Application of Fuzzy Logic in Central Composite Design for Additives Optimization in Expansive Soil Treatment

Clifford Ugochukwu Nwoji[1], Chijioke Christopher Ikeagwuani[2*], Ekene Jude Nwankwo[3], Chukwudi Humphery Ukwueze[4], Chinonyelum Ugochukwu Asogwa[5]

[1,2,3,4,5] *Civil Engineering Department, University of Nigeria, Nsukka, Enugu State, Nigeria*

*Correspondence: Chijioke C. Ikeagwuani; chijioke.ikeagwuani@unn.edu.ng; +2347036527888

Abstract- This present study integrated fuzzy logic in central composite design (CCD) to optimize multi-additives for expansive soil treatment. The multi-additives, which included sawdust ash (SDA), quarry dust (QD) and ordinary Portland cement (CM), ranged from 0-20% for SDA, 0-20% for QD and 2-8% for CM. Responses such as California bearing ratio and differential free swell were evaluated using the CCD and preprocessed using grey relational analysis. The preprocessed responses were set as input variables in the fuzzy inference system of fuzzy logic to determine the multiple performance characteristics indices (MPCI). Next, the effect of each factor level on the mean MPCI was calculated and the factor level that maximized the mean MPCI value was taken as the optimal level for that factor. Thereafter, the optimum combination of additives (20% SDA+20%QD+8%CM) was determined. Laboratory experiment performed on the optimum combination of additives clearly revealed that fuzzy logic can be integrated in CCD to optimize multi-additives for the improvement of expansive soil.

Introduction

Expansive soils are problematic soils that pose serious challenges to engineers whenever they are encountered in practice. Arid and semi-arid regions are places where expansive soils are found (Soltani & Estabragh, 2015; Gourley, Newill, & Schreiner, 1993; Estabragh, Rafatjo, & Javadi, 2014). Expansive soils can also be found in sub-Saharan Africa especially countries such as Cameroon and Nigeria. Most of the expansive soils found in Nigeria are black cotton soil (BCS) that possesses a high amount of montmorillonite, a clay mineral that is notorious for the perennial shrink-swell behaviour of the soil (Ikeagwuani & Nwonu, 2019; Nwonu & Ikeagwuani, 2019). This clay mineral, which has the potential to absorb moisture during wet season causing excessive change in volume, is responsible for the numerous undesirable qualities the soil is related with when used either as foundation material or as subgrade in highway construction. As a result, different mitigation strategies are employed to strengthen the soil. One of such strategies is the stabilization of the soil either with chemical or mechanical mode.

Chemical mode of stabilization involves the utilization of chemical additives to alter the chemical properties of the soil for its improvement. The chemical additives are grouped into traditional and non-traditional additives. The traditional additives basically include lime, cement and fly-ash while the non-traditional additives include sawdust ash, lime kiln dust, cement kiln dust, pulverized coal bottom ash, mine tailings, tire rubber powder to mention but a few. Other numerous additives abound in literature that has been employed to improve the properties of expansive soils. However, what is glaring from literature is that most researchers fail to adopt optimization techniques to optimize the additives for the improvement of expansive soils. A commonly utilized optimization technique in other disciplines is the response surface methodology (RSM) (Ikeagwuani et al, 2020).

Despite RSM wide applicability and effectiveness in tackling several optimization problems, it is only effective for the optimization of a single response related problem. Perhaps, this explains the reluctance of geotechnical and highway engineers to utilize them in the optimization of additives for expansive soil improvement. Consequently, this study integrated fuzzy logic in the central composite design, a variant of RSM, to optimize multiple additives for the treatment of the properties of expansive soil.

Materials and Method

The materials used in this study were BCS and the additives, which include quarry dust (QD), sawdust ash (SDA) and ordinary Portland cement (CM).

Materials

Black cotton soil: The BCS sample was collected from a site (Ikeagwuani et al, 2019) in Numan (9^{o}29’10’’LN, 12^{o}02’36’’LE), Adamawa state, Nigeria that has been earlier studied and well-documented. Hand carved method of sampling was used for the collection of the soil samples at 1.5m depth measured below the surface of the ground. As shown in Table 1, the soaked and unsoaked California (CBR) values that were respectively 4.5% and 8.7%, and the plasticity index that was obtained as 48.7% are all indicative of the fact that the soil possesses weak geotechnical properties and therefore cannot be used for pavement construction.

