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A HOLISTIC APPROACH TO ASSESSMENT OF VALUE OF INFORMATION (VOI) WITH FUZZY DATA AND DECISION CRITERIA

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Abstract: *Classical decision and value of information theories have been applied in the oil and gas industry from the 1960s with partial success. In this research, we identify that the classical theory of value of information has weaknesses related with optimal data acquisition selection, data fuzziness and fuzzy decision criteria and we propose a modification in the theory to fill the gaps found. The research presented in this paper integrates theories and techniques from statistical analysis and artificial intelligence to develop a more coherent, robust and complete methodology for assessing the value of acquiring new information in the context of the oil and gas industry. The proposed methodology is applied to a case study describing a value of information assessment in an oil field where two alternatives for data acquisition are discussed. It is shown that: i) the technique of design of experiments provides a full identification of the input parameters affecting the value of the project and allows a proper selection of the data acquisition actions, ii) when the fuzziness of the data is included in the assessment, the value of the data decreases compared with the case where data are assumed to be crisp; this result means that the decision concerning the value of acquiring new data depends on whether the fuzzy nature of the data is included in the assessment and on the difference between the project value with and without data acquisition, iii) the fuzzy inference system developed for this case study successfully follows the logic of the decision-maker and results in a straightforward system to aggregate decision criteria.*

Key words: *Value of information, fuzzy logic, design of experiments, uncertainty, decision making.*

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1. Introduction

The classical methodology for the Value of Information (VOI) assessment has been used in the oil and gas industry since the 1960s, even though it is only recently that more applications have been published. It is commonly acknowledged that, due to a large number of data acquisition actions and the capital investment associated with it, the oil and gas industry is an ideal domain for developing and applying the VOI assessments.

The current methodology for the VOI has several weaknesses for its applicability in oil and gas projects, and the objective of this research is to present a complete theory for VOI that overcomes those weaknesses.

The weaknesses found in the current VOI theory are the following:

1) Typically, the classical approach for VOI assessment is carried out when it has been identified that the value of the project depends on an uncertain input variable that may be better defined if a specific piece of data is acquired. This approach lacks a complete analysis of the project uncertainties and the impact that the different inputs and their interactions have on the project's value. This procedure to assess the value of acquiring data can limit the opportunities to improve the project's value.
2) The classical approach to VOI does not provide an integrated assessment of the impact that a specific data-gathering activity may have on the uncertainty of more than one variable.
3) VOI does not consider that the data to be acquired may carry uncertainties that are due not only to randomness but also to fuzziness.
4) Although the utility value is a well-known concept, most of the times, it is not used in VOI assessments.
5) The criteria used by decision-makers for making decisions (e.g. to reject a project or to accept a data acquisition proposal) are fuzzy. However, the results from the classical VOI assessment are crisp numbers; the handling of this dichotomy requires different tools from the ones used in the classical approach for VOI.

The aim of this research is to address the gaps identified in the classical methodology for the VOI by integrating three existing techniques from other domains. Firstly, the research identifies that the Design of Experiments (DOE) approach can be used in the VOI for providing a holistic assessment of the complete set of uncertain parameters, selecting the ones that have the most impact on the value of the project, and supporting the selection of the data acquisition actions for evaluation. Secondly, the fuzziness of the data is captured through membership functions, and the expected utility value of each financial parameter is estimated using the probability of the states conditioned to the membership functions (in the classical methodology, this is conditioned to crisp values of the data). Thirdly, a fuzzy inference system is developed for making the VOI evaluation, with the human decision-making logic integrated into the assessment process, and several financial parameters aggregated into one.

A case study, taken from the oil and gas industry, is discussed to show a successful application of the proposed methodology.

2. Literature review

Value of Information is a theory for deciding whether it is worthwhile to acquire information in the frame of a project's value; this will happen when new data is used to change a decision that would be made differently without that information and when the value of the project increases after data is acquired.

VOI theory was developed by Schlaifer (1959) and later developed further by Grayson (1960), Raiffa and Schlaifer (1961), Newendorp (1967) and Raiffa (1968) in the context of business administration. One of the first references of VOI in the oil and gas industry is Grayson's (1960) application of VOI to uncertain drilling decisions.

Newendorp (1967) discusses a VOI problem including the risk attitude of the decision-maker described through the use of the exponential utility function; this same author (Newendorp, 1972) reviews in great detail the Bayes' theorem and its application for VOI assessment.

A series of works from several authors in the oil and gas industry shows an increasing interest in using VOI as a tool for making decisions. Dougherty (1971) shows several straightforward applications of VOI for the oil and gas industry. Warren (1983) discusses the case study of a field development decision regarding initiating, rejecting or postponing a project decision until more information is gathered; Lohrenz (1988) reviews four examples of the value of data acquisition using decision trees; Silbergh and Brons (1972) debate several methods of project valuation, utility functions, and VOI. Moras, Lesso, and MacDonald (1987) show the value associated with different numbers of observation wells to monitor underground gas storage. Gerhardt and Haldorsen (1989) show several applications of VOI for typical examples of decisions in subsurface problems; Dunn (1992) discusses the VOI of well logs while Stibolt and Lehman (1993) do the same for seismic data.

