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Selection of Candidate Well for Stimulation: A Comparison of Conventional Method and Artificial Intelligence Techniques (Fuzzy Logic)

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Abstract

The research examined the use of fuzzy logic strategies in selecting wells for stimulation, contrasting it with the conventional method relying on experience. Previous studies considered factors like skin, porosity, permeability, production rate, reservoir pressure, reserve quantity, and net-pay thickness. The focus shifted to fuzzy logic-based artificial intelligence, specifically the Mamdani fuzzy inference method, considering GOR, skin factor, permeability, water cut, payout time, production rate, reservoir pressure, stimulation cost, and benefit. The study diverged from the traditional, labor-intensive method. Results highlighted Wells 1, 6, 10, 12, 15, and 20 as excellent candidates, with Wells 2, 8, and 17 as very good choices. Wells 4, 9, 11, 14, and 16 showed good potential, while Wells 3, 5, 7, 13, and 18 were poor candidates. Well 19 emerged as a potential candidate, emphasizing the need for nuanced techniques like fuzzy inference. Identifying high-potential wells enhances profitability and avoids investing in unqualified candidates, reducing risks to health and the environment.

Keywords: *Fuzzy logic; Mamdani inference; Membership function; Fuzzy sets; Linguistic variable.*

1. Introduction

Well simulation is performing major maintenance or remedial treatments on an oil and gas well. Utilizing various stimulation techniques, such as hydraulic fracturing, acid fracturing, chemical squeezes, and heat treatments, can help economically stimulate damaged wells and improve well productivity [1]. Candidate well selection presents the first difficulty of the re-fracturing technique [2]. This is because, in the first place, it involves the quantitative assessment of numerous individual member characteristics as well as their overall influence. Following initial hydraulic fracturing operations, refracturing, also known as re-fracking, is a re-stimulation method to enhance production and combat the production decline in unconventional reservoirs [3]. The intricate nonlinear interaction between several characteristics is hard to explain [4].

Increasing the rate at which the formation naturally delivers hydrocarbon is the primary goal of a stimulation treatment [5]. Two techniques can be employed to remove formation damage and improve well production: matrix acidizing and hydraulic/acid fracturing. To disperse or dissolve contaminants that hinder well production in sandstone reservoirs or to build new, unimpaired channels in carbonate reservoirs, matrix stimulation by acidizing involves injecting an acid or solvent below the formation's fracturing pressure [6]. Matrix acidizing should be used only in wells with strong skin effects that cannot be ascribed to perforation efficiency, partial penetration, or other mechanical completion features [6]. Matrix acidizing involves the dissolution of the rock matrix (carbonate and silicate) using mud acid i.e. HCl + HF. Rather than manually assessing each well's performance, the primary goal of this effort was to automate the selection of non-performing candidates. This cuts down on the time and work needed to locate underperforming wells.

A matrix stimulation candidate selection method was created by [7]. In matrix acidizing, acid flow is confined to the formation's natural pores and flow channels at a bottom hole pressure less than the fracturing pressure of the formation. The purpose is to increase the permeability and porosity of the producing formation. While hydraulic fracturing involves injecting fluids at a pressure higher than the formation fracture gradient, is to dissolve the fracture wall in relatively high permeability formations without causing damage, hence creating a route of high conductivity. On the other hand, relatively low permeability carbonate reserves might potentially be suitable for acid fracturing. Another important element that greatly influences whether refracturing is successful or unsuccessful is technical feasibility [8-9]. To create linear flow channels to the wellbore, the reservoir is hydraulically fractured, and the fractured sides are etched with acid [6].

Candidate well selection or recognition is the process of locating and picking wells for rehabilitation operations that have the potential to yield higher and more favorable economic performance [10]. To deliver the best solution and prevent revenue loss from improper treatment, it is crucial to carefully pick the candidate by describing the cause of the productivity impairment. Stimulation failure could be caused by poor candidate selection, inaccurate treatment design, and improper field procedures [11]. The process of selecting candidate wells entails first determining which wells are not producing as much as they should, and then assessing the well in question for any possible technical issues. [12].

Numerous researchers in this field have conducted studies on a variety of techniques for determining if a well is suitable for stimulation, with the assessment method depending on the well's geology and fluid parameters. A methodical approach was presented by [13] to enable a field engineer to assess a well's likelihood of refracturing based on an examination of readily available reservoir data as well as field production data. Using information from 300 Codell tight gas wells, a case study in the Wattenberg field effectively tested the well-selection approach. Reorientation of stress, initial completion quality, initial production drop, and reservoir depletion surrounding the well of interest were all considered as selection criteria for re-fracturing candidates [14].

Scholars have created several alternative methods for candidate selection for stimulation. Kniazev *et al.* [15] divided the various methods into three categories: advanced, mixed conventional, and conventional. To do hard computing, an analytical model that clearly outlines the standards by which a well is judged to be a good candidate for stimulation or not must be developed [16]. The expert engineer must establish these guidelines based on his experience in the field. Engineering and geological analysis were employed in the conventional approach, artificial intelligence (AI) was used in the advanced approach, and a combination of the conventional and advanced techniques was used in the mixed approach which is considered in this paper.

This study compares the most reliable stimulation mechanisms, taking into account both traditional and artificial intelligence approaches. A contemporary approach called "soft computing" is based on the ideas of flexibility, ambiguity, and approximation. To more effectively address difficult engineering issues, this strategy focuses on a variety of computer paradigms, including machine learning (ML), artificial neural networks, evolutionary algorithms, and fuzzy logic [17]. Fuzzy logic, an artificial intelligence technique, enables modeling inference under uncertainty. Compared to the hours needed for traditional geological and engineering tests, the AI methods take a very short amount of time to perform [18]. FLS has been widely used in various aspects of petroleum engineering, including reservoir characterization for reservoir evaluation [19], drilling/completion operations [20-21], and stimulation treatment, due to its advantages in dealing with uncertainty [22].

According to [23], to determine the useful factors and their impact on the selection of candidate wells for hydraulic fracturing treatment through decision-making, Zeng *et al.* [24] conducted a study. They employed multicriteria decision-making techniques, which offered a strong instrument for assessing parameters, particularly when some are qualitative and dependent on the expertise of experts. A group of decision-makers identified fourteen (14) useful parameters to select the candidate wells. Subsequently, the analytical hierarchy approach was employed to determine the numerical significance of every parameter in the selection of candidate wells. They demonstrated that when it comes to the selection of candidate wells, productivity is the most important aspect, whereas water cut and production methods have the least influence.

