Fuzzy Data Analysis Methodology for the Assessment of Value of Information in the Oil and Gas Industry

Martin Vilela, Gbenga Oluyemi and Andrei Petrovski
Robert Gordon University
Sir Ian Wood Building, Garthdee Road, Aberdeen, AB10 7QB
Scotland, UK
{m.j.vilela-ibarra, g.f.oluyemi, a.petrovski}@rgu.ac.uk

***Abstract*— To manage uncertainty in reservoir development projects, the Value of Information is one of the main factors on which the decision is based to determine whether it is necessary to acquire additional data. However, subsurface data is not always precise and is characterized by a certain level of fuzziness. In this paper, a model is formulated to assess the Value of Information in the oil and gas industry in cases where the data proposed to be acquired is imprecise. The methodology is based on the use of fuzzy data modelling and analysis aimed at providing decision support for oil field developers. An oilfield from North Africa is used as a case study to show how the methodology works. This work shows how the analysis can be utilized to reach financial decisions on the necessity of additional data acquisition.**

Keywords—* *Fuzzy modelling, Value of Information; Uncertainty and Risks; Decision analysis and support; Oil and Gas Industry application.

I. INTRODUCTION

Decision making is a central process in any business; in particular, the Oil and Gas Industry makes decisions routinely which could impact the business on short, medium or long terms. A key element for making consistent and robust decisions is to use a prescriptive method to assess each alternative option [1] and [2]; the need for using such methods is even greater when the variables concerning the decision carry uncertainties.

Over the past years, numerical techniques for model-based optimisation, parameter estimation and decision making related to subsurface hydrocarbon reservoirs have developed rapidly. It has also become possible to acquire detailed reservoir information through utilisation of well-based sensors and the usage of advanced measurement methods. Many of the newly introduced technologies, however, come at a significant cost, and the assessment of associated Value of Information (VoI) becomes increasingly important, especially at the field development and planning phases [3].

The development of offshore and onshore fields is considered a high-risk operation, involving considerable investment in complex uncertain scenarios. During the development phase, various sources of uncertainties may coexist: (1) geological uncertainties, associated with recoverable reserves and flow characteristics; (2) operational uncertainties, related to production system availability; and (3) economic uncertainties, such as oil price, capital expenditures and operational expenditures [4].

Three main approaches to managing uncertainty have been identified [4]: (1) acquiring information to reduce geological uncertainty; (2) adding flexibility to the production system, allowing for contingencies to be put in place at a cost; and (3) defining a robust strategy able to cope with the range of possible scenarios.

This study focuses on the first and third approaches, and the type of decisions explored in this paper are those associated with data acquisition, specifically, data acquisition in the context of subsurface evaluations. In the subsurface domain, variables defining the reservoir and its production are only partially known and uncertainty is present in all evaluations. Imprecise values of these variables produce uncertainty in the reservoir production forecast, which makes it difficult to assess the financial benefits of developing the field or even decide whether to perform tasks to optimize hydrocarbon production. The uncertainty in the project outcome poses the risk of financial losses, which need to be avoided.

In most cases, data can be acquired to better understand the uncertainties and hopefully to reduce them; however, the value of acquiring data is not measured by uncertainty reduction *per se*, but by the reduction of risk and by an increased project value.

The works of [5], [6] and [7] made pioneering contributions in the field of decision-making for data acquisition; subsequently, more research and applications, such as [8] and [9], amongst others, expanded the scope of the subject and provided more robustness to the methodology. The VoI method is rooted in the broader field of Decision Analysis [1].

Due to the importance of reservoir characterization, various methods for acquiring reliable reservoir properties have been proposed, including computation intelligence and machine learning methods – artificial neural networks (ANN) in particular, which have shown great characterization potential by inferring reservoir properties from well log data [10]. Some machine learning methods take into consideration the Value of Information, to assist in dealing with uncertainties [4].

More applications have enriched the process of assessing the VoI decision problem from a methodology perspective [11], [12] and [13]; however, this methodology was based on the assumption that the data to be acquired is crisp. Even for the problems, when fuzzy approaches to data analysis were used, they were focused on data pre-processing for other analytical techniques [14] and [15], rather than on analyzing imprecise data itself for decision making or support. At the same time, in subsurface projects in the oil and gas industry, as well as in other application domains, there are many important cases where data cannot be reliably described by a crisp value [16]. The main contribution of this paper is the development of a methodology to implement fuzzy modelling of VoI when the data is inherently vague and/or imprecise.

