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Fuzzy Knowledge Based System for Suitability of Soils in Airfield Applications

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Abstract

Proper design of roads and airfield pavements requires an in-depth soil properties evaluation to determine suitability of soil. Soft computing is used to model soil classification system's dynamic behaviour and its properties. Soft computing is based on methods of machine learning, fuzzy logic and artificial neural networks, expert systems, genetic algorithms. Fuzzy system is a strong method for mimicking human thought and solves question of confusion. This paper proposes a new decision-making approach for soil suitability in airfield applications without a need to perform any manual works like use of tables or chart. A fuzzy knowledge - based approach is built to rate soil suitability in qualitative terms for airfield application. The proposed model describes a new technique by defining fuzzy descriptors using triangular functions considering the index properties of soils as input parameters and fuzzy rules are generated using fuzzy operators to classify soil and rate its suitability for airfield applications. The data obtained from the results of the laboratory test are validated with the results of the fuzzy knowledge-based system indicating the applicability of the Fuzzy model created. The approach developed in this work is more skilled to other prevailing optimization models. Due to its system's flexibility, it can be suitably customized and applied to laboratory test data available, thus delivering a wide range for any geotechnical engineer.

Keywords: Classification System; Triangular Fuzzy Sets; Decision Tree Algorithm; Expert System.

1. Introduction

Soil classification is one of the key prerequisites any geotechnical engineer requires to have, either in the underground construction works or in the construction works on the high way. The classification of the soil must be done annually and at regular intervals for highway or metro building alignment. For example, The Handbook on Quality Assurance for Rural Roads states that the soil classification tests have to be performed for one km or part of each source [1]. The sheer volume of soil classification reports that need to be produced and stored for easy report management and quick recovery becomes an onerous task for huge projects like metro construction or highway construction where the reports are manually prepared and stored in access and recovery files.

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Soft Computing's basic purpose is to bring intelligence into the machine. Some elements or attributes of intelligence must be defined in order to construct intelligent machine. Soft computing does not reflect a single technique. Instead, it's a group (or) association of distinct methodologies. The aim of new approaches is to reduce the system's complexity while retaining its maximum usefulness and therefore, to reduce the modelling time on computational cost. Soft computing is used to model the dynamic behaviour and properties of the soil classification system. Soft computing adorns inaccuracy, ambiguity, partial truth, and approximations. Soft computing is based on methods of machine learning, fuzzy logic, artificial neural networks, genetic algorithms, expert systems. Fuzzy system is a strong means for mimicking human thought and solves question of confusion. Fuzzy decision tree approach has been enforced to many real-world problems. Samui et al. (2009) reviewed the application of soft computing techniques to the characterization of expansive soil [2].

Cho and Kurup (2011) proposed a decision tree method for the classification and reduction of electronic nose data in terms of dimensionality [3]. In 2012. Modeling of suspended sediment concentration in kasol in India was demonstrated by Kumar et al., using Fuzzy logic and decision tree algorithms [4]. Yakar and Celik (2014) introduced a model for evaluating highway alignment, integrating GIS Multi-criteria decision taking [5]. A fuzzy model for contaminated soil parameters was developed by Umesha et al. (2014) [6]. Based on the fuzzy classification [7], Effati et al. anticipated crash frequency on two-lane, two-way roads in 2015. The crucial factors in the construction industry were addressed by Shariati et al. (2017) using a fuzzy approach [8]. Ogunleye et al. (2018) developed a fuzzy logic method for soil fertility forecasting by interpreting the values of nitrogen, phosphorus, and potassium (NPK) obtained from traditional soil testing to know their soil levels [9]. Using fuzzy logic Kierzkowski and Kisiel (2017) [10] suggested a model for choosing an optimal structure for the evaluation of a security control lane and security control process at an airport by considering efficiency of prohibited item detection, capacity and level of service. Sadjadi and Khalkhali (2018) conducted challenges in geotechnical investigation for tunneling in urban areas. The research/study primarily focused on the prerequisite for the study of geotechnical properties such as choosing the right TBM, ground water level, and engineering properties of soils [11]. Rezaee and Yousefi (2018) suggested a decision-making approach for recognizing and examining airport risk by giving consideration to cause effect relationships that illuminates the performance of the airport using Fuzzy Cognitive Map (FCM) method [12].

Vyas et al. (2019), by adopting non-destructive technique, suggested a novel decision-making methodology built on fuzzy SWOT for maintenance of airfield pavements and integrated condition assessment. The approach fortified is superior to the other accepted optimization models [13]. Borse and Agnihotr (2019) developed a crop yield model using fuzzy rule based system by considereing criterions such as rainfall, humidity temperature, evaporation by taking in to cosideration crop yield for 15-year and verified by coefficient of correlation [14]. In 2020 an objective approach was developed by Vyas et al., using soft-computing technique to rank and grade airfield pavement conditions by collecting data through visual surveys and field tests [15]. Sujatha et al. (2020), proposed a fuzzy expert system for classification of soils for engineering purposes by using triangular membership functions to evaluate soils based on engineering properties [16]. Sujatha et al. (2020), proposed a fuzzy rule based system for highway research board classification of soils using fuzzy decision tree algorithm to evaluate qualitative soil classification [17]. Moonjun et al. (2020) assessed the usefulness of fuzzy logic in increasing efficiency in soil mapping by contemplating Lithology and terrain criterions as predictor variables [18].