Selecting candidate wells for stimulation is a challenging process. The fuzzy logic technique performs well when no mathematical model is obtainable for a problem such as in the case of the selection of a candidate well for stimulation. Without a doubt, inaccuracies, uncertainties, and brittle correlations across data sets are problems in the selection of wells for stimulation [25]. Fuzzy logic (FL) is therefore a more effective strategy for resolving these issues. Therefore, a well-structured artificial intelligence approach to candidate well selection will intensify the task of identifying a suitable candidate for this expensive operation and improve the overall well performance.

Additionally, many papers were devoted to examining deep learning methods for solving the task of selecting candidates for well stimulations [16]. Prior research on this subject has reportedly considered several variables, such as skin, porosity, permeability, production rate, reservoir pressure, reserve quantity, and net-pay thickness. Additionally, they have given special attention to the area of artificial intelligence based on fuzzy logic. The Gas-Oil Ratio (GOR), skin factor, permeability, water cut, payout time, production rate, reservoir pressure, stimulation cost, and stimulation benefit were all included in the development of the Mamdani fuzzy inference system in this research.

I elucidated that this methodology would facilitate the development of enhanced standards for the identification of the ideal well, while simultaneously accounting for the wells' economic attributes. The distinction between my research direction and the conventional selection process—which was renowned for being labor-intensive, time-consuming, and not very accurate—was brought to light. I stated that I would carefully evaluate each well on an individual basis using the conventional method, and I would grade them according to the previously indicated standards. I would then contrast this with the artificial intelligence method, keeping in mind that human mistakes are likely to happen when working with large datasets.

2. Literature review

This work considers twenty different wells to select the best candidate for stimulation using the conventional approach and artificial intelligence techniques (fuzzy logic). These wells are situated in the Niger Delta region and are examined based on their skin factor, GOR, permeability, water cut, reservoir pressure, stimulation benefit, stimulation cost, payout time, well inflow quality indicator (WIQI), pressure transient well test analysis, and decline rate analysis.

The conventional method of selecting candidate wells for hydraulic fracturing is complex and does not have a well-defined globally accepted approach [18].

2.1. Skin factor

The skin factor, frequently abbreviated as "S," is another critical measure used in the oil and gas industry to evaluate well performance and is a key criterion for the selection of potential candidate wells for stimulation. The skin factor is a representation of the stimulation or harm caused to the wellbore by being close to it. The skin factor is relevant for the selection of candidate wells for stimulation in the following way:

1. Positive skin ($S > 0$): The presence of near-wellbore damage, which lowers the effective permeability of the reservoir close to the wellbore, is indicated by a positive skin factor. Positive skin factors are frequently associated with underperforming wells because of things like drilling mud invasion, formation damage, or scale buildup. Acidizing or hydraulic fracturing are excellent options for these wells to be stimulated to repair the damage and increase productivity.

2. Negative skin (S < 0): The presence of a negative skin factor near the wellbore denotes a favorable stimulating effect. This may happen when prior stimulation treatments have been effective in raising well production. Unless other factors indicate that additional treatments are essential, it might not be necessary to stimulate the well further in such circumstances.
3. Zero skin (S = 0): A skin factor of zero indicates that there is no stimulation or harm caused by a near-wellbore. These wells may still benefit from stimulation even when they don't have near-wellbore problems if other factors like reservoir pressure or decline rate indicate that the well's production could be increased.

2.2. Productivity index

The productivity index (PI), a key statistic in reservoir engineering, is used to evaluate how well-equipped an oil or gas well is to extract hydrocarbons from a reservoir. The pressure drop across the reservoir, the wellbore circumstances, and the fluid characteristics are taken into account to calculate the well's productivity. The PI is a dimensionless number that, depending on the chosen unit system, is often stated in terms of barrels per day per pound per square inch (bbl/day/psi) or cubic meters per day per Pascal (m^3/day/Pa). The formula for calculating the productivity index (PI) of a well is as follows:

$$\mathrm{PI} = \frac{Q}{\Delta \mathrm{P}} * \frac{1}{\mu} \qquad (1)$$

where: PI: productivity index (bbl/day/psi or m^3/day/Pa); Q: flow rate of hydrocarbons from the well (bbl/day or m^3/day); ΔP: pressure drop across the reservoir (psi or Pa); μ: viscosity of the hydrocarbons (centipoise or Pascal-seconds).

The productivity index is used to choose potential wells for stimulation operations in the manner described below:

1 Prioritizing stimulation candidates: Wells with low PI values are given more priority for additional evaluation and stimulation operation consideration. By addressing the issues that limit the well's productivity, stimulation aims to raise its PI. Acidizing or hydraulic fracturing are two examples of stimulation procedures that can improve or restore reservoir connection close to the wellbore, raising the PI.

2 Finding underperforming wells: When comparing the productivity index values of several wells in a field, those with low values may be candidates for stimulation. Low PI values could be a sign that the well is not producing as much as it could be given the reservoir conditions. This could be because of formation damage, problems around the wellbore, or other concerns.

2.3. Decline rate analysis

Decline rate analysis is a vital technique for evaluating the performance of oil or gas wells over time by analyzing their production decline curves. It offers insights into how production rates change as reservoir pressure decreases and can be used to choose candidate wells for stimulation operations. Here's how decline rate analysis works and how it can be used for well stimulation:

1. Examining historical production data from a well or a collection of wells is required for decline curve analysis. Production rates, total production, and time are frequently included in this information. Decline curves can be produced to show how the well's production has changed over time by graphing this data and examining the trends.
2. Candidates for stimulation include wells that exhibit higher decline rates than anticipated or that have recently had a significant fall in production. These wells may benefit from stimulation procedures like acidizing or hydraulic fracturing, which could potentially lengthen their useful lives.

