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A FUZZY INFERENCE SYSTEM APPLIED TO VALUE OF INFORMATION ASSESSMENT FOR OIL AND GAS INDUSTRY

Martin Vilela*[1], Gbenga Oluyemi [1] and Andrei Petrovski [2]

[1] School of Engineering, Robert Gordon University, Aberdeen, United Kingdom
[2] School of Computing, Robert Gordon University, Aberdeen, United Kingdom

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Abstract: *Value of information is a widely accepted methodology for evaluating the need to acquire new data in the oil and gas industry. In the conventional approach to estimating the value of information, the outcomes of a project assessment relate to the decision reached following Boolean logic. However, human thinking logic is more complex and include the ability to process uncertainty. In addition, in value of information assessment, it is often desirable to make decisions based on multiple economic criteria, which, independently evaluated, may suggest opposite decisions. Artificial intelligence has been used successfully in several areas of knowledge, increasing and enhancing analytical capabilities. This paper aims to enrich the value of information methodology by integrating fuzzy logic into the decision-making process; this integration makes it possible to develop a human thinking assessment and coherently combine several economic criteria. To the authors' knowledge, this is the first use of a fuzzy inference system in the domain of value of information. The methodology is successfully applied to a case study of an oil and gas subsurface assessment where the results of the standard and fuzzy methodologies are compared, leading to a more robust and complete evaluation.*

Key words: *Value of information, fuzzy logic, fuzzy inference system, oil and gas industry, uncertainty.*

1. Introduction

1.1. Review of Value of information

Value of information (VoI) is a prescriptive methodology embedded in the discipline of decision analysis that has the aim of assessing the value assocted with gathering

* Corresponding author.
E-mail addresses: m.j.vilela-ibarra@rgu.ac.uk (M. Vilela), g.f.oluyemi@rgu.c.uk (G. Oluyemi), a.petrovski@rgu.ac.uk (A. Petrovski).

information. To that end, the methodology maximizes an objective function, which defines the value of a project.

Grayson (1960), Raiffa and Schlaifer (1961) and Newendorp (1967) were the pioneers in the field of decision making for data acquisition in the oil and gas industry. Subsequently, more research and applications, such as those of Warren (1983), Lohrenz (1988), Demirmen (1996), Newendorp and Schuyler (2000) and Koninx (2000), among others, expanded the scope of the subject, adding more robustness to the methodology.

Recently, more applications have emerged, like those of Clemen (1996), Coopersmith and Cunningham (2002), Suslick and Schiozer (2004), which enrich the process of assessing the VoI decision problem from a methodological perspective. Several papers, such as Walls (2005) and Vilela et al. (2017), have discussed the use of utility theory in VoI assessment in the oil and gas industry. Similarly, Santos and Schiozer (2017) discussed the impact of the risk attitude of the decision makers in VoI assessments. Kullawan et al. (2017) developed a discretized-programming approach, based on value of information, to optimize stochastic-dynamic the geosteering operations. Steineder et al. (2018) discussed the maximization of the VoI on a horizontal polymer pilot project. All these researchers used one or more crisp decision criteria to make decisions.

In the oil and gas industry, the scope of a project varies from the complex exploitation of hydrocarbon fields to theoretical reservoir studies or laboratory tests. Project's economic benefits are calculated based on the estimated figures of hydrocarbons' production and price, operating cost, taxes, royalties, and investments. All these figures carry uncertainties because it is not possible to predict their future fluctuations accurately, in particular, future hydrocarbon production is uncertain due to a combination of:

(a) the uncertainties associated with the reservoir parameters (permeability, thickness, top reservoir, well producibility, aquifer support, etc.);

(b) the uncertainties associated with the methods used to estimate future production based on the reservoir parameters (dynamic reservoir models, decline curve analysis, etc.)

On occasion, additional data can be acquired to change the uncertainty in the reservoir parameters; however, acquiring data involves a cost that could be greater than the benefits of the data. Changes in the reservoir parameters' uncertainties translate into changes in the value of the project. In general, acquiring additional data makes sense in cases in which the outcome from the data acquisition can change the decisions being made.

For a project with uncertain outcomes, the VoI is the difference between the expected value (EV) of the project with and without the newly acquired data (Clemen, 1996):

$$VOI = EV_{with\ information} - EV_{without\ information} \tag{1}$$

where both values, $EV_{with\ information}$ and $EV_{without\ information}$, assess the outcome of the project in these circumstances and refer to a future situation.

In the 'without-information' case, for κ possible scenarios (which include endorsing the project with the current knowledge and uncertainties and the alternative of relinquishing it), the EV of the project corresponding to the j^{th} scenario is defined as:

$$V\left(a_j\right) = \sum_{i=1}^{n} u_{ji}\, p\left(s_i\right) \tag{2}$$

where u_{ji} is the value of the state of nature s_i for the scenario a_j and $p(s_i)$ is the prior probability of the state of nature s_i. The most often used decision criterion is to select the alternative that maximizes the EV:

$$EV\left(a^*\right) = \max_j EV\left(a_j\right) \tag{3}$$

Equation (3) is the $EV_{without\ information}$ term shown in Equation (1).

