depth and near the bottom. If it is not desired to create a model according to different inputs, the most used model is the one that outputs the bottom stream velocity components at certain depths from the surface. With these input combinations, two-input models are built and different fuzzy subset numbers are tried for each variable and the input combination and fuzzy subset number that gives the best result for each model output is determined. fuzzy subsets of inputs are defined by triangular membership functions and for calibration, control and test data using various numbers of fuzzy subsets; The performance values of correlation (R), root mean square error (OKHK), mean absolute error (OMH), normalized root mean square error (NOCHC) and normalized mean absolute error (NOMH) and the changes of these values are examined. For each modeled stream velocity component, a stream profile is created by considering the best models and their performance.

s. Modeling of Resilient Pavement Disturbances

In the system, the cumulative equivalent number of axle loads, minimum temperature, sunshine intensity and total precipitation data are used as input data, and the distortion prediction value (RN) value to be calculated is taken as the output parameter. It is recommended to assign the sizes in the form of gaussian membership degrees.

t. Modeling of Soil Liquefaction Potential

Membership functions are created for the parameters of ground water level and soil percentage clay content selected as inputs to the model. Soil liquefaction probability is selected as the output parameter. The rule examples for the developed model can be applied as follows:

If (ground water level is high) (liquefaction is low)
If (ground water level is low) (high liquefaction)
If (clay percentage is medium) then (liquefaction is medium)
If (low clay percentage) (high liquefaction)

It is recommended to use triangular or trapezoidal membership functions in calculations.

u. Application to the Aircraft Landing Control Problem

In order to find the appropriate control force for the final approach and landing phase of the aircraft with the help of fuzzy logic; The problem of finding the control force corresponding to the desired altitude and vertical velocity pair needs to be addressed. Putting the wheels on the runway at a certain speed, the aircraft and the passengers, crew, equipment, etc. very important for As the altitude increases, the desired speed also increases, and as the altitude decreases, the theoretical speed decreases and becomes zero. In this way, the aircraft is prevented from being damaged during landing. Altitude and vertical speed are taken as two input variables, and control force is taken as output. Then, “Altitude”, “Vertical Velocity” and “Force” membership functions are created. Here the trapezoidal function is recommended.

v. Classification of Soils

The liquid limit of the part passing through the sieve determined by the percentage values of the passing grains of the 10, 40,… 200 sieves used in the soil classification system.

Plasticity Index properties and Group Index values are selected as input parameters and soil definition as output parameter. Membership functions (preferably triangular or trapezoidal) are formed for inputs and outputs and transformed into linguistic expressions (over sieve, under sieve, too little, little, medium, too much, etc.). Thus, the rule base is created for the ground definition. The first enabling class is the ground class. The model soil definition created as a result of fuzzy extraction and clarification process is performed.

3.2. Studies in Civil Engineering and Evaluation

Fuzzy logic has been widely used in civil engineering in parallel with other engineering over time. These applications did not remain with structural engineering, but were also applied in other branches. According to the researches, fuzzy logic applications are mostly used in hydraulics and then in structural engineering. In this section, information is given about the last period of the publications in the

literature. For previous studies (Adeli, 2001;Uygunoğlu and Yurtçu; Uğur and Baykan, 2016) publications can be consulted.

a. Structural Engineering

Metaxiotis et al. They worked on the usability of fuzzy logic in DSSs. For this purpose, new fuzzy logic models have been made in DSSs in many different industries. As a result of the research, the difficulties in conducting different and more researches were identified and pointed out new ways for solution (Metaxiotis et al., 2003).

Şahin and Bedirhanoğlu applied approximate fuzzy logic to determine the compressive strength concrete reinforced with fibrous polymers. The estimates found with the UN were compared with the ACI 440 and DBHYYHY 2006 regulations. As a result of the paper, it was found out that the estimates obtained by the UN method were quite successful (Şahin and Bedirhanoğlu, 2008).

Topçu and Sarıdemir investigated the change in compressive strength of concretes prepared using fly ash containing high and low lime, using ANN and FL methods. Within the scope of the study, 180 samples taken from 52 different mixtures obtained from the literature were used. ANN and BM methods were very successful in estimating concrete compressive strength (Topçu and Sarıdemir, 2008).