II. Model Formulation

Let us assume there exist a set of n discrete states of nature (cases) $s_1, \ldots \ldots s_n$ describing the range of possible project outcomes; each state has a prior probability $p(s_i)$ where:

$$\sum_{i=1}^{n} p(s_i) = 1 \tag{1}$$

Probabilities in (1) are known as "prior probabilities" because they represent the current belief (i.e. before the acquisition of new data) regarding the probability that a state occurs. Experts assign those probabilities based on experience and judgment.

Now, let us assume that there is a decision problem which has m alternative solutions included in the set A:

$$A = \{a_1. a_2. a_3 \ldots \ldots \ldots a_m\} \tag{2}$$

For each pair – an alternative a_j and state of nature s_i – there is a value u_{ji} which materializes in the future if the alternative a_j and state s_i occur.

The Expected Value (EV) corresponding to the j^{th} alternative is defined as:

$$EV(a_j) = \sum_{i=1}^{n} u_{ji} p(s_i) \tag{3}$$

Typically, the decision criterion used is to select the alternative with the maximum EV:

$$EV(a^*) = \max_j EV(a_j) \tag{4}$$

Equation (4) represents the value of the project without information (indeed, with the actual information) which, in the subsurface domain typically includes several meaningful uncertainties in the input parameters which will result in uncertainties in the outcomes.

There are situations where additional data could be acquired (in the future) which can reduce the uncertainty level in the input parameters responsible for the spread (uncertainties) in the outcomes results; acquiring those data would impact on the value of each discrete state but would also modify the probabilities assigned to each state. The net effect of the changes to the values and probabilities of the states (cases) results in a change of the project's value [11].

$$VOI = EV_{with\ information} - EV_{without\ information} \tag{5}$$

In general, both values, $EV_{with\ information}$ and $EV_{without\ information}$, represent our beliefs of what could be the outcome of the project in two different circumstances, both referring to a future situation.

Let us assume that the outcomes of the data proposed to be acquired are discretized in the following set X of r values:

$$X = \{x_1, \ldots \ldots \ldots \ldots, x_r\} \tag{6}$$

Reliability probabilities $p(x_k|s_i)$ are assigned by experts in the same manner as the prior probabilities; reliability probabilities represent the probability of the data accurately identifying the states of nature.

Fuzzy logic captures the vagueness through the membership function, which is mapped from a given universe of discourse X to a unit interval containing the membership values.

For a fuzzy set, the probability of a fuzzy event $\widetilde{M}$ is [17]:

$$P(\widetilde{M}) = \sum_{k=1}^{r} \mu_{\widetilde{M}}(x_k) p(x_k) \tag{7}$$

where $\mu_{\widetilde{M}}(x_k)$ is the membership function $\mu_{\widetilde{M}}$ evaluated in the value x_k.

The posterior probabilities of the states of nature given the fuzzy event $\widetilde{M}$ are obtained using Bayes' theorem assuming that the reliability and prior probabilities and the membership functions of the fuzzy events are known:

$$P(s_i|\widetilde{M}) = \frac{\sum_{k=1}^{r} p(x_k|s_i)\mu_{\widetilde{M}}(x_k)p(s_i)}{P(\widetilde{M})} = \frac{P(\widetilde{M}|s_i)p(s_i)}{P(\widetilde{M})} \tag{8}$$

where in (8), the fuzzy reliability probabilities are:

$$P(\widetilde{M}|s_i) = \sum_{k=1}^{r} p(x_k|s_i)\mu_{\widetilde{M}}(x_k) \tag{9}$$

An orthogonal fuzzy system is a set θ of fuzzy sets, $\theta = \{\widetilde{M}_1, \widetilde{M}_2, \ldots \ldots \widetilde{M}_l\}$ satisfying the condition that:

$$\sum_{f=1}^{l} \mu_{\widetilde{M}_f}(x_m) = 1 \quad \{\text{for all } x_m \in X\} \tag{10}$$