The application of Fuzzy knowledge-based system for geotechnical engineering is very much limited and to best of the knowledge, fuzzy systems to discuss the suitability of soil in airfields application have not been applied. There are no fixed rules for developing a fuzzy knowledge-based system, even though a general outline can be followed based on previous successful applications in such problems.

In this paper a fuzzy knowledge-based approach is built to measure soil suitability in qualitative terms for airfield applications, the proposed model describes a new technique for subdividing the universe of discourse into numbers of intervals depending on the index properties of the soil. The proposed knowledge-based model is implemented in MATLAB (Math Works Inc. 2015) modeling environment. The index properties of soil are the input parameters which if fuzzified by defining fuzzy sets and corresponding triangular membership functions are computed. Fuzzy operators are used to define the relationship between the fuzzy input parameters to derive fuzzy fitness rules which is an inference engine to predict soil types and their suitability for airfield applications. Laboratory test data are collected and are used to validate the results of the fuzzy knowledge-based system. The results obtained coincides with the laboratory test results indicating the proposed model can be used for airfield applications.

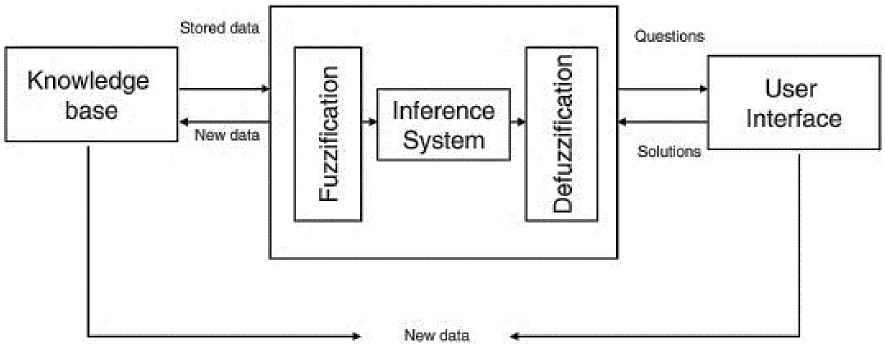

Figure 1. Basic architecture of a fuzzy expert system.

2. Review of Fuzzy Set Theory

In this section we give a brief introduction into the theory of fuzzy sets, fuzzy set operations and fuzzy logic, as far as it is needed for the understanding of the presented fuzzy logic expert system Fuzzy set theory is a versatile method of which imprecise data can be accepted. The key benefit is that, unlike other modelling approaches, expert opinion can be used in the fuzzy set theory [19, 20].

2.1. Definition

Let D be a nonempty set. A fuzzy set Q in D is characterized by its membership function $A: D \to [0,1]$ and A is interpreted as the degree of membership of element l in fuzzy set Q for each $l \in D$.

In fuzzy set theory, fuzzy sets are denoted by membership functions. In practice, membership functions are selected arbitrarily. The most widely used membership functions are usually represented in triangular, trapezoidal, Gaussian forms [20]. The triangular function defined by parameters a, b and $c,$ where a ≤ b ≤ c is defined by

$$\mu_Q(x) = \max\left[min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right)\right] \tag{1}$$

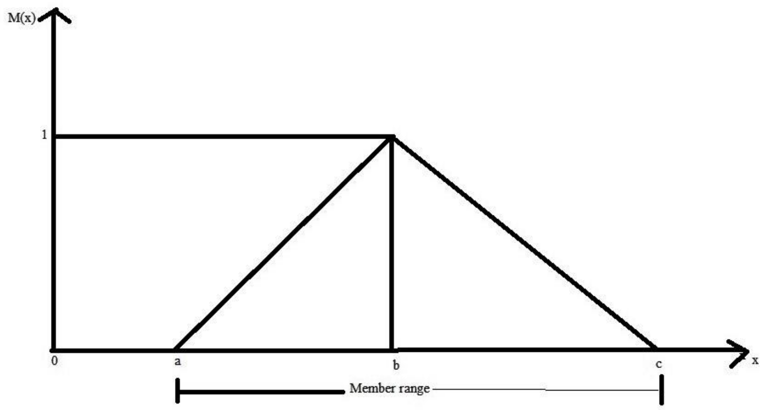

Figure 2. Triangular Fuzzy number

2.2. Operations on Fuzzy Sets

Let A and B be two fuzzy sets of the universe of discourse X with membership function $A(g)$ & $B(g)$, respectively.

- The union of the fuzzy sets A & B is defined by $A \cup B(g) = \max[A(g), B(g)],\ \forall g \in X$.
- The intersection of A and B, is defined by $A \cap B(x) = \min[A(g), B(g)]$, $\forall g \in X$.
- The complement of A, denoted by $\bar{A}$, is defined by $\bar{A}(g) = 1 - A(g),\quad \forall g \in X$.