2.4. Well inflow quality indicator (WIQI)

WIQI stands for "Well Inflow Quality Indicator." An additional relative metric for assessing the effectiveness of a well's drilling and completion is the well inflow quality indicator (WIQI). The ratio of a well's actual productivity index to its productivity index without skin is what is meant by this definition. It is a diagnostic metric that shows how good a well was finished, whether it was done initially, after rework, recompletion, or stimulation. The way to get this is to do a BHP survey right away after finishing something or coming back in. The well inflow quality indicator is established by comparing PI actual to PI Ideal. WIQI measures how good a well is producing

$$\mathrm{WIQI} = \frac{PIactual}{PIideal} \tag{2}$$

The actual productivity index can be calculated using the formula 3-4:

$$\mathrm{PI} = 7.08 \times 10^{-3} \times kh\ /\ \mu\beta \times \ln \frac{\mathrm{re}}{\mathrm{rw}} \tag{3}$$

$$\mathrm{PI} = 7.08 \times 10^{-3} \times kh/\mu\beta\ \times \ln\ \mathrm{re}\frac{7.0}{\mathrm{rw}} + S_c \tag{4}$$

where: Q = production rate ($\frac{STB}{D}$); P_r = reservoir pressure (psi); P_{wf} = well flowing pressure (psi); K = permeability (mD); D_p = draw down (psi); μ = viscosity (cP); B = formation volume factor rb/stb; Re = reservoir radius (ft); R_w = well radius (ft).

The productivity index measures an oil well's productivity. As long as the flowing bottom-hole pressure P_{wf} is higher than the bubble point pressure (Pb), the PI will typically remain constant across a variety of production rates, i.e. the IPR will be a straight line. The inflow performance relationship will curve and become rate-dependent below Pb.

2.5. Artificial intelligence techniques using fuzzy logic

2.5.1. Fuzzy logic

A method of processing variables called fuzzy logic permits the processing of several different truth values using a single variable. Fuzzy logic uses heuristics to generate a range of precise conclusions while attempting to solve problems with an open, imprecise spectrum of facts. Fuzzy is a synonym for uncertain, ambiguous, vague, or unclear. A computational method based on the degree of truth is fuzzy logic. A fuzzy logic system generates a specific output by using linguistic variables and the degree of truth of the input. Fuzzy algorithms are relatively easy to develop because they resemble natural language, but they could need extensive testing and verification. The nature of the output depends on the condition of this input. Fuzzy logic is a valuable tool for addressing uncertain and imprecise problems in the field of reservoir evaluation [26]. Most uncertainties in intricate systems, including petroleum systems, result from a lack of precision or an inability to do the necessary measurements. This was theoretically developed to describe uncertainty and vagueness in language difficulties to gain formal tools to cope with intrinsic imprecision in various types of problems. According to Castro et al., complex system modeling is seen as a generalization of the conventional set theory. The fuzzy set and fuzzy logic, which attempt to depict how the brain manipulates exact information, are the cornerstones of fuzzy systems [27].

Mohaghegh [28] used the Fuzzy Logic (FL) technique to forecast the pore pressure during drilling. Drilling factors, such as weight on bit, rotary speed, rate of penetration, mud weight, bulk density, porosity, and compressional time, were used to make the forecast in addition to log data. Several empirical models were compared with the outcomes of the Fuzzy Logic tool. With a low average absolute percentage error (AAPE) of 0.234 percent and a high correlation coefficient (R) of 0.998, the FL approach provided an accurate estimate of the formation pressure. FL performed better than all previously released models.

2.5.2. Fuzzy set theory

Fuzzy logic provides the means to compute with words (human language). With fuzzy logic, experts are no longer forced to summarize their knowledge in a language that machines or computers can understand. What traditional expert systems failed to achieve finally became a reality with the use of fuzzy expert systems [29]. Fuzzy logic is made up of fuzzy sets, which are a way of expressing non-statistical vagueness and approximate reasoning, which includes operations used to make inferences [29].

Fuzzy sets allow for the representation of concepts in human reasoning that crisp sets cannot. For instance, the set of "tall people" may include individuals who are unquestionably tall (i.e., with the highest degree of "membership" to the set), as well as individuals who are not as tall but unquestionably not short (i.e., with a lower degree of membership). The net set, or classical set, or set refers to a collection of distinct and well-defined objects [30].

Formally, a fuzzy set A is defined by a membership function, represented by A: U [0, 1], which translates an element u to its degree of membership; in other words, A(u) is the degree of membership of u to A, given a universe of discourse U and u as its generic constituent. If A is a regular set, then the results of its membership function A(u) can only be either 1 or 0.

Numerous definitions and characteristics of fuzzy sets are also direct extensions of those for regular sets. Examples include:

1. the fuzzy set A is empty if and only if $\mu A(u) = 0, \forall u \in U$;
2. two fuzzy sets A and B are equal if and only if $\mu A(u) = \mu B(u), \forall u \in U$;
3. the complement of A, denoted by A, is defined by $\mu A\ (u) = 1 - \mu A(u)$;
4. the fuzzy set A is contained in B if and only if $\mu A(u) \leq \mu B(u), \forall u \in U$;
5. the union of fuzzy sets A and B is a fuzzy set C, defined by $\mu C(u) = \max(\mu A(u), \mu B(u)), u \in U$;
6. the intersection of fuzzy sets A and B is a fuzzy set C, defined by $\mu C(u) = \min(\mu A(u), \mu B(u)), u \in U$.

2.5.3. Fuzzy logic system

Creating a fuzzy logic system consists of four basic steps:

i. A set of membership functions must be defined for each variable, whether it be an input variable or a result variable. A word, such as high, medium, or low, serves as the typical representation of a membership function, which determines how much a variable's value belongs to the group concerning a universe of discourse.
ii. Statements or rules that connect the MFs of each variable to the outcome are defined, typically using a series of IF-THEN statements. The rules are also weighted in order of their importance concerning their linguistic variable. One rule can be as follows: If the skin factor (linguistic word represented by an MF/antecedent) is positive, then the well (conclusion/consequent) is a good candidate for stimulation. Usually, the skin is given a higher weight as it is the main determinant factor in selecting a damaged well for stimulation.
iii. The mathematical evaluation of the rules is performed, and the outcomes are merged. Aggregation is the method used to evaluate each rule.
iv. Defuzzification is the method used to evaluate the resulting function as a sharp number

