Fuzzy expert system for assessing the quality of well completion in complicated geological conditions

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Abstract

This study presents an expert system utilizing fuzzy logic to evaluate well completion quality in geologically intricate environments, exemplified by the diverse oil and gas resources of Azerbaijan. Traditional evaluation methods, often dependent on expert judgment and inconsistent field evaluations, struggle with confusing and qualitative input data. To address this issue, we developed a fuzzy inference model incorporating critical geological and operational variables like as perforation density, reservoir pressure gradient, completion fluid compatibility, mud loss severity, and formation permeability. To establish a fuzzy rule basis derived from field experience and expert knowledge, these characteristics were transformed into linguistic variables. The Completion Quality Index (CQI) is a quantifiable and interpretable measure of completion efficacy, serving as the model's output. A combination of synthetic and empirical field data was employed to evaluate the system, and the findings indicate that the model can facilitate decision-making by generating outcomes that are dependable, flexible, and comprehensible to people. The proposed technique enhances the reliability of well completion quality evaluation under uncertainty, offering engineers a potentially valuable resource under difficult drilling conditions.

Keywords

Fuzzy logic, Uncertainty modeling, Expert systems, Completion quality index, Complex wells.

1. Introduction

The caliber of well completion significantly influences the long-term productivity and economic feasibility of hydrocarbon wells, especially in geologically intricate formations. These formations frequently exhibit significant heterogeneities, encompassing sudden lithological variations, diverse stress regimes, cracked zones, unconsolidated strata, and erratic pressure profiles. These complications provide considerable difficulties in choosing suitable completion procedures that guarantee optimal well integrity, minimal formation damage, and maximum reservoir contact.

Historically, completion design has depended on predictable procedures, engineering heuristics, and fixed formation assessment models. Nonetheless, these traditional methods frequently prove inadequate in scenarios marked by ambiguity, ambiguous data, and several interrelated geological and operational factors. In recent decades, advancements in soft computing, notably Fuzzy Logic (FL) and Fuzzy Expert Systems (FES), have provided potential options for informed decision-making in uncertain contexts.

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Fuzzy logic, established by Zadeh (1965), offers a mathematical foundation for describing and reasoning with ambiguous, incomplete, or linguistic data, a frequent occurrence in subsurface evaluations. In contrast to binary logic systems, fuzzy logic accommodates values in varying degrees, rendering it suitable for representing imprecise characteristics such as "high porosity," "moderate pressure drawdown," or "low formation stability." These attributes enable fuzzy logic to connect precise numerical models with human thinking, allowing engineers to articulate expert knowledge using IF–THEN rules derived from observable patterns and domain expertise.

In contemporary hydrocarbon exploration and production, optimizing well completion in geologically complex formations has emerged as a significant problem. Subsurface heterogeneity, fractured zones, variable pressure profiles, and lithological discontinuities provide considerable uncertainty in the assessment and decision-making process. Conventional deterministic methods, although extensively utilized, may prove inadequate in these circumstances due to their restricted ability to manage ambiguous, qualitative, or partial information.

Fuzzy logic-based approaches have become prominent in petroleum engineering and geosciences to solve this issue. Fuzzy logic offers a mathematical framework that reflects human reasoning, facilitating the appropriate understanding of language variables like “high permeability” or “moderate mud loss.” Recent investigations have illustrated the efficacy of fuzzy systems in intricate geotechnical fields, encompassing groundwater site selection using hydro-geoelectric characteristics and GIS technologies [1], as well as investment decision-making in oil and gas ventures utilizing hybrid fuzzy-rule systems [2]. Fuzzy logic has been utilized to forecast critical drawdown in sand-prone wells, enhancing dependability in the management of production hazards.

In geologically complex situations, such as fault-prone basins or marginal subsags, the integration of fuzzy logic with other intelligent systems, such as artificial neural networks, has demonstrated enhanced prediction efficacy. Recent study in Eastern China demonstrates that the integration of fuzzy reasoning with neural networks has markedly improved fault structure predictions, particularly under conditions of ambiguity and uncertainty [4].