3. Proposed Fuzzy Rule-based Inference Model

To design the framework of fuzzy knowledge-based system some experts have defined the parameters and ranges of the membership functions. The input parameters considered for the proposed Fuzzy Knowledge based system are particle size less than 4.75 mm, particle size less than 0.075 mm, uniformity coefficient, curvature coefficient, liquid limit, plastic limit is based on expert's knowledge and Fuzzy knowledge-based approach by experimental studies.

The proposed system is developed in MATLAB based on the input and output variables, and the fuzzy sets for the input parameters with maximum and minimum values are defined and fuzzy rules are generated using max-min principle [21]. Fuzzy decision tree algorithm is used to construct fuzzy fitness rules [22]. The rules are verified if they suitably reflect the expert's knowledge and are reviewed if they are correct. If any of the rules contain a mistake, the rule is substituted. After checking of all the rules, defuzzification is performed to generate crisp outputs for the model or system. A new surface is being created which provides us with soil suitability for airfield applications.

3.1. Algorithm

Algorithm to demonstrate the proposed Fuzzy Knowledge based system for Soil Profile Data is as follows.

Input: Create FIS, The training sample of Particle size lesser than 4.75 mm, 0.075 mm, uniformity coefficient, coefficient of curvature, liquid limit, and plastic limit.

Output: A FIS trained to classify the soil samples with suitability of soil for airfield applications.

Step 1. FIS=Create Fuzzy Inference System;

Step 2. Indian Standard Classification system = Read particle size lesser than 4.75 mm, 0.75 mm, uniformity coefficient, coefficient of curvature, liquid limit, plastic limit.

Step 3. Class = Totper (Indian Standard Classification of soil);

Step 4. Suitability = Fuzzify (Class);

Step 5. Call Fuzzy Fitness Rules;

Step 6. Fuzzy Output Classification = Fuzzy Inference Engine (Suitability);

Step 7. Crisp Output = Defuzzify (Fuzzy Output Classification);

Step 8. Suitability (Indian Standard classification of soil) = Crisp Output;

Step 9. Display suitability of soil.

4. Research Methodology

4.1. Data Collection

Soil samples are obtained from database on soil index and engineering properties, based on field and laboratory test conducted.

4.2. Linguistic Variables

The input parameters are fuzzified and fuzzy sets are defined using the fuzzy linguistic variables, extremely few (EF), few (F), less (L), Moderately Less (ML), Moderately High (MH), High (H), Extreme (E), Extremely High (EH) as shown in Table 1. The Min and Max values would be used as the range for the membership functions of the measured input variables. The fuzzy linguistic variable defined to rate the suitability of classified soil for airfield application is shown in Table 2.

Table 1. Fuzzy sets for the input variables

Linguistic variables (membership functions)	Input variables					
	Particle size lesser than 4.75 mm	Particle size lesser than 0.075 mm	Uniformity Coefficient	Coefficient of curvature	Plasticity Index	Liquid limit
EF	-	[0, 2.5]	-	-	-	-
F	[0, 25]	[0, 5]	[0, 2]	-	[0, 2]	[0, 17.5]
L	[0, 50]	[2.5, 8.5]	[0, 4]	[0, 1]	[0, 4]	[0, 35]
ML	-	[5, 12]	[2, 5]	[0, 5.2]	[2, 5.5]	[17.5, 42.5]
M	[25, 75]	[8.5, 31]	[4, 6]	[1, 3]	[4, 7]	[35, 50]
MH	-	[12, 50]	[5, 8]	[2, 6.5]	[5.5, 33.5]	[42.5, 75]
H	[50, 100]	[31, 75]	[6, 10]	[3, 10]	[7, 60]	[50, 100]
E	[75, 100]	[50, 100]	[8, 10]	[6.5, 10]	[33.5, 60]	[75, 100]
EH	-	[75, 100]	-	-	-	-

Table 2. Fuzzy Linguistic variables for suitability of classified soil

Ratings	Fuzzy Linguistic Variable
Excellent	E
Good to Excellent	GE
Good	G
Fair to Good	FG
Fair	F
Poor to fair	PF
Poor	P
Poor to very poor	VP
practically impervious	PI
Poor to practically impervious	PPI
Not Suitable	NS
Almost none	AN
None to very slight	NVS
Slight	S
Very slight	VS
Slight to medium	SM
Slight to high	SH
Medium	ME
Medium to high	MEH
Medium to very high	MEVH
High	HI
Very high	VHI

5. Membership Functions

The membership function for the input parameters are defined by triangular functions. Triangular function will have a range of three values (Lower limit, mid-point, Upper limit). The fuzzy membership function built for particle size less than 4.5 mm, particle size less than 0.075 mm, uniformity coefficient, coefficient of curvature, liquid limit, plasticity index is shown in Figure 3, 4, …, 8.

