



Assessment of Rock Aggregate Quality Through Fuzzy Inference System

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Abstract In this study, Fuzzy Inference System (FIS) was adopted to evaluate the rock aggregate quality. For this purpose, some technical standards for coarse aggregates were integrated into the FIS analyses as threshold values. As a result, several membership functions were established using rock aggregate properties such as water absorption by weight (w_a), flakiness index (FI), Los Angeles abrasion value (LA AV), and magnesium sulfate soundness (M_{wl}). Based on 48 if–then rules, the implementation and verification of the proposed FIS model were carried out using sixteen rock types whose field performances as coarse aggregate were previously evaluated [i.e., low quality (LQ), average quality (NQ), high quality (HQ), etc.] by field engineers. The results obtained from the FIS analyses were declared a Rock Aggregate Quality Assessment Rating (RQAR), where higher RQAR values indicate rock aggregates with higher quality. The results obtained from the FIS analyses are almost in good agreement with those obtained from the field performances of the investigated rocks. However, the number of cases should be increased to improve the proposed FIS model. In

this context, the number of if–then rules membership functions can be rearranged according to the need. This study, in this manner, can be declared a case study indicating how to quantity rock aggregate quality based on FIS analyses.

Keywords Rock aggregate · Crushed stone · Aggregate properties · Quality assessment · Fuzzy inference system

1 Introduction

After World War II, the construction and building industry started to develop because it was required to rebuild and redesign buildings and engineering-related infrastructures. Today, it is still a growing sector, as an increasing world population causes industrialization, urban expansion, and infrastructure improvement (Smith 2017; Meddah 2017). Therefore, construction aggregates are the primary raw materials used in most engineering fields, such as buildings, roads, highways, railways, and bridges. For example, the European Aggregates Association (UEPG 2009) explained that one meter squared of the concrete structure comprises approximately two tons of aggregates that clearly show the considerable demand for natural and/or recycled aggregates. Hence, aggregates with satisfactory quality are indispensable elements for the global industry. More profoundly, the physical and mechanical properties of rock aggregates are

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the main factors in selecting the type of aggregates proper to use in various engineering fields (Šernas et al. 2016). Furthermore, rock aggregates used for hot asphalt mixtures should satisfy the highest requirements of shape index and abrasion resistance to ensure proper bonding in aggregate particles and a strong skeleton in the asphalt mixture (Vaitkus et al. 2017).

Researchers have attempted to quantify rock aggregate quality depending upon several methodologies. These evaluations commonly involve laboratory test results and technical guidance of relevant standards. For example, variations in coarse aggregate types influence the modulus of elasticity in concrete structures (Beshr et al. 2003). Kamal et al. (2006) attempted to quantify rock aggregate quality using several testing methods such as aggregate impact value (AIV), aggregate crushing value (ACV), Los Angeles abrasion value (LAAB), and flakiness index (FI). In that study, some aggregates from Pakistan were evaluated for their use as a subbase material. Min and Han (2016) investigated the influence of low-quality aggregate on the engineering properties of concrete. Accordingly, researchers found that exploded debris clays and sea sands were declared low-quality aggregates that considerably decreased the strength properties of concrete. High-quality rock aggregates have also been regarded for concrete and bituminous pavement mixtures in many aspects (Akbulut et al. 2011; Brand et al. 2015; Beushausen and Dittmer 2015; Thomas et al. 2018; Choorackal et al. 2019). Kamani and Ajalloeian (2019) evaluated the mechanical degradation of carbonate aggregates using some rock strength tests.

On the basis of their laboratory test results, several correlations were obtained between the LAAB and uniaxial compressive strength (UCS) and point load index (PLI) of rocks. Using such correlations, rock aggregate quality can easily be assessed through highly repeatable testing methods. Recently, Köken et al. (2020) also investigated rock aggregate quality using a novel Analytic Hierarchy Process (AHP). In that study, four different rock types were evaluated for their use in bituminous paving mixtures. Apart from the strength properties of rock aggregates, Kusumawardani and Wong (2020) reported that the shape of the aggregate influences the performance of the paving mixtures. The studies mentioned above have mainly utilized laboratory test results to evaluate rock

aggregate quality for different purposes. Generally, investigating the rock aggregate quality for construction and building purposes is based on various testing methodologies such as water absorption (w_a), AIV, ACV, LAAB, freezing–thawing, flakiness index (FI), and sodium (M_{wl}) and magnesium (M_{wl}) soundness tests. These tests have been standardized according to the ASTM, BS, and EN standards, and some technical requirements for rock aggregates are summarized in Table 1.