For fuzzy events, if the fuzzy system is an orthogonal set and with the data outcome represented by the fuzzy set $\widetilde{M}_k$, the EV of the alternative j^{th} is given by:

$$EV(a_j|\widetilde{M}_f) = \sum_{i=1}^{n} a_{ij} p(s_i|\widetilde{M}_f) \tag{11}$$

The optimum alternative given the fuzzy set $\widetilde{M}_k$ is the one that maximises the EV:

$$EV(a^*|\widetilde{M}_f) = \max_j EV(a_j|\widetilde{M}_f) \tag{12}$$

The unconditional maximum EV takes the form:

$$EV(a^*_\emptyset) = \sum_{f=1}^{l} EV(a^*|\widetilde{M}_f) p(\widetilde{M}_f) \tag{13}$$

Finally, the VoI is the difference between the EV with information and the EV without information, as in (13) and (4):

$$VOI = EV(a^*_\emptyset) - EV(a^*) \tag{14}$$

To deal with the uncertainty associated with vagueness and imprecision in the data available we are proposing to use a fuzzy logic approach tried and tested in many simulation environments [15] and other application domains, including smart electrical grids [16].

III. APPLICATION OF FUZZY APPROACH TO VOI

The value of projects with uncertain values could be impacted when additional information regarding the inputs is gathered.

In the oil and gas industry, especially in the subsurface domain, there are situations where the data is vague or diffuse; however, in the literature, there are no reported cases of the use of fuzzy data in assessing VoI.

A. Case Study Reservoir Description

In this paper, an oilfield located in North Africa is used as a case study to evaluate a VoI problem where the data proposed to be acquired is "fuzzy".

The project consists of a profitable economic exploitation of a sandstone oil field made of three isolated blocks of good quality rock with a thin hydrocarbon column. Two compartments with similar petrophysical properties - blocks A and B - have been drilled and produced using three vertical wells each. The Oil Column Thickness (OCT) of the wells ranges between a minimum of 11 ft. and a maximum of 42 ft., with an average of 38 ft. and 16.1 ft. for blocks A and B respectively.

Blocks A and B are separated by a North-South fault with a throw of circa 25 ft. that isolates the blocks from each other; the isolation of the blocks has been confirmed with production and injection data from the wells. Seismic vertical resolution is between 20–30 ft., making it challenging to select the reservoir top and base with enough accuracy to detect structural shifting in the wells.

Due to the nature of the reservoir and the performance of analog reservoirs, each producer was drilled in patterns with a nearby injector well, for pressure maintenance and sweep efficiency.

B. Reservoir Performance

Oil production started 8 years ago from block A (January 2010) and two 2 years later from block B. Fig. 1 and 2 show the historical and forecast oil rates of the existing wells up to 2029 when the 20-year concession license expires; qualitatively all wells have performed alike but the main difference has been the initial oil production rates of the wells.

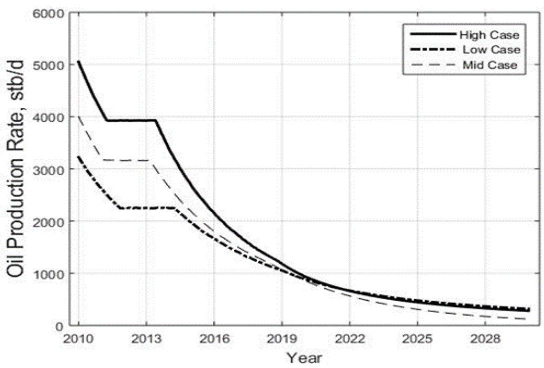

Figure 1. Historic and forecast wells performance of block A.

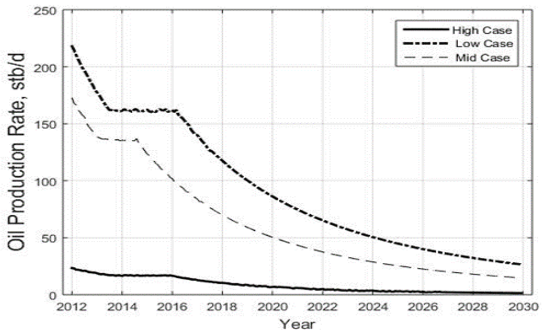

Figure 2. Historic and forecast wells performance of block B

Table 1. Oil column thickness (OCT) and initial oil rate (IOR) of existing wells

Well	Oil Column Thickness, ft.	Initial Oil Rate, stb/d
WA1	41.1	5,053
WA2	30.9	3,224
WA3	33.8	4,009
WB1	12.1	23
WB2	19.1	218
WB3	17.2	173

Wells performance have shown that the higher the OCT the higher the Initial Oil Rate (IOR) as shown in Table 1.

This correlation has a few drawbacks because of uncertainties of the measured OCT:

- During operation of the Repeat Formation Tester (RFT) there have been repeated failures in the data, and interpretations have been ambiguous.
- Log interpretation (petrophysical well evaluation based on Log data) does not show a crisp indication of OCT.
- The limits of the transition zone are not clearly defined.

C. Facilities and Drilling Strategy

Facilities to manage fluid production and injection in block A area were designed in modules. The first module was completed and commissioned by the end of 2009; the aim of this facility was to manage the production and injection of fluids for the three producer wells and three injector wells in block A.

One year after production in block A started, it was decided to continue the reservoir development, adding block B to production; the same development strategy was used as implemented in block A. First oil started in January 2012 with full facilities and three producers, adding the injector wells one year later; it was also decided that production and injection in block B would be managed through an additional module installed in the block A facility; in this way, production and injection fluids are pumped through flowlines from block B to block A, which are 2 km apart.

D. Current Results

After blocks A and B have been in production for 8 and 6 years respectively, the assessment of the operator company is that while block A has been a success in terms of oil recovery and financial benefits, the opposite has been the case for block B, which has shown limited oil recovery, resulting in financial losses.

IV. DECISION PROBLEM

The field operator needs to decide whether to continue with the development of the field toward block C, or whether to restrict the reservoir development to the current productive blocks A and B.

A. Problem Alternatives

In this paper, an oilfield located in North Africa is used as a case study to evaluate a VoI problem where the data proposed to be acquired is imprecise or "fuzzy".

A.1 No data acquisition alternative

This alternative entails the development of block C based on the current information. Facilities and flowlines will take 6 months to be ready and available (they will be ready by July 2018); the rig can be spud in three months (by March 2018), taking another three months to drill and complete the first well. Oil production could start six months from now (by July 2018) with one well; every three months another well will be added to the stream, completing the full development with three producer wells in six months. Injector wells will be drilled after the producer wells are completed.

A.2 Data acquisition alternative

The second alternative is to acquire additional information prior to deciding whether to develop block C. The main uncertainty is the well productivity; however, well productivity is related to the size of the OCT; it is believed that drilling an appraisal well in block C can unlock this project and give the necessary information to decide whether developing block C would be financially profitable.

In assessing this alternative, the following assumptions are taken: three months to have the rig available, meaning that drilling of the appraisal well should start by March 2018. The outcome of the data acquisition, the size of the OCT, should be available by April 2018, followed by one month-long final assessment and internal consultation process for the decision. Thus, a decision regarding the development of block C will be made by Jun 2018.

The acquisition of data will, therefore, push back the development of the block: the building of facilities will be postponed to June 2018. In a similar manner, because the appraisal well will be the deciding element, the rig contract will only be for one well; if the decision taken is to continue to full development, another contract will have to be signed for the drilling of the remaining wells.

A.3 Relinquish the development of block C

The last alternative is to relinquish the development of block C and continue only with the development of blocks A and B. In this alternative, there will be a loss of 34 MMUS$ due to the fraction of the total cost of the reservoir which was divided between the three blocks.

B. Fuzzy Value of Information Methodology

For this analysis, there are three discrete production levels for block C: high, medium and low production cases. The high case corresponds to the situation where the OCT of block C is between 35 and 46 ft. and well type is an average of wells in block A; the low case corresponds to the situation where the OCT of block C is between 11 and 22 ft. and well type is an average of wells in block B; the medium case corresponds to the situation where the OCT of block C is between 23 and 34 ft. with well type defined as the mean average of wells in block A and B.

B.1 No data acquisition alternative

In the alternative where development is begun without further data acquisition, there are three potential production profiles, corresponding to the high, mid, and low cases. Table 2 shows the prior probabilities assigned and the values calculated for each state of nature.