Demirmen (1996) broadens the use of VOI by using it in the two types of appraisal activities: screening, and optimization; this is one of the first references that discuss the use of VOI on a complete Oil and gas project and, open the possibility to use this tool as a means for ranking subsurface appraisal activities. Koninx (2000) reviews VOI from a methodological perspective and discuss important criteria that should be taken into consideration when data is proposed to be acquired such as the value of assurance and value of creation; Bratvold, Bickel, and Lohne (2007) show how to make a VOI assessment and discuss a statistical review of the published work about VOI which indicates that it is still far from being a standard application in the oil and gas industry and conclude with identification and discussions of the possible causes of the limited use of VOI in the oil and gas industry.

New insight on VOI is shown by Kullawan, Bratvold, and Bickel (2014) by applying VOI to real-time geosteering operations and by Vilela, Oluyemi and Petrovski (2018, 2019a) by introducing the fuzzy nature of the data in the VOI assessment.

In the previous works, VOI was applied on "isolated" data-gathering activities related to one of the project uncertainties, by assessing the impact that acquiring such data had on the value of the project; however, from a project standpoint, the essential objective is the identification and quantification of the benefits that are likely to come from any possible data acquisition activities that maximize the project value and not just one of the possible data acquisition activities, without considering the uncertainties in the complete project. The identification and definition of the data acquisition activities that maximize the project's value can be made using the technique of DOE.

Uncertainty can be aleatoric (related with noise inherent in the observations; it is unavoidable) and epistemic (related with models used to mimic the reality; it is feasible to be reduced by additional data acquisition). In problems characterized by epistemic uncertainty in the input and/or output variables, it is important to know what are the ranges of variability and the relative importance that each of the input variables has on the range of variability and values of the output variables. Design of Experiments is a structured and organized methodology to conduct and analyze experiments by defining each one by a specific set of values for the input parameters; the experiments (or simulation runs) should be performed to assess the impact that input parameters and their interactions have on the output variables (Montgomery, 2005). DOE has been used for improving the performance of processes and reducing result variability and cost (Telford, 2007). DOE is used to understand a system or process by means of experimentation; Figure 1 shows that the input parameters, combined by the system or process under consideration, are affected by factors (controllable and uncontrollable) which produce the output parameters.

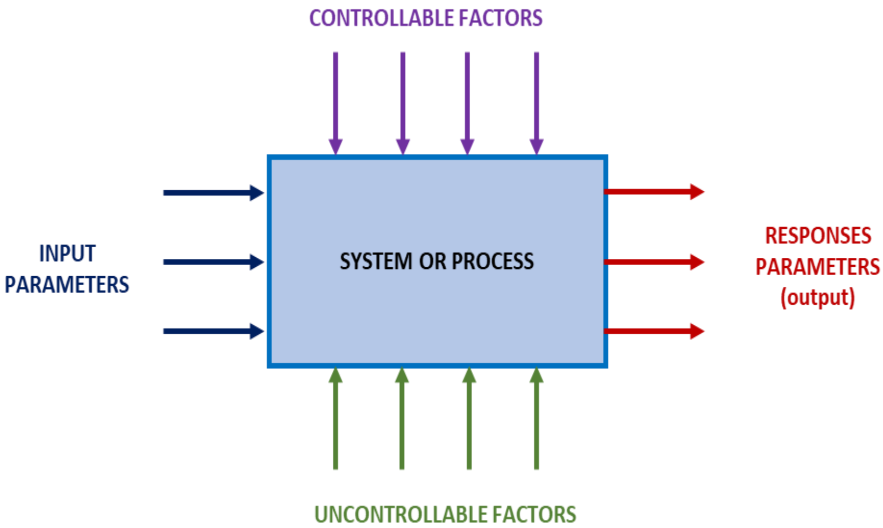

Figure 1. Diagram of the design of experiments approach

DOE was invented by statistician Ronald Fisher (1935) to understand the factors involved in increasing the crop yield in the UK, and its foundations were completed thanks to the work of Box and Wilson (1951), Box, Hunter and Hunter (1978) and Box and Draper (1987). Law and Kelton (1991) and Myers and Montgomery (2002) develop DOE methods for simulations proposes; DOE has expanded its applications to several domains such as the chemical industry (Yang, Bi, and Mao, 2002; Sjoblom et al., 2005; Ruotolo and Gubulin, 2005), materials (Suffield, Dillman, and Haworth, 2004; Liao, 2003; Hoipkemeier-Wilson et al., 2004), industrial engineering (Tong, Kwong, and Yu, 2004; Galantucci, Percoco, and Spina, 2003; Du et al., 2002), electronic (Ogle and Hornberger, 2001) or mechanical engineering (Passmore, Patel and Lorentzen, 2001; Nataraj, Arunachalam, and Dhandapani, 2005; Farhang-Mehr and Azann, 2005; Cervantes and Engstrom, 2004), aerospace (Zang and Green, 1999) and the analysis and optimization of nonlinear systems (Sacks et al., 1989).