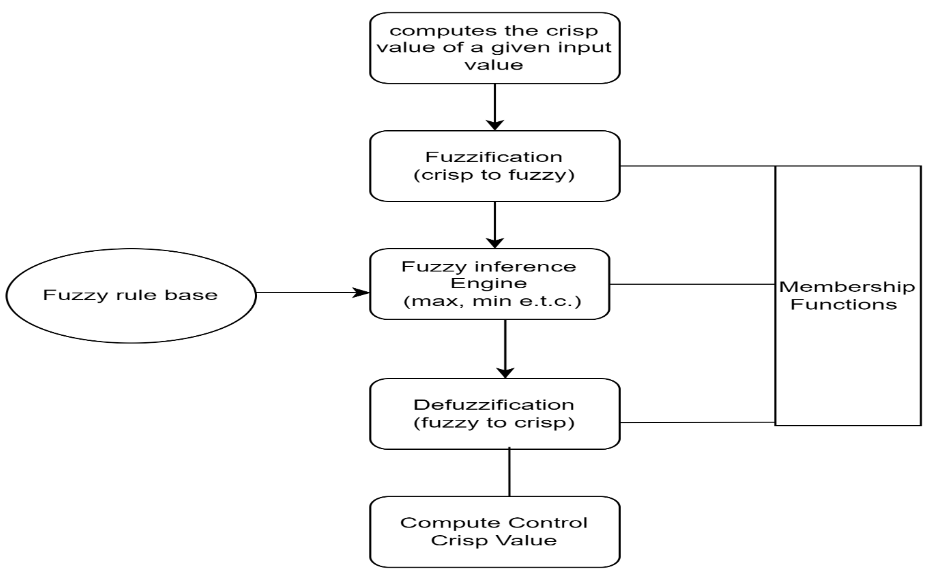

Fig 1. A fuzzy logic architecture.

The following is a basic explanation of FLS's structure:

Input: Nine input variables—often referred to as linguistic variables or parameters—are accepted by the algorithm in this instance. These inputs serve as a substitute for the factors or situations that the system will take into account while making decisions. These variables include the skin factor, permeability, water cut, payout duration, production rate, reservoir pressure, stimulation benefit, cost, and payout.

Fuzzification: Each input variable is mapped to one or more fuzzy sets during the fuzzification stage. A membership function that assigns a degree of membership to each input value for each fuzzy set defines a fuzzy set. This method transforms exact (crunchy) input values into fuzzy sets that support partial membership. The skin factor for example has values within the range of [-20, 20] and values from -∞ to zero are Negative, while values within zero to +∞ are positive skin factors. I used the Gaussian membership function to define this linguistic variable as shown in Fig 2 below.

Knowledge Base (Rule Base): The knowledge base is a set of rules describing the relationships between the inputs and outputs. The usage of "IF-THEN" phrases or other such structures is common when expressing these rules in everyday English. Each rule describes how to combine the fuzzy sets of the input variables to obtain the fuzzy sets of the output variables. A rule could say, for example, "IF skin factor is positive AND Stimulation cost is low, AND stimulation benefit is high AND permeability is low THEN candidate ranking for stimulation is very good." This is just one of the rules defined in this work. Some of the other rules used in this work are shown in Table 2 below. Furthermore, developing the fuzzy rule foundation can occasionally be a difficult task that calls for a solid grasp of the dynamics of the system in question [31].

Inference Engine: The inference engine is in charge of utilizing the fuzzy input data and the rules from the knowledge base. Using the membership values of the input variables as a starting point, it calculates the degree to which each rule is adhered to. The membership values are combined in line with the rules using a variety of fuzzy logic operators, such as AND and OR. Before starting the inference process, it is crucial to provide each fuzzy rule in the rule base a weight value, which can be any number between 0 and 1.

Every rule in the rule base is subject to this procedure. This phase takes a single integer as input, which is provided by the rule antecedent for each rule. The output is an output fuzzy set that can be scaled (product method) or truncated (minimum method) [32]. The fuzzy rule inference can be seen in Fig 12 of the appendix and the output is based on the input parameter of a given well.

Aggregation: The fuzzy output sets produced by each rule are combined after the inference engine has applied each rule. The different fuzzy sets are combined throughout the aggregation phase into a single fuzzy output set that represents the overall output. Taking the maximum, minimum, or weighted average of the fuzzy sets are frequent aggregation technique.

Defuzzification: It is necessary to convert the system's final output from a fuzzy set to an actual value that may be used for commands or decision-making. Defuzzification is the process of selecting a single output value or range that best captures the total set of fuzzy outputs. Defuzzification can be accomplished using a variety of approaches, such as centroid, mean of maximum (MOM), and weighted average. But in this case, the centroid defuzzification was applied.

Outputs: The output values represent the actions the system took in terms of decision or control. These output values are frequently used to run a system, make decisions, or give suggestions based on the input data and the rules listed in the knowledge base.

Feedback (Optional): In some fuzzy logic systems, a feedback loop might exist, enabling the system to modify itself and enhance performance over time. To improve the behavior of the system, adjustments can be made to the rules, the membership functions, or other factors.

3. Methodology

3.1. Mamdani inference deployment

Twenty wells in the Niger Delta were evaluated for stimulation in this paper, with consideration given to the following factors: skin factor, reservoir pressure, production rate, GOR, payout time, cost and value of stimulation, permeability, and water cut. In the Mamdani inference, they are represented as the linguistic variable. Usually, more than one MF is used for each input variable as a single MF can only define one fuzzy set [32]. The data used in this work is in Table 1.

Table 1. Data used in the development of the Mamdani fuzzy inference system.

WELL NUMBER	SKIN FACTOR	GAS-OIL-RATIO(scf/bbl	RESERVOIR PRESSURE(psi)	PAYOUT TIME(months)	STIMULATION COST($)	STIMULATION BENEFIT($)	WATER CUT(%)	PERMEABILITY(mD)	PRODUCTION RATE(bopd)
1	20	100	3000	16	60 000	300 000	10	8	400
2	5	200	1500	18	25 000	280 000	6	18	1000
3	-5	1000	700	24	45 000	50 000	20	10	500
4	3	800	2000	20	50 000	150 000	7	15	1400
5	-8	1000	900	15	60 000	30 000	15	8	900
6	10	400	2500	16	20 000	200 000	4	20	1500
7	-10	1000	1100	23	70 000	80 000	18	19	700
8	7	250	3500	12	40 000	350 000	9	21	1200
9	1	120	2200	21	65 000	120 000	25	11	1100
10	3	650	2500	15	30 000	200 000	3	22	1400
11	2	700	1800	13	50 000	140 000	5	14	700
12	12	150	2900	15	55 000	280 000	5	9	750
13	-6	1100	600	18	100 000	65 000	17	70	1300
14	-9	200	4000	13	20 000	120 000	30	30	4000
15	13	300	3000	12	35 000	230 000	25	2	890
16	0	320	900	17	21 000	100 000	16	34	1500
17	9	100	1000	19	75 000	270 000	13	17	1600
18	-20	1500	4500	10	10 000	40 000	10	60	4500
19	3	500	2300	23	45 000	70 000	45	15	1400
20	8	350	3200	24	40 000	250 000	30	60	1200

Except for the skin factor, where membership functions are positive, zero, and negative, the membership function definitions for all linguistic variables are low, medium, and high. These linguistic variables are the inputs of this system and are represented visually using the Gaussian membership function for the skin factor and the water cut as shown in Figs 2 and 3.