Notwithstanding these advancements, the utilization of fuzzy expert systems specifically designed to assess well completion quality is nonetheless immature. Previous studies have concentrated on either discrete operational factors or zone selection, lacking a complete fuzzy framework that amalgamates several geological and operational inputs into a singular Completion Quality Index (CQI). This paper offers a fuzzy expert system aimed at addressing this gap by systematically evaluating completion quality using characteristics like perforation density, pressure gradients, formation permeability, and mud loss severity. Leveraging domain expertise and prior fuzzy logic applications [5, 6], this approach aims to enhance decision consistency and mitigate the effects of uncertainty in completion planning.

Notwithstanding these breakthroughs, a significant study gap persists in the creation of specialized fuzzy expert systems that assess and enhance well completion quality under intricate geological settings. Most current models concentrate either on selection or screening (e.g., whether to complete or not) or on particular elements such as stimulation design; nevertheless, few systems offer a comprehensive evaluation of completion "quality" and its optimization under uncertain subsurface circumstances.

This work seeks to address that deficiency by creating a Fuzzy Expert System (FES) that methodically evaluates completion quality based on geological, petrophysical, and operational characteristics pertinent to wells in structurally and lithologically complex formations. The suggested system would deliver expert-level advice on finishing approaches and assess the "quality" of a given design utilizing fuzzy metrics. Parameters like wellbore stability, skin factor, productivity index, completion efficiency, and risk level will be amalgamated into a cohesive inference engine designed to provide actionable information.

The system aims to function as an effective decision-support tool for engineers engaged in planning and optimizing well completions in complex reservoirs by utilizing the synergistic advantages of fuzzy rule-based logic, modular knowledge representation, and expert-driven heuristics. It also seeks to be adaptable and expandable for future incorporation of machine learning modules, real-time data streams, and field case validation, eventually enhancing intelligent, data-informed petroleum operations.

2. Case Study

Following professional consultation, literature review, and field data analysis from intricate wells in the South Caspian Basin, five critical factors were identified as inputs. Each parameter is delineated using fuzzy linguistic sets (Table 1) and membership functions that represent operational uncertainty and variability.

Table 1
Input variables which has effect on CQI and their linguistic terms

Input Variable	Linguistic Terms
Formation Permeability	Low, Medium, High
Mud Loss Severity	None, Moderate, Severe
Fluid Compatibility	Poor, Fair, Good
Perforation Density	Sparse, Moderate, Dense
Pressure Gradient	Low, Medium, High

To deploy the fuzzy expert system, actual or synthetically produced field data must be linked to the established fuzzy sets. Data from ten wells situated in geologically intricate reservoirs were selected for this purpose (Table 2). These wells demonstrate differing levels of formation permeability, operational fluid loss, perforation techniques, and pressure dynamics. The intricacy of these wells encompasses factors such as fractured carbonates, heterogeneous sandstone reservoirs, and areas with elevated differential pressures, all of which substantially affect the results of completion operations.

Table 2
Input parameters for wells in complex geological conditions

Well ID	Formation Permeability (mD)	Mud Loss Severity (0–10)	Fluid Compatibility (0–10)	Perforation Density (%)	Pressure Gradient (0–1)
W1	120	6.5	4.2	45	0.75
W2	450	2	7.8	85	0.82
W3	80	7	3	35	0.65
W4	300	5.5	6	70	0.6
W5	180	3	5.5	60	0.4
W6	280	7.5	6.5	75	0.85
W7	600	1	8.5	90	0.95
W8	90	6.8	2.2	30	0.5
W9	350	4.5	7	80	0.7
W10	220	6	3.5	50	0.55

To implement fuzzy logic, each precise input value for the chosen wells must be converted into fuzzy language concepts. The procedure termed fuzzification translates numerical data into language states through established membership functions. Triangular membership functions were selected for their simplicity, computing efficiency, and appropriateness for systems reliant on engineering judgment. Each linguistic phrase (e.g., low, medium, high) is characterized by a triangle delineated by three parameters: a (lower bound), b (peak), and c (upper bound). These triangles ascertain the extent to which a specific input value is associated with a particular fuzzy category [7]:

$$\mu(x) = \begin{cases} 0 & x \leq a \text{ or } x \geq c \\ \dfrac{x-a}{b-a} & a < x \leq b \\ \dfrac{c-x}{c-b} & b < x < c \end{cases} \tag{1}$$

Where μ(x) is the degree of membership (from 0 to 1).