Computational deterministic experimentation (e.g. used for dynamic reservoir simulation) differs from real-world experimentation in the fact that the former does not have a random error as the latter has; in practical terms, that means we always get the same output using a specific set of input parameters. Similar to real-world experimentation, the objective of simulation experimentation is to determine the factors that have a large impact on the response, getting the results with the least number of simulation runs (Law, 2015).

The first applications of DOE in the oil and gas industry were by Damsleth, Hage, and Volden (1992), Egeland et al. (1992) and Larsen, Kristoffersen, and Egeland (1994); after those applications, DOE has been used for identifying the main geological parameters responsible for oil recovery (White et al., 2001); for uncertainty integration to quantify their impact on original oil in place, recoverable reserves and production profiles (Corre, de Feraudy and Vincent, 2000); for assessing uncertainties in production profiles (Venkataraman, 2000); for investigating the impact of geologic heterogeneities and uncertainties in different development schemes (Wang and White, 2002); and for defining the minimum number of reservoir simulation runs needed to identify and quantify the factors responsible for the uncertainties of the reservoir performance (Peake, Abadah and Skander, 2005). Additionally, studies on production forecasting and ultimate recovery estimates representing the numerical reservoir simulation by a surrogate response surface model are discussed by Friedmann, Chawathe and Larue (2001) and Murtha et al. (2009), while Dejean and Blanc (1999) discuss DOE, dividing the uncertain factors into uncontrollable and controllable and adapting DOE accordingly, and Law (2017) discuss the workflow for applying DOE to simulation modelling.

Capturing all the uncertainties that the project may have and their impact on the output variables is of great importance in order to determine which data is worthwhile to acquire.

In 1965, Lotfi Zadeh published the paper “Fuzzy sets” where he describes the mathematics of fuzzy numbers and how fuzzy logic can be used to describe events with a partial degree of belonging to sets. Founded on this work, Bellman and Zadeh (1970), Lakoff (1978), Dunn (1992), Bezděk (1993, 2014), Negoita and Ralescu (1977), Goguen (1967), Bandler and Kohout (1978), Sugeno and Murofushi (1987), Sugeno and Kang (1988), Mizumoto and Tanaka (1976, 1981), Tanaka, Taniguchi, and Wang (1999), Zimmermann and Sebastian (1994), Zimmermann (1996), etc. continue the development of the new theory. Zadeh (1968) showed how fuzzy events could be described using fuzzy set theory. In 1971, Zadeh published “Quantitative Fuzzy Semantics”, where he developed the formal elements of the fuzzy logic and its applications.

Fuzzy inference is the process of mapping a set of input variables onto a set of output variables using fuzzy logic; in general, there are two ways of doing that: Mamdani and Sugeno, depending on the way the outputs are determined. The first Fuzzy Inference System (FIS) was a fuzzy controller for a steam engine developed by Assilian and Mamdani (1974) where fuzzy logic was used to convert heuristic control rules into an automatic control strategy; the first real implementation of a fuzzy controller was made by Lauritz Peter Holmblad, and Jens-Jørgen Østergaard (1980), who developed the commercial system of fuzzy control working for F.L. Smidth & Co. in a cement factory in Denmark (Larsen, 1980; Umbers and King, 1980), which resulted in one of the first successful tests runs on a full-scale industrial process. Subsequent applications of fuzzy logic in several domains have been reported: the assessment of water quality in rivers (Ocampo, 2008); improvements in the quality of image expansion (Sakalli, Yan and Fu, 1999); the differential diagnosis of non-toxic thyropathy (Guo and Ling, 2008); the development of a fuzzy logic controller for a traffic junction (Pappis and Mamdani, 1997); the design of a sensor-based fire monitoring system for coal mines using fuzzy logic (Muduli, Jana and Mishra, 2018); estimation of the impact of tax legislation reforms on potential tax (Musayev, Madatova, and Rustamov, 2016); pipeline risk assessment (Jamshidi et al., 2013); the diagnosis of depression (Chattopadhyay, 2014); the assessment of predicted river discharge (Jayawardena et al., 2014); calculation of geological strength indices and slope stability assessments (Sonmez, Gokceoglu and Ulusay, 2004); regulation of industrial reactors (Ghasem, 2006); the use of a fuzzy logic approach for file management and organization (Gupta, 2011). Similarly, in the oil and gas industry, fuzzy logic has been used for a 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); estimating the strength of rock using FIS (Sari, 2016); and predicting the rate of penetration in shale formations (Ahmed et al., 2019). Fuzzy logic has been used in combination with other Artificial Intelligence techniques such as Adaptative Neuro-Fuzzy Inference System (ANFIS) in practical applications, e.g. to predict 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 and Olugbenga, 2018) and to make decisions in the application of fuzzy inference systems for VOI in the oil and gas industry (Vilela, Oluyemi, and Petrovski, 2019b).

From a methodological perspective, a FIS can be understood as a general procedure that transforms a set of input variables into a set of outputs, following the dataflow shown in Figure 2.