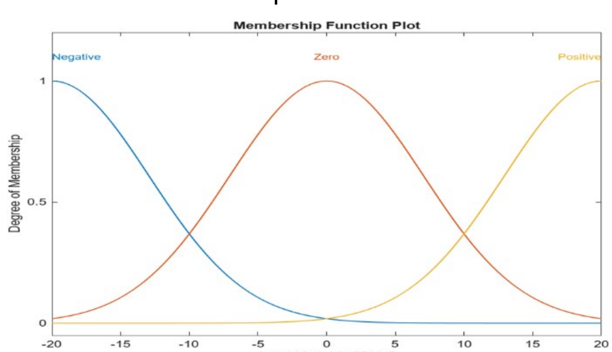

Fig 2. Membership function plot for skin factor.

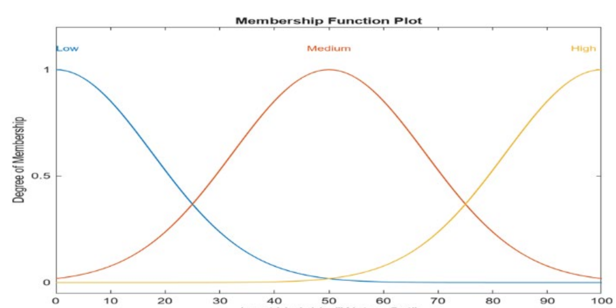

Fig 3. Membership function plot for water cut .

The triangular membership function for the reservoir pressure, Permeability, stimulation cost, and benefit is shown in Figs. 4, 5, 6, and 7.

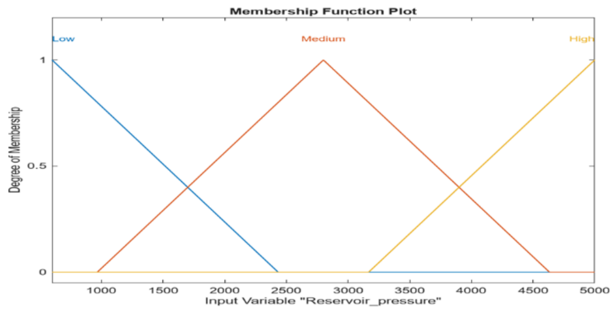

Fig 4. Triangular membership function plot of reservoir pressure.

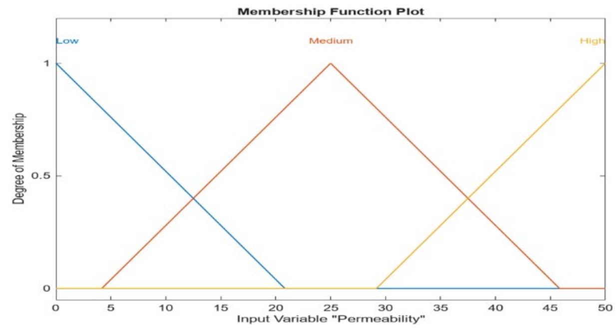

Fig 5. Membership function plot for permeability.

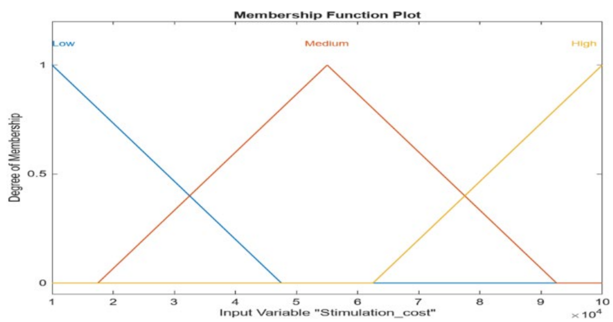

Fig 6. Membership function plot of stimulation cost.

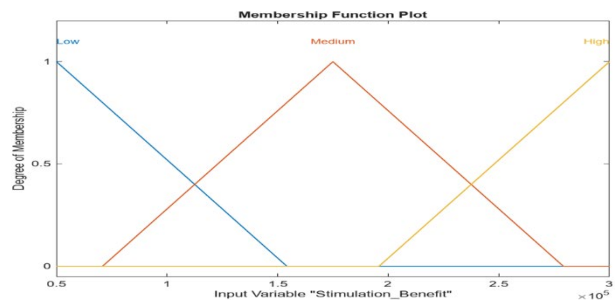

Fig 7. Membership function plot of stimulation benefit.

The GOR is represented using the difference of sigmoid in Fig 8 and the payout time with the two-sided sigmoid MF in Fig 9 while the production rate is with trapezoidal MF and this can be seen in Fig 10. The candidate ranking is the output and its linguistic terms are poor, MAYBE, good, very good, and excellent. They are represented using the Gaussian MF as shown in Fig 11.

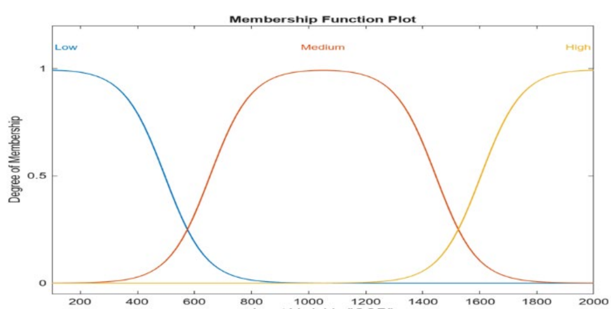

Fig 8. Membership function plot of Gas-oil-ratio (GOR).