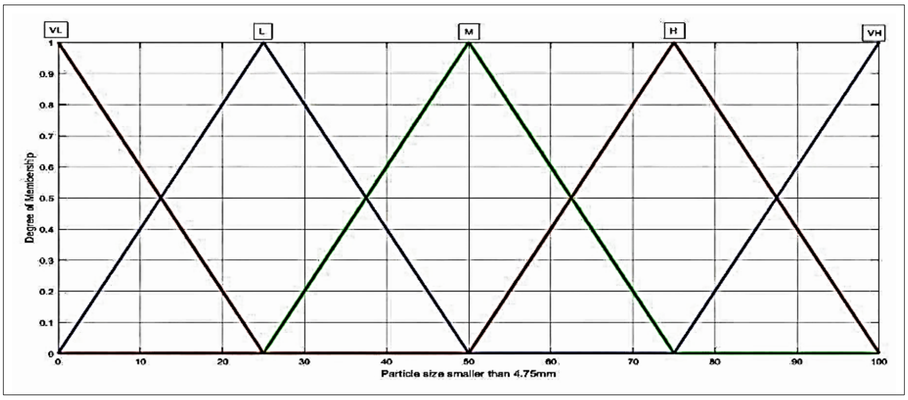

Figure 3. Fuzzy membership function for particle size lesser than 4.75 mm

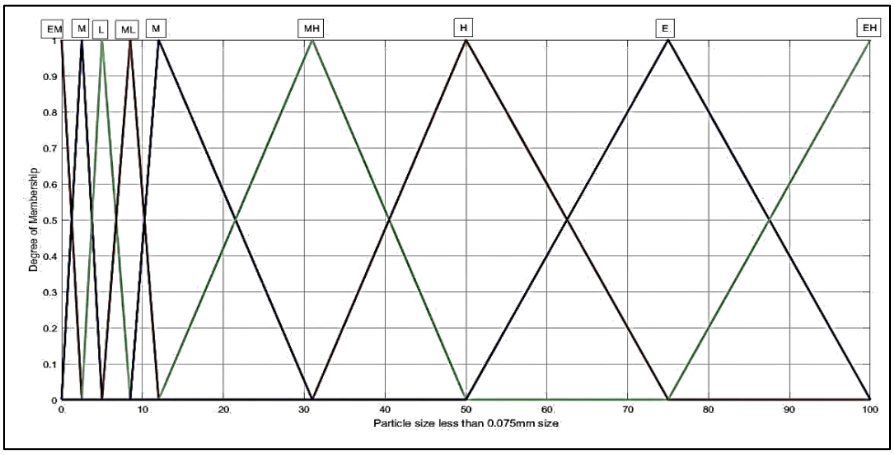

Figure 4. Fuzzy membership function for particle size lesser than 0.075 mm

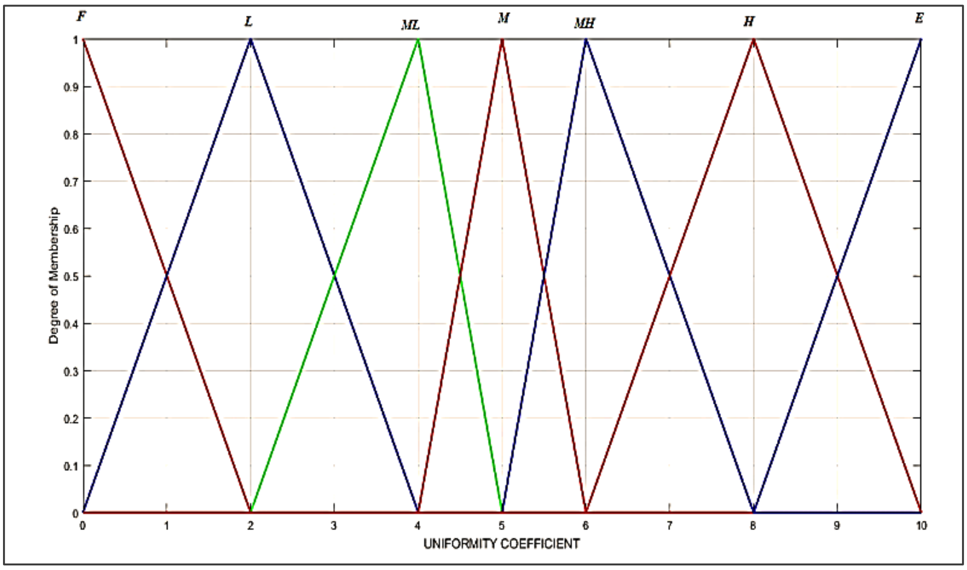

Figure 4. Fuzzy membership function for uniformity coefficient

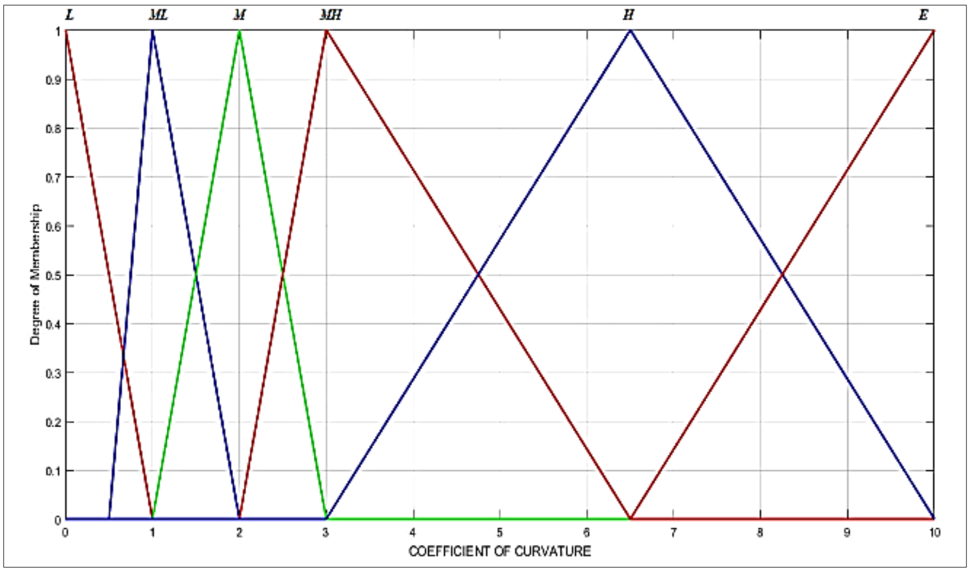

Figure 5. Fuzzy membership function for coefficient of curvature

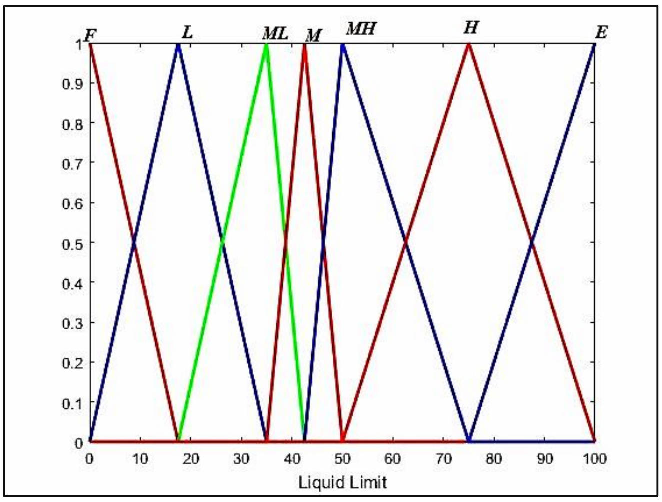

Figure 7. Fuzzy membership function for Liquid limit