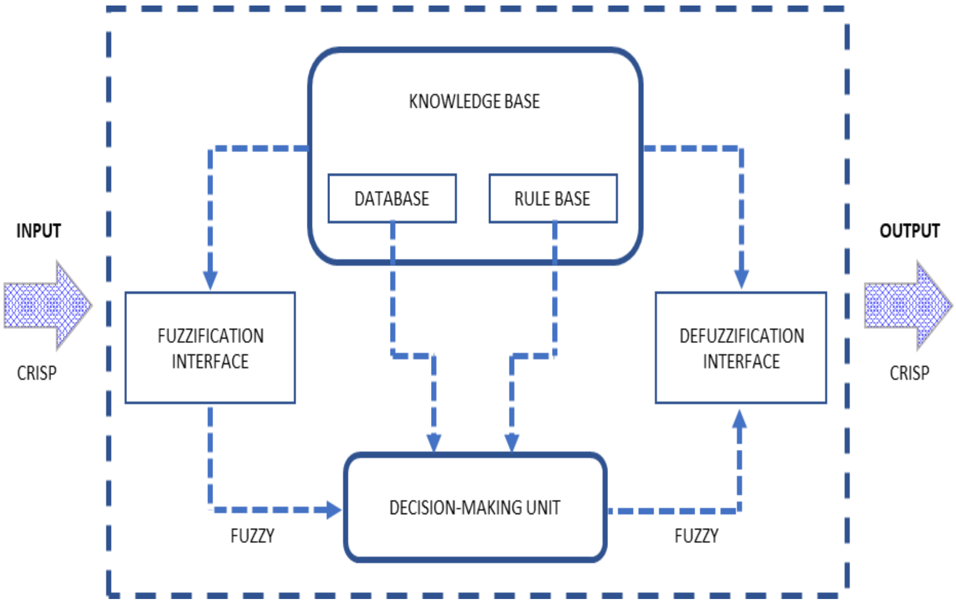

Figure 2. Fuzzy inference system dataflow

3. Case Study

3.1. Reservoir information

This case study is based on a clastic reservoir; four explorations and appraisal wells have already been drilled, the first three wells showing good production test results while the fourth well, located in the south of the reservoir, shows inferior results; these test results correlate well with the reservoir quality observed in the four wells; the differences in reservoir quality are attributed to diagenesis processes that occurred in the reservoir.

Figure 3 shows the four wells in the dynamic simulation model.

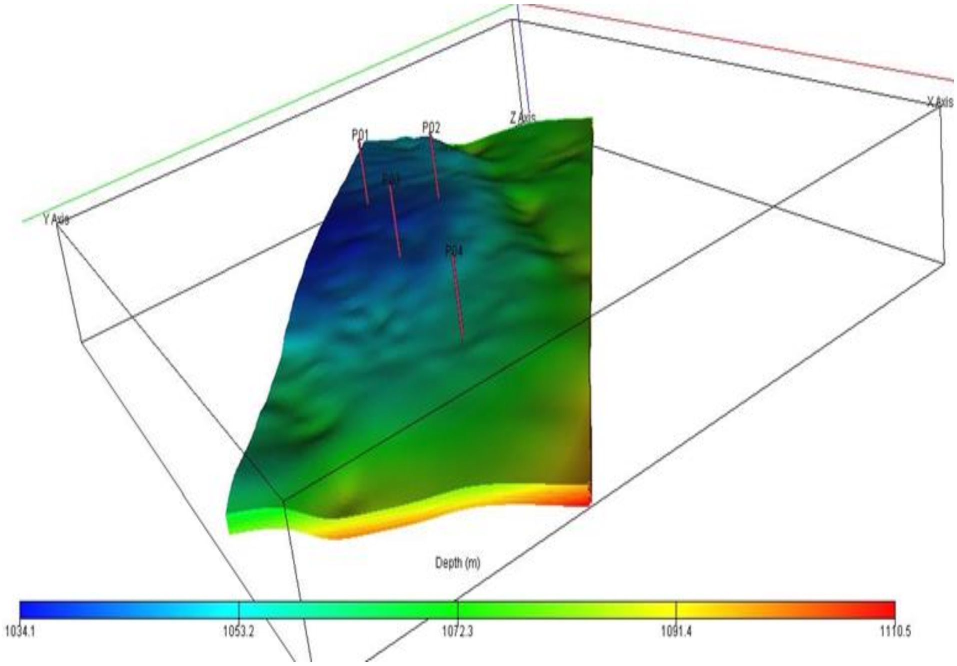

Figure 3. Structural map of the field with the exploration and appraisal wells

3.2. Project subsurface uncertainties

The technical team agreed that six parameters are carrying most of the subsurface uncertainty of this project: i)horizontal permeability distribution (PXY), ii)vertical permeability (PZE), iii)relative permeability (RPE), iv)aquifer strength (AQU), v)Oil-to-Water contact (OWC) and, vi)well Productivity Index (PI) value multiplier (WPI); these parameters and their range of uncertainty are shown in Table 1.