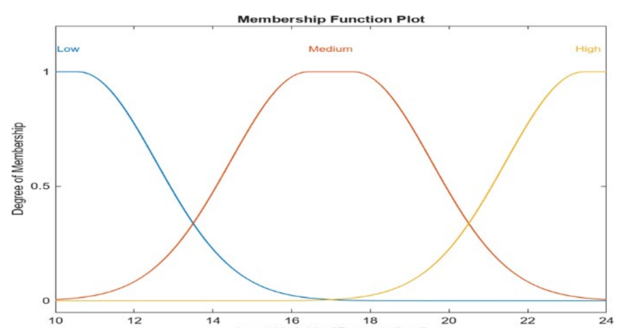

Fig 9. Membership function plot of payout time.

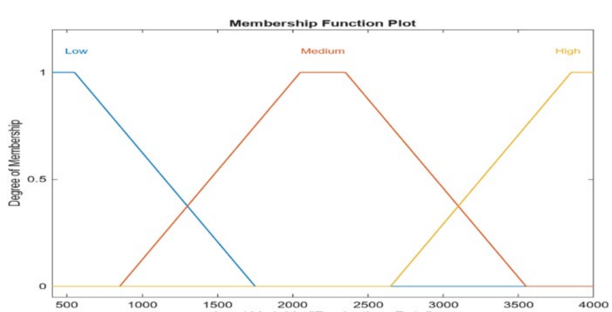

Fig 10. Membership function plot of production rate.

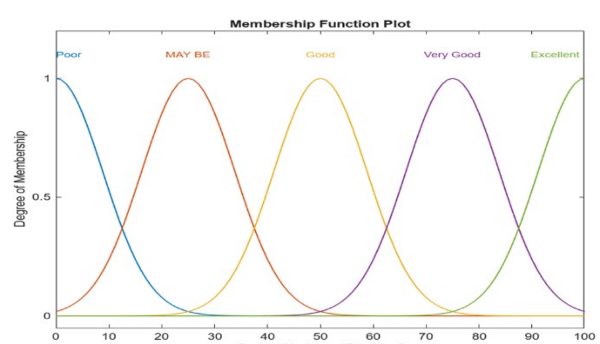

Fig 11. Membership function plot of the output candidate ranking.

The definition of the rule base follows which requires a good understanding of the well parameters and assigning a greater weight to the skin factor. The Mamdani fuzzy knowledge base is the rule-based system proposed in 1974 by Mamdani as a fuzzy logic controller.

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves all the pieces that are described as membership function, Logical operation, and If-Then-Rule. The fuzzy inference system takes 9 input parameters and computes the output ranking for each well using the fuzzy rules defined which can be If skin factor is positive reservoir pressure is high AND GOR is low AND payout time is low AND stimulation benefit is high AND stimulation cost is low AND water cut is medium AND permeability is low AND production rate is low THEN candidate ranking is Excellent. During fuzzy inference, parallel IF-THEN rules are used to project input variables onto the output space [33]. Fig. 13 in the appendix is a flowchart showing the processes involved in developing the Mamdani fuzzy inference to rank this candidate well in order of their suitability for stimulation. Some of the rules defined in this paper are shown in the Table 2.

Table 2. Fuzzy rules defined.

	Rule	Weight	Name
1	If Skin is Negative and GOR is Low and Reservoir_pressure is ...	0.1	rule1
2	If Skin is Zero and GOR is Low and Reservoir_pressure is Medi...	0.1	rule2
3	If Skin is Positive and GOR is Low and Reservoir_pressure is H...	0.3	rule3
4	If Skin is Negative and GOR is Medium and Reservoir_pressur...	0.1	rule4
5	If Skin is Zero and GOR is Low and Reservoir_pressure is High...	0.1	rule5
6	If Skin is Positive and GOR is Medium and Reservoir_pressure ...	0.8	rule6
7	If Skin is Negative and GOR is High and Reservoir_pressure is ...	0.2	rule7
8	If Skin is Zero and GOR is Low and Reservoir_pressure is Medi...	0.3	rule8
9	If Skin is Positive and GOR is Medium and Reservoir_pressure ...	0.5	rule9
10	If Skin is Negative and GOR is Medium and Reservoir_pressur...	0.1	rule10
11	If Skin is Zero and GOR is Low and Reservoir_pressure is Medi...	0.1	rule11
12	If Skin is Positive and GOR is Medium and Reservoir_pressure ...	0.5	rule12
13	If Skin is Zero and GOR is High and Reservoir_pressure is Low...	0.1	rule13
14	If Skin is Positive and GOR is Medium and Reservoir_pressure ...	0.5	rule14
15	If Skin is Negative and GOR is Medium and Reservoir_pressur...	0.1	rule15
16	If Skin is Positive and GOR is High and Reservoir_pressure is L...	0.3	rule16
17	If Skin is Positive and GOR is Medium and Reservoir_pressure ...	0.2	rule17
18	If Skin is Positive and GOR is Low and Reservoir_pressure is H...	0.8	rule18

4. Result and discussion

In this paper, twenty different wells from the Niger Delta region are considered based on nine parameters to make a well-informed decision and take into account the benefit associated with our choice of well for stimulation. The data and the candidate ranking are shown in Table 3.

Table 3. Final ranked result of the Mamdani inference.

WELL NUMBER	SKIN FACTOR	GAS-OIL-RATIO(scf/bbl	RESERVOIR PRESSURE(psi)	PAYOUT TIME(months)	STIMULATION COST($)	STIMULATION BENEFIT($)	WATER CUT(%)	PERMEABILITY(mD)	PRODUCTION RATE(bopd)	RANKING
1	20	100	3000	16	60 000	300 000	10	8	400	Excellent
2	5	200	1500	18	25 000	280 000	6	18	1000	Vey Good
3	-5	1000	700	24	45 000	50 000	20	10	500	Poor
4	3	800	2000	20	50 000	150 000	7	15	1400	Good
5	-8	1000	900	15	60 000	30 000	15	8	900	Poor
6	10	400	2500	16	20 000	200 000	4	20	1500	Excellent
7	-10	1000	1100	23	70 000	80 000	18	19	700	Poor
8	7	250	3500	12	40 000	350 000	9	21	1200	Very Good
9	1	120	2200	21	65 000	120 000	25	11	1100	Good
10	3	650	2500	15	30 000	200 000	3	22	1400	Excellent
11	2	700	1800	13	50 000	140 000	5	14	700	Good
12	12	150	2900	15	55 000	280 000	5	9	750	Excellent
13	-6	1100	600	18	100 000	65 000	17	70	1300	Poor
14	-9	200	4000	13	20 000	120 000	30	30	4000	Good
15	13	300	3000	12	35 000	230 000	25	2	890	Excellent
16	0	320	900	17	21 000	100 000	16	34	1500	Good
17	9	100	1000	19	75 000	270 000	13	17	1600	Vey Good
18	-20	1500	4500	10	10 000	40 000	10	60	4500	Poor
19	3	500	2300	23	45 000	70 000	45	15	1400	MAYBE
20	8	350	3200	24	40 000	250 000	30	60	1200	Excellent

Well 1,7,11,13,16 and 20.