Table 1. Properties of BCS

S/No	Property		Description
1	Specific gravity		2.6
2	Sand		8.9%
3	Fines		91.1%
4	Liquid limit		72.3%
5	Plastic limit		23.6%
6	Plasticity index		48.7%
7	Optimum moisture content		24.8%
8	Maximum dry density (BSL)		1.48g/cm^3
9	AASHTO classification		A-7-6 (48)
10	USCS classification		CH
11	CBR	Unsoaked	8.7%
		Soaked	4.5%
12	DFS		72%

Quarry dust: QD used as one of the additives in this study was obtained from a quarry industry that is located at Ugwuaji fly-over in Enugu state (7^o 32’ 47’’LN, 6^o 27’ 31’’LE) Nigeria.

Sawdust ash: SDA was obtained after the incineration of sawdust collected from Timber dumpsite in Kenyatta, Enugu, Nigeria. Sawdust is a solid waste whose disposal has continued to portend great challenge to the lumber industry and indeed the entire world.

Ordinary Portland cement: CM with grade 32.R was sourced commercially from Nsukka, in Enugu State, Nigeria.

Method

BS 1377 (BS 1377, 1990) procedure was adopted to determine all the properties of the BCS except the differential free swell (DFS) that was determined using (IS 2720 Part 40, 1977). The properties of the natural BCS specimen evaluated included grain size distribution, Atterberg limits, specific gravity, compaction characteristics and CBR. The CBR and DFS tests were carried out on the mix ratio generated by the central composite design (CCD). Samples for the CBR test were cured for 7 days.

Optimization procedure

In this present study and as mentioned earlier, three additives were selected as independent variables (process factors or parameters) to be optimized. The independent variables are CM, SDA and QD. They are shown in Table 2 with their various ranges in actual and coded values. Minitab version 17 was used to develop the designed experiments (generated array) that were subsequently utilized for the determination of the responses (CBR and DFS). Each experimental run in the designed experiment was performed in triplicate and their average value were determined and used for the analysis thereafter. Four center runs were chosen in the development of the experimental design. The value of the star points (∝) used in this study was fixed at 1.00 which implies that it is the central composite face-centered (CCF), a variant of the CCD that was used in this study. In all, there were 18 experimental runs used in the determination of the responses. The experimental layout is shown in Table 3 while the expression used for the generation of the experimental run is written as:

$$E_r = 2^k + 2k + n_c \qquad (1)$$

Where, E_r represents the number of design experiments or experimental runs, k is the number of factors or independent variables and n_c signifies the number of center runs.

Table 2. Process factors and level for optimization

Factors	**Actual unit (%)**		**Coded unit**	
	Low	High	Low	High
CM	2	8	-1	1
SDA	0	20	-1	1
QD	0	20	-1	1

Table 3. Layout of experiment

Expt. No.	**CM (%)**	**SD (%)**	**QD (%)**	**A**	**B**	**C**
1	2	0	0	1	1	1
2	8	0	0	3	1	1
3	2	20	0	1	3	1
4	8	20	0	3	3	1
5	2	0	20	1	1	3
6	8	0	20	3	1	3

7	2	20	20	1	3	3
8	8	20	20	3	3	3
9	2	10	10	1	2	2
10	8	10	10	3	2	2
11	5	0	10	2	1	2
12	5	20	10	2	3	2
13	5	10	0	2	2	1
14	5	10	20	2	2	3
15	5	10	10	2	2	2
16	5	10	10	2	2	2
17	5	10	10	2	2	2
18	5	10	10	2	2	2

Fuzzy logic integration in CCF

To optimize the additives by integrating fuzzy logic in the CCF, the mean values of the responses in each of the experiment were preprocessed using the grey relational analysis, which are expressed in Eqs. (2) and (3). Eq. (2) is used to project large response while Eq. (3) is used to project small response.