Table 2. Prior probabilities and values for the three states of nature

State of Nature	Prior probability (fraction)	Value (MMUS$)
s_1 = high	0.25	636
s_2 = medium	0.50	263
s_3 = low	0.25	-119

Based on the prior probabilities and values shown in Table 2 and, using Equations (3) and (4) in Section II, for the "no additional data" alternative the EV of this project is estimated to be 261 MMUS$.

B.2 Data acquisition alternative

To assess the value of acquiring new data, the range of possible outcomes of OCT (11 – 47 ft.) is discretised into 12 intervals, each 3-ft. long.

The reliability probabilities assigned by the experts' members of the technical team are shown in Table 3.

Table 3. Reliability probabilities showing the mid value of each interval

	$x_1 = 45$	$x_2 = 42$	$x_3 = 39$
$p(x_k\|s_1)$	0.250	0.250	0.220
$p(x_k\|s_2)$	0.000	0.000	0.000
$p(x_k\|s_3)$	0.000	0.000	0.000
	$x_4 = 36$	$x_5 = 33$	$x_6 = 30$
$p(x_k\|s_1)$	0.180	0.100	0.000
$p(x_k\|s_2)$	0.050	0.200	0.250
$p(x_k\|s_3)$	0.000	0.000	0.000
	$x_7 = 27$	$x_8 = 24$	$x_9 = 21$
$p(x_k\|s_1)$	0.000	0.000	0.000
$p(x_k\|s_2)$	0.250	0.200	0.050
$p(x_k\|s_3)$	0.000	0.100	0.180
	$x_{10} = 18$	$x_{11} = 15$	$x_{12} = 12$
$p(x_k\|s_1)$	0.000	0.000	0.000
$p(x_k\|s_2)$	0.000	0.000	0.000
$p(x_k\|s_3)$	0.220	0.250	0.250

Three fuzzy events for the OCT are considered; large OCT, $\widetilde{M}_1$, medium OCT, $\widetilde{M}_2$, and low OCT, $\widetilde{M}_3$.

Table 4 includes the membership values per each interval. Fig. 3 displays the shape of the curves that describe the membership functions used in this assessment.

Table 4. Membership function values

	$x_1 = 45$	$x_2 = 42$	$x_3 = 39$
$\mu(\widetilde{M}_1\|x_k)$	0.75	0.73	0.67
$\mu(\widetilde{M}_2\|x_k)$	0.15	0.15	0.18
$\mu(\widetilde{M}_3\|x_k)$	0.10	0.12	0.15
	$x_4 = 36$	$x_5 = 33$	$x_6 = 30$
$\mu(\widetilde{M}_1\|x_k)$	0.55	0.28	0.10
$\mu(\widetilde{M}_2\|x_k)$	0.25	0.44	0.57
$\mu(\widetilde{M}_3\|x_k)$	0.20	0.28	0.33
	$x_7 = 27$	$x_8 = 24$	$x_9 = 21$
$\mu(\widetilde{M}_1\|x_k)$	0.02	0.00	0.00
$\mu(\widetilde{M}_2\|x_k)$	0.61	0.59	0.44
$\mu(\widetilde{M}_3\|x_k)$	0.37	0.41	0.56
	$x_{10} = 18$	$x_{11} = 15$	$x_{12} = 12$
$\mu(\widetilde{M}_1\|x_k)$	0.00	0.00	0.00
$\mu(\widetilde{M}_2\|x_k)$	0.30	0.12	0.10
$\mu(\widetilde{M}_3\|x_k)$	0.70	0.88	0.90

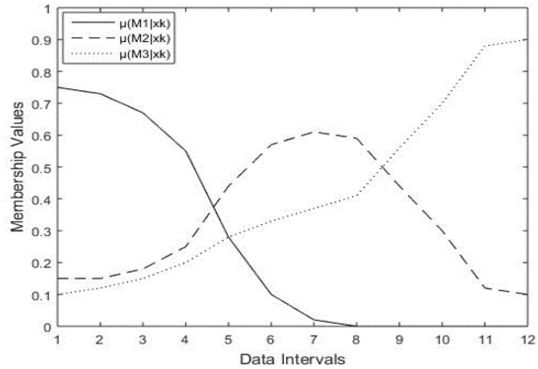

Figure 3. Membership functions used in the assessment

The shape of the membership functions in Figure 3 follows the understanding that experts have regarding the ambiguity of the data to be acquired. The range of values of the OCT has three intervals labelled 1, 2 and 3 according to the value measured; the experts believe that due to fuzziness in the data, the values measured in the interval 1 not only belong to the membership function $\mu(\widetilde{M}_1|x_k)$ but also belongs to the membership function $\mu(\widetilde{M}_2|x_k)$; the degree of belonging to each membership function is different; this similarly occurs with the intervals 2 and 3. In general, the membership functions were built assuming that when high values of OCT are reported those values have a degree of belonging not only in the "large" OCT membership function but also in the "medium"; however, when low values of OCT are reported data mostly belongs to the membership function "low".

Using Equations (8) and (9) in Section II and Tables 3 and 5, the fuzzy reliability probabilities and the fuzzy posterior probabilities are computed, and the results are shown in Tables 5 and 6.

Table 5. Fuzzy reliability probabilities

	s_1	s_2	s_3
$p(\widetilde{M}_1\|s_k)$	0.644	0.114	0.000
$p(\widetilde{M}_2\|s_k)$	0.204	0.535	0.259
$p(\widetilde{M}_3\|s_k)$	0.152	0.351	0.741

Table 6. Fuzzy posterior probabilities

	$\widetilde{M}_1$	$\widetilde{M}_2$	$\widetilde{M}_3$
$p(s_1\|\widetilde{M}_k)$	0.739	0.133	0.095
$p(s_2\|\widetilde{M}_k)$	0.261	0.698	0.440
$p(s_3\|\widetilde{M}_k)$	0.000	0.169	0.465

The EVs of both alternatives, per each fuzzy interval, are calculated using Equation (11); results are summarized in Table 7.

Table 7. Expected Fuzzy Values

	$\widetilde{M}_1$	$\widetilde{M}_2$	$\widetilde{M}_3$
$EV(A_1 \vert \widetilde{M}_k)$	524	236	112
$EV(A_2 \vert \widetilde{M}_k)$	-34	-34	-34

Using Equations (12) and (13) in Section II and Tables 6 and 7, the expected fuzzy value for the data acquisition project is estimated to be 251 MMUS$.

Thus, with fuzzy data acquisition, according to Equations (14) in Section II, the VoI is estimated to be -10 MMUS$. Based on this assessment, therefore, it would not be recommended to acquire new data before developing block C, because the VoI for the fuzzy data used does not support this decision.

V. CONCLUSIONS

Having assessed the VoI in the oil and gas industry for the cases described in this paper, a conclusion of significant practical importance could be drawn on the necessity to acquire additional data for making a financial decision. The method proposed makes use of the fuzzy data modelling and analysis based on membership functions to assess the VoI.

To deal with difficulties and complexity of valuing additional information to manage uncertainties in oil field development, we proposed a prescriptive methodology of analyzing and using imprecise data through the introduction of fuzzy membership functions. To generate a meaningful result from the suggested assessment approach, the form of the membership functions should properly capture the degree of fuzziness of the data outcomes.

In the case of a VoI assessment, it is of critical importance to clarify from the beginning whether the data is crisp or fuzzy, so the appropriate assessment is made. In the case study discussed in this paper, we applied the proposed fuzzy VoI methodology to the data set available and identified uncertainties with the highest potential for information acquisition, subsequently evaluating its necessity.

The main contribution of the work can be summarized as follows:

- it has been identified that there are situations found in the oil and gas industry where the VoI is impacted not only by the uncertainty associated with our lack of knowledge on the project input variables but also by the imprecision associated with the outcomes of the data proposed to be acquired;
- fuzzy data modelling is proposed to integrate the data imprecision into the VoI assessment;
- practical application of the methodology is shown using an oil and gas case study project.

The proposed methodology has been applied on a case study where wells productivity depends on one predictor, the oil column thickness; based on the wells information available. No other predictor has been found to be associated with the productivity of the wells. However, it is desirable to have more than one predictor associated with the objective function before making decisions involving significant budgets. This methodology can be similarly applied to cases where the objective functions that define the value of the project depend on more than one predictors – for instance, the internal pressure of the liquid in the reservoir, the reservoir's capacity, the subsurface ground conditions, and the like.

The future work will address the problem of applying Fuzzy Inference Systems in a more general VoI assessment.

REFERENCES

[1] Howard, R. (1966). Decision Analysis: Applied Decision Theory. The Proceedings of the Fourth International Conference on Operational Research, ed. D. B. Hertz and J. Melese. New York: John Wiley & Sons, Inc

[2] Raiffa, H. (2007). A Personal Account of How it got started and evolved. Advances in Decision Analysis. Cambridge University Press, 1st Edition. pp. 1-17.

[3] Barros, E., Jansen, J., Van den Hof, P. (2015). Value of information in parameter identification and optimisation of hydrocarbon reservoirs. Internation Federation of Automatic Control, PapersOnLine, **48-6** (2015), pp. 229-35. DOI: 10.1016/j.ifacol.2015.08.036.

[4] Santos, S., Gaspar, A., Schiozer, D. (2017). Value of information in reseervoir development projects: Technical indicators to prioritize uncertainties and information sources. Journal of Petroleum Science and Engineering, **157** (2017), pp. 1179-91. DOI: 10.1016/ j.petrol.2017.08.028.

[5] Grayson, C.J. (1960). Decision Under Uncertainty; Drilling Decisions by Oil and Gas Operators. Harvard University. Division of Research. Graduate School of Business. Boston, USA. First Edition.

[6] Raiffa, H., Schlaifer, R. (1961). Applied Statistical Decision Theory. Division of Research, Graduate School of Business Administration, Harvard University, Boston, USA. Third Edition.

[7] Newendorp, P. (1967). Application of Utility Theory to Drilling Investment Decisions. Ph.D. Dissertation, Department of Engineering, University of Oklahoma, USA.

[8] Demirmen, F. (1996). Use of Value of Information Concept in Justification and Ranking of Subsurface Appraisal. Paper SPE 36631 presented at the Society of Petroleum Engineers, Annual Technical Conference, and Exhibition, Denver, Colorado, USA, 6–9 October.

[9] Newendorp, P. and Schuyler, J. (2000). Decision Analysis for Petroleum Exploration, 2nd Edition, Planning Press, USA.

[10] Wang, B.,. Wang, X., Chen, Z. (2013). A hybrid framework for reservoir characterisation using fuzzy ranking and an artificial neural network. Computers & Geoscience, **57** (2013), pp. 1-10. DOI: 10.1016/ j.cageo.2013.03.016.

[11] Clemen, R. (1996). Making Hard Decisions. Duxbury Press. Second Edition. California, USA

[12] Coopersmith, E.M., and Cunningham, P.C. (2002). A Practical Approach to Evaluating the Value of Information and Real Option Decisions in the Upstream Petroleum Industry. Paper SPE 159587 presented at the Society of Petroleum Engineers, Annual Technical Conference and Exhibition, San Antonio, Texas, USA, 29 September–2 October.

[13] Suslick, S., Schiozer, D. (2004). Risk Analysis Applied to Petroleum Exploration and Production: An Overview. Journal of Petroleum Science and Engineering, Vol 44, n.2, pp.1-9.

[14] Chen, B., He, J., Wen, X.-H., Chen, W., Reynolds, A. (2017). Uncertainty qualification and value of information assessment using proxies and Markov chain Monte Carlo method for a pilot project.

Journal of Petroleum Science and Engineering, **157** (2017), pp. 328-39. DOI: 10.1016/ j.petrol.2017.07.039.

[15] Aliyarov, R. Y., Ramazanov, R. A. (2016). Prediction of multivariable properties of reservoir rock by using fuzzy clustering. Proceedings of the 12th International Conference on Applications of Fuzzy Systems and Soft Computing, August 2016, Vienna, Austria. Procedia Computer Science, 102 (2016), pp. 434-40. DOI: 10.1016/j.procs.2016.09.423.

[16] Malakhov, A., Kopyriulin, P., Petrovski, S., Petrovski, A. (2012). Adaptation of Smart Grid Technologies: The use of Computational Intelligence for reliability estimation and maintenance schedule. Proceedings of the World Congress on Computational Intelligence, WCCI 2012, Brisbane, Australia. FUZZ IEEE, Cat. #: CPF12FUZ-USB, pp. 934-39. DOI: 10.1109/FUZZ-IEEE.2012.6251193

[17] Ross, T. (2010). Fuzzy Logic with Engineering Applications. Third Edition. John Wiley & Sons, Chichester, West Sussex, United Kingdom.