However, the implementation of the rock aggregate quality assessment requires technical guidance and experience. In addition to this, qualitative evaluations based on laboratory test results are sometimes challenging due to personal judgments. To minimize personal misconceptions about the quality assessment of rock aggregate and maximize the lifespan of aggregate-related engineering structures, machine learning methods would provide practical and straightforward information.

For the last decades, successful machine learning methods have been applied to solve several engineering geological problems (Monjezi et al. 2009; Razani et al. 2013; Adoko et al. 2013; Rezaei 2018; Ray et al. 2021; Bazarbay and Adoko 2021; Gu et al. 2021). Novel FIS models were introduced for the studies mentioned above. Apart from FIS, other machine learning methods such as adaptive neuro-fuzzy inference system (ANFIS), artificial neural networks (ANN), gene expression programming (GEP), and support vector machine (SVM) were also used to investigate several problems in engineering geology (Singh et al. 2012; Mohamad et al. 2015; Li and Tan 2017; Armaghani et al. 2018; Köken 2021; Ray et al. 2021).

In this study, several applications of FIS were carried out to assess the quality of the rock aggregate according to the standardized technical requirements. For this purpose, technical specifications based upon w_a , FI, LAAB, and M_{wl} values (Table 1) were integrated into the FIS analyses as threshold values. Consequently, rock aggregate quality assessments were performed using a simple FIS approach. Furthermore, the proposed FIS model was attempted for 16 different rock types previously used as coarse aggregates with various qualities (i.e., low quality, average quality, high quality, etc.) in Turkey. Finally, the predicted and once evaluated rock aggregate qualities were compared to investigate the suitability and consistency of the proposed FIS approach.

Table 1 Technical requirements for rock aggregates (modified after Kamani and Ajalloeian 2019)

Test	Maximum value (%)	Purpose	References
AIV	30	Pavement wearing surfaces	BS 882 (1992)
	20	Concrete aggregates	Waltham (2009)
	25	General aggregates	Harrison and Bloodworth (1994)
	50	Subbase course	
	30	Bituminous surface dressing	IS 2386-4 (1963)
ACV	30	Subbase material	IS 2386-4 (1963)
	24	Surface coursing	Harrison and Bloodworth (1994)
LAAV	40	Paving mixtures	ASTM D692 (2015)
	50	Subbase material	BS EN-13043 (2002)
	30	Surface treatment	
	30	Armour stone	TS EN 1097-2 (2020)
	35	Rockfill	TS EN 1097-2 (2020)
	40	Road aggregates	TS EN 1097-2 (2020) , ASTM C131/C131M-14 (2020)
	50	Coarse aggregate in concrete	ASTM C33/C33M-13 (2013)
w_a	2.0	Paving mixtures	Tahmoorian et al. (2017)
	2.0	Gabion stone	TS EN 1367-2 (2011)
	1.8	Armour stone	TS EN 13755 (2014)
	3.0	Coarse aggregate	TS EN 1097-6 (2013)
M_{wl}	10	Gabion stone	TS EN 1367-2 (2011)
	18	Paving mixture	ASTM D692 (2015)
	8	Armour stone	KGM (2013)
	18	Coarse aggregate	KGM (2013)
	10	Rockfill	TS EN 1367-2 (2011)
FI	20	Coarse aggregate	BS EN 933-3 (2012)
	20	Filter material	KGM (2013)
	30	Subbase material	BS EN 933-3 (2012)
	35	Concrete aggregate	TS 706 EN 12620 + A1 (2009)

Bolded values (e.g. 3.0) were adopted to evaluate rock aggregate quality in the fuzzy logic analyses as threshold values

2 Applications on Rock Aggregate Quality Assessment Through FIS

This study adopted FIS as a research tool to establish a predictive model to evaluate rock aggregate quality. Fuzzy sets were first introduced by Zadeh (1965) as a mathematical way to represent linguistic vagueness. The advantage of the FIS comes from the fact that the opinions or experiences of users could be integrated into such analyses by adopting fuzzy sets.