Similarly, in the '*with-information*' alternative, for κ possible scenarios and for each possible data outcome, x_k, the EV for the j^{th} alternative is:

$$EV\left(a_j|x_k\right) = \sum_{i=1}^{n} u_{ji}\, p(s_i \mid x_k) \tag{4}$$

where u_{ji} is the value of the state of nature s_i for the scenario a_j; $p(s_i|x_k)$ is the posterior probability of the state s_i given the outcome x_k; and the term $EV(a_j|x_k)$ is the expected project value for the j^{th} alternative given the outcome x_k.

Similarly, as in the '*without-information*' case, the optimum alternative in the '*with-information*' case for a given data outcome x_k (EV conditioned on the outcome x_k) is the one that maximizes the EV:

$$EV\left(a^*|x_k\right) = \max_j EV(a_j \mid x_k) \tag{5}$$

The unconditional maximum EV (which is the EV of the project considering the data acquisition outcomes) is the sum of the conditional EV weighted with the corresponding marginal probabilities:

$$EV\left(a^*\right) = \sum_{k=1}^{n} EV(a^* \mid x_k)\, p(x_k) \tag{6}$$

The VoI is the difference between the estimates of EV in Equation (6) and Equation (3).

So far, the discussion has focused on the classical methodology to assess the VoI in a decision problem in which the output values (hydrocarbon production, total benefits, etc.) are uncertain due to uncertainties in the input variables; these uncertainties have been included using probabilistic measures. In the next section, we will include the imprecision in the input variables by making use of fuzzy logic.

1.2. Review Fuzzy Logic

Fuzzy logic, pioneered by Zadeh (1965), is one of the most prolific areas of artificial intelligence, which has enriched the analysis of challenging and complex problems. Bellman and Zadeh (1970) introduced an important distinction between randomness and fuzziness: while randomness relates the uncertainty concerning membership or non-membership of an object or event to a non-fuzzy set (a crisp set), fuzziness deals with classes in which there may be degrees of membership (between the full and the no-membership relationship).

These distinct sources of uncertainties are managed during different phases of the VoI assessment:

Phase 1) Assessing: assesses, using one or more decision criteria, whether the new data add value to the project or not.

Phase 2) Categorization: relates the values obtained during the assessing phase to the options available for the decision problem.

During the Phase 1, the uncertain nature of the input variables (e.g. reservoir parameters) and outcome values (e.g. financial benefits or economic parameter values) is captured using probabilistic analysis based on EV calculations.

In the standard VoI approach, Phase 2 is implemented using crisp criteria to make decisions that do not correspond with human fuzzy thinking for making decisions. Following Bellman and Zadeh (1970), the uncertainty related to fuzziness is a major source of uncertainty in many decision processes.

In classical set theory, the events (values) belong (or not) to sets in a crisp manner that is represented by the "characteristic function", defined by Equation (7), which is a mapping from the input variables to the Boolean set $\{0,1\}$:

$$\mu_M = \begin{cases} 1, & x_k \in M \\ 0, & otherwise \end{cases} \tag{7}$$

Thus, an event (e.g. X) belongs totally or not at all (1 or 0) to a set; these kinds of relationships follow Boolean logic.

As a practical example, in subsurface reservoirs, the characteristic function allows establishing a Boolean relationship (1 or 0, i.e. totally belongs or totally excluded) between quantitative input variables (e.g. reservoir depth of 5000 ft) and descriptive terms (e.g. deep reservoir). Fuzzy logic extends the mapping between events and sets using the membership function (MF) to include all the values between 0 and 1, [0,1]; mathematically, the MF is a mapping from a given universe of discourse "X" to the continuous unit intervals that are the membership values. Equation (8) shows the mathematical expression for the MF:

$$\mu_{\tilde{M}}(x) = \{ y \ / y \in [0,1] \} \tag{8}$$

which shows that the values of the MF belong to the interval [0,1]. The membership values measure the degree of belonging of each event to a given set, representing the "degree of membership" of the mentioned event to that set. In this logic, an event (e.g. reservoir depth of 5000 ft) belongs partially (with a value between 0 and 1) to a set (e.g. deep reservoir).

In the standard VoI, the results of the assessment are a set of crisp values that measure the project benefits or losses of the different alternatives under evaluation. Comparing those values with a set of threshold values, a decision is made regarding the project fate; however, a decision made in this manner is limited because it does not follow the human thinking for decision making which works with fuzzy categories like "the project is viable to endorse", "the project is unviable to endorse" or "the project needs reframing".

1.3. Review Fuzzy Inference Systems

In practice, fuzzy logic is implemented through a process called a "fuzzy inference system" (FIS). A FIS is a non-linear procedure that derives its output based on fuzzy reasoning and a set of IF-THEN rules. The FIS performs approximate reasoning like the human brain, albeit in a much more straightforward manner.