$$NS_i = \frac{G_i(j) - minG_i(j)}{maxG_i(j) - minG_i(j)} \tag{2}$$

$$NS_i = \frac{maxG_i(j) - G_i(j)}{maxG_i(j) - minG_i(j)} \tag{3}$$

NS_i denotes the normalized $G_i(J)$ value for the j^{th} response in the i^{th} experiment (referred to as $G_i(j)$ data comparability sequence)

Shortly after preprocessing the responses, the multiple performance characteristics indices (MPCI) were evaluated. Firstly, the crisp inputs were fuzzified using appropriate membership function (MF). Next, fuzzy rules were generated using the Mamdami fuzzy inference system. This was followed by the aggregation of the rule outputs using the max-min inference operation to obtain the fuzzy output. Thereafter, the fuzzy output obtained was defuzzified to obtain the crisp output.

Results and discussion

Fuzzy logic – CCF analysis

Firstly, the obtained responses were preprocessed. The CBR was preprocessed using Eq. (2) while the DFS was preprocessed using Eq. (3). The results are displayed in Table 4. The preprocessed reponses, which were taken as the input variables in the fuzzy inference system (Fig. 1), were fuzzified using the triangular MF (Fig. 2). Two fuzzy sets (Small (S) and Large (L)) were used for the input variables while three fuzzy sets were used for the output variable (Small (S), Medium (M) and Large (L)). Thereafter, fuzzy rules were generated as shown in Table 5. This was subsequently followed by the aggregation of the rule output using the max-min inference operation to determine the fuzzy output. Lastly, the fuzzy ouptput were defuzzified using the center of gravity defuzzification to obtain the MPCI as shown in Table 6 and Fig. 3. The surface view of the relationship between the preprocessed inputs and output is shown in Fig. 4. The entire operation was executed in MATLAB.

After obtaining the MPCI, the optimum combination of additives was evaluated. This was performed by determining the average value of the comparability sequence for every MPCI that appear on the same factor level and the factor level that maximizes the average MPCI was selected as the optimal level for that factor. The result obtained is shown in Table 7. As depicted in Table 7, the optimum combination of additives is A3 B3 C3.

Table 4. Preprocessed responses

Expt. No.	A	B	C	CBR(%)	DFS (%)	NS_{cbr}	NS_{dfs}
1	1	1	1	25.68	41.69	0.04331	0.05380
2	3	1	1	30.68	35.47	0.17375	0.20658
3	1	3	1	48.91	25.38	0.64936	0.45443
4	3	3	1	60.56	3.28	0.95330	0.99730
5	1	1	3	24.02	43.88	0.00000	0.00000
6	3	1	3	52.43	20.17	0.74119	0.58241
7	1	3	3	42.61	26.01	0.48500	0.43896
8	3	3	3	62.35	3.17	1.00000	1.00000
9	1	2	2	36.75	39.13	0.33212	0.11668
10	3	2	2	42.25	26.60	0.47561	0.42447
11	2	1	2	39.71	36.16	0.40934	0.18963
12	2	3	2	44.50	20.25	0.53431	0.58045
13	2	2	1	57.07	3.76	0.86225	0.98551
14	2	2	3	49.63	9.54	0.66815	0.84353
15	2	2	2	41.44	22.52	0.45447	0.52469
16	2	2	2	47.61	26.21	0.61544	0.43405
17	2	2	2	44.09	27.89	0.52361	0.39278
18	2	2	2	45.14	26.48	0.55100	0.42741