Because wells 1, 6, 10, 12, and 15 have high returns on investment, a high positive value for skin factor—a sign of formation damage—and a short recovery time from increased oil production, these wells are considered excellent candidates for stimulation using either hydraulic fracturing or matrix acidizing. Stimulation can increase these wells' permeability.

Well 19.

Because of the relatively high water cut in this well, accuracy in judgment calls for precision. If a certain well zone is the source of the water cut, it might be able to isolate that zone while promoting the other zones. However, in this instance, the well's strong positive skin factor and high stimulation benefit indicate that damage is to blame. This well is therefore seen as a strong contender

WELL 2, 8, and 17

This well has a high rate of return on investment hence it is seen to be wise to stimulate it. The high positive skin factor, which is an unmistakable sign of formation damage, is also noteworthy. Hydraulic fracturing is the most effective technique to increase the permeability of these deposits. This well's GOR suggests that there is a large

amount of oil there, and stimulating it will boost the productivity of this well's moderate production. Well number 2, 8, and 17 are very good candidate for stimulation.

Well 4,9,11,14, and 16

The depiction of these wells' economic feasibility is quite noteworthy. In addition to ensuring a large return on investment, stimulating these wells will eventually repair the damage in this particular well. In well 16, the low reservoir pressure suggests that the oil is not flowing as freely as it could. By making the rock that surrounds the wellbore more permeable, stimulation can aid in improving the flow of oil. A low gas-to-oil ratio (GOR) suggests that the well is producing more oil than gas. This suggests that stimulating the well would be a wise decision. Hence, this well are good candidate for stimulation.

Well 3,5,7,13, and 18.

These wells are regarded as poor candidate wells for stimulation, in addition to having a negative skin that indicates the well is undamaged. This low return on investment is concerning. A poor candidate well for stimulation is indicated by the high GOR and low reservoir pressure.

5. Conclusion

Six wells are excellent candidates for stimulation, one well is under probability for stimulation, three wells are very good candidates for stimulation, five other wells are good candidates, and five are deemed to be poor candidates for stimulation (hydraulic fracturing or matrix acidizing), according to a series of analyses and examinations conducted on each well. Two wells are considered unsuitable for stimulation, but the other two may be candidates.

When compared to the time needed for geological and engineering analysis using the modern conventional method, the number of hours needed to finish the artificial intelligence operations is negligible. The traditional method uses geological and engineering study, which is laborious, unpleasant, and time-consuming.

Because this research endeavor uses fuzzy logic, an artificial intelligence technique that models reasoning under imprecision, it has received popularity in the petroleum business. To rank and forecast twenty distinct wells against nine properties—skin factor, water cut, GOR, permeability, reservoir pressure, payment time, stimulation cost, stimulation benefit, and production rate—a fuzzy logic evaluator had to be developed. The projected ranking result showed that five wells were strong contenders and six wells were exceptional candidates. One well was a potential possibility, five wells were deemed unsuitable, and three wells were regarded as very good candidates.

Artificial intelligence techniques ought to be extensively utilized, particularly in the petroleum business where a substantial amount of data needs to be processed and results must be obtained quickly. Artificial intelligence can process data on its own and is less expensive than the traditional method, which is also incredibly stressful and time-consuming.

Fuzzy logic is helpful in inference modeling when there is a significant level of uncertainty since it may represent high imprecision. When data volumes are low, the traditional method—which includes engineering examination of the oilfield's properties—should be used.

The conventional method relies on human expertise, experience, and industry knowledge to make decisions about well selection. Geologists, reservoir engineers, and other experts typically assess various well parameters manually. While the AI techniques, including fuzzy logic, are data-driven and can process large datasets efficiently. They can handle various data sources, including real-time measurements and sensor data.

Fuzzy logic models can optimize well selection by considering multiple parameters simultaneously. They can find patterns and relationships within data that might be challenging for human experts to identify.

Due to the significant time investment in geological and engineering assessment, the traditional method of selecting candidates for well stimulation should only be taken into consideration when little data is involved; Because fuzzy logic can describe inference under imprecision for a specific problem when no mathematical model is available, artificial intelligence approaches like fuzzy logic can manage massive data sets. To rate wells eligible for stimulation, a decent fuzzy evaluator should be constructed with a suitable rule foundation.