The FIS is one of the most prolific applications of fuzzy logic. It has been used recently in very different areas and within various problem domains, such as: the assessment of

water quality in rivers (Ocampo, 2008), the improvement of image expansion quality (Sakalli et al., 1999), the differential diagnosis of non-toxic thyropathy (Guo & Ling, 2008), the development of a fuzzy logic controller for a traffic junction (Pappis & Mamdani, 1997), maintenance scheduling of Smart Grid systems (Malakhov et al., 2012), the design of fire monitoring sensors in coal mines using fuzzy logic (Muduli et al., 2017), the estimation of the impact of tax legislation reforms on the tax potential (Musayev et al., 2016), pipeline risk assessment (Jamshidi et al., 2013), depression diagnosis (Chattopadhyay, 2014), river discharge prediction assessments (Jayawardena et al., 2014), geological strength index calculation and slope stability assessments (Sonmez et al., 2004), the regulation of industrial reactors (Ghasem, 2006) and the use of a fuzzy logic approach for file management and organization (Gupta, 2011). In the domain of the oil and gas industry several applications of FIS have been reported such as the streamline based fuzzy logic workflow to redistribute water injection by accounting for operational constraints and number of supported producers in a pattern (Bukhamseen et al., 2017), the identification of horizontal well placement (Popa, 2013), for estimating strength of rock using FIS (Sari, 2016), for predicting the rate of penetration in shale formations (Ahmed et al., 2019). Fuzzy logic has been used in combination with others Artificial Intelligence techniques such as Adaptative Neuro-Fuzzy Inference system (ANFIS) on practical applications, e.g. for predicting the inflow performance of vertical wells producing two-phase flow (Basfar et al., 2018) or to predict geomechanical failure parameters (Alloush et al., 2017); FIS has also been used in conjunction with Analytical Hierarchical processes to evaluate the water injection performance in heterogeneous reservoirs (Oluwajuwon & Olugbenga, 2018).

From the point of view of applications, there are two kinds of FIS (Guillaume, 2001):

1) Fuzzy expert systems or fuzzy controllers: fuzzy rules built on expert knowledge. This kind of FIS uses the ability of fuzzy logic to model natural language.

2) Automatic learning from data: neural networks have become the most popular tool using a numerical performance index, typically based on the mean square error. These kinds of development are distinguished by their accuracy, and their main drawback is their "black-box" approach.

For the current application, we will focus on the first kind of FIS.

From a methodological perspective, the FIS can be understood as a general procedure that transforms a set of input variables into a set of outputs, following the workflow shown in Figure 1.

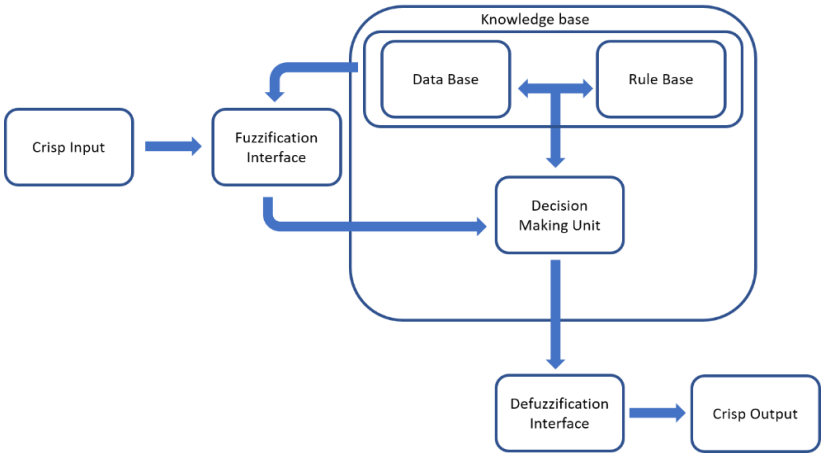

Figure 1. Fuzzy inference system

As shown in Figure 1, FIS as a procedure entailing five blocks in which the inputs and outputs are in crisp form.

For a Mandani FIS, shown in Figure 1, the outcome is a crisp number, independently of the number of crisp parameters used the asses the value of the project (e.g. NPV, DPI, IRR, etc.); this is FIS aggregation process; in general, higher FIS values means higher value of the project and vice versa.

1.4. Objective of this research work

The objective of this work is to investigate whether considering the fuzzy nature of human thinking can impact the decision's assessment in VoI problems, especially in oil and gas projects; to reach this objective we integrate Fuzzy Inference System into the VoI assessment.