Due to this advantage, a wide range of problems from social sciences to various engineering disciplines has been investigated in a detailed manner. For example, the Mamdani algorithm (Mamdani and Assilian 1999) is one of the most efficient techniques

to solve complex geological engineering problems in FIS analyses (Fig. 1).

In this study, important rock aggregate properties such as w_a , FI, LAAV, and M_{wl} values were considered in the FIS analyses to evaluate rock aggregate quality. However, the ACV and AIV values were not considered in this study since both are closely related to the LAAV (Palassi and Danesh 2016; Teymen 2019). Based on the technical requirements for the coarse aggregates (Table 1), several triangular membership functions were established as input parameters (Fig. 2) in the FIS analyses.

Several triangular membership functions are shown in Fig. 2. In this figure, different rock aggregate properties with numerous subdivisions (q_1 , q_2 , etc.) point out single judgments on rock aggregate

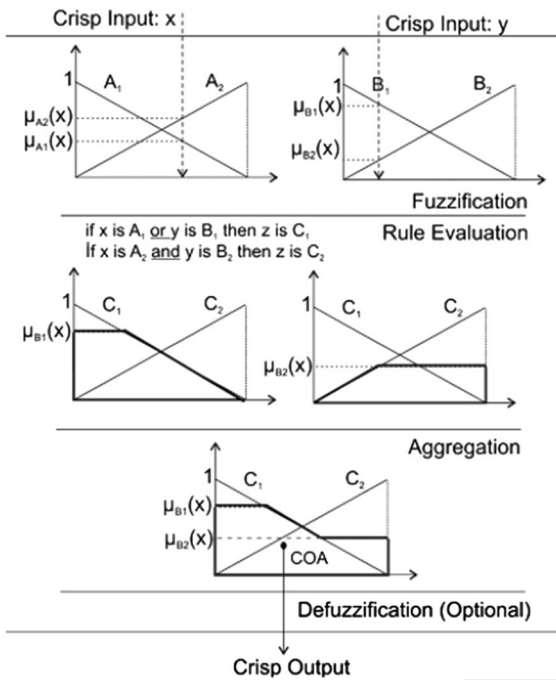
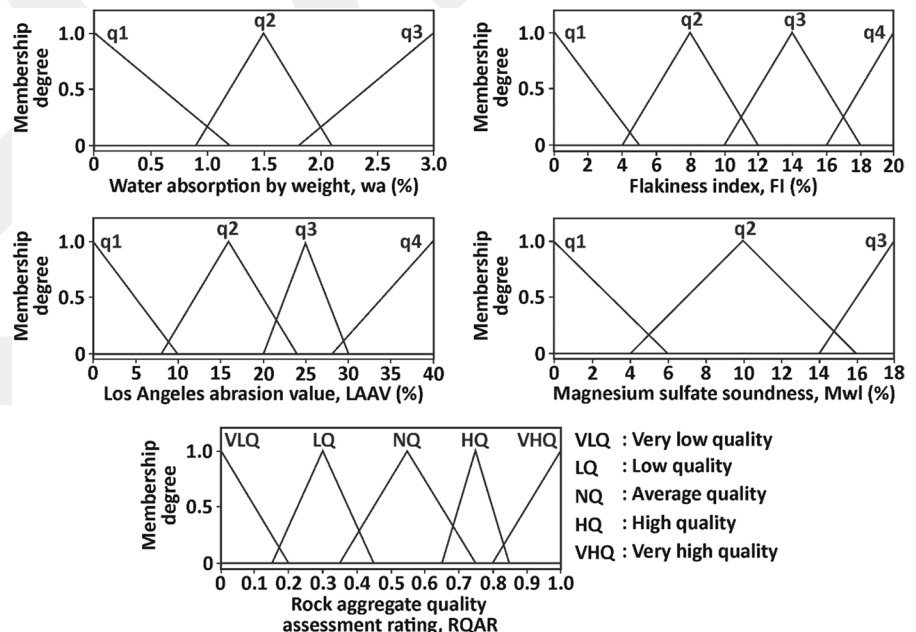


Fig. 1 Generalized scheme of the Mamdani style fuzzy inference (Osna et al. 2014)

quality. The determination of the subdivisions in rock aggregate properties was based on a heuristic approach. The FIS runs on every change in

Fig. 2 Membership functions adopted in the FL analyses



membership functions more profoundly until the most consistent results are achieved for each case. Obviously, although it is a time-consuming process, it can be one of the feasible solutions to obtain more precise FIS models to the best of the authors' knowledge.

