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Abstract: Decision-making support (DMS) methods are widely used for technical, economic, social and environmental assessments within different energy sectors, including upstream oil and gas, refining and distribution, petrochemical, power generation, nuclear power, solar, biofuels, and wind. The main aim of this paper is to present a comprehensive literature review and classification framework for the latest scholarly research on the application of DMS methods in the upstream oil and gas industry. To achieve this aim, a systematic review is conducted on the current state-of-the-art and future perspectives of various DMS methods applied to different upstream operations (such as exploration, development and production) which take place prior to shipping of crude oil and natural gas to the refineries for processing. Journal and conference proceeding sources that contain literature on the subject are identified, and based on a set of inclusion criteria the related papers are selected and reviewed carefully. A framework is then proposed to classify the literature according to the year and source of publications, type of fossil fuel sources, oil and gas field's lifecycle phases, data collection techniques, decision-making methods, and geographical distribution and location of case studies. The proposed literature classification and content analysis can help upstream oil and gas industry stakeholders such as field owners, asset managers, service providers, policy makers, environmentalist, financial analyst, and regulatory agencies to gain better insight about their business activities with well-informed decision-making processes.

Decision Support Methods and Applications in the Upstream Oil and Gas Sector

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Abstract

Decision-making support (DMS) methods are widely used for technical, economic, social and environmental assessments within different energy sectors, including upstream oil and gas, refining and distribution, petrochemical, power generation, nuclear power, solar, biofuels, and wind. The main aim of this paper is to present a comprehensive literature review and classification framework for the latest scholarly research on the application of DMS methods in the upstream oil and gas industry. To achieve this aim, a systematic review is conducted on the current state-of-the-art and future perspectives of various DMS methods applied to different upstream operations (such as exploration, development and production) which take place prior to shipping of crude oil and natural gas to the refineries for processing. Journal and conference proceeding sources that contain literature on the subject are identified, and based on a set of inclusion criteria the related papers are selected and reviewed carefully. A framework is then proposed to classify the literature according to the year and source of publications, type of fossil fuel sources, oil and gas field's lifecycle phases, data collection techniques, decision-making methods, and geographical distribution and location of case studies. The proposed literature classification and content analysis can help upstream oil and gas industry stakeholders such as field owners, asset managers, service providers, policy makers, environmentalist, financial analyst, and regulatory agencies to gain better insight about their business activities with well-informed decision-making processes.

Keywords

Decision-making; Asset management; Decision support system (DSS); Upstream Oil and gas.

1. Introduction

Despite the unprecedented increase in the use of renewables - wind, solar, biofuels, hydro, waste, geothermal and tidal energy - to support electricity generation in the last decade, many countries still produce significant amount of energy from burning fossil fuels, mainly crude oil, coal, and natural gas. According to a recent report published by the World Energy Council (2017), oil remains the world's leading fuel, accounting for about one-third of global energy consumption, followed by coal and natural gas with around %29 and %24 respectively. The oil and gas industry is divided into three major sectors of upstream, midstream, and downstream. The upstream sector is the most capital-intensive and important segment of the three in the oil and gas business, as this is where crude oil and natural gas are produced. The upstream oil and gas includes all activities related to the exploration and extraction of crude oil and natural gas which take place prior to shipping products to the refineries for processing.

Over the past four decades, the upstream oil and gas industries have applied various ways of well-informed business decision-making to increase production volume, reduce costs, improve safety, enhance operational performance, and protect the environment. Many of the decision-making problems in upstream oil and gas sector are complex in nature, involve uncertainties and risks, and require significant input from practitioners and policy-makers. The concept of decision analysis was first applied in the 1960s to solve oil and gas 'exploration' problems in the upstream sector (Huang *et al.*, 1995). Since then, the concept has been used in decision-making for a number of other important areas such as field development, production, maintenance of wells and facilities, life extension and decommissioning, etc. (Animah and Shafiee, 2018).

