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FUZZY-LOGIC ASSESSMENT OF ROCK BOLT SUPPORT CONFIGURATIONS IN UNDERGROUND MINING

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Abstract

This paper examines a fuzzy inference system for assessing rock-bolt support configurations in an underground drift. Bolt length, diameter and number of bolts are used to estimate maximum displacement and safety factor. The system was parameterized from 16 finite-element configurations previously introduced in an ANN-based study and its outputs were compared with the numerical results. Mean absolute errors were 0.67 mm for displacement and 0.043 for safety factor. The fuzzy model also reproduced 15 of 16 classifications against a 10 mm displacement criterion, indicating useful and interpretable screening capability for preliminary support design.

Keywords: *fuzzy logic, rock bolt support, underground mining, finite element method, decision support*

1. INTRODUCTION

Rock-bolt support design requires the simultaneous interpretation of excavation geometry, rock-mass response and several support parameters. Although numerical analysis can represent these interactions, repeated calculations for many bolt configurations are time-consuming, while empirical design rules often contain gradual boundaries and linguistic engineering judgments. Fuzzy set theory was introduced to represent partial membership and imprecise information [1,2], and inference provides a transparent framework for converting IF–THEN rules into numerical outputs [3]. These features have supported applications in rock-mass classification and tunnel-support prediction [4,5].

A previous paper by the authors used artificial neural networks to reproduce finite-element method (FEM) results for 16 rock-bolt configurations in a T3 orebody drift at the Jama Bor mine [1]. The ANN provided an efficient numerical surrogate, but its internal mapping was primarily data-driven.

The present paper addresses the same engineering problem from a different perspective: a rule-based fuzzy inference system (FIS) is examined as an interpretable support-assessment tool. The objective is to quantify agreement between FIS and FEM outputs, evaluate preservation of the engineering ranking of support configurations, and test whether the model can screen cases against a practical displacement criterion. The analysis is intended as a comparative assessment rather than an independent validation or a universal design procedure.

2. EXPERIMENTAL

2.1. Numerical dataset

The numerical dataset and excavation model are those introduced in [1]. The analyzed drift has a width of approximately 4.5 m and a height of 4.3 m and is in hydrothermally altered andesite near the T3 orebody of the Jama Bor mine. Sixteen FEM configurations were produced by combining four bolt lengths (1.6, 1.8, 2.0 and 2.2 m), two diameters (22 and 24 mm) and two bolt quantities in the crown (8 and 10). Maximum displacement ranged from 7.2 to 13.9 mm, while the calculated safety factor ranged from 1.02 to 1.55. These values form the numerical reference set for the fuzzy assessment.

2.2. Fuzzy inference system

A fuzzy inference system (FIS) was constructed with three inputs and two outputs. Each input was represented by three overlapping linguistic sets, while each output was represented by five sets. The complete combination of the three input states resulted in 27 IF–THEN rules. The rule base followed the engineering trend that longer, thicker and more numerous bolts generally reduce displacement and increase the safety factor. The aggregated output was converted into a crisp value using centroid defuzzification. Table 1 summarizes the variable universes and linguistic partitions, while Figure 1 presents the workflow.

Table 1. *Input and output variables of the fuzzy inference system*

Variable	Role	Range	Sets
Bolt length	Input	1.6–2.2 m	short, medium, long
Bolt diameter	Input	22–24 mm	small, medium, large
Number of bolts	Input	8–10	few, medium, many
Maximum displacement	Output	7.2–13.9 mm	very low to very high (5 sets)
Safety factor	Output	1.02–1.55	very low to very high (5 sets)

The three input membership sets were centred at 1.6, 1.9 and 2.2 m for bolt length, 22, 23 and 24 mm for bolt diameter, and 8, 9 and 10 for number of bolts, respectively.

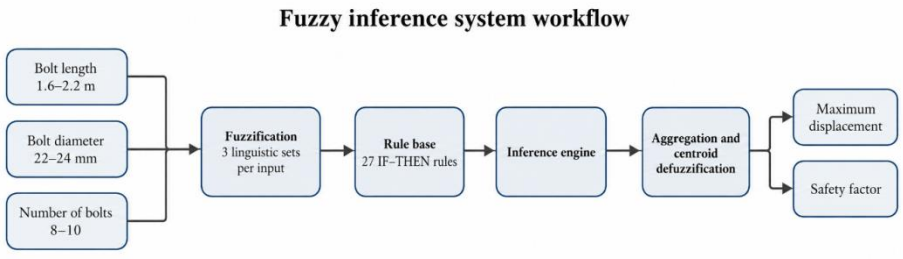


Figure 1. *Structure of fuzzy inference system used for support assessment*

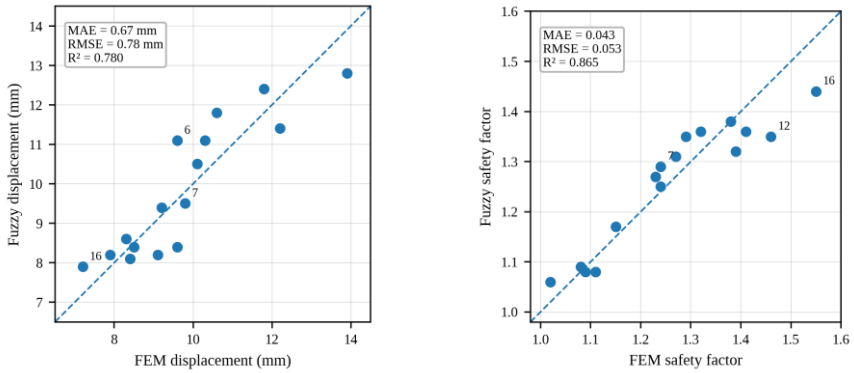
Agreement was quantified by the mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), coefficient of determination (R^2), and

Spearman rank correlation. A second check compared FEM and fuzzy classifications using a 10 mm maximum-displacement criterion. Because the membership functions and rules were established from the same 16-case domain, the calculated statistics represent internal agreement and screening consistency, not independent predictive validation.