After determining the membership functions, the If-then rules (Table 2) were loaded into the MATLAB environment to complete the proposed FIS model. In this study, a total of 48 if-then rules were described in the context of the FIS analyses. The established if-then rules are based on the technical assistance of some rock aggregate manufacturers in Turkey. An illustration of the proposed FIS interface is given in Fig. 3.

3 Implementation and Verification of the Proposed FIS Model

Based on the explanations given in the previous section, a feasible FIS model was developed to evaluate rock aggregate quality. The implementation of the proposed model depends upon inputting some aggregate properties of w_a , FI, LAAV, and M_{wl} .

Consequently, some surface and contour plots were developed by inputting some theoretically logical aggregate properties, which are given in Fig. 4. In that context, rock aggregate quality assessment

Table 2 If–then rules for the proposed FL model

Rule	Explanation
R1	If w_a is q1 and FI is q2 and LAAV is q3 and M_{wl} is q2 then output is NQ
R2	If w_a is q1 and FI is q2 and LAAV is q2 and M_{wl} is q2 then output is HQ
R3	If w_a is q1 and FI is q2 and LAAV is q4 and M_{wl} is q1 then output is NQ
R4	If w_a is q1 and FI is q3 and LAAV is q3 and M_{wl} is q2 then output is NQ
R5	If w_a is q1 and FI is q3 and LAAV is q4 and M_{wl} is q1 then output is NQ
R6	If w_a is q2 and FI is q3 and LAAV is q3 and M_{wl} is q2 then output is LQ
R7	If w_a is q3 and FI is q3 and LAAV is q4 and M_{wl} is q3 then output is VLQ
R8	If w_a is q1 and FI is q2 and LAAV is q3 and M_{wl} is q1 then output is HQ
R9	If w_a is q2 and FI is q4 and LAAV is q4 and M_{wl} is q2 then output is LQ
R10	If w_a is q2 and FI is q3 and LAAV is q3 and M_{wl} is q2 then output is NQ
R11	If w_a is q1 and FI is q2 and LAAV is q2 and M_{wl} is q1 then output is NQ
R12	If w_a is q1 and FI is q2 and LAAV is q3 and M_{wl} is q1 then output is HQ
R13	If w_a is q3 and FI is q3 and LAAV is q4 and M_{wl} is q3 then output is VLQ
R14	If w_a is q2 and FI is q2 and LAAV is q4 and M_{wl} is q2 then output is LQ
R15	If w_a is q2 and FI is q3 and LAAV is q3 and M_{wl} is q3 then output is VLQ
R16	If w_a is q3 and FI is q3 and LAAV is q4 and M_{wl} is q2 then output is LQ
R17	If w_a is q1 and FI is q2 and LAAV is q2 and M_{wl} is q2 then output is HQ
R18	If w_a is q2 and FI is q2 and LAAV is q2 and M_{wl} is q2 then output is HQ
R19	If w_a is q1 and FI is q2 and LAAV is q2 and M_{wl} is q1 then output is VHQ
R20	If w_a is q2 and FI is q3 and LAAV is q3 and M_{wl} is q2 then output is NQ
R21	If w_a is q1 and FI is q3 and LAAV is q3 and M_{wl} is q2 then output is HQ
R22	If w_a is q1 and FI is q3 and LAAV is q4 and M_{wl} is q2 then output is LQ
R23	If w_a is q1 and FI is q2 and LAAV is q2 and M_{wl} is q2 then output is HQ
R24	If w_a is q1 and FI is q3 and LAAV is q2 and M_{wl} is q1 then output is VHQ
R25	If w_a is q1 and FI is q2 and LAAV is q2 and M_{wl} is q1 then output is VHQ
R26	If w_a is q1 and FI is q1 and LAAV is q1 and M_{wl} is q1 then output is VHQ
R27	If w_a is q3 and FI is q4 and LAAV is q4 and M_{wl} is q3 then output is VLQ
R28	If w_a is q3 and FI is q4 and LAAV is q4 and M_{wl} is q2 then output is LQ
R29	If w_a is q3 and FI is q4 and LAAV is q4 and M_{wl} is q3 then output is LQ
R30	If w_a is q2 and FI is q2 and LAAV is q3 and M_{wl} is q2 then output is NQ
R31	If w_a is q2 and FI is q2 and LAAV is q2 and M_{wl} is q2 then output is NQ
R32	If w_a is q3 and FI is q3 and LAAV is q3 and M_{wl} is q2 then output is NQ
R33	If w_a is q2 and FI is q2 and LAAV is q1 and M_{wl} is q2 then output is HQ
R34	If w_a is q2 and FI is q2 and LAAV is q2 and M_{wl} is q2 then output is NQ
R35	If w_a is q1 and FI is q4 and LAAV is q4 and M_{wl} is q2 then output is NQ
R36	If w_a is q1 and FI is q2 and LAAV is q3 and M_{wl} is q1 then output is HQ
R37	If w_a is q2 and FI is q2 and LAAV is q3 and M_{wl} is q2 then output is VLQ
R38	If w_a is q1 and FI is q3 and LAAV is q4 and M_{wl} is q2 then output is NQ
R39	If w_a is q1 and FI is q2 and LAAV is q4 and M_{wl} is q1 then output is LQ
R40	If w_a is q2 and FI is q2 and LAAV is q4 and M_{wl} is q2 then output is NQ
R41	If w_a is q3 and FI is q3 and LAAV is q4 and M_{wl} is q2 then output is NQ
R42	If w_a is q1 and FI is q2 and LAAV is q3 and M_{wl} is q2 then output is VHQ
R43	If w_a is q2 and FI is q2 and LAAV is q3 and M_{wl} is q4 then output is VLQ
R44	If w_a is q1 and FI is q2 and LAAV is q3 and M_{wl} is q3 then output is NQ
R45	If w_a is q1 and FI is q2 and LAAV is q4 and M_{wl} is q3 then output is LQ
R46	If w_a is q1 and FI is q2 and LAAV is q4 and M_{wl} is q2 then output is LQ
R47	If w_a is q1 and FI is q2 and LAAV is q4 and M_{wl} is q2 then output is NQ

Table 2 (continued)

Rule	Explanation
R48	If w_a is q1 and FI is q1 and LAAV is q2 and M_{wl} is q1 then output is VHQ

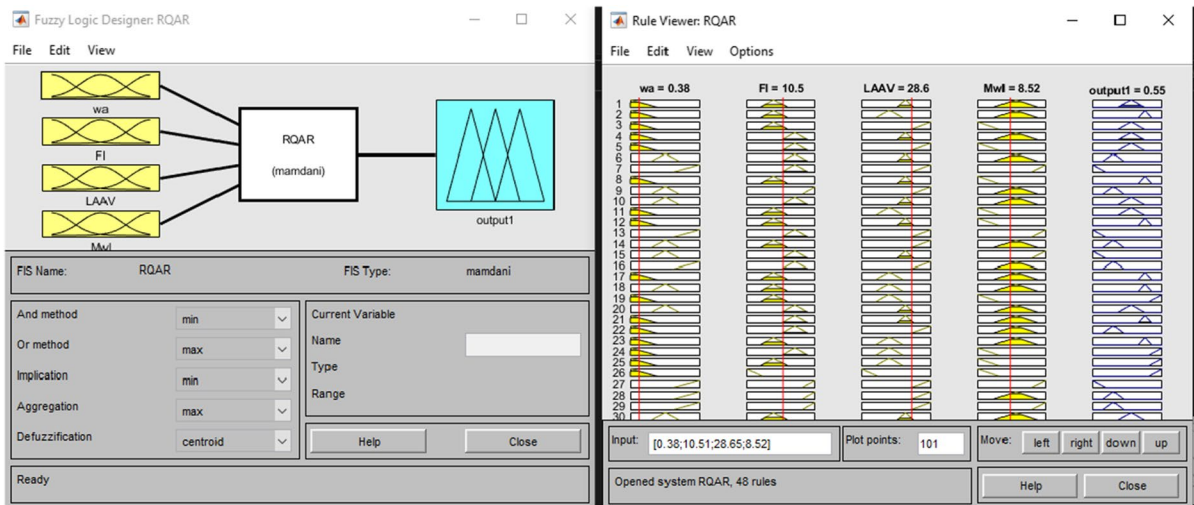


Fig. 3 The proposed FIS interface in the MATLAB environment

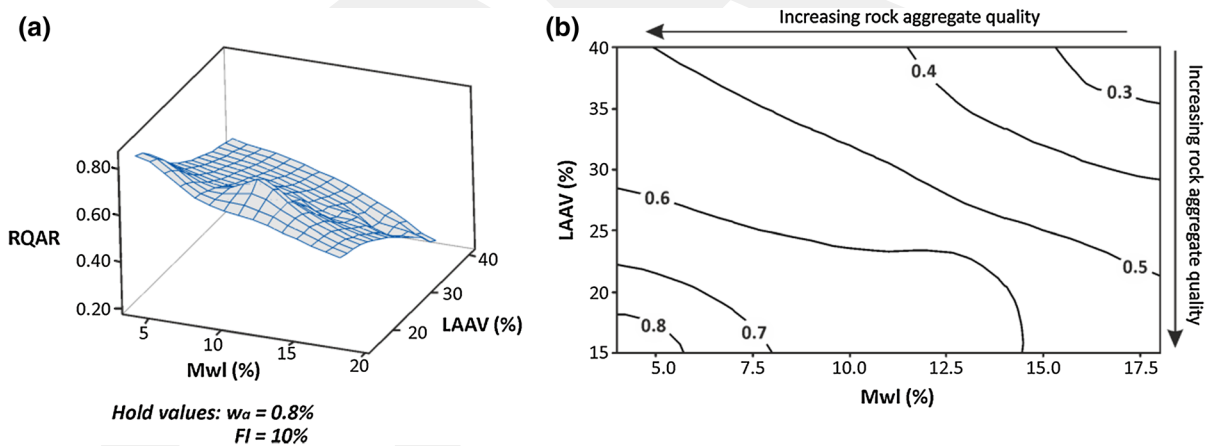


Fig. 4 Implementation of the proposed FL model **a** surface plot, **b** contour plot

rating (RQAR) values can be determined using the triangular membership functions (Fig. 2) and if-then rules (Table 2) in the FIS analyses. This function to evaluate the rock aggregate quality is the proposed FIS model that can generate several RQAR values for each rock type. Greater RQAR values indicate rock aggregates of higher quality (Fig. 2).

The proposed FIS model was verified using laboratory test results of some rock aggregates, which were previously used as coarse aggregates in some engineering projects in Turkey. The laboratory test results of the investigated rocks are listed in Table 3. In addition, the performance evaluation of the investigated rock aggregates was carried out by field engineers, which was also given in that table. As seen in Table 3,