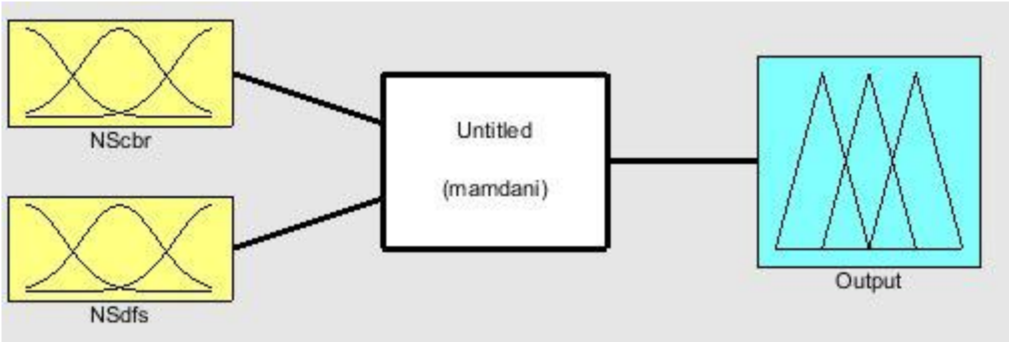
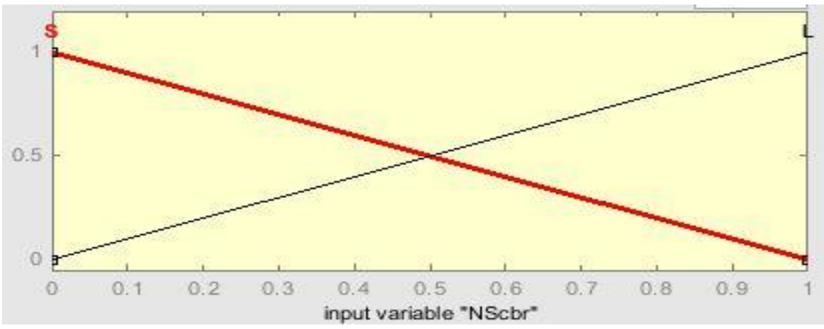
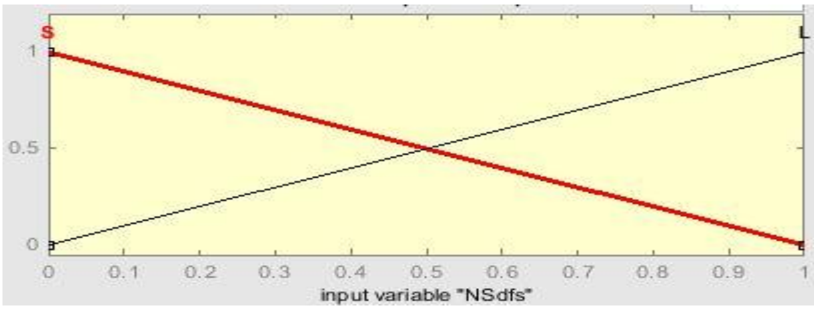


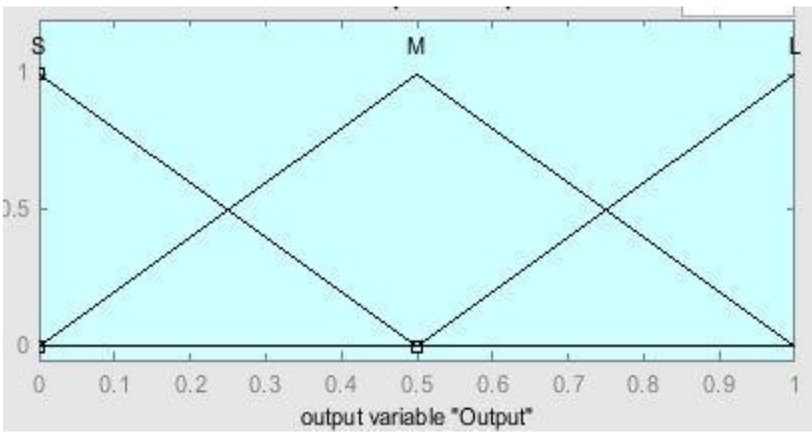
Fig. 1. Fuzzy inference system



(a)



(b)



(c)

Fig. 2. Membership function: (a) Preprocessed CBR; (b) Preprocessed DFS and (c) Output