3. RESULTS AND DISCUSSION

3.1. Agreement with finite-element results

The fuzzy outputs follow the FEM response trends for both stability indicators. Figure 2 compares calculated and fuzzy values with the 1:1 line. For maximum displacement, MAE was 0.67 mm, RMSE 0.78 mm and MAPE 6.73%. The corresponding values for safety factor were 0.043, 0.053 and 3.27%. The coefficients of determination were 0.780 and 0.865, respectively. Rank preservation was stronger than the absolute-fit statistics, with Spearman coefficients of 0.917 for displacement and 0.928 for safety factor. This indicates that the rule system is especially useful for comparative screening and ordering of support alternatives.



(a) (b)

Figure 2. *Fuzzy outputs versus FEM results: (a) maximum displacement; (b) safety factor*

Table 2. *Agreement statistics for the fuzzy inference system*

Statistic	Maximum displacement	Safety factor
MAE	0.67 mm	0.043
RMSE	0.78 mm	0.053
MAPE	6.73%	3.27%
R^2	0.780	0.865
Spearman rank coefficient	0.917	0.928
Maximum absolute error	1.50 mm	0.11

3.2. Support-screening interpretation

The fuzzy model reproduced the displacement classification in 15 of the 16 configurations, corresponding to 93.8% agreement. The only mismatch was conservative: configuration 6 had a FEM displacement of 9.6 mm, while the fuzzy estimate was 11.1 mm. No configuration with FEM displacement above 10 mm was incorrectly accepted by the fuzzy system. Figure 3 shows this threshold comparison and the location of the single mismatch.

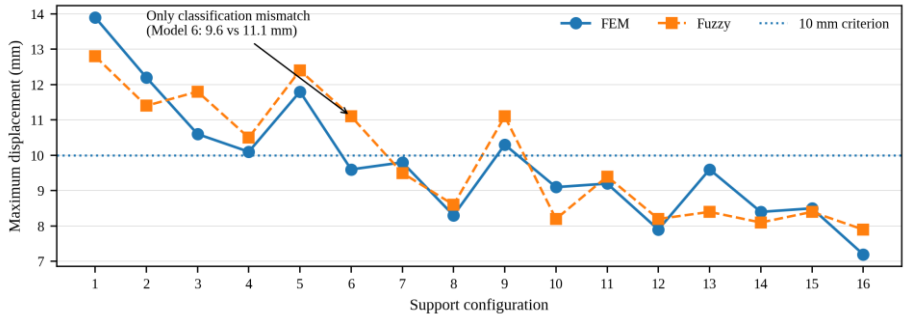


Figure 3. *FEM and fuzzy displacement values relative to the 10 mm screening criterion*

The rule-based model also retained the principal engineering interpretation of individual cases. Configuration 16 (2.2 m length, 24 mm diameter and 10 bolts) remained the strongest alternative: FEM produced 7.2 mm and a safety factor of 1.55, while the fuzzy system gave 7.9 mm and 1.44. A less intensive near-threshold case, configuration 7 (1.8 m, 22 mm and 10 bolts), produced 9.8 mm and 1.24 by FEM and 9.5 mm and 1.29 by fuzzy inference. This case illustrates how the FIS can support transparent screening of a practical design candidate without claiming a universal optimum. Final selection must still include support cost, installation constraints, site variability, and field monitoring.

Compared with the ANN approach reported previously [1], the main advantage of the FIS is not higher numerical accuracy but interpretability. Membership functions and IF–THEN rules make the assumed engineering relationships explicit and can be reviewed or modified by the designer. The main limitation is that rule definition and membership ranges are dependent on the original numerical domain. Extrapolation to different excavation dimensions, stress states or rock-mass conditions would require additional FEM cases and site calibration. A hybrid workflow combining numerical analysis, fuzzy screening and monitoring is therefore more appropriate than using any one method in isolation [6].

4. CONCLUSION

A fuzzy inference system was applied to the assessment of 16 rock-bolt support configurations for an underground drift. The model reproduced the FEM response with MAE values of 0.67 mm for maximum displacement and 0.043 for safety factor, while preserving the configuration ranking with Spearman coefficients above 0.91. Against a 10 mm displacement criterion, 15 of 16 cases were classified consistently and the single mismatch was conservative. The fuzzy system also retained the identification of the strongest configuration and provided a transparent interpretation of a near-threshold design case. These results support the use of fuzzy logic as an interpretable preliminary screening tool that complements, but does not replace, FEM analysis and field verification. Future work should include independent validation cases, additional rock-mass and support variables, and calibration against monitoring data.

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