Table 3 Performance evaluation of the proposed fuzzy logic model

Rock type	Location	w_a (%)	FI (%)	LAAV (%)	M_{wl} (%)	RQAR	Field performance evaluation	Description based on the proposed FL model
Limestone	Eflani /Karabuk	0.38	10.51	28.65	8.52	0.55	NQ	NQ
Limestone	Pınarbaşı / Kastamonu	1.24	10.52	28.45	8.64	0.37	NQ	LQ-NQ
Limestone	Eregli /Zonguldak	0.64	8.17	31.11	3.94	0.45	NQ	LQ-NQ
Dolomitic limestone	Eregli /Zonguldak	0.85	16.52	27.99	8.27	0.61	NQ	NQ
Dolomitic limestone	Akcakoca / Duzce	0.63	7.49	25.15	3.14	0.84	HQ	HQ-VHQ
Andesite	Gokcebey /Zonguldak	1.93	14.22	27.61	16.07	0.08	VLQ	VLQ
Basaltic andesite	Eregli /Zonguldak	0.74	8.51	17.55	4.07	0.68	HQ	NQ-HQ
Dacite	Karabuk / Yenice	1.33	10.44	24.01	8.26	0.38	NQ	LQ-NQ
Gabbro	Yenice /Karabuk	0.17	14.25	15.45	3.58	0.92	VHQ	VHQ
Andesite	Filyos Zonguldak	3.89	10.62	34.64	18.89	0.09	VLQ	VLQ
Basaltic Andesite	Eregli / Zonguldak	0.74	8.51	17.55	4.07	0.67	NQ	NQ-HQ
Basalt	Abdipasa / Bartin	0.68	5.14	13.74	3.18	0.68	HQ	NQ-HQ
Basaltic andesite	Ilıca / Kutahya	0.32	4.30	15.40	1.17	0.68	HQ	NQ-HQ
Granodiorite	Karabuk / Yenice	0.75	13.96	25.03	4.94	0.60	NQ	NQ
Granodiorite	Havran / Balıkesir	0.34	16.71	20.26	0.74	0.91	HQ	VHQ
Diorite	Gokcebey / Zonguldak	0.54	6.58	21.87	4.05	0.71	NQ	NQ-HQ

w_a : water absorption by weight (TS EN 1097-6 2013), FI: Flakiness index (BS EN 933-3 2012), LAAV: Los Angeles abrasion value (TS EN 1097-2 2020), M_{wl} : Magnesium sulfate soundness (TS EN 1367-2 2011), RQAR: Rock aggregate quality assessment rating, VLQ: Very low quality, LQ: Low quality, NQ: Average quality, HQ: High quality, VHQ: Very high quality

the results obtained from the FIS analyses are almost in good agreement with those obtained from the field performances of the investigated rocks. However, it should be mentioned that a significant number of cases (9/16) were determined at the intersection of proposed quality titles. For example, limestone from Pınarbaşı/Kastamonu was determined between Low quality (LQ) and average quality (NQ), whereas basaltic andesite from Ilıca/Kutahya was described as NQ and high quality (HQ).

These intersections or peer evaluations can show the flexibility of the proposed FIS model. Meanwhile, it can also designate the necessity of such improvements in the model. It means that while the consistency of the FIS model is deemed appropriate, several improvements need to be made to this model. There is no doubt that the if–then rules (Table 2) or membership functions (Fig. 2) can be rearranged or improved based on other laboratory test results or technical guidance.

The relationships between the RQAR values with the considered rock aggregate properties were also

obtained through Pearson’s correlation analyses. Accordingly, the w_a and M_{wl} are highly associated with the RQAR, whereas LAAV is moderately correlated. Although rock aggregate shape properties are critical phenomena at the level of applications, no significant correlations were obtained between the RQAR and FI. Briefly, Pearson’s correlation analyses indicated that apart from the FI, the RQAR is negatively correlated with the considered rock aggregate properties, where w_a and M_{wl} are dominant on the RQAR (Table 4).

Table 4 Correlation matrix of the considered rock aggregate properties

w_a	FI	LAAV	M_{wl}
−0.815	−0.06	−0.688	−0.889

4 Conclusions

The present study introduced a FIS model to evaluate rock aggregate quality. Based on some technical requirements (Table 1), several triangular membership functions were founded (Fig. 2). A predictive model was established in the light of 48 if–then rules depending upon the FIS methodology.

The paths to implement the proposed FIS model were given in this document, and it was concluded that higher RQAR values point out rock aggregates with higher quality. The verification of the proposed FIS model was also carried out using 16 rock types whose field performances were previously evaluated by field engineers. The results obtained from the FIS analyses are almost in good agreement with those obtained from the field performances of the investigated rock types. Therefore, the proposed FIS model seems flexible and can be declared a case study on quantifying the rock aggregate quality. With this model, the possible performance of rock aggregates can be inferred.

Furthermore, it can also be used to estimate the maintenance interval of rock aggregates by correlating the matter of time with the RQAR values. However, the consistency of the proposed FIS model is only valid for sixteen rock types. Hence, more studies are required to observe the similarities and difficulties in evaluating rock aggregate quality by increasing the number of case studies. In this way, the membership functions and/or if–then rules stated in this study can be improved.

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Data Availability Enquiries about data availability should be directed to the authors.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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