Table 1. Uncertain parameters: low, medium, and high values

Uncertain parameters	Low	Medium	High
Horizontal permeability	Extended diagenesis	Medium case diagenesis	Local diagenesis
Vertical permeability (mD)	0.01	0.50	10.00
Relative permeability	Co=3.1 / Cw=3.3 / Sorw=0.15	Co=2.5 / Cw=4.4 / Sorw=0.17	Co=1.8 / Cw=5.5 / Sorw=0.20
Aquifer strength, AQU Vol. / AQI PI STB/(STB/d/psi)	$2.5e^{9}$ / 217	$2.52e^{11}$ / 434	$2.52e^{13}$ / 868
Oil/water contact (m)	1,070	1,075	1,080
Well PI multiplier	0.90	8.90	18.40

The uncertainty associated with the distribution of the reservoir quality is captured by three different scenarios built to represent the high, medium and low cases for the property distribution to the south of the reservoir; due to the lack of data in this field, the range of variability in vertical permeability, relative permeability curves, and aquifer strength are taken from analogous fields. The range of values for oil-to-water contact is defined by the values observed in the three wells drilled, and the well PI multipliers are the figures used to history match the test results. The dynamic model used to generate the production profiles was made using the Eclipse software (Schlumberger™).

The operator company responsible for this field must decide whether to proceed with or to terminate, the project; however, the acquisition of new data can change the value of the project and impact that decision. Acquiring data carries a cost and possible delay in the project start; these negative impacts may be worthwhile if compensated by the positive effects of risk reduction and an increase in the project's value.

3.3. Assessment of project value of information

The assessment of the value of data acquisition starts with the screening phase, which consists of the identification of the input variables that have the most impact on the objective variable, which in this case is the utility of the Net Present Value (UNPV). In this case, study, having six input variables (the uncertain variables described in Table 1), sixty-six dynamic simulation cases should be set and run (each variable is evaluated at its low and high values).

Figure 4 shows the cumulative oil production of these sixty-six simulations runs.

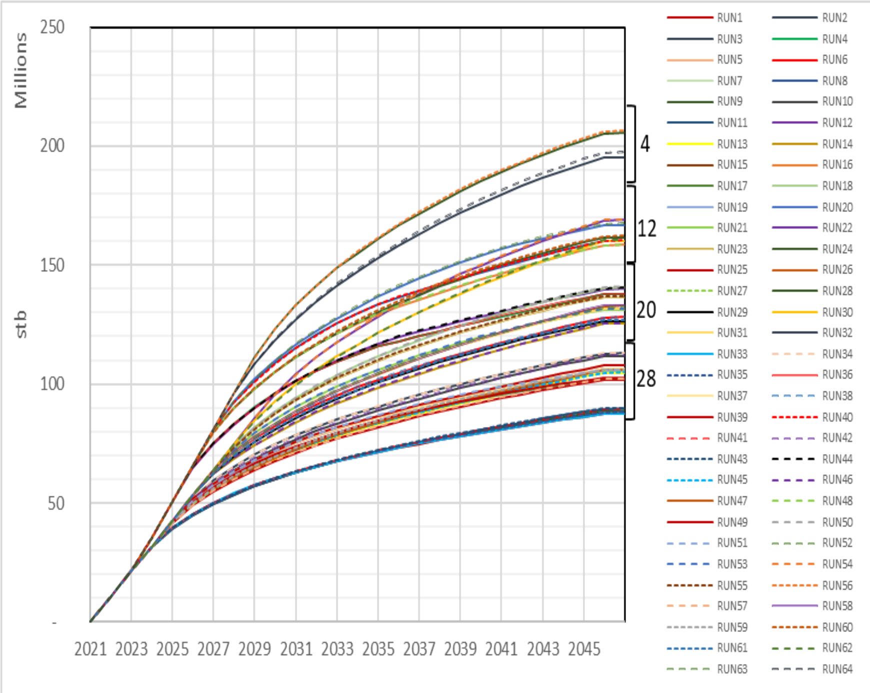

Figure 4. Uncertainty in cumulative oil production

The financial model used to evaluate the project benefits is built using Excel software (Windows Office); this model includes the oil production forecast resulting from the simulation runs and the CAPEX (capital expenditure or investment), OPEX (operational expenditure), oil price forecast; for this analysis, no other financial factor was included.

As discussed by Walls (2005), the utility function used is exponential, which in this case study will have a tolerance factor (TF) of $ 4,000 MM; this TF is representative of the company's historic attitude toward risk for oil and gas exploitation projects. For a reference on utility function in the oil and gas industry, see Vilela, Oluyemi, and Petrovski (2017).

In Figure 5, a Pareto plot of the effects shows that the variables with the larger impact on the objective variable are A (OWC), E (AQU), C (REP), B (PXY), AB (OWC/PCY), and AC (OWC/REP), where the last two correspond to the interaction effect of the first four variables; in conclusion, the most relevant parameters for the study are A, E, C and B, which correspond to OWC, AQU, REP and PXY.