In recent years, a spectrum of qualitative and quantitative decision-making support (DMS) methods has been proposed in the literature to assist stakeholders in the upstream oil and gas sector to better understand reservoir characteristics, simulate field operations, develop low carbon production technologies, and make justifiable business decisions regarding exploration and development of both green and brown fields. As stated in Bratvold *et al.* (2009), DMS methods can help practitioners not only in performing technical and diagnostic tests of equipment but also in complying with regulatory and risk management requirements. Typical DMS methods used within the upstream sector include: operational research methods such as linear programming, integer programming, and goal programming; economic analysis methods such as cost-benefit analysis (CBA), real options analysis (ROA), and life cycle costing (LCC); statistical methods such as probabilistic approaches, simulation-based methods, and decision tree analysis (DTA); and environmental assessment methods such as environmental life cycle assessment (ELCA).

Strantzali and Aravossis (2016) indicated that the use of single-criterion approaches have historically dominated decision-making in the upstream oil and gas sector. However, given the complexity and conflicting interests of involved actors in the decision making process, the use of multi-criteria evaluation techniques is gaining momentum. Such techniques are able to consider simultaneously multiple attributes of different decision-making problems in the upstream sector (such as selecting the best drilling techniques and vessels, choosing the most appropriate maintenance strategies for different systems and components on oil and gas platforms, determining the most environmentally friendly end-of-life strategies for wells, identifying the most viable decommissioning processes for facilities, etc.). Moreover, in order to account for uncertainties associated with practitioners' subjective perception and experience in decision-making, soft computing methods such as fuzzy set theory, rough set theory, artificial intelligence (AI), and neural networks (NN) are increasingly becoming popular.

Despite the growing use of decision analytics approaches in upstream, midstream, and downstream oil and gas sectors in recent years, the literature on classification of the methods employed to support the decision-making processes in these sectors has been very limited (Deore, 2012). This paper aims to conduct a systematic review on the current state-of-the-art and future perspectives of the application of various DMS methods in the upstream oil and gas industry. The review is based on an exhaustive assessment of the studies identified in relation to the topic, including scholarly articles in refereed academic journals and conference proceedings between the years 1977 and 2016. A framework is also proposed to classify the literature according to the year and source of publication, type of fossil fuel source, oil and gas field development phase, data collection technique, decision-making method, and geographical location of the case studies. The findings of this review can be very useful to upstream oil and gas industry stakeholders, including field owners, asset managers, service providers, policy makers, environmentalist, financial analyst, and regulatory agencies to gain current state-of-the-art knowledge about well-informed decision-making, find out how to determine the most effective DMS method for each problem, and to identify real-life applications and case studies.

The structure of the paper is organized as follows. In Section 2, the most commonly used decision-making support methods in the oil and gas industry, and in particular the upstream sector, are introduced. The review methodology as well as the classification framework are presented in Section 3, and the observation and findings of the classification process are reported in details in Section 4. Finally, the concluding remarks and future research directions are given in Section 5.

2. Decision-making support (DMS) methods

The most commonly used decision-making support (DMS) methods in the oil and gas industries include operational research (OR), cost-benefit analysis (CBA), real options analysis (ROA), life cycle costing (LCC), environmental life cycle assessment (ELCA), Monte-Carlo simulation (MCS), decision tree analysis (DTA), multi-criteria decision analysis (MCDA), fuzzy logic analysis (FLA) and artificial intelligence (AI). In what follows, a brief description of these methods and their application to the upstream sector are presented.

2.1 Operational research (OR)

OR models include a model representing the logical and mathematical relationships between variables, an objective function with which alternative solutions are evaluated, and constraints that restrict solutions to feasible values. This mathematical model can be either a linear programming (LP) or a non-linear programming (NLP) problem. In LP, all objectives and constraints are linear functions, however, in NLP, at least one of constraints or the objective function is a non-linear function. The decision variables of an OR model can be continuous, or integer, or a mixture of both. Integer programming (LP) is a model whose all variables are constrained to take integer values, whereas in mixed-integer programming (MIP) only some of the decision variables are required to have integer values.

Goal programming (GP) is a relatively new OR model that has been proposed as an approach for the analysis of problems involving multiple, conflicting objectives. The basic approach of GP is to specify an aspiration level for each of the objectives and then seek a solution that minimizes the weighted sum of deviations of these objective functions from their respective goals. GP problems, depending on the type of their mathematical model, can be solved by either LP, NLP, IP or MILP.

2.2 Cost-benefit analysis (CBA)

CBA concept offers decision-makers the opportunity to evaluate the economic viability of different technologies, projects and policies. A key strength of this approach is that it provides results that are compatible to market mechanisms. CBA evaluation process involves summing up the equivalent money value of present costs of a project or policy and compare the result with the present value of benefits in order to ascertain if the project or policy is worthwhile. A project or policy is considered beneficial if the sum of its benefits becomes greater than the sum of its costs or when the benefit to cost ratio is greater than one.

2.3 Real options analysis (ROA)

One of the limitations of the CBA approach is that not all costs or benefits (e.g. cost of human injury/death) of a project or policy can be expressed in monetary equivalents (Hammond, 1966). For this reason, those decision-making outcomes that cannot be easily assigned a monetary value may introduce a level of uncertainty into cost or benefit calculations, hence restricting the applicability of the CBA method. ROA, also termed as real options valuation (ROV), is an extension of CBA approach that can be used for evaluating the value of options associated with a decision under uncertainty. The tool can help stakeholders decide on investments that might be delayed, expanded, abandoned, or repositioned. ROA is useful for the analysis of investment projects in the upstream sector, such as the development of oil fields (Jafarizadeh and Bratvold, 2009; Silitonga, 2015). Oil field development projects are an example of multiyear investment that is subject to many uncertainties during the whole lifetime of the project. The ROA approach involves the following steps: (1) create the structure for the problem, (2) develop a model of the decisions, uncertainties, and outcomes over time, (3) gather data for estimating outcome values in each scenario, and (4) perform analysis comparing alternatives and identifying action plans.

2.4 Life cycle costing (LCC)

The LCC analysis concept was originally introduced by the U.S. Department of Defence (DoD) in the 1970s (Ghosh *et al.*, 2018) to assist stakeholders and decision makers in conducting systematic assessment of costs of a project or policy. Since then, it has been applied to a wide variety of projects in different industries including oil and gas energy (Fuller and Peterson, 1996). This approach has helped upstream oil and gas stakeholders improve systems/components design, prioritize capital-intensive exploration activities, support comparative assessment of two or more investment projects, optimize operation and maintenance (O&M) strategies, determine whether life-extension is a viable consideration when production equipment reach end of their lives, etc.

In contrast to CBA, the LCC method calculates all direct costs associated with a project or a policy without taking indirect costs (or benefits) into account. The evaluation process involves the summation of discounted cash flows that accrue cost elements over the life cycle of a project/asset/policy with an appropriate discount rate. Over the last few years, the LCC method has evolved with life cycle cost-benefit (LCCB) and activity-based life cycle costing (AB-LCC) analysis approaches (for more see Thoft-Christensen, 2012; Animah *et al.*, 2018). The disadvantage of the LCC approach is similar to those associated with the CBA method. Thoft-christensen (2008) indicated the high discount rate set by different countries may render this approach inaccurate.

2.5 Environmental life cycle assessment (ELCA)

ELCA is a holistic and integrated approach for overall assessment of environmental compatibility of a project, policy, an activity or a product over its whole life cycle. The ELCA of a product comprises a "cradle-to-grave" assessment by considering the environmental consequences of various phases of the product life cycle, including: raw material acquisition phase, design/development phase, manufacturing phase, distribution phase, O&M phase, and end-of-life phase (Jacquemin *et al.*, 2012).

Conducting a ELCA study in the upstream oil and gas industry can help field owners better understand the material usage as well as environmental performance (such as emission of greenhouse gases, including CO_2, CH_4, N_2O, H_2S, etc.) of various upstream operations (exploration and production). For more details on ELCA applications in the upstream oil and gas sector, readers can refer to the following references: Aycaguer *et al.* (2001); Goodwin *et al.* (2012); Garg *et al.* (2013).

2.6 Monte-Carlo simulation (MCS)

MCS is a computerized mathematical method that relies on repeated random sampling and statistical analysis to obtain numerical results. In this method, the likelihood of occurrence of events are sampled at random from a probability distribution which is chosen based upon the type of problem under investigation. Each discrete sample set is referred to as an iteration and the resulting outcome from the calculations for that sample is recorded. This process will be repeated hundreds or thousands of times to obtain an estimate of mean probability of occurrence of the event. The accuracy of the estimate is dependent on the number of iterations performed. MCS has been vastly used in many applications within the upstream oil and gas The applications include risk assessment, reservoir evaluation, hydraulic fracturing of wells, and enhanced recovery processes (Macmillan, 2000).

2.7 Decision Tree analysis (DTA)

DTA uses graphical models to represent the sequence of decisions, events and their anticipated outcomes (Dey, 2002). The analysis is structured in a form of a tree with branches representing the possible action-event combinations. The conditional payoffs are obtained for each decision by considering various action-event combinations. The DTA method is appropriate when decision-making procedures are multi-stage, e.g. when an event takes place over a sequence of stages. This makes the DTA method logically structured and suitable for decision-making problems (Dey, 2012). According to Cheldi *et al.* (1997), DTA is used in the oil and gas industry mainly for quantitative risk assessment. One important feature of the DTA method is the calculation of expected monetary value (EMV), which is used as the basis to compare different decision options and choose the best one.

2.8 Multi-criteria decision analysis (MCDA)

MCDA method is one of the popular and commonly used DMS methods in the oil and gas energy industry. This method is increasingly becoming popular for decision-making in the upstream sector because the conventional single-criterion decision-making approaches cannot deliver appropriate results considering the complexity of field exploration and development activities. The MCDA method provides a flexible approach to solve complex problems with multiple attributes (e.g. technical, economic, social, legal and environmental) by helping stakeholders to make clear and consistence decisions.

Up to date, several MCDA methods have been developed for solving complex decision-making problems in the oil and gas industry. The most widely used MCDA methods include: Weighted Sum Model (WSM), Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Multi-Attribute Utility Theory (MAUT), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Preference Ranking Organization Method Of

Enrichment Evaluation (PROMETHEE), Elimination and Choice Expressing Reality (ELECTRE), Vlsekriterijumska Optimizacija I KOmpromisno Resenje (VIKOR). A brief discussion of each of these methods, with an attempt to highlight advantages and disadvantages, follows.

2.8.1 Weighted sum model (WSM)

This is the best known and simplest MCDA method (Shafiee, 2015a). WSM is also referred to as the simple addictive weighting (SAW) in the literature as it is suitable for handling single dimensional problems. The fundamental principle behind this method is to determine weighted sum of rating for each alternative considered in decision analysis. According to Kabir *et al.* (2014), to apply WSM correctly, all criteria should be single dimensional, i.e. cost-type or benefit-type. For this reason, Caterino *et al.* (2009) suggested that WSM is not efficient for solving complex decision-making problems which involve different types of criteria and decision variables.

2.8.2 Analytic hierarchy process (AHP)

The analytical hierarchy process (AHP) was developed by Saaty (1980) and since then this method has been applied to solve complex problems in various industries including oil and gas. The method helps decision makers to break down complex decision-making problems into hierarchical structure with goal at the top, followed by criteria, sub-criteria and alternatives (Zio, 1996). In AHP, to select the best alternative, decision-maker performs pairwise comparison of evaluation criteria and alternatives and then test the consistency of the pairwise comparison by computing an index called consistency ratio (CR). The weight for pairwise comparison is obtained using Saaty's fundamental scale of 1-9, where 1 indicates equal importance, 3 moderate importance, 5 strong importance, 7 very strong importance, and 9 indicates extreme importance. The values of 2, 4, 6, and 8 are assigned to indicate compromise values of importance.

2.8.3 Analytic network process (ANP)

The analytical network process (ANP) is a generalized form of the AHP method, but the difference is that in contact to AHP, the basic structures of ANP are networks. This is because AHP has been criticized for structuring the decision-making problems in hierarchical manner (Meade and Presley, 2002; Shafiee, 2015b). Also, Saaty (1996) suggested the use of ANP for solving the problems in which there is dependence between alternatives or criteria.

2.8.4 Multi-Attribute Utility Theory (MAUT)

This MCDA method takes into account the decision makers' preferences as a utility function for a set of possible attributes associated with alternatives. The best alternative is the one that maximizes the decision-makers' expected utility function. With respect to single attribute utility, the utility function can either be separated additively or multiplicatively (Pohekar and Ramachandran, 2004).

2.8.5 Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS is a useful MCDA method for ranking and selection of alternatives based on distance measures. The basic concept of this method is that the selected alternative should have the shortest geometric distance from the positive ideal solution and the longest geometric distance from the negative ideal solution. The TOPSIS method ranks alternatives in ascending or descending order of preference, which makes it easier to identify the best solution. Thus, decision makers' preference order of alternatives is obtained through comparison of Euclidean distances (Pohekar and Ramachandran, 2004).

2.8.6 Preference Ranking Organization Method Of Enrichment Evaluation (PROMETHEE)

PROMETHEE was developed by Brans and Vincke (1985) to outrank a set of finite alternatives with respect to conflicting criteria and then select the best alternative. The PROMETHEE method uses positive and negative preference flows for different alternatives in order to produce ranking in relation to decision weights (Kabir *et al.*, 2014). There are different methods of PROMETHEE described in the literature, including PROMETHEE I (partial ranking), PROMETHEE II (complete ranking), PROMETHEE III (ranking based on intervals), PROMETHEE IV (continuous case), PROMETHEE V (PROMETHEE II and integer linear programming), PROMETHEE VI (weights of criteria are intervals) and PROMETHEE GAIA (graphical representation of PROMETHEE) (Silva *et al.*, 2010). The most popular and commonly used techniques among the family of PROMETHEE methods include PROMETHEE I and PROMETHEE II & II (Emovon *et al.*, 2018). According to Vinodh and Jeya Girubha (2012) PROMETHEE II is applied to rank alternatives because it establishes a complete ranking or pre-order of alternatives.

2.8.7 Elimination and Choice Expressing Reality (ELECTRE)

ELECTRE uses an indirect method to rank alternatives by means of pair comparison under each criteria (Cheng *et al.*, 2002). Several versions of the ELECTRE method have been developed since its conception in the mid-1960s (Kabir *et al.*, 2014), with ELECTRE TRI and ELECTRE III being the most popular and commonly used methods among the family of ELECTRE methods. One of the key strength of ELECTRE is its applicability even when there is missing information.

2.8.8 Vlsekriterijumska Optimizacija I KOmpromisno Resenje (VIKOR)

VIKOR is a compromising MCDA method that determines compromise ranking of alternatives (Zeleny and Cochrane, 1982). The main objective of using this method is to select a suitable alternative that is possibly close to the ideal solution. It introduces a multi-criteria ranking index based on the particular measure of 'closeness' to the 'ideal' solution

(Sayadi *et al.*, 2009). The distance measure used in the VIKOR method is a family of L_p-metrics that is used as an aggregation function in a compromise programming.

2.9 Fuzzy logic analysis (FLA)

FLA is a powerful methodology which was introduced by Zadeh (1965) to deal with uncertainties in human judgments during decision-making. In FLA, fuzzy sets rather than crisp sets are used to determine the membership of a variable. Fuzzy sets are often presented by linguistic terms such as 'low temperature', 'high pressure', etc. In general, the output of a FLA is a fuzzy set expressed as a distribution of possibilities. FLA has been successfully applied in many different areas of upstream oil and gas sector, including reservoir characterization, drilling, permeability and rock type estimation, petroleum separation, and hydraulic fracturing (see Zoveidavianpoor *et al.*, 2012).

2.10 Artificial intelligence (AI)

AI is defined as the theory and development of computer systems able to support decision-making processes that normally require human intelligence. In other words, AI is the use of computer algorithms to attempt to replicate the human ability to learn, reason and make decisions. AI includes a wide range of techniques such as artificial neural networks (ANN), generic algorithm (GA), support vector machine (SVM), etc. Applications of AI tools in various operations of the upstream oil and gas sector can be found in the literature (see Mohaghegh and Khazaeni, 2011). For instance, for drilling decision-making the readers can refer to Bello *et al.* (2016), and for further details about oil production forecasting the readers are recommended to read Sheremetov *et al.* (2013).

2.11 Hybrid decision analysis methods

Hybrid decision analysis methods such as hybrid MCDA methods, combined MCDA and fuzzy logic methods, etc. are a powerful group of DMS methods which can assist decision-makers in handling miscellaneous information, divergence in stakeholders' preferences, interconnected or contradicting criteria, and uncertain environments (Dinmohammadi and Shafiee, 2017).

2.11.1 Hybrid MCDA methods

Majority of the classical MCDA methods have practical limitations. In order to improve their strengths and eliminate their weaknesses, some hybrid MCDA models have been developed in the literature, e.g. SWM-AHP, ANP-TOPSIS. A hybrid MCDA method is an effective decision-making method which involves the integration of two or more appropriate MCDA methods for solving complