Application of Fuzzy Logic in Civil Engineering

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1 Abstract

Fuzzy principles are applied on a platform in the engineering industry. We are aware that the field of civil engineering differs fundamentally from other disciplines. It implies that the ideas never completely address the issue at hand. This is because, in contrast to other disciplines, testing the prototype for a civil engineering project is extremely unlikely due to its complexity and typically enormous size. The application of theoretical solutions is therefore questionable. Furthermore, constraint satisfaction issues are problems we face in engineering.

2 Introduction

Clearly, there are ample instances of uncertainty in the field of civil engineering. The employment of fuzzy notions is thus primarily driven by the complexity, uncertainty, and vagueness of decision-making in real-world structures. The fuzzy notion has been shown by experts to be a beneficial tool that may be successfully used for civil engineering challenges in order to find the best answer. There has been an increase in interest in using these ideas to solve engineering difficulties over the past ten years. Additionally, difficult issues can be solved more quickly and effectively by combining fuzzy notions with Genetic Algorithms and Neural Networks, leading to the best possible solution.

The fact is that a designer must obviously make a number of decisions when creating an engineering product. Particularly in civil engineering, the available theory never completely matches the actual problem, and testing prototypes is not as common as it is in other engineering fields. Regarding what is to be built, he must provide the builder sufficient directions so that it may be built. He uses information of various kinds—both professional and commercial—in making these judgments, and he necessarily must exercise substantial judgement in evaluating this information. This is true because manufacturing sectors often employ production line techniques to produce huge quantities of the same product, whereas civil engineering projects are frequently "one-off" works. As a result, there is a lot of ambiguity when applying theoretical solutions to real-world civil engineering issues. Since the public has highly high expectations for the safety of bridges, buildings, and other structures, the designer must obviously take this into consideration.

While the general population is willing to accept a somewhat high risk of mortality when operating a motor vehicle, they often anticipate a very low danger that the bridge they are travelling over will collapse. Before the development of science, information accessible about the material's behaviour and strength, and civil engineering was a craft. Though the art of engineering evolved as a result of the utilisation of scientific information by engineers, the uncertainty surrounding the practical application of the new knowledge was still managed by rules of thumb. Today's engineer has a tremendous arsenal of scientific theory at his disposal to guide him in his design choices, but there is still a great deal of ambiguity surrounding how well the theories will apply to real-world issues, and rules of thumb are still widely used.

Because fuzzy models can be developed with ambiguity and imprecision in knowledge representation, fuzzy notions offer a simple means of handling complicated issues. As a result, it is appropriate for situations where it is challenging to precisely express real-world design problems mathematically.

3 Uncertainty in Civil Engineering

The execution of any engineering project is fraught with uncertainty, as was made clear in the prior discussion. Three categories—human based uncertainty, system based uncertainty, and random uncertainty—have been used to discuss the nature of this uncertainty. These three types of uncertainty are challenging to forecast, and current approaches—embodied in dependability theory—tend to focus mostly on random uncertainty. The nature of random uncertainty and that of system and human uncertainty, however, differ fundamentally from one another.

Uncertainty regarding a system that is properly defined and specified is a component of randomness. In actuality, the ambiguity around the output of such a system derives solely from the ambiguous nature of the system's characterising parameters. On the other hand, uncertainty that is caused by people and uncertainty that is caused by systems both come from a "vagueness" or lack of precision in our understanding of a proposition, an event, or a system. In other words, even when the parameters are clearly described, any forecast about the phenomenon under examination will be less certain the more poorly we comprehend its fundamental definition.

Given below are six additional kinds of uncertainty that are crucial to engineers in structural civil engineering projects:

- Structures whose creators have a good understanding of how they will behave. When an exceptionally high load or extremely low strength value happens at random, structural failure could result.
- Structures whose behaviour is poorly understood, i.e., a high degree of system uncertainty. However, the designer is aware of this and can typically account for the uncertainty by making cautious design decisions.
- Buildings that function properly up until they sustain damage from an unforeseeable external event, such as a fire, an automobile accident, an earthquake, etc.
- Failure of a structure can be attributed to the designer's failure to account for some fundamental mode of behaviour that is not well understood by current technology. With this kind of structure, this form of behaviour has probably never before been crucial; a fundamental structural parameter may have altered so significantly from earlier uses that the new behaviour becomes crucial. Alternately, the structure can totally be of a new type or use novel components or construction methods.
- Buildings that fail because the designer misunderstood a concept that is well known to technology at the time.
- Buildings that malfunction as a result of a building fault. Poor site management, ineffective inspection processes, and ineffective communication amongst those involved in design and construction will all contribute to these problems.

4 Real-World Applications

4.1 Fuzzy Analysis of Pipe Networks

In order to analyse the hydraulic behaviour of pipe networks, inaccurate or ambiguous values are frequently used. Old pipes' roughness coefficient, which gets harder to measure as the network ages, and the demands on the network, which can fluctuate greatly depending on how many users are connected to it, are typical instances of these quantities. These are qualities for which there is frequently only semi-quantitative data, which usually entails some subjectivity and cannot, therefore, be expressed with precise values or through statistical distributions.

Some examples of applications:

- Calculate the potential for the discharges and piezometric heads to be affected by the uncertainties of the information that is currently known.
- How the hydraulic issue may be articulated within the framework of the fuzzy approach.

4.2 Optimization of Steel Structures by Fuzzy Genetic Algorithm

Constrained evaluation in actual engineering practise involves a variety of sources of error and approximation. When an optimization algorithm is compelled to perfectly satisfy the design constraints, it may fail to find the global optimal solution within the bounds of widely accepted approximations. In order to optimise steel structures subject to the constraints of the AISC allowable stress design specifications, a fuzzy augmented Lagrangian genetic algorithm (GA) is utilized. This fuzzy augmented Lagrangian GA takes into account the fuzziness in the constraints.

The fuzzy membership function for the objective function and the constraints are intersected using the max-min method of Bellman and Zadeh to determine the membership function for the fuzzy domain. Constraints and the objective function are implemented using nonlinear quadratic fuzzy membership functions.

The new fuzzy GA's characteristics and benefits include recognizing the fuzziness and imprecision of the code-based design restrictions, increasing the possibility of finding the overall best solution, enhancing convergence, and requiring less overall computer processing time.

Some examples of advantages:

- Recognizing and taking into account the fuzziness and ambiguity of the code-based design constraints.
- Reduction in the optimal weight's value.
- Increasing the chance of reaching the overall ideal.
- Reduction in the total amount of time needed for computer processing and the number of iterations.

4.3 Evaluation of Alternative Construction Technology

A decision maker's preference for possible gains or aversion to predicted disadvantages are not reflected in the expected monetary values of technology choices. To model a decision maker's value system, formal decision analysis approaches must be used, such as the utility theory-based method.

A fuzzy-logic-based, risk-incorporating methodology to appraising new building technology is an alternative to those conventional methods, with the goal of generating consistent technology implementation decisions. According to a set of user-defined linguistic criteria that is indicated the technique can produce a consistent evaluation of the available possibilities as evidenced by experimental results.

4.4 Fuzzy Logic Controller for Lunar Mining System

Utilizing planetary resources close to Earth decreases the requirement for and expense of carrying materials into Earth orbit, which is a significant advantage. The moon's location makes it the perfect place to gather the ingredients required to support space activities. The dynamic, unstructured lunar environment, where conditions are very variable and unexpected, is where the lunar excavation will take place. It is vital to remove human operators from this dangerous environment by using autonomous mining (excavation) devices. This machine needs a structure for its control system that can recognise, plan, sense, and manage dynamic machine movements in real time on the moon.

Some of its renowned features are:

- To divide the site into excavation sections and creates tactical plans to carry out its task- move, dig section and scan the surroundings.
- To assess data from bucket torque sensors and establish the condition of the bucket excavation for upcoming control measures, pattern recognition techniques are used.

4.5 Optimizing Sludge Application using Fuzzy-Set Apprroach

Engineering challenges that cannot be solved with true precision due to the decision criteria utilised can benefit from fuzzy sets. Engineering decisions are made utilising a combination of subjective input, engineering judgement, and objective scientific knowledge. Engineers can use fuzzy sets to structure these fuzzy inputs of information into a logical problem-solving method. For each environmental factor, a collective belief in the application sites is calculated using fuzzy membership functions. This opinion represents the degree of assurance in utilising the selected locations for the secure application of wastewater sludge.

A mixed-integer-optimization model can be used to explain the challenge of choosing a land application technique with the lowest possible cost. The cost of sludge disposal in this model is directly impacted by two decision variables. The first decision variable, shown by the integer variable t_j, is the total number of trips taken to carry sludge from the treatment plant to site j. The second decision variable, represented by the binary decision variables x_j (0–1), determines whether or not site j is chosen for sludge application. When applying sludge to site j, the cost of making t_j trips is represented as:

$$Cost_j = Cd_j t_j + R_j x_j$$

where

C: transportation cost per unit

d_j: round-trip distance for site j

R_j: rental expense for site j

4.6 Real Time Reservoir Operation depicted by Fuzzy Model

For multipurpose real-time reservoir operation, a fuzzy rule-based control model is built. Total fuzzy similarity, a novel approach to fuzzy inference that is mathematically supported, is employed, and it is contrasted with the more conventional Sugeno-style approach. In particular, the seasonal variation in both operational aims and hydrological variables is investigated by taking into account the inputs as season-dependent relative values rather than employing absolute values. A straightforward, approachable model structure is made possible by the inference drawn over time.