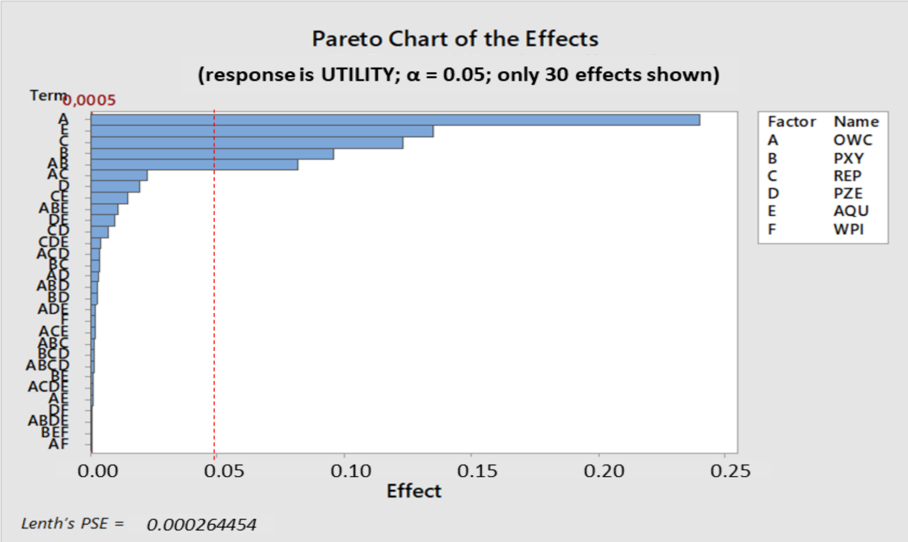

Figure 5. Pareto chart of the effects of the parameters, with a significance level of 0.05

This interpretation is confirmed by using the normal plot, as shown in Figure 6.

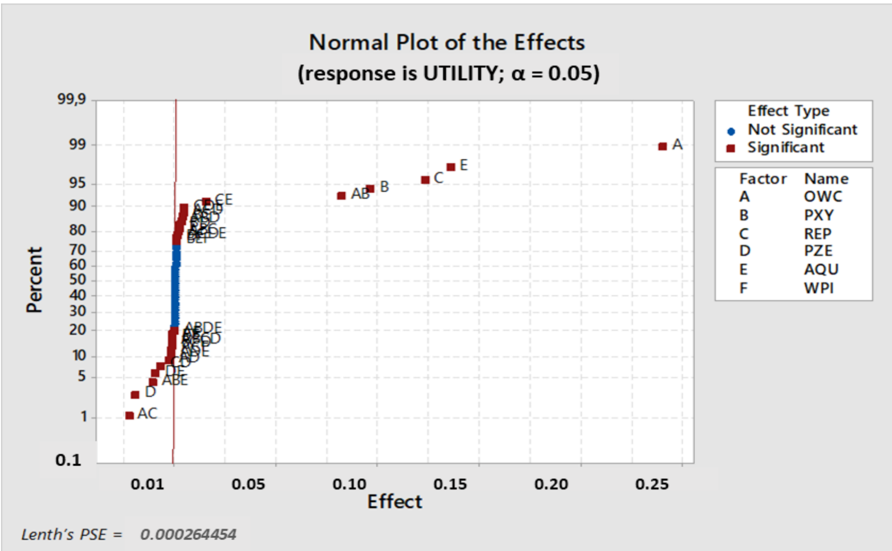

Figure 6. Normal plot of the effects of parameters, with a significance level of 0.05

Based on these four relevant variables already identified, sixteen dynamic models need to be evaluated corresponding to running each input variable to the low and high values while keeping the rest of variables at the medium level; the outcomes of those models should be further assessed in terms of values (NPV, IRR) and utility values (UNPV, UIRR).

The technical team estimates the prior probabilities of occurrence for each of these sixteen cases.

Two alternatives for data acquisition are considered: i) drilling a new well and performing an extended well test, and ii) performing an extended well test on an existing well.

1) Drilling a new well and performing an extended well test
2) By drilling a new well and performing an extended well test, the four uncertain input variables will be impacted; the new well should be located between the three wells with good properties and the well with bad properties; this well will de-risk the PXY distribution and the OWC; in addition, a new core sample can be taken to assess the relative permeability; the extended well test will be used to obtain the aquifer parameters.
3) Performing an extended well test on an existing well
4) By using one of the existing wells for performing an extended well test, only the uncertainty related to the aquifer strength can be investigated, keeping the remaining uncertainties at the same level as in the case without data acquisition.
5) Bayes' theorem should be applied to incorporate the value of the new data in the project value; to do that, reliability probability for all the combinations state-data outcome should be estimated, and those values are converted by means of the Bayes' theorem in the posterior probabilities, which are used for calculating the project value for each alternative.
6) In this research study, two different cases are assessed: the case where the data are treated as crisp, and the case where the data are treated as fuzzy. In the latter case, the uncertainty in the data due to imprecision is captured by using membership functions - for doing that, three membership functions are defined: M_1 or high, M_2 or medium, and M_3 or low. Here, high means that the compound effect of data acquisition over the four variables is high, although in one or more variables that may not be the case. The same applies to medium and low membership functions. The value assigned to each compound state for each membership function describes the degree of membership that the compound state has in the respective membership function and, the compound value of the four variables in the membership function is the average value. Tables 2a. and 2b. show the membership functions M_1, M_2 and M_3 for each potential data outcome in the case of drilling a new well and performing an extended well test alternative.

Table 2a. Membership functions for the first eight compound parameters for drilling a new well and performing an extended well test

	(hhhh)	(hhhl)	(hhlh)	(hhll)	(hlhh)	(hlhl)	(hllh)	(hlll)
M_1	0.638	0.550	0.525	0.438	0.500	0.413	0.388	0.300
M_2	0.250	0.263	0.275	0.288	0.250	0.263	0.275	0.288
M_3	0.113	0.188	0.200	0.275	0.250	0.325	0.338	0.413

Table 2b. Membership functions for the last eight compound parameters for drilling a new well and performing an extended well test

	(lhhh)	(lhhl)	(lhlh)	(lhll)	(llhh)	(llhl)	(lllh)	(llll)
M_1	0.525	0.438	0.413	0.325	0.388	0.300	0.275	0.188
M_2	0.263	0.275	0.288	0.300	0.263	0.275	0.288	0.300
M_3	0.213	0.288	0.300	0.375	0.350	0.425	0.438	0.513

For the case of using an existing well, the membership functions M_1, M_2 and M_3 corresponding to high, medium and low are calculated. In this case (using an existing well), the only parameter that is evaluated is the aquifer strength. The Tables 3a. and 3b. show the value assigned to each compound state within the three membership functions, which reflects the degree of membership that the state has in the corresponding membership function for the "performing an extended well test on an existing well" alternative.

Table 3a. Membership functions for the first eight compound parameters for performing an extended well test on an existing well

	(hhhh)	(hhhl)	(hhlh)	(hhll)	(hlhh)	(hlhl)	(hllh)	(hlll)
M_1	0.700	0.700	0.700	0.700	0.150	0.150	0.150	0.150
M_2	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200
M_3	0.100	0.100	0.100	0.100	0.650	0.650	0.650	0.650

Table 3b. Membership functions for the last eight compound parameters for performing an extended well test on an existing well

	(lhhh)	(lhhl)	(lhlh)	(lhll)	(llhh)	(llhl)	(lllh)	(llll)
M_1	0.700	0.700	0.700	0.700	0.150	0.150	0.150	0.150
M_2	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200
M_3	0.100	0.100	0.100	0.100	0.650	0.650	0.650	0.650

In the decision phase, on the top of the UNPV already used in the screening phase, the Internal Rate of Return (IRR) and its utility value (UIRR) are used.

The FIS was built using MATLAB® R2015a software with triangular and truncated triangular functions. The values involved in the decision are UNPV and UIRR, and their fuzziness is represented with three membership functions for each one: UNPV_High, UNPV_Medium, UNPV_Low, UIRR_High, UIRR_Medium, and UIRR_Low. The decision options are "to endorse", "not to endorse" or "to reframe" the project.

IF…THEN rules are designed to reflect the imprecision in the decision process. For this case study, nine rules were created, as shown in Table 4.

Table 4. Decision-making rules for the FIS

Decision rules #	IF	THEN
Rule 1	(UNPV is UNPV_LOW) AND (UIRR is UIRR_HIGH)	(DECISION IS REFRAMING)
Rule 2	(UNPV is UNPV_LOW) AND (UIRR is UIRR_MEDIUM)	(DECISION IS NO_ENDORSEMENT)
Rule 3	(UNPV is UNPV_LOW) AND (UIRR is UIRR_LOW)	(DECISION IS NO_ENDORSEMENT)
Rule 4	(UNPV is UNPV_MEDIUM) AND (UIRR is UIRR_HIGH)	(DECISION IS ENDORSEMENT)
Rule 5	(UNPV is UNPV_MEDIUM) AND (UIRR is UIRR_MEDIUM)	(DECISION IS REFRAMING)
Rule 6	(UNPV is UNPV_MEDIUM) AND (UIRR is UIRR_LOW)	(DECISION IS NO_ENDORSEMENT)
Rule 7	(UNPV is UNPV_HIGH) AND (UIRR is UIRR_HIGH)	(DECISION IS ENDORSEMENT)
Rule 8	(UNPV is UNPV_HIGH) AND (UIRR is UIRR_MEDIUM)	(DECISION IS ENDORSEMENT)
Rule 9	(UNPV is UNPV_HIGH) AND (UIRR is UIRR_LOW)	(DECISION IS REFRAMING)

3.4. Case study results

Expected value assessment using crisp and fuzzy data

1) The expected value for drilling a new well and performing an extended well test data acquisition

Table 5 shows the results of the evaluation for the case of *drilling a new well and performing an extended well test*

Table 5. Expected value assessment for *drilling a new well and performing an extended well test* data acquisition proposal