2. Application

2.1. Reservoir Description

An exploration campaign conducted in Algeria discovered a medium-sized oil field located at 5200 ft. TVD SS. Four wells were drilled—the discovery well and three appraisal wells. The range of original oil in place (minimum and maximum figures) has been assessed; the fluid characteristics are known based on samples taken from the appraisal wells. The operator's technical team has estimated, based on the available information, technical experience, and analogue fields, that the main source of subsurface uncertainty is the well productivity. The four wells drilled were tested for six hours; however, considerable uncertainty remains regarding well productivity due to reasons described in Table 1.

Table 1. Causes of well productivity uncertainty

Reason for uncertainty	Comment
Quality and reliability of the well test	Possible calibration issues on well testing equipment
Duration of the tests	Well test period too short, no enough to reach stabilized flow

Based on the information gathered during the exploration phase and from similar fields in the same basin, a material balance model is built to represent the forecast oil rate for the high, medium and low development scenarios, as shown in Figure 2.

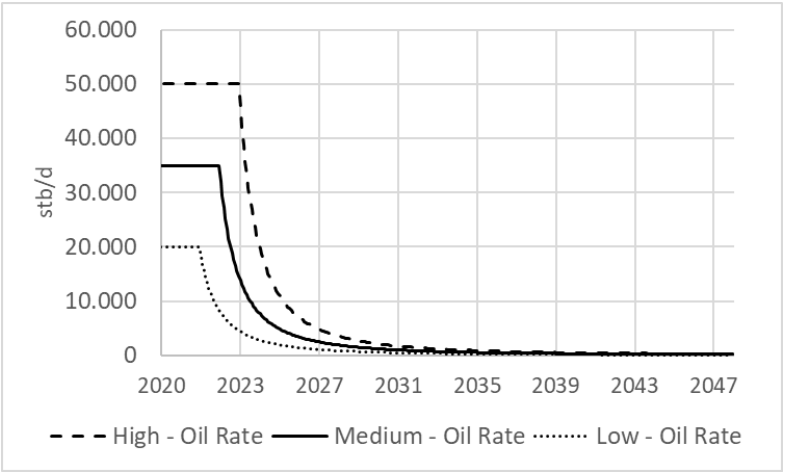

Figure 2. High, medium and low cases of the oil production rate

The difference between the profiles is the well model used in each case. The full development of the field includes twelve vertical wells, four of which have already been drilled—at present these are "suspended", to be used in the development phase of the project if a decision is taken to move the project forwards; otherwise, those wells should be abandoned entirely.

The rig will be available in four months, and each well can be drilled in two months; the duration of the campaign to drill and complete the remaining eight wells included in the development plan is sixteen months. The first period of oil production was planned to have a fixed plateau rate followed by a period of oil rate decline (Figure 2).

2.2. Decision Problem

At this stage, the operator company must decide whether acquiring additional information would increase the project's value.

Alternative A: without-information. The decision on project development is made based on the current information using the expected value (EV) of the net present value (NPV) and the discounted profit to investment ratio (DPI), which is discussed further in Section 3.3. Prior probabilities are assigned according to the technical team members' judgment on the subjective probabilities of realizing the different states of nature; the economic parameters are estimated based on the assumptions and assessments included in the high-, medium- and low-production scenarios. If this option is chosen, the first oil can be reached in two years' time, including facilities and wells.

Alternative B: with-information. Additional information is acquired regarding the uncertain parameters of the reservoir and, subsequently, based on the outcomes of the data obtained, a decision is made on the future development of the project. The operator's technical team has estimated, based on the reservoir and fluid properties, that, to obtain meaningful well test results, the minimum well test duration per well should be four months. It was decided that two of the appraisal wells could be used to perform an extended well test (EWT) in each one. Following these assumptions, there will be a delay of one year (four months rig move + eight months EWT) compared with the without-information alternative.

After the test results have been gathered, the technical team expects to have a more certain criterion to assign well deliverability, although uncertainty will still be present

because the data are not perfect. The cost associated with the well test in these two wells is US$20 million. It should be considered that, if the project is relinquished now, the US$90 million already spent on exploration and appraisal will be lost; additionally, the abandonment cost for the 4 drilled wells, US$4 million, and the facilities' abandonment cost, US$10 million, should be added to the economic evaluation. If new data are acquired and afterwards the decision is made to abandon the project, the cost of the data acquisition must be added to the previously mentioned costs.

The outcome of the assessment of the alternatives without-information and with-information will result in one of the following options:

1) the project is viable to endorse: it will proceed to the development phase, which necessitates a large investment;

2) the project is not viable to endorse : it will be relinquished, carrying the losses associated with the exploration costs;

3) the project needs additional analysis before deciding: it will be reframed.

2.3. Economic Parameters for Decision Making

Two economic parameters are used to make the decision: the net present value (NPV) and the discounted profit to investment ratio (DPI). The NPV is the yearly net cash flow discounted to the weighted average cost of capital (WACC—the average rate of return with which a company expects to compensate all its different investors, in which the weights are the fraction of each financing source in the company's target capital structure), which in this case is 10.5%; the DPI is the result of dividing the discounted net cash flow by the discounted sum of the investment using the WACC. The values of NPV and DPI are shown in Section 2.4.2.