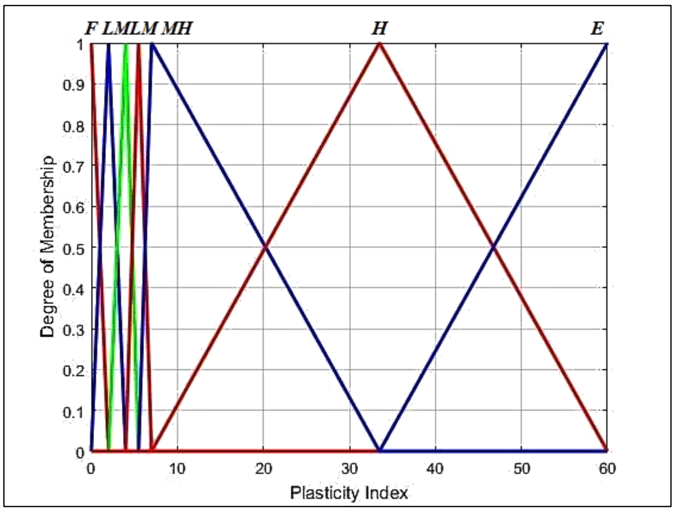

Figure 8. Fuzzy membership function for plasticity index

6. Fuzzy Fitness Rules Generated

Fuzzy Fitness Rules are developed on the basis of IS norm and soil index properties [22]. The proposed Fuzzy knowledge-based system algorithm for Soil Profile Information, classifies the soil and effectively predicts the suitability of classified soil in airfield applications to set up the human development [23]. Fuzzy rule to predict the suitability of classified soil are as follows:

- If (particle size lesser than 4.75 mm is L) Λ (particle size lesser than 0.075 mm is F) Λ (uniformity coefficient is M) Λ (coefficient of curvature is M) ⇒ (soil type is Well graded Gravel (GW) and its rating are Value as subgrade when not subject to frost action is E, Value as sub-base when not subject to frost action is E, Value as base when not subject to frost action is G, Potential frost Action is NVS, Compressibility and Expansion is AN and Drainage characteristics is E).
- If (particle size lesser than 4.75 mm is L) Λ (particle size lesser than 0.075 mm is F) Λ (uniformity coefficient is L) Λ (coefficient of curvature is L, H) ⇒ (soil type is Poorly graded Gravel (GP) and its rating are Value as subgrade when not subject to frost action is GE, Value as sub-base when not subject to frost action is G, Value as base when not subject to frost action is FG, Potential frost Action is NVS, Compressibility and Expansion is AN and Drainage characteristics is E).
- If (particle size lesser than 4.75 mm is H) Λ (particle size lesser than 0.075 mm is F) Λ (uniformity coefficient is H, E) Λ (coefficient of curvature is M) ⇒ (soil type is Well graded Sand (SW) and its rating are Value as subgrade when not subject to frost action is G, Value as sub-base when not subject to frost action is FG, Value as base when not subject to frost action is P, Potential frost Action is NVS, Compressibility and Expansion is AN and Drainage characteristics is E).
- If (particle size lesser than 4.75 mm is H Λ (particle size lesser than 0.075 mm is F) Λ (uniformity coefficient is L, M) Λ (coefficient of curvature is L, H) ⇒ (soil type is Poorly graded Sand (SP) and its rating are Value as subgrade when not subject to frost action is FG, Value as sub-base when not subject to frost action is F, Value as base when not subject to frost action is PNS, Potential frost Action is NVS, Compressibility and Expansion is AN and Drainage characteristics is E).
- If (particle size lesser than 4.75 mm is L) Λ (particle size lesser than 0.075 mm is MH, E) Λ (plasticity index is L) ⇒ (soil type is Silty Gravel (GM) and its rating are Value as subgrade when not subject to frost action is GE, Value as sub-base when not subject to frost action is G, Value as base when not subject to frost action is FG, Potential frost Action is SM, Compressibility and Expansion is VS and Drainage characteristics is FP).
- If (particle size lesser than 4.75 mm is L) Λ (particle size lesser than 0.075 mm is MH, E) Λ (plasticity index is H) ⇒ (soil type is Clayey Gravel (GC) and its rating are Value as subgrade when not subject to frost action is G, Value as sub-base when not subject to frost action is F, Value as base when not subject to frost action is PNS, Potential frost Action is SM, Compressibility and Expansion is S and Drainage characteristics is PPI).
- If (particle size lesser than 4.75 mm is H) Λ (particle size lesser than 0.075 mm is MH, E) Λ (plasticity index is H), ⇒ (soil type is Clayey Sand (SC) and its rating are Value as subgrade when not subject to frost action is PF, Value as sub-base when not subject to frost action is P, Value as base when not subject to frost action is NS, Potential frost Action is SH, Compressibility and Expansion is SM and Drainage characteristics is PPI).

- If (particle size lesser than 0.075 mm is E) Λ (liquid limit is L) Λ (plasticity index is L) ⇒ (soil type is Low Compressibility Silt (ML/OL) and its rating are Value as subgrade when not subject to frost action is PF, Value as sub-base when not subject to frost action is NS, Value as base when not subject to frost action is NS, Potential frost Action is MEVH, Compressibility and Expansion is SM and Drainage characteristics is FP).
- If (particle size lesser than 0.075 mm is E) Λ (liquid limit is L) Λ (plasticity index is H) ⇒ (soil type is Low Compressibility Clay (CL) and its rating are Value as subgrade when not subject to frost action is PF, Value as sub-base when not subject to frost action is NS, Value as base when not subject to frost action is NS, Potential frost Action is MH, Compressibility and Expansion is M and Drainage characteristics is PI).
- If (particle size lesser than 0.075 mm is E) Λ (liquid limit is M) Λ (plasticity index is L) ⇒ (soil type is Silt with Intermediate Plasticity (MI/OI) and its rating are Value as subgrade when not subject to frost action is PF, Value as sub-base when not subject to frost action is NS, Value as base when not subject to frost action is NS, Potential frost Action is MEVH, Compressibility and Expansion is SM and Drainage characteristics is FP).
- If (particle size lesser than 0.075 mm is E) Λ (liquid limit is M) Λ (plasticity index is H) ⇒ (soil type is Clay with Intermediate Plasticity (CI) and its rating are Value as subgrade when not subject to frost action is PF, Value as sub-base when not subject to frost action is NS, Value as base when not subject to frost action is NS, Potential frost Action is MH, Compressibility and Expansion is M and Drainage characteristics is PI).
- If (particle size lesser than 0.075 mm is E) Λ (liquid limit is H) Λ (plasticity index is L) ⇒ (soil type is Silty with High Plasticity (MH/OH) and its rating are Value as subgrade when not subject to frost action is P, Value as sub-base when not subject to frost action is NS, Value as base when not subject to frost action is NS, Potential frost Action is MVH, Compressibility and Expansion is H and Drainage characteristics is FP).
- If (particle size lesser than 0.075 mm is E) Λ (liquid limit is H) Λ (plasticity index is H) ⇒ (soil type is Clay with High Plasticity (CH) and its rating are Value as subgrade when not subject to frost action is PVP, Value as sub-base when not subject to frost action is NS, Value as base when not subject to frost action is NS, Potential frost Action is M, Compressibility and Expansion is H and Drainage characteristics is PI).

7. Results and Discussion

The soil data from various sources available from data base are taken with input parameters, particle size less than 4.75 mm size, 0.075 mm size, coefficient of curvature, uniformity coefficient, liquid limit, plastic limit and the ratings for suitability of soil for airfield applications as output. Table 4 shows the 15 soil samples considered to validate the proposed knowledge-based system. The proposed system is implemented in MATLAB (Math Works Inc. 2015) modeling environment. The Input values of the 15 soil samples considered are shown in Table 3. The input values of the 15-soil samples considered are fuzzified and their membership values using triangular functions are calculated and the values are as shown in Tables 5 –10. We use the generated fuzzy rules to rate the soils for its suitability in airfield applications are shown in Table 11.