To illustrate this process, three wells (W1, W3, and W6) were chosen from the dataset as exemplars of low, medium, and high-quality completion scenarios amid unpredictable and intricate geological conditions (Table 3).

Table 3
Membership triangles function's recap of parameters

	Fuzzy Set	a	b	c
Formation Permeability (mD)	Low	0	100	250
	Medium	150	300	500
	High	400	600	800
Mud Loss Severity (0–10)	None	0	1	2
	Moderate	1	5	7
	Severe	6	8	10
Fluid Compatibility (0–10)	Poor	0	2	4
	Fair	3	5	7
	Good	6	8	10
Perforation Density (%)	Sparse	0	25	40
	Moderate	30	50	70
	Dense	60	80	100
Pressure Gradient (0–1)	Low	0	0.2	0.4
	Medium	0.3	0.5	0.7
	High	0.6	0.8	1

Their input data will be fuzzified utilising the membership functions established for each parameter. The outcomes will produce membership degrees within the fuzzy sets, which will serve as input for the fuzzy inference system that finally computes the Completion Quality Index (CQI).

Let us compute instances for wells W1, W3, and W6.

Well W1 Calculations:

1. Formation Permeability = 120

Low (0–100–250): $x=120>100 \Longrightarrow \mu=(250-120)/(250-100)=130/150=0.867$

Medium (150–300–500): $x=120<a=150 \Longrightarrow \mu=0$

High: $x=120<a=400 \Longrightarrow \mu=0$

Low = 0.867, Medium = 0, High = 0

2. Mud Loss = 6.5

Moderate (1–5–7): $5<x=6.5<7 \Rightarrow \mu=(7-6.5)/(7-5)=0.25$
Severe (6–8–10): $6<x=6.5<8 \Rightarrow \mu=(6.5-6)/(8-6)=0.25$
Moderate = 0.25, Severe = 0.25
3. Fluid Compatibility = 4.2
Poor (0–2–4): $x=4.2>c=4 \Rightarrow \mu=0$
Fair (3–5–7): $3<x=4.2<5 \Rightarrow \mu=(4.2-3)/(5-3)=1.2/2=0.6$
Poor = 0, Fair = 0.6
4. Perforation Density = 45
Sparse (0–25–40): $x=45>c=40 \Rightarrow \mu=0$
Moderate (30–50–70): $30<x=45<50 \Rightarrow \mu=(45-30)/(50-30)=0.75$
Sparse = 0, Moderate = 0.75
5. Pressure Gradient = 0.75
Medium (0.3–0.5–0.7): $x=0.75>c=0.7 \Rightarrow \mu=0$
High (0.6–0.8–1.0): $0.6<x=0.75<0.8 \Rightarrow \mu=(0.75-0.6)/(0.8-0.6)=0.75$
Medium = 0, High = 0.75

Well W3 Calculations:
1. Permeability = 80
Low (0–100–250): $0<x=80<100 \Rightarrow \mu=(80-0)/(100-0)=0.8$
Low = 0.8, Medium = 0, High = 0
2. Mud Loss = 7.0
Moderate (1–5–7): $x=7.0 \Rightarrow \mu=7-77-5=0$
Severe (6–8–10): $\mu=(7.0-6)/(8-6)=0.5$
Moderate = 0, Severe = 0.5
3. Fluid Compatibility = 3.0
Poor (0–2–4): $2<x=3.0<4 \Rightarrow \mu=(4-3)/(4-2)=0.5$
Fair (3–5–7): $x=3.0=a \Rightarrow \mu=0$
Poor = 0.5, Fair = 0
4. Perforation Density = 35
Sparse (0–25–40): $25<x=35<40 \Rightarrow \mu=(40-35)/(40-25)=0.33$
Moderate (30–50–70): $30<x=35<50 \Rightarrow \mu=(35-30)/(50-30)=0.25$
Sparse = 0.33, Moderate = 0.25
5. Pressure Gradient = 0.65
Medium (0.3–0.5–0.7): $0.5<x=0.65<0.7 \Rightarrow \mu=(0.7-0.65)/(0.7-0.5)=0.25$
High (0.6–0.8–1.0): $\mu=(0.65-0.6)/(0.8-0.6)=0.25$
Medium = 0.25, High = 0.25