In their study of Felipe Nunez et al., a hybrid fuzzy strategy controller was designed and implemented for column floatation. The Auditor is applicated in a 10-column cleanup phase, followed by a sequential scheme with two audit levels. Auditor is designed according to 3 different methods determined by a recovery-oriented domain partition. As a result of the research; It was concluded that the Auditor kept the process in the normal operating scenario 80% of the time analyzed. When only local control is operated, the normal operating scenario is encountered in 43% of the calculated time. The results also showed that the auditor had negative standard deviations in recovery and concentrate grade despite changes in feed quality. It has been shown that it can increase the concentration and recovery average values (Nunez et al., 2010).

Golafshani et al.' s study was about the determination of bond strength of steel bars attached to concrete was studied.. For this, they

used UN and ANN methods. Experimental data of the beam test were used for the training and validation of the models. The results proved that UN and ANN have good predictive capacity (Golafshani et al. 2012).

Gülbandilar and Koçak examined the factors affecting the setting time of Portland Cement using fuzzy logic method. For this, silica fume and fly ash were used as input parameters. Experimental results were compared with BM results and high correlation values (0.96–0.92) were found. These results proved that the model proposed with the fuzzy logic method can be used in the cement industry (Gülbandilar and Koçak 2013).

Ahumada et al. studied the fuzzy logic model for ground motion attenuation models. For this, they used the earthquake magnitude and the distance from the source. Based on these data, they created fuzzy sets. The application of the model was used in records of earthquakes of magnitude 5 or greater that occurred in the USA and Taiwan. The fuzzy approach has been proven to yield positive rational analytical results in the measurement of ground motion records typically determined with high uncertainty. Testing the model with an independent dataset confirmed its accuracy in estimating PGA values (Ahumada et al., 2015).

Beycioğlu et al. used the Fuzzy logic model to determine the flexural and compressive strength of concretes mixed at high temperatures. The results showed that the BM method is an alternative method for evaluating the mechanical properties of concrete at high temperatures (Beycioğlu et al., 2017).

Akcay and Manisalı (2018) used the UN method for the contractor selection decision in construction works. For this, a UN-based decision model was envolved which would include other issues that will affect quality and time while making the most economically advantageous bid decision for tenders in construction works. Since electronic tools were used in public procurement, it has been concluded that the model created within the scope of this study can be used in practice (Akcay and Manisalı, 2018).

Allali et al. used the UN method to assess building damage after an earthquake. The results showed that the theory-based assessment was consistent with the observed values for 90% of the buildings studied. (Allali et al., 2018).

Usta et al. In their study, they evaluated the seismic damages of existing buildings using the UN method. In the light of the information obtained from the sources gathered in the study, in which the fuzzy theory can be used to evaluate the scale of structural risk and damage caused by earthquakes in buildings, it was concluded that the UN model provides simplicity, speed and flexibility when deciding on the damage assessment of buildings (Usta et al., 2018).

In their study, Mohanaselvi and Hemapriya, UN method to determine earthquake damage estimates. Buildings are divided into three groups according to their damage levels as low, medium and high. It has been observed that the UN method provides a very high degree of success in estimating the damage degree of buildings (Mohanaselvi and Hemapriya, 2019).

Alaneme and Mbadike modeled the strength of the cemented portion and green concrete modified using fuzzy logic approach using PBA/BN ranging from 0-50%. Mamdani-FIS was used To develop an expert smart model. They used the fuzzy logic method as it fully takes into account the uncertainty of well-defined parameters. Thus, the strength development property of green concrete was tried to be determined. MLR models MAPE and RMSE were used to fit the model results. The results obtained showed that the fuzzy logic method was suitable for the change of setting time of PBA/BN-concrete. Thus, the method showed good results in predicting mechanical properties (Alaneme and Mbadike, 2021).

Sari and Latief used the fuzzy logic method to estimate occupational health and safety costs. The model performs well in performing calculations quickly and accurately. They thought that with the use of the model, especially for the project cost calculation, it could be done in a short time and the estimated cost estimation would give accurate results. The fuzzy control model was used to determine the classes of contract value. Neural network with fuzzy result output was used as learning input. Therefore, the percent absolute error of the tested dataset for the adapted model is quite accurate. As a result of the

research, they concluded that the cost value found with the fuzzy model is a better MAPE value than the results of the regression analysis (Sari and Latief, 2021).