Example where model was tested.

- A controlled lake in Finland named Lake Paijanne serves as an example for the control model.

The model is calibrated to both better fulfill the new multipurpose operational objectives established by experts and to simulate the actual operation. The results that were achieved using the current inference approaches were similar.

5 System and Random Uncertainty Analysis

Given below is an example of where uncertainty analysis is used to determine the carrying capacity of a steel column:

A structural member's carrying capacity under end compressive loads depends on a number of variables. The end restrictions that the column is subject to because they are a part of a larger structure are the most significant of these, the column's original shape, any lingering strains, and how narrow it is along its longitudinal axis. There is a significant degree of scatter in the failure load, according to test findings gathered over time from numerous laboratories throughout the world. Frequently, information like the initial slope and residual stress distribution are not captured, which of course makes it more difficult to use the data for design and goals. It is uncommonly cost-effective to produce optimum pin ending circumstances in an actual structure, hence tests are frequently conducted on columns with those parameters. Curves are fitted to lower bounds on the data for specific categories of structural cross section in order to make practical use of the data.

In our example, $M = \sigma_c/\sigma_y$ a non-dimensional parameter, the ratio of permissible compressive stress σ_c to yield stress σ_c and L is the effective length of the column, r_y is the minimum radius of gyration of the cross-section, and E is Young's modulus, which is a measure of longitudinal slenderness modulus. A part of the column's actual length makes up the effective length. For hypothetical end conditions, this can be precisely determined, but for implementation in a real construction, the designer must make a determination regarding the expected end restraint values for the column.

The following is how a deterministic calculation would proceed. Given is a column having the following dimensions: 3 m in length, 3800 mm^2 in cross section, 30.5 mm in gyration radius, 200 kN/mm^2 in Young's modulus, and 245 N/mm^2 in yield stress. The effective length is 0.8 x 3 m, or 2.4 m, if the effective length factor is determined to be 0.8. Now,

$$\lambda = \frac{2.4*10^3}{30.5*\pi\sqrt{200*10^3/245}} = 0.88$$

If the column is subjected to a 550 kN applied load, then the applied stress is

$$f_c = \frac{550*10^3}{3800} = 145N/mm^2$$

and the respective ratio becomes

$$m = \frac{f_c}{\sigma_c}$$

However, this computation makes no mention of the degree of uncertainty in the solution. We will now describe the same calculation with the effective length factor treated as a fuzzy variable and the relation between M and A treated as a fuzzy relation. Let L be, for instance, each element divided by 3m, or 0.7/0.4, 0.8/0.9, and 0.9/0.6. If r_y, E, and are deterministic as before,

$$\lambda = 0.7/0.3, 0.8/0.7, 0.9/0.9, 1/0.6$$

and

$$\sigma_c = M * \sigma_y = 122/0.3, 147/0.6, 171/0.8, 196/0.8, 220/0.6, 245/0.4, 269/0.1$$

Assuming the applied load (W) is a random variable, the following values will be taken

PW= 750 kN = 0.1

PW= 650 kN = 0.2

PW= 550 kN = 0.6

PW= 450 kN = 0.1

The ratio becomes,

$$\frac{f_c}{\sigma_c} = \frac{W}{A*\sigma_c} = m$$

whereas the normalising factor becomes

$$0.1 \text{ x } 5.4 + 0.2 \text{ x } 4.6 + 0.6 \text{ x } 4.2 + 0.1 \text{ x } 3.4 = 4.32$$

6 Conclusion

It takes scientific knowledge to do civil engineering. However, estimating the uncertainty surrounding the implementation of a scientific calculation is very challenging due to the public's need for high levels of safety and the absence of a prototype testing facility. A lot of judgement is made based on past experience, and this must be used more effectively in the future. System uncertainty can be estimated using fuzzy sets, and probability measures of both system and random uncertainty can be computed. Those who view engineering as an applied science will claim that the use of such approaches as those suggested above would lead in a loss of objectivity in the calculations and would claim that the usage of fuzzy relations that were derived subjectively is invalid. But as was already mentioned, in order to apply the objective calculations to actual engineering problems, judgments about what constitutes a valid starting point for a calculation and what the findings at the end entail in terms of the decisions that need to be made must be made.

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