Values	No data	Crisp data	Fuzzy data
NPV (MM $)	3.02	12.19	−9.78
IRR (%)	−2.30	−2.49	−2.49
UNPV	−0.0069	0.0006	−0.0074
UIRR	−0.2536	0.2665	−0.2741

UNPV analysis

When UNPV is used as a decision criterion, Table 6 shows that when the classical methodology has used the value of "*drilling a new well and performing an extended well test* alternative is higher than the value of "*do not acquire data" alternative*; however, when the fuzzy nature of the data is included in the analysis, the value of "*drilling a new well and performing an extended well test" alternative* is reduced, and indeed the "*no data acquisition"* alternative is better than data acquisition. This change in the decision when the fuzzy characteristics of the data are included in the analysis is maintained in the case of using values instead of utility values.

UIRR analysis

When UIRR is used as a decision criterion, the "*drilling a new well and performing an extended well test" alternative* has a lower value than the value of "*do not acquire data" alternative* in both cases, crisp and fuzzy data; and this assessment holds in case values are used instead of utilities.

2) The expected value for performing an extended well test on an existing well data acquisition

For this alternative, Table 6 shows the results of the evaluation.

Table 6. Expected value assessment for *performing an extended well test on an existing well* data acquisition proposal

Values	No data	Crisp data	Fuzzy data
NPV (MM $)	3.02	98.04	97.31
IRR (%)	−2.30	−1.53	−1.53
UNPV	−0.0069	0.0197	0.0174
UIRR	−0.2536	−0.1752	−0.1798

UNPV analysis

Using UNPV as a decision criterion, and with the classical methodology for the data acquisition case of *performing an extended well test on an existing well,* the data acquisition alternative has a higher value than the value of "*do not acquire data"* alternative whether the data is crisp or fuzzy. The same conclusion is reached using values instead of utilities.

UIRR analysis

When the UIRR is used as a decision criterion to assess the case of *performing an extended well test on an existing well*, the classical methodology shows that the best project is the data acquisition alternative, because both crisp and fuzzy acquisition have higher values than the value of "*do not acquire data"* alternative; a similar conclusion is reached when values are used instead of utilities.

Fuzzy inference system assessment using crisp and fuzzy data

Tables 7 and 8 show the outcomes of the fuzzy inference assessments of the case of drilling a new well and performing an extended well test and performing an extended well test on an existing well.

Table 7. FIS assessment for drilling a new well and performing an extended well test data acquisition proposal

Values	No data	Crisp data	Fuzzy data
FIS values	−0.217	−0.170	−0.359
FIS utility	−0.274	−0.268	−0.289

Table 8. FIS assessment for *performing an extended well test on an existing well* data acquisition proposal

Values	No data	Crisp data	Fuzzy data
FIS values	−0.217	0.444	0.444
FIS utility values	−0.274	−0.171	−0.178

Considering the results shown in Table 7 for *drilling a new well* and *performing an extended well test*, using crisp data, both values and utility values (bring about through the utility function) indicate the best alternative is "*acquire data"* or *drill the well and perform an extended well test"*; however, when the fuzzy characteristics of the data is included in the assessment, the best alternative switched to "*do not acquire data"*.

Table 8 shows that for "*performing an extended well test on an existing well" alternative*, both objective functions, FIS values, and FIS utility values, indicate that the best alternative is "*acquire data"* or "*perform an extended well test on an existing well"*. The inclusion of the fuzzy characteristics of the data in the analysis does not change the results.

4. Conclusions and recommendations

The inclusion of the fuzzy characteristics of the data that deal with aleatoric, but also affect epistemic uncertainties, in the VOI assessment is very important because it can have a significant impact on the final decisions. In the case study discussed in this paper for "*drilling a new well and performing an extended well test" alternative*, the decision switched from "*do not acquire data"* to "*acquire data"* when the fuzzy data nature of the data is included in the analysis. It was observed that in "*performing an extended well test on an existing well" alternative*, that switch does not occur. That happens because of two reasons: i) the difference in values and utility values between the two alternatives: "*performing an extended well test on an existing well"* and "*do not acquire data"* is not large and, ii) the degree of fuzziness or the level of vagueness assigned to the data as described by the membership functions. In general, it is observed that when the fuzzy characteristic of the data is included in the analysis, the value of the data acquisition is reduced.

Using a fuzzy inference system allows for the aggregation of two or more decision criteria (NPV, IRR, etc.) within only one decision criterion that summarizes the result of the assessment; the several decision criteria can be weighted as desired into the FIS.

DOE is a robust theory suitable for analysis of VOI problems and steering the decision process for selecting the data acquisition actions that provide the optimum value to the project; proceeding in this way ensures that the decision process fits the needs of the oil and gas industry.

However, the membership functions and utility functions still carry a large degree of subjectivity and further work is required to assess the level of subjectivity and how this might impact VOI analysis.

In the near future, additional research efforts should be dedicated to the use of machining learning to support the decision-making process by integrating the normative and descriptive elements of the decision process in a coherent and rational manner.

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