Appendix

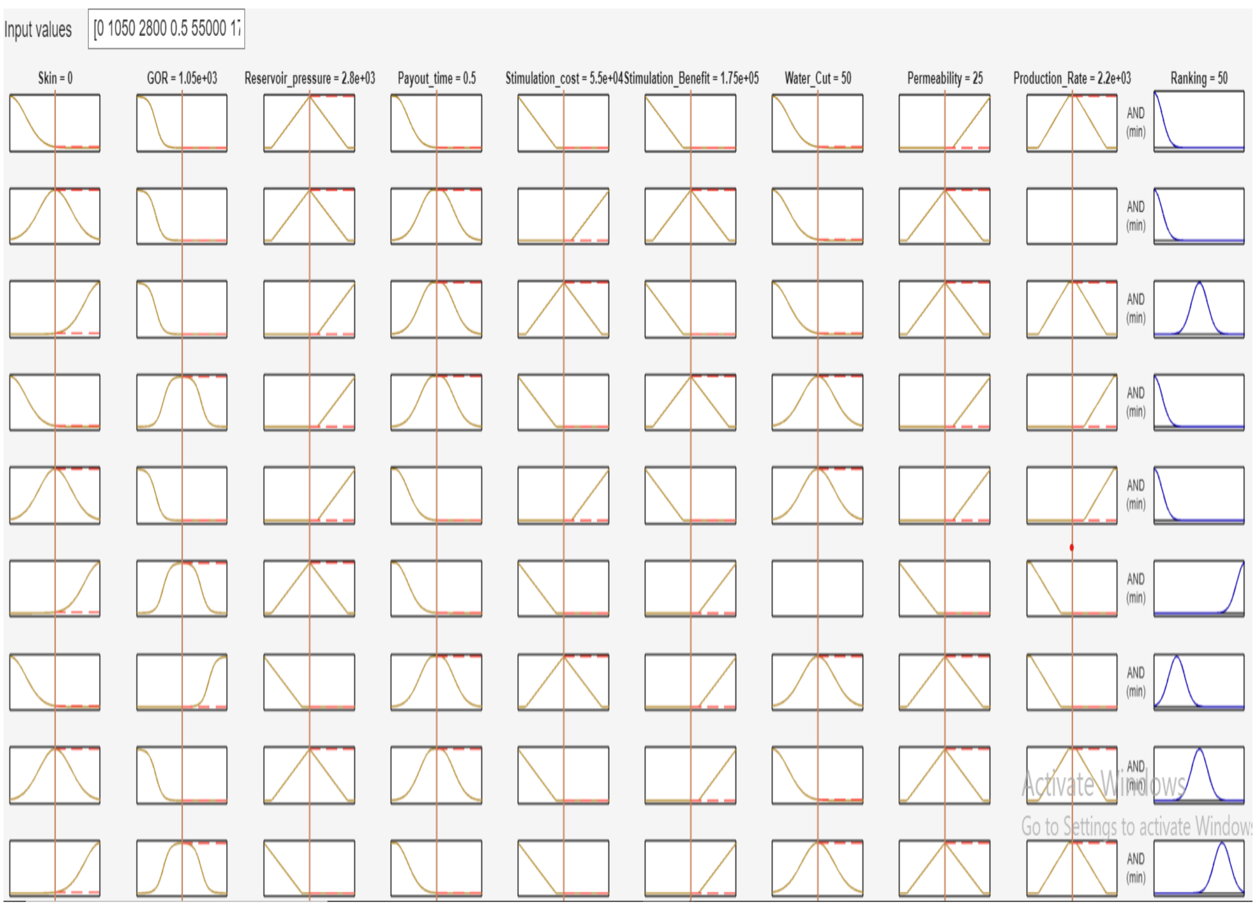

Fig 12. The rule inference of the fuzzy logic system.

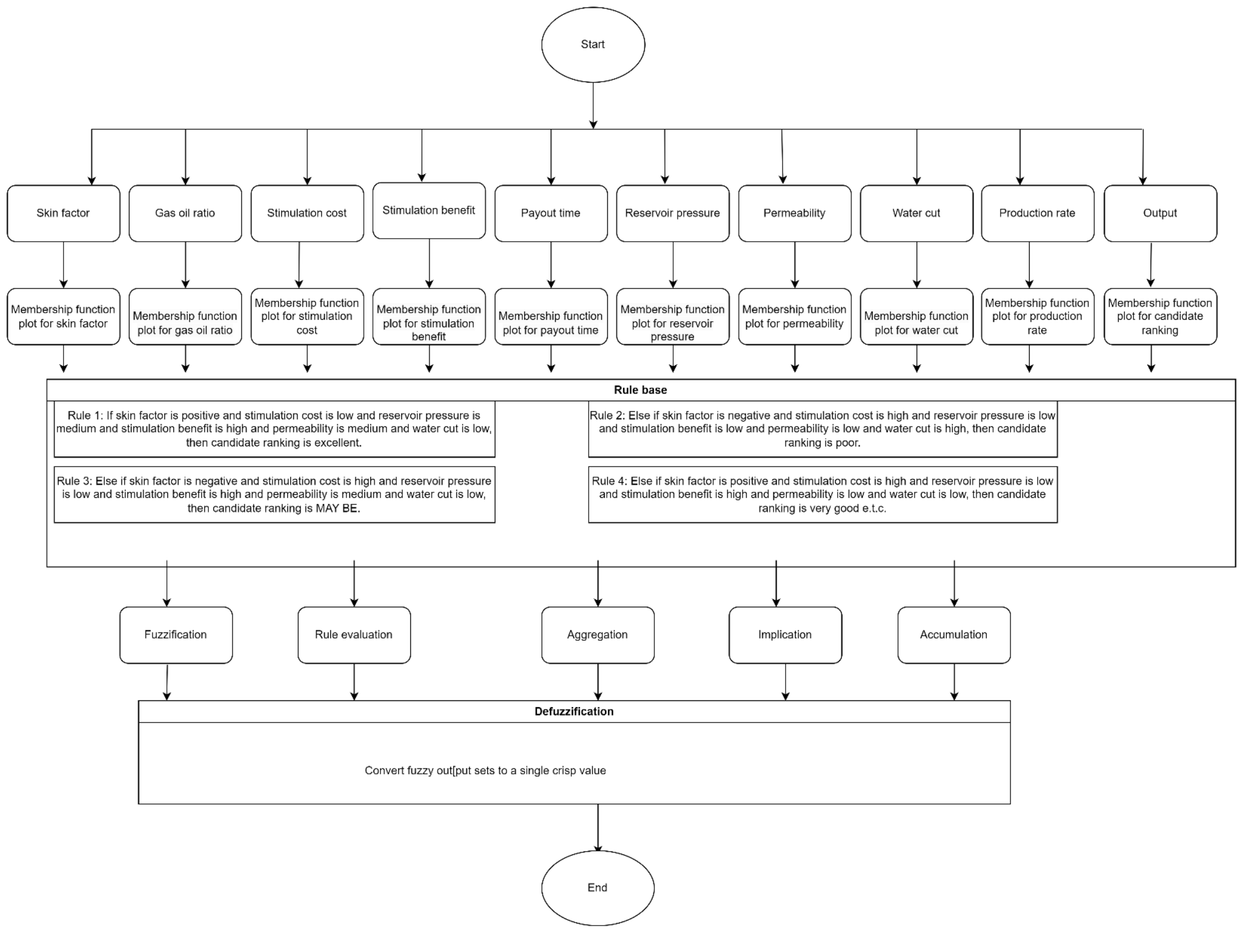

Fig 13. flowchart illustrating the step-by-step processes to obtain the desired result.

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