Table 5. Fuzzy rules

Rule No	NS_{cbr}	NS_{cbr}	**Output**
1	S	S	S
2		L	M
3	L	S	M
4		L	L

Table 6. MPCI values

Expt. No.	**A**	**B**	**C**	NS_{cbr}	NS_{dfs}	**MPCI**
1	1	1	1	0.04331	0.05380	0.221
2	3	1	1	0.17375	0.20658	0.343
3	1	3	1	0.64936	0.45443	0.518
4	3	3	1	0.95330	0.99730	0.789
5	1	1	3	0.00000	0.00000	0.163
6	3	1	3	0.74119	0.58241	0.563
7	1	3	3	0.48500	0.43896	0.512
8	3	3	3	1.00000	1.00000	0.837
9	1	2	2	0.33212	0.11668	0.391
10	3	2	2	0.47561	0.42447	0.481
11	2	1	2	0.40934	0.18963	0.425
12	2	3	2	0.53431	0.58045	0.522
13	2	2	1	0.86225	0.98551	0.714
14	2	2	3	0.66815	0.84353	0.605
15	2	2	2	0.45447	0.52469	0.496
16	2	2	2	0.61544	0.43405	0.508
17	2	2	2	0.52361	0.39278	0.485
18	2	2	2	0.55100	0.42741	0.496

Table 7. Mean MPCI of the factors

Parameter	**Level**		
	1	2	3
A	0.361	0.531	0.603*
B	0.343	0.522	0.636*
C	0.517	0.476	0.536*