Well W6 Calculations:
1. Permeability = 280
Medium (150–300–500): $\mu=(280-150)/(300-150)=130/150=0.867$
Medium = 0.867
2. Mud Loss = 7.5
Severe (6–8–10): $\mu=(7.5-6)/(8-6)=0.75$
Severe = 0.75
3. Fluid Comp. = 6.5
Fair (3–5–7): $5<x=6.5<7 \Rightarrow \mu=(7-6.5)/(7-5)=0.25$
Good (6–8–10): $\mu=(6.5-6)/(8-6)=0.25$
Fair = 0.25, Good = 0.25
4. Perforation Density = 75
Dense (60–80–100): $\mu=(75-60)/(80-60)=15/20=0.75$
Dense = 0.75
5. Pressure Gradient = 0.85

High (0.6–0.8–1.0): μ=(0.85–0.8)/(1–0.8)=0.25
High = 0.25

Fuzzification was conducted for three exemplary wells chosen from intricate geological settings, in accordance with the previously stated triangular membership functions. Each distinct input parameter was associated with one or more fuzzy sets, and the relevant degrees of membership were calculated (Table 4).

Table 4

Fuzzified Values of Parameters for Selected Wells

Well	Parameter	Linguistic Term	Membership Value (μ)
W1	Formation Permeability (120)	Low	0.867
		Medium	0
	Mud Loss Severity (6.5)	Moderate	0.25
		Severe	0.25
	Fluid Compatibility (4.2)	Fair	0.6
	Perforation Density (45)	Moderate	0.75
	Pressure Gradient (0.75)	High	0.75
W3	Formation Permeability (80)	Low	0.8
	Mud Loss Severity (7.0)	Severe	0.5
	Fluid Compatibility (3.0)	Poor	0.5
	Perforation Density (35)	Sparse	0.33
		Moderate	0.25
	Pressure Gradient (0.65)	Medium	0.25
		High	0.25
W6	Formation Permeability (280)	Medium	0.867
	Mud Loss Severity (7.5)	Severe	0.75
	Fluid Compatibility (6.5)	Fair	0.25
		Good	0.25
	Perforation Density (75)	Dense	0.75
	Pressure Gradient (0.85)	High	0.25

Table 4 encapsulates the outcomes of the fuzzification procedure. For each input parameter, the pertinent fuzzy term(s) with non-zero membership values are presented alongside their corresponding membership scores.

This fuzzification phase allows the fuzzy inference engine to handle ambiguous, overlapping, and expert-derived information while assessing the Completion Quality Index (CQI). Well W1, characterised by moderate permeability and substantial mud loss, demonstrated considerable intersections in the "Moderate" and "Severe" mud loss classifications, whereas Well W6 displayed pronounced affiliation with the "Medium" permeability and "Dense" perforation categories. These findings illustrate the diversity and uncertainty inherent in real-world completion design, hence validating the application of fuzzy modelling techniques in quality evaluation.

The computation of the Completion Quality Index (CQI) for certain wells drilled in intricate geological settings, particularly Well W6, is required through the application of fuzzy logic principles. The study employs a systematic decision-making framework to manage uncertainty, imprecision, and expert evaluations characteristic in petroleum engineering operations. The methodology comprises four essential steps:

1. Employing previously fuzzified input parameters such as formation permeability, mud loss severity, fluid compatibility, perforation density, and pressure gradient;

2. Implementing a systematic collection of fuzzy IF–THEN rules, based on engineering expertise and practical experience;

3. Processing the ambiguous input data using a Mamdani-type fuzzy inference model, which emulates human reasoning by consolidating rule-based decisions; and 4. Generating a measurable output through the centroid defuzzification method, which converts fuzzy results into a singular, interpretable CQI value on a continuous scale.

This methodology aims to offer a versatile, transparent, and mathematically rigorous instrument for assessing the quality of well completions amidst uncertainty, enabling engineers to make better informed and consistent judgements in geologically intricate settings. The foundation of fuzzy rules, determined by the quantity of membership functions for each input, comprises 35=243 rules. Table 5 presents examples of fuzzy rules.

Table 5
Fuzzy base rules method and its implementation on CQI

Rule No.	Conditions (IF...)	THEN CQI
R1	Permeability is Low AND Mud Loss is Severe	Poor
R2	Permeability is Medium AND Mud Loss is Moderate AND Fluid Compatibility is Fair	Good
R3	Perforation is Dense AND Pressure Gradient is High	Excellent
R4	Permeability is Low AND Fluid Compatibility is Poor	Poor
R5	Permeability is Medium AND Perforation is Dense AND Fluid Compatibility is Good	Excellent
R6	Mud Loss is Severe AND Fluid Compatibility is Fair AND Pressure Gradient is High	Fair
R7	Permeability is Medium AND Mud Loss is Severe AND Perforation is Dense AND Pressure Gradient High	Good

The suggested fuzzy expert system is especially implemented for Well W6 as a representative example. The objective is to calculate its CQI by amalgamating empirical input values with linguistic evaluations and analysing the conversion of expert-defined criteria into a conclusive quality score. This not only corroborates the model but also demonstrates its practical utility in facilitating well completion decisions (Table 6).

Table 6

Membership values recap for Well 6

Parameter	Linguistic Term	μ
Formation Permeability	Medium	0.867
Mud Loss	Severe	0.75
Fluid Compatibility	Fair	0.25
Fluid Compatibility	Good	0.25
Perforation Density	Dense	0.75
Pressure Gradient	High	0.25

In a fuzzy expert system, rule assessment is a pivotal process wherein the system assesses the degree to which each rule influences the final output. Every rule structured as an IF–THEN statement links fuzzy input conditions (antecedents) to a fuzzy output (consequent). The intensity or level of activation of a fuzzy rule is determined by the lowest membership value among its input conditions. This approach embodies the notion that a rule's efficacy is contingent upon its least robust contributing element. When many rules are concurrently active, their effects are combined in the output fuzzy set.

The output of the proposed fuzzy expert system is assessed using a triangle membership function (Table 7).

Table 7

Output membership functions

CQI Grade	Range (Triangular)	Representative Crisp Value (center)
Poor	[0–20–40]	20
Fair	[30–50–70]	50
Good	[60–75–90]	75
Excellent	[85–95–100]	95

The Mamdani process is employed to derive the fuzzy inference of the suggested expert system. This mechanism is founded on the mini-max composition of fuzzy rules and the centroid method for deriving the system output. Table 8 illustrates the CQI outcomes for Wells W1, W3, and W6.

Table 8

CQI values for wells

Well	CQI (Defuzzified)	Linguistic Grade
W1	≈ 60.00	Good
W3	≈ 45.00	Fair
W6	≈ 73.33	Good

Conclusion

The fuzzy expert system was utilised to assess the Completion Quality Index (CQI) for three wells (W1, W3, and W6) situated in intricate geological environments. The selection of these wells was based on variability in critical factors, including formation permeability, mud loss severity, fluid compatibility, perforation density, and pressure gradient, all of which were fuzzified utilising triangle membership functions.

The Mamdani inference model utilised a structured array of fuzzy IF–THEN rules to process the fuzzified input for each well. The rules were assessed utilising the minimum membership method, with several rules activating concurrently in instances of overlapping criteria. The centroid defuzzification method was utilised to generate a precise CQI value for each instance.

The findings indicated that well W6 attained the highest CQI value of 73.33, signifying a commendable completion quality. This indicates significant permeability and dense perforation, despite mild difficulties with fluid compatibility and pressure gradients. W1 achieved a score of 60.00, classified as good, yet marginally less favourable owing to a more moderate performance across parameters. Well W3, with a CQI of 45.00, was classified as fair, mainly due to reduced permeability and inadequate fluid interaction conditions.

The results validate that the fuzzy expert system can proficiently amalgamate ambiguous, linguistic, and numerical inputs to generate an interpretable index that facilitates decision-making. The model facilitates comparative performance evaluation among wells, rendering it an effective instrument for optimising completion procedures in geologically intricate settings.

Declaration on Generative AI

During the preparation of this work, the authors used GPT-4 in order to: Grammar and spelling check. After using these tools/services, the authors reviewed and edited the content as needed and takes a full responsibility for the publication's content.

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