Table 4. Input values of the soil samples

Soils	Input Values					
	Particle size lesser than 4.75 mm (percentage)	**Particle size lesser than 0.075 mm (percentage)**	**Uniformity Coefficient**	**Coefficient of curvature**	**Liquid limit**	**plastic limit**
1	25	10	-	-	20	15
2	10	3	4.5	3.5	-	-
3	10	35	-	-	25	22
4	100	100	-	-	40	32
5	85	80	-	-	28	25
6	75	3	4.3	6	-	-
7	90	78	-	-	26	16
8	80	25	-	-	40	37
9	70	40	-	-	45	22
10	90	78	-	-	75	45
11	33	24	5.4	2.9	-	-
12	45	30	-	-	25	15
13	94	3	5.8	0.4	-	-
14	100	65	-	-	80	25
15	10	70	0	0	20	14

Table 5. Membership Values corresponding to particle size lesser than 4.75 mm

Soils	F	L	M	H	E
1	0	1	0	0	0
2	0.6	0.4	0	0	0
3	0.6	0.4	0	0	0
4	0	0	0	0	1
5	0	0	0	0.6	0.4
6	0	0	0	1	0.6
7	0	0	0	0.4	0.6
8	0	0	0	0.8	0.2
9	0	0	0.2	0.8	0
10	0	0	0	0.4	0.6
11	0	0.68	0.32	0	0
12	0	0.2	0.8	0	0
13	0	0	0	0.24	0.76
14	0	0	0	0	1
15	0.6	0.4	0	0	0

Table 6. Membership Values corresponding to Particle size lesser than 0.075 mm

Soils	EF	F	L	ML	M	MH	H	E	EH
1	0	0	0.5714	0.4286	0	0	0	0	0
2	0	0.8	0.2	0	0	0	0	0	0
3	0	0	0	0	0	0.7895	0.2105	0	0
4	0	0	0	0	0	0	0	0	1
5	0	0	0	0	0	0	0	0.8	0.2
6	0	0.8	0.2	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0.88	0.12
8	0	0	0	0	0.3158	0.6842	0	0	0
9	0	0	0	0	0	0.5263	0.4737	0	0
10	0	0	0	0	0	0	0	0.88	0.12
11	0	0	0	0	0.3685	0.6315	0	0	0
12	0	0	0	0	0.0526	0.9474	0	0	0
13	0	0.8	0.2	0	0	0	0	0	0
14	0	0	0	0	0	0	0.4	0.6	0
15	0	0	0	0	0	0	03334	0.6666	0

Table 7. Membership values corresponding to Uniformity Coefficient

Samples	F	L	ML	M	MH	H	E
1	0	0	0	0	0	0	0
2	0	0	0.5	0.5	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0.3	0.7	0	0	0
7	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0
11	0	0	0	0.6	0.4	0	0
12	0	0	0	0	0	0	0
13	0	0	0	0.2	0.8	0	0
14	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0

Table 8. Membership values corresponding to Coefficient of Curvature

z	L	ML	M	MH	H	E
1	0	0	0	0	0	0
2	0	0	0	0.8571	0.1429	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0
5	0	0	0	0	0	0
6	0	0	0	0	0.1429	0.8571
7	0	0	0	0	0	0
8	0	0	0	0	0	0
9	0	0	0	0	0	0
10	0	0	0	0	0	0
11	0	0	0.1	0.9	0	0
12	0	0	0	0	0	0
13	0.6	0.4	0	0	0	0
14	0	0	0	0	0	0
15	0	0	0	0	0	0

Table 9. Membership values corresponding to Plasticity Index

Samples	F	L	ML	M	MH	H	E
1	0	0	0.3333	0.6667	0	0	0
2	0	0	0	0	0	0	0
3	0	0.5	0.5	0	0	0	0
4	0	0	0	0	0.9623	0.0377	0
5	0	0.5	0.5	0	0	0	0
6	0	0	0	0	0	0	0
7	0	0	0	0	0.18868	0.81132	0
8	0	0.5	0.5	0	0	0	0
9	0	0	0	0	0.3962	0.6038	0
10	0	0	0	0	0.1321	0.8679	0
11	0	0	0	0	0	0	0
12	0	0	0	0	0.8868	0.1132	0
13	0	0	0	0	0	0	0
14	0	0	0	0	0	0.18868	0.81132
15	0	0	0	0	0.509	0.491	0

Table 10. Membership function corresponding to Liquid Limit

Samples	F	L	ML	M	MH	H	E
1	0.1428	0.8572	0	0	0	0	0
2	0	0	0	0	0	0	0
3	0	0.7428	0.2572	0	0	0	0
4	0	0.1714	0.8286	0	0	0	0
5	0	0.5714	0.4286	0	0	0	0
6	0	0	0	0	0	0	0
7	0.0857	0.9143	0	0	0	0	0
8	0	0	0.73334	0.2666	0	0	0
9	0	0.7428	0.2572	0	0	0	0
10	0	0	0	0.6667	0.3333	0	0
11	0	0	0	0	0	0	0
12	0.1428	0.8572	0	0	0	0	0
13	0	0	0	0	0	0	0
14	0	0.5714	0.4286	0	0	0	0

The analysis of the 15- soil samples considered are as shown

Sample 1:

Laboratory test result of a soil sample are:

- Particle size lesser than 4.75 mm - 25%;
- Particle size lesser than 0.075 mm – 10%;
- Uniformity Coefficient – 4.5;
- Coefficient of Curvature – 2.5.