Key * optimal level of factor

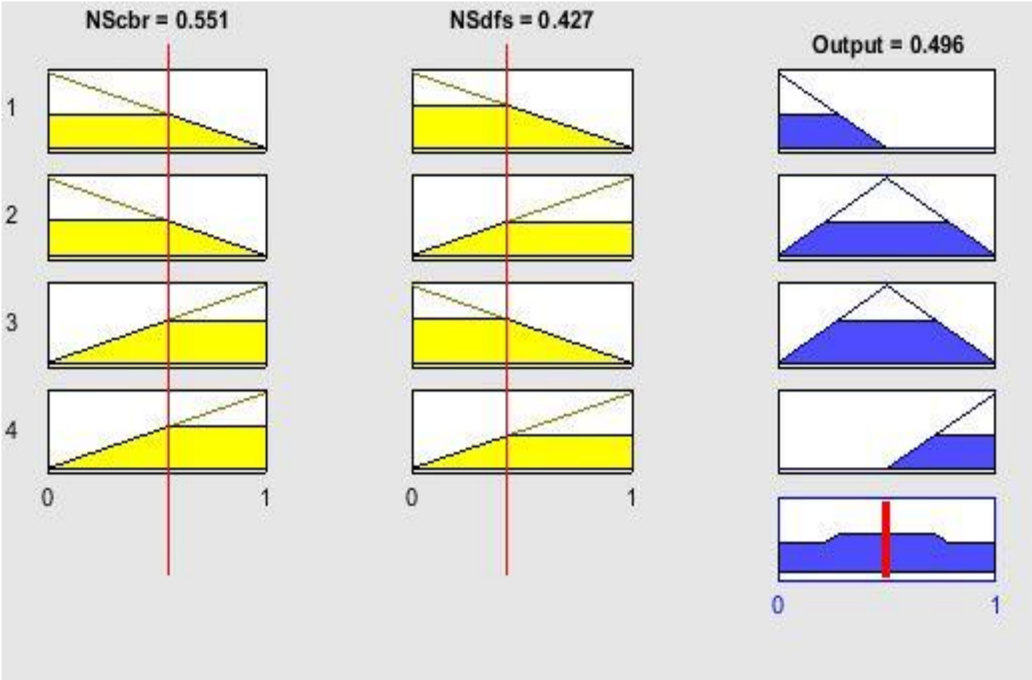


Fig. 3. Sample of fuzzy rule viewer for MPCI

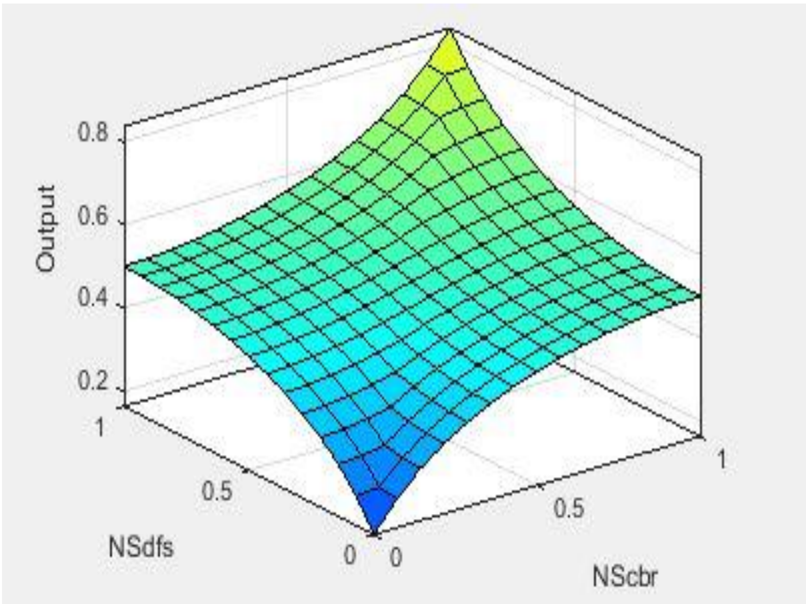


Fig. 4. Relationship between the preprocessed inputs and output

Experimental validation

The optimum combination of additives (A3 B3 C3) obtained from the analysis is already contained in the experimental run in Table 3 so there was no need to perform any laboratory experiment to confirm the result obtained from the analysis. It is evident from Table 3 that optimum values of the CBR and DFS were 62.35% and 3.17% respectively. This is clear indication that there were improvements in the CBR and DFS of the expansive soil.

The improvement in the CBR and DFS of the soil could be attributed to the increase in its mechanical strength, which was caused by the micro-filler effect experienced between the QD and the soil as well as the base ion exchange effect between the ionized SDA and the montmorillonite in the clay.

Conclusion

This present study integrated fuzzy logic in CCD to optimize multi-additives (CM, SDA and QD) for the improvement of the CBR and DFS of an expansive soil. The result from the analysis showed that the optimum combination of additives obtained was A3 B3 C3, which incidentally is the same as the optimal value, obtained from the experimental run performed in the laboratory. The result from the laboratory experiment showed significant improvement in the CBR and DFS of the expansive soil. The improvement was adduced to the micro-filler and base ion effect experienced between the additives and the expansive soil.

References

BS 1377. (1990). Method of Testing Soils for Civl Engineering Purposes. In *British Standard Institution.* London.

Estabragh, A. R., Rafatjo, H., & Javadi, A. A. (2014). Treatment of an expansive soil by mechanical and chemical techniques. *Geosynthetics international, 21*(3), 233-243.

Gourley, C. S., Newill, D., & Schreiner, H. D. (1993). Expansive soils: TRL's research strategy. *Proceedings of 1st international symposium on engineering characterisitcs of arid soils*, (pp. 247-260). London, England.

Ikeagwuani, C. C., & Nwonu, D. C. (2019). Emerging trends in expansive soil stabilisation: A review. *Journal of rock mechanics and geotechnical engineering, 11*(2), 423-440.

Ikeagwuani, C. C., Agunwamba, J. C., Nwankwo, C. M., & Eneh, M. (2020). Additives optimization for expansive soil subgrade modification based on Taguchi grey relational analysis. *International journal of pavement research and technology*(DOI: https://doi.org/10.1007/s42947-020-1119-4), 1-15.

Ikeagwuani, C. C., Obeta, I. N., & Agunwamba, J. C. (2019). Stabilization of black cotton soil subgrade using sawdust ash and lime. *Soils and foundations, 59*(1), 162-175.

IS 2720 Part 40. (1977). Indian Standards method of test for soils. In *Bureau of Indian standards.* New Delhi.

Nwonu, D. C., & Ikeagwuani, C. C. (2019). Evaluating the effect of agro-based admixture on lime-treated expansive soil for subgrade material. *International journal of pavement engineering*(Doi:10.1080/10298436.2019.1703979), 1-16.

Soltani, A., & Estabragh, A. R. (2015). Treatment of expansive soils with quality saline pore water by cyclic drying and wetting. *Desert, 20*(1), 73-82.