2.4. Classical VoI Assessment

As discussed in Section 1.1, the VoI is described by Equation (1); in this section, the classical approach to the VoI is discussed.

2.4.1. Decision rules

Based on the operator's portfolio of projects, the criterion for making decisions on projects with a financial investment higher than US$500 million is: A) a project with NPV lower than US$100 million is unviable to endorse, which means that it is relinquished, B) a project with NPV higher than US$500 million is viable to endorse and, C) a project with NPV between US$100 million and US$500 million is reframed to find alternative development options.

Regarding the DPI: A) a project with DPI higher than 0.5 is viable to endorse, B) a project with DPI lower than 0.0 is unviable to endorse and, C) a project with DPI between 0.0 and 0.5 should be reframed.

2.4.2. VoI assessment for the without-information and with-information alternatives

For the without-information alternative, Table 2 shows the prior probabilities, the calculated NPV, and DPI of each state of nature and the EV of the without-information alternative.

Table 2. Prior probabilities, NPV, DPI and expected values for the *without-information* alternative

State of nature	Prior probabilities (%)	NPV (US$ million)	DPI (fract.)
S1=High	25	2,139	2.27
S2=Medium	40	414	0.42
S3=Low	35	-631	-0.61
EVNPV-A1 (US$ million)	479		
EVNPV-A2 (US$ million)	-102		
EVNPV (US$ million)	479		
EVDPI-A1 (fraction)	0.52		
EVDPI-A2 (fraction)	-1.00		
EVDPI (fraction)	0.52		

For the with information alternative, the technical team members estimated the reliability probabilities for the well test. It is acknowledged that, in a developed field, wells perform differently depending on their location and well test results are representative of a specific location; additionally, the duration of the test, although designed to capture the well performance, might not be long enough to assess the long range well operation. Table 3 shows the reliability probabilities of the well test estimated by the technical team members.

Table 3. Reliability probability of the well test

Reliability probability	X1=High productivity	X2=Medium productivity	X3=Low productivity
$p(x_k\|s_1)$	0.9	0.1	0.0
$p(x_k\|s_2)$	0.1	0.8	0.1
$p(x_k\|s_3)$	0.0	0.1	0.9

Reliability probabilities are used together with prior probabilities to obtain posterior probabilities, which are combined with the project values to generate the expected value of the net present value (EVNPV) and the EV of the discounted profit to investment ratio (EVDPI). The results of these assessments are shown in Table 4.

Table 4. Posterior probabilities, residual probabilities and expected values for the *with-information* alternative

	X1=High productivity	X2=Medium productivity	X3=Low productivity
$p(s_1\|x_k)$	0.85	0.07	0.00
$p(s_2\|x_k)$	0.15	0.84	0.11
$p(s_3\|x_k)$	0.00	0.09	0.89
$p(x_k)$	0.27	0.38	0.36
$EVNPV(A_1\|x_k)$	1,667	357	-497
$EVNPV(A_1\|x_k)$	-114	-114	-114
$EVNPV(A_1\|x_k)$	1.667	357	-114
$\underline{EVNPV(US\$\ million)}$	537		
$EVDPI(A_1\|x_k)$	1.76	0.37	-0.48

	X1=High productivity	X2=Medium productivity	X3=Low productivity
$EVDPI(A_1\|x_k)$	-1.00	-1.00	-1.00
$EVDPI(A_1\|x_k)$	1.76	0.37	-0.48
$\underline{EVDPI(\ fraction)}$	0.44		

2.4.3. Results of the VoI using the classical approach

Decision based on NPV: Based on the results obtained in Section 2.4.2, and using the decision rules (Section 2.4.1), it can be concluded that, the without information project should be reframed and the with information project should be endorsed. In this manner, acquiring data increase the project's value; Summarizing, according to the NVP figures, the preferred alternative is to perform the well test (the with-information alternative) and, depending on the data outcomes, decide whether the project should be endorsed or not.

Decision based on DPI: Using DPI as the decision criterion, the without-information alternative suggests endorsing the project, while the with-information alternative suggests reframing the project; summarizing, the alternative that maximizes the DPI is the without information one, which means that it is not recommended to perform the well test.

At this stage, using two financial criteria, we have two contrasting recommendations about the future of the project.

Making a decision using these crisp criteria does not include the sophisticated elements used by human thinking in which, the criteria may overlap. In addition, from the independent NPV and DPI results, it is not clear which is the optimum alternative unless some form of weighted valuation is made by combining the two economic parameters into one.

2.5. FIS VoI Assessment

Up to this stage, the criterion to decide the future of the project has been based on linguistic variables like "not endorse", "endorse", "viable", "unviable", "high", "medium" and "low". Indeed, a crisp relationship is established between the NPV and DPI and the linguistic variables: if the NPV is less than US$ $\boldsymbol{X}$ million, the project is "unviable to endorse", if the NPV is higher than US$ $\boldsymbol{Y}$ million, the project is "viable to endorse" and if the NVP is higher than $\boldsymbol{X}$ but lower than $\boldsymbol{Y}$, the project should be reframed; similar relationships apply to the DPI criterion.