The illustration of the proposed fuzzy Knowledge based system is as shown:

The input values are fuzzified in terms of fuzzy descriptors.

- Particle size lesser than 4.75 mm in terms of fuzzy descriptors are F, L, M, H, E and the corresponding membership values obtained are 0, 1, 0, 0, 0.
- Particle size lesser than 0.075 mm in terms of fuzzy linguistic variable are EF, F, L M, ML, M, MH, H, E, EH and the corresponding membership values obtained are 0, 0.5714, 0.4286, 0, 0, 0, 0, 0, 0.
- Plasticity index in terms of fuzzy linguistic variable are F, L, ML, M, MH, H, E and the corresponding membership values obtained are 0, 0, 0.3333, 0.6667, 0, 0, 0.
- Liquid limit in terms of fuzzy linguistic variable are F, L, ML, M, MH, H, E and the corresponding membership values obtained are 0.1428, 0.8572, 0, 0, 0, 0.

Now the generated fuzzy rules are applied to the fuzzified parameters of the soil sample. Using the combination of MAX – MIN operator the degree of possibility of each fuzzy rule is calculated. Fuzzy rule 6 gets 0.8333 as the highest degree of possibility. Therefore, soil sample 1 is classified as Clayey Gravel (GC), and its rating are Value as subgrade when not subject to frost action is G, Value as sub-base when not subject to frost action is F, Value as base when not subject to frost action is PNS, Potential frost Action is SM, Compressibility and Expansion is S and Drainage characteristics is PPI. This soil class and its rating coincides with the laboratory test results.

The analysis done for sample 1 is repeated for sample 2. fuzzy rules are applied and the degree of possibility of all the fuzzy rules are calculated. Fuzzy rule 1 gets the highest degree of possibility 0.64. Therefore, Sample 2 is classified as Well graded Gravel (GW) and its rating are Value as subgrade when not subject to frost action is E, Value as sub-base when not subject to frost action is E, Value as base when not subject to frost action is G, Potential frost Action is NVS, Compressibility and Expansion is AN and Drainage characteristics is E. This soil class and its rating coincides with laboratory test results.

The above analysis is repeated for sample 3, 4, 5, …, 15. For each of the soil samples the highest degree of possibility, soil class and its ratings are summarized in Table 11.

Table 11. Degree of possibility and the ratings of the soil samples

Soil Sample	Highest degree of Possibility value	Soil type	Value as Subgrade when not subject to frost Action	Value as Sub-base when not subject to frost Action	Value as base when not subject to frost Action	Potential frost Action	Compressibility and Expansion	Drainage characteristics
1	0.8333	GC	G	F	PNS	SM	S	PPI
2	0.64	GW	E	E	G	NSV	AN	E
3	0.5989	GM	GE	G	FG	SM	VS	FP
4	0.8962	OI	P	NS	NS	MEH	MEH	P
5	0.71	ML	PF	NS	NS	MEVH	SM	FP
6	0.8314	SP	FG	F	PNS	NVS	AN	E
7	0.7710	CL	PF	NS	NS	MEH	M	PI
8	0.7284	SM	FG	FG	P	SH	VS	FP
9	0.7334	SC	PF	P	NS	SH	SM	PPI
10	0.9148	OH	PVP	NS	NS	M	HI	PI
11	0.82	GW	E	E	G	NSV	AN	E
12	0.8321	GC	G	F	PNS	SM	S	PPI
13	0.7680	SP	FG	F	PNS	NVS	AN	E
14	0.9223	SC	PF	P	NS	SH	SM	PPI
15	0.8038	CL	PF	NS	NS	MEH	ME	PI

8. Conclusion

The qualitative problems in engineering are solved using mathematical models in deterministic form. Before embarking on any construction project, soil classification is the basic prerequisite that any geotechnical engineer needs to learn. But uncertainties occur because of the dynamic nature of the problem. This proposed fuzzy knowledge-based model has shown how fuzzy logic, as an expert system can be applied to determine soil type and its suitability in airfield applications. The flexibility of the system empowers the validation of the rules defined in the system which is implemented in MATLAB programming environment. The proposed fuzzy knowledge-based model has the advantage that once the model is trained, it can be used as an accurate and quick tool for predicting the soil type and its rating for suitability in airfield applications without a need to perform any manual work such as using tables or charts.

9. Declarations

9.1. Author Contributions

A. Sujatha, L. Govindaraju, N. Shivakumar, and V. Devaraj contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript. All authors have read and agreed to the published version of the manuscript.

9.2. Data Availability Statement

The data presented in this study are available in article.

9.3. Funding

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9.4. Conflicts of Interest

The authors declare no conflict of interest.

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