Moreno et al. They tried Art-Risk 3.0 software and fuzzy method. Conservation of historical buildings was used as data in research. In the study, the efficiency of Art-Risk 3.0 was applied and investigated on 500 theoretical cases. This time, before and after the restoration of a Mudejar-Gothic church in Seville, Spain, values were taken. As a result of the research, it was seen that Art-Risk 3.0 software was successful in evaluating the environmental and restoration activity impacts. Risk, vulnerability and functional service life of the buildings were taken as parameters. In addition, with Art-Risk 3.0, it was determined that fuzzy logic and the most troublesome elements could be used in restoration (Moreno et al., 2022).

b. Transportation engineering

In study of Filipapo et al., They aimed for a new model that prioritizes environmentally friendly highway renovation with a multi-criteria fuzzy model that requires decisions about which road segments demand those operations and services. A sample comparing two road segments, sub-criteria, and weighting the criteria, sensitivity analyzes were performed to apply proposed model. According to the results, multi-criteria fuzzy model was found to be suitable (Filipapo et al., 2007).

In their work, Ki and Ray used fuzzy logic method to extract the field fitness map. They also used AHP to compare with fuzzy logic model. The research determined that fuzzy logic and AHP draw quite different index maps from each other in terms of best points and fitness scores. It also showed that the fuzzy logic model works well for spatial decision making and the best positions of BMPs in the subregion (Ki and Ray, 2014).

An et al. used the fuzzy method in risk decision analysis. For this, the fuzzy multiplicative consistency method was chosen. Pairwise comparison matrices were used in the calculations. Researchers proposed the modified FAHP. The application of this method ensures that all system comparisons are checked. It has been shown that the method can predict the consistency of judgments in a short time. They

made an application to prove that the method was suitable. As a result of the research, it was shown that with the application of the method, the rail system risks can be handled effectively and efficiently. (An et al., 2016).

In Pathak and Kansal studies, a fuzzy logic method was created through MATLAB software for measuring, also ranking risk factors of highway construction projects. Because fuzzy logic is used in all four parameters of aimed model can be managed. Three real case studies were applied practically to demonstrate the working of the proposed model. At the end of study, the case studies provided ranking of risk factors according to the calculated risk index values. (Pathak and Kansal, 2020).

In Study of Sharma et al., different design and performance features were identified and appropriately combined to form the fuzzy AHP- hierarchical model. It could be used for giving a single performance index value. Researchers have developed a design and performance evaluation index (DSPAI) for highways using the fuzzy AHP technique. The resulting index was applied to some existing and recently constructed highways and expressways in the Delhi NCR region of the Indian Subcontinent. The advantage of such a design and performance index model was that it could help compare and rank two or more motorways or motorways based on their design and performance characteristics. Some determinations and suggestions were made for better performance scores of highways and highways (Sharma et al., 2021).

Thakur's work, the Motor Domestic Road Bridge Programme, was a project initiated by the Department of Local Infrastructure in February 2011. The aim of the project was to evaluate and analyze the risk factors that cause cost overrun and delay time of completed bridges and use this knowledge to reduce risks in future projects. He developed a fuzzy inference system-based model using MATLAB to calculate risk indices based on survey questionnaires. The study identified State regulations/contract, insufficient budget allocation and unexpected ground conditions to the lowest bidder as the highest risk factors causing cost overrun and time delay in local road bridge construction. Afterwards, a risk management plan including risk response planning for mitigation for significant risk factors was prepared. It was concluded that the risk indices obtained from the study can be used as

weighting factors to develop a neuro-fuzzy-based prediction model (Thakur, 2021).

f. Geotechnical Engineering

Tün used SCPT data applied at 40 different points of the alluvial ground in the Eskişehir settlement area. The relationship of the soil parameters measured from the CPT with the magnitude of the extreme resistance “qc” (MPa) and the lateral friction “fs” (MPa), shear wave velocity (Vs) was investigated. In determining this relationship, besides classical comparison methods, "fuzzy logic" approaches, which were used in situations where uncertainty exists, were used. Known facts in terms of soil properties were used in comparative analyzes and the uncertainties on the created model were eliminated as much as possible or the existence of uncertainty was accepted and the analyzes were adapted according to these rules. As a result, shear wave velocity calculations were made using the soil parameters obtained by the CPT method (Tün, 2013).

Sünbül et al. wrote a study on determining soil liquefaction potential using the UN method. The researchers determined the liquefaction potential of the city of Adapazarı, where ground liquefaction occurred during the 1999 Marmara Earthquake; They created a UN model by using percentage clay values, grain distribution and groundwater level values in the soil. It was revealed that results estimated by Fuzzy logic could be used because it quickly and accurately predicts the relationship between earthquake resistant soil parameters and was more practical than other methods (Sünbül et al., 2015).