However, it is worth recognizing that these criteria are fuzzy and not always aligned. The fuzziness occurs because, if the project NPV is US$ $\boldsymbol{X-\varepsilon}$ million, where $\boldsymbol{\varepsilon}$ is a given amount, the crisp logic decision criterion catalogues the project as "unviable to endorse", although $\boldsymbol{\varepsilon}$ could be "small" compared with $\boldsymbol{X}$. In the same manner, if the project value is US$ $\boldsymbol{Y+\varepsilon}$, in a crisp decision, the project is catalogued as "viable to endorse", although $\boldsymbol{\varepsilon}$ could be "small" compared with $\boldsymbol{\varepsilon}$.

The no alignment between the criteria happens because very often the two indices, NPV and DPI, can produce a contradictory assessment of the same problem; for example, it could be the case that, using the NPV, the project is "viable to endorse" but, using the DPI, the project is "unviable to endorse" or vice versa, as has been witnessed in this case study.

These cases suggest that fuzzy logic can be used advantageously to make VoI decisions by providing a more versatile tool to assess these decision problems; fuzzy logic is implemented through the FIS.

2.5.1. FIS building and application

The FIS used in this work was developed using MATLAB. The input parameters in the FIS are the NPV and DPI; for each input parameter, six Membership Functions are built, representing the linguistic variables high NVP or NVP viable to endorse, low NVP or NVP unviable to endorse, mid NVP or NVP for reframing, high DPI or DPI viable to endorse, low DPI or DPI unviable to endorse and mid DPI or DPI for reframing; the corresponding MFs are: NVP HIGH, NVP MID, NVP LOW, DPI HIGH, DPI MID and DPI LOW.

In MATLAB, a set of predefined MFs—triangular-shaped functions—are selected. These MFs are chosen because they capture the technical team members' interpretation of the degree to which the NPV and DPI figures belong to the three categories into which the range of potential values are divided. Equation (9) shows the mathematical form of the triangular-shaped MF:

$$f(x;a,b,c)=\begin{cases}0 & x\le a\\ \dfrac{x-a}{b-a} & a\le x\le b\\ \dfrac{c-x}{c-b} & b\le x\le c\\ 0 & c\le x\end{cases} \tag{9}$$

The comparison between the output of the FIS for the with-information and that for the without-information alternative indicates which alternative has more value (the better decision).

A Mamdani FIS with the centroid defuzzification method was used in this assessment. Figure 3 shows the design of the FIS using MATLAB.

In Section 1.3 we show the Figure 2 which describe the FIS process; that figure is shown below but now numbering the steps, in order, we are following in this work

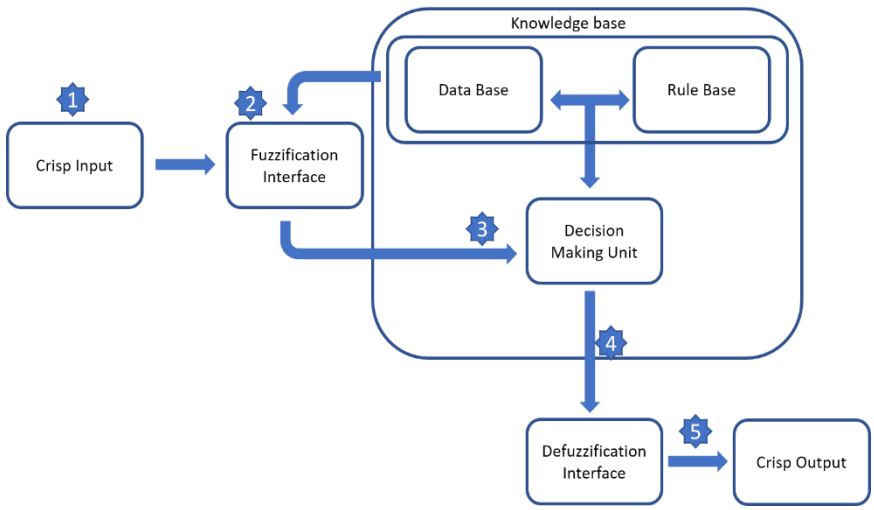

Figure 3. FIS implementation

Step1: the crisp data is generated, in this case, the project value, NPV and DPI

Step 2: data is fuzzified using the membership function located in the data base; those MF describe the degree of belonging of different input values which is defined according with the analyst belief. In this work, the MF used for NPV and DPI are shown in Figure 4 and Figure 5.

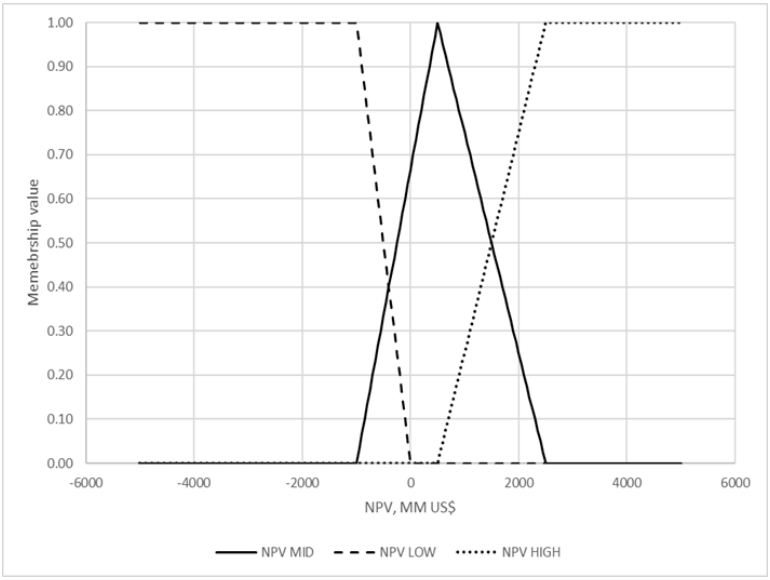

Figure 4. Membership Function for NPV (input)

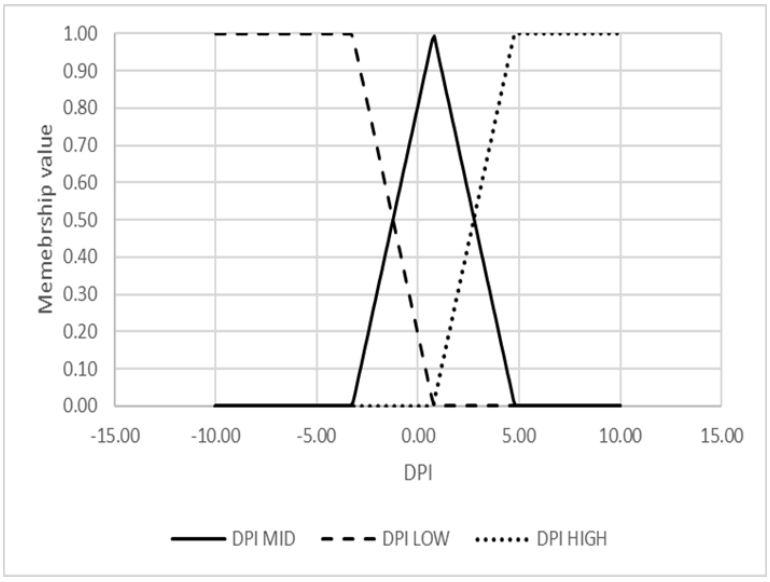

Figure 5. Membership Function for DPI (input)

Step 3: once input variables are fuzzified, the decision rules, which are part of the knowledge base, are applied to the membership functions in the Decision-making unit; in the Mandani type inference, the decision rules are a mapping from the input

membership function to the output membership functions, which are also part of the knowledge base; the rules aggregation process generate the fuzzy outcome.

The output membership functions used in this work, describing the different decision options are show in Figure 6.

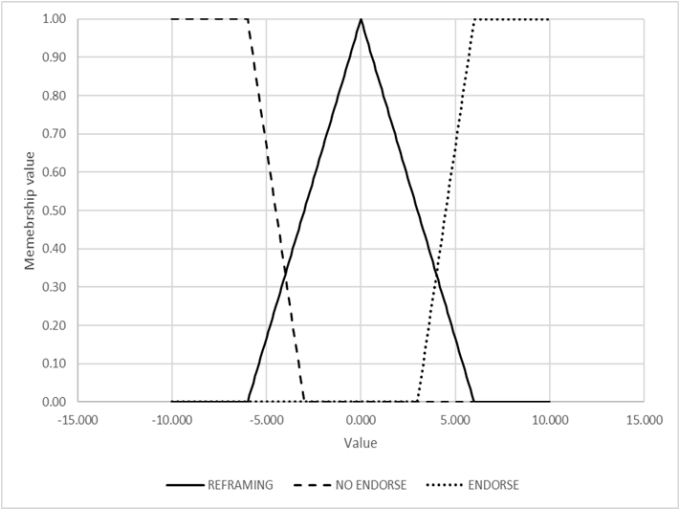

Figure 6. Membership Function for the decision (output)

The decision rules indicate the manner in which the two fuzzy financial parameters combine to result in a fuzzy decision. In this work we define the rules shown in Table 5 to include the cases of interest.

Table 5. Fuzzy rules

RULES	IF	THEN
Rule 1	(NPV is NPV_HIGH) & (DPI is DPI_HIGH)	ENDORSE
Rule 2	(NPV is NPV_HIGH) & (DPI is DPI_MID)	ENDORSE
Rule 3	(NPV is NPV_HIGH) & (DPI is DPI_LOW)	REFRAMING
Rule 4	(NPV is NPV_MID) & (DPI is DPI_LOW)	REFRAMING
Rule 5	(NPV is NPV_LOW) & (DPI is DPI_LOW)	NO ENDORSE
Rule 6	(NPV is NPV_LOW) & (DPI is DPI_HIGH)	REFRAMING
Rule 7	(NPV is NPV_MID) & (DPI is DPI_MID)	ENDORSE

Step 4: fuzzy output gets into the defuzzification interface to generate crisp output.

Step 5: the value of the project is the crisp out; different crisp outputs are compared and, the one with the higher value is the optimum decision.

The MFs of the NVP are chosen in accordance with past decisions taken by the decision maker, as discussed in Section 1.2. The rationale for the selection of these MFs is that, for very high or very low NPV values, the NPV belongs to only one set, the NPV_HIGH or the NPV_LOW, with a membership value of 1; for the intermediate NPV value, the NPV belongs partially to the three fuzzy sets. This fuzzy representation of the criteria for categorizing the project is based on past decisions made by the field operator company. The selection of the MFs needs to be updated once more decisions have been taken.

The MFs for the DPI are chosen following the same procedure used for the NPV.

The authors define a set of seven rules that determine the logic of this decision; these rules (IF-THEN rules) are made by pairs of NPV and DPI figures and a consequential sentence (THEN). The rules do not pretend to be exhaustive but must be coherent. All the rules were built using the AND connector; although, in general, they can be defined equally well with OR.

2.5.2. FIS applied to the without-information and with-information alternatives; VOI assessment

Referred to Section 1.3, the outcome of FIS (a crisp number) is the value of the project resulting from aggregating the project's values in terms of NPV and DPI; in addition, the FIS assessment includes the imprecision in the terms used to decide whether a project worth or not to endorse (Section 2.2).

For evaluating the project using the FIS developed in Section 2.5.1, the crisp values for NPV and DPI estimated in Section 2.4.2 Table 2 (US$479 million and 0.52), are input in the FIS; the outcome of the assessment made by the FIS indicates that the value associated with the without-information alternative is 7.2.

Similarly, in the with-information alternative, the NPV and DPI figures (US$537 million and 0.44), contained in Table 3, are input in the FIS; as a result, the FIS assessment for the with-information alternative is 6.97.

Due to the fact that, the value of the FIS for the without-information alternative is higher than the value of the FIS for the with-information case, the best alternative for the decision problem discussed is to endorse the project now and move it forward to the development phase without acquiring additional data.

This result is explained by the fact that, although the data acquisition reduces the uncertainty regarding well deliverability, the cost of this data acquisition, in terms of the additional investment and oil production delay, is higher than the increased project value due to uncertainty reduction.

3. Conclusions

In this study, an FIS has been successfully implemented with the aim of assessing the VoI of an oil and gas project. In the discussed case study, the use of the FIS was able to introduce the fuzzy thinking of the decision maker into a subsurface VoI assessment while removing ambiguity coming from the use of more than one economic parameter for decision making.

The proposed methodology for VoI assessment using FIS has improved the conventional approach because:

1) instead of using a Boolean relationship between project valuation and project decision, the FIS uses a fuzzy human thinking approach to make decisions;

2) the FIS uses a coherent method to integrate more than one criterion into the assessment, while, in the conventional VoI approach, when more than one criterion is used, they can reach contradictory outcomes which conduct to inconclusive assessment.

In addition to the aspects discussed above, the FIS provides a tool for "self-learning" in which the quality of the VoI assessments can be improved through continuous updating of the decision-making unit, knowledge base, and fuzzification and defuzzification interfaces with actual decisions, progressively generating a more robust FIS and making the system act closer and closer to the way in which humans make decisions. The FIS brings the VoI methodology closer to the decision maker's reasoning.

These are important advantages of the fuzzy compared with the classical VoI assessment.

The fuzzy approach for VoI assessment requires a longer and more complex analysis of the data to be acquired and their outcomes. However, this additional effort worth due to the impact it has in the decision.

As a summary, the use of the FIS makes it possible to have a system that can integrate the linguistic variables that are part of human language, reasoning, and understanding, but not necessarily part of the Boolean logic used in the standard VoI, into the prescriptive VoI assessment.

VoI assessment using the FIS brings the decision-making process one step forward with respect to the classical VoI approach. To have tools and methods that replicate the human reasoning process for assessing VoI increases the confidence of the decision maker in those procedures, thereby increasing their use and making the tools more reliable.

Decisions are made by human, and because human thinking is approximated more accurately by imprecise logic than by crisp logic, this research work successfully develop a methodology that integrate the human logic in the VoI assessment, in special to problems in the oil and gas industry; the integration of the imprecise thinking and terminology in the VoI is made through the use of FIS.

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