Yurtcu and Özocak conducted a study on the determination of the compaction index of fine-grained soils by artificial intelligence methods and statistical methods. FL and ANN models were used in the study. Ultimately, they found that ANN gave better results than fuzzy logic. (Yurtcu and Özocak, 2016).

The aim of Sihagé's research was to apply fuzzy logic and artificial neural network (ANN) based models to hydraulic conductivity calculation of soil. A decagon devices, Inc. used in it. All measurements were made for initial state of fly ash mixed with rice husk ash and sand. For modelling, 70% of the data was applied for

training and 30% for testing. As a result of the research, the coefficient of 0.8662 calculated with ANN showed that the method worked well (Sihag, 2018).

Tokgöz and Yılmaz applied a previously developed fuzzy classification process to minimize the uncertainties that occur when the definition points sometimes fall on or near the lines separating the soil classes. In this fuzzy classification process, the perpendicular definition spatial distances scores on the plasticity to lines separating the boundaries were taken into account. The fuzzy plasticity and fuzzy ground values of the definition points were calculated using the sigmoid function. Fuzzied ground sets were provided with the help of fuzzy processors. The proposed fuzzy classification process was applied on 100 laboratory data and provided fuzzy soil sets were matched with the classical soil sets (Toksöz and Yılmaz, 2019).

Arbabsiar used a multi-stage fuzzy logic modeling in geotechnical risk analysis. Here, the risk situation of tunneling rock tunneling machine work was examined. 12 parameters that affect formation of geotechnical danger situation, gathered in 5 sets chosen input parameters. Risk level was determined for output parameter. The model used data from 58 geological sites in the Zagros/Iran tunnel in Iran to check for fit. At the end of the study, the risk ratios determined using the fuzzy logic-based model and the field measurements were compatible with each other. (Arbabsiar et al., 2020).

g. Hydrolic Engineering

The applicability of Fuzzy logic for water level in Dhaka (Bangladesh) region was investigated in study of Liong et al.. For this, a fuzzy rule-based flood model was developed and suitable sensitivity analysis was applied on variables of input. For implementing analysis, a new model was determined by reducing input number and results were evaluated. In the study, a more effective and successful model was developed with fuzzy logic using fewer input variables than the previous prediction model (Liong et al., 2000).

Mahabir et al. investigated that the BM method could be applied to the estimation of seasonal runoff and it was found that there was no evidence for Lodge Creek and Middle Creek basins. A rule-based UN forecasting model was developed for the Lodge Creek watershed. This

model was then tested for the adjacent Middle Creek watershed. Results were compared with previously proposed statistical-based studies for these basins and it was seen that the behavior of the BM method was better than classical models (Mahabir et al., 2003).

Nayak et al. studied FL model in determining the precipitation-flow relationship in real-time flood modeling. For this, Narmada Stream flow forecasting models were established by using hourly flow and precipitation variables in the watershed (India) and a fuzzy rule-based flood forecasting model was developed. According to results, BM method could be successfully applied in precipitation-flow analysis (Nayak et al., 2004).

Farboudfam et al. used genetic programming to predict river flow and investigated the memory rule for prediction accuracy. In their research, they used the data of Ligvan River in the Urmia lake basin between 1997-2001. They used the daily time series to model the flow drainage over five days by genetic programming. They have seen that ANN establishment in river flow forecating is less accurate than genetic programming. As a result, they found that genetic programming could be used successfully in river flow prediction (Farboudfam et al ,2009).

Bisht and Jangid developed ANFIS and Linear Multiple Regression (MLR) methods for flow estimation in rivers. They consired that ANN models and FLM were applicable for flow prediction in rivers. With the developed models, they trained and tested the data of the Gadavri river. When they compared the data, it was found out that results of developed ANFIS models were better than traditional models such as MLR (Bisht and Jangid 2011).

Anusree and Varhese studied the daily flow estimation with the data obtained from the basin outlet of the Karuvannur river in the Thrissur region. They used multiple nonlinear regression (MNLR) method, ANN method and ANFIS methods in their studies. They further developed their models by taking precipitation data from nine rain stations. They created the combinations from different precipitation-flow and different time data. As a result, they observed that the daily flow estimation of the ANFIS model gives more reliable estimations than the ANN and MNLR methods (Anusree and Varhese 2016).

Bardzadeh et al. developed a more advanced flow prediction model by applying data reprocessing techniques on ANFIS in their studies. They combined Wavelet Multiple Resolution Analysis and ANFIS model to develop the WNF model. They received monthly flow estimates from the Ellen Brook River stations in Australia and the Railway Parade stations in Western. They then combined the wavelet coefficients with NFM. Models were developed tonext step based on the Sugeno System. Performance tests were performed with m-s-e and n-c-c. At the end of the study, they observed that the ANFIS model and WNF models gave better results, especially in long-term predictions (Bardzadeh et al., 2018).

Özdulkar et al. used the UN method to estimate the daily evaporation amount. In the study, USGS evaporation data between 2008-2012 were used. Among the Mamdani-Fuzzy Logic (M-BM) and Sugeno-Fuzzy Logic (S-BM) based methods used in the study, the highest success was obtained from the S-BM method (Özdulkar et al, 2019).

Belvederesi et al. used the Athabasca River, as the study area to estimate the flow with a new technique. They used the one-entry sequential ANFIS model in their study. They used measured data near the source as data after estimating delivery times between the four stations. The results of this method are compared with non-sequential and multiple-input ANFISs from each of the four hydrometric stations. They found that this method, which they studied, provides accurate data over long distances and wassuitable for predicting flow over long periods (Belvederesi et al., 2020).

Yadav et al. developed an intelligent hybrid artificial intelligence model for river flow prediction in their work. They made monthly flow estimation of Mahanadi river. They used GA-ANN. For development of GA-ANN model, 20 years of flows were taken from the Tikarapara station of the Mahanadi river. Parameters such as precipitation, water level, sediment yield, temperature were chosen for estimating ANN prediction model. They compared GA-ANN with ANN. As a result of study, it was observed that the GA-ANN model gave better results than the ANN’s (Yadav et al.,2020).

Büyükkaracığan applied FL model for determining the financial dimension of flood. he used peak flow data of a station on Murat River.

For this purpose, by using fuzzy Logic Cost Curve, flow rate and level values, flood damages with different return times were estimated. Flood Peak values were calculated according to the synthetic method and flood frequency analysis. Among the 24 different models applied in flood frequency analysis, the Log-Pearson Type III model gave the best result. Possible and recurrent flood currents resulting from these precipitations were calculated by the Log-Pearson Type III method and the Mockus method. After than, FL model was applied for the flood risk management of Murat River floodplain. The best flood control measures for the study area wereemerged with fuzzy logic modeling (Büyükkaracığan, 2022).

4. CONCLUSION

The application areas of fuzzy logic are very wide in human life. The greatest benefit it provides is that it enables the easy modeling of learning through experience, which is unique to human beings, and the ability to express ambiguous concepts mathematically. Therefore, it is particularly suitable for approximating nonlinear systems.

When the results are examined, it has been observed that fuzzy logic gives more appropriate results to human thinking and judgment compared to the sharp and uncompromising boundaries of classical logic.

In addition, it can be said that the fuzzy logic solution softens the sharp transitions of the traditional and classical solution and gives a certain flexibility, thus helping to obtain more reliable results.

fuzzy logic gives results closer to reality and to human thought, decision-making mechanism in the solution of problems encountered in daily life and involving uncertainties. This situation has been demonstrated with applications.

Fuzzy logic method is used in many different civil engineering disciplines due to its success in reaching an effective solution among many design parameters. Expert system such as selection of carrier system, control of standards, vulnerability of structures under earthquake risk, determination of soil properties, superstructure, material mixture calculation, air traffic control, planning of transportation systems, control of traffic flow and accident analysis, estimated cost of road infrastructure order; genetic algorithms for optimal sizing of structures; modeling of complex behavior of concrete, static and dynamic analysis of structures, risk analysis, solution of plates and shells, earthquake resistant structure design, damage assessment, dynamic analysis of bridges, analysis of soil liquefaction

and soil parameters, optimization and control applications, dam safety, river flow predictions, hydroclimatological studies are some of the studies in progress.

This method, which has a wide usage area, also has a great potential for use in civil engineering problems. However, it should be known that regardless of the method used, the numbers obtained are only to give an idea to the engineer. To evaluate this knowledge requires sound engineering thinking, analysis, synthesis and the ability to master the behavior of the materials used.

It is appropriate to use fuzzy logic method in civil engineering to increase the efficiency and reliability of project design and construction works. The fuzzy logic method is easy to understand and not difficult to implement as software. It provides an algorithm suitable for computer applications that can be used in decision making processes. Fuzzy logic can provide support in automating some tools used in engineering services.

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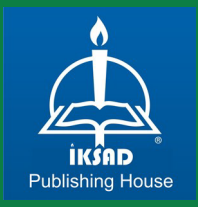

ISBN: 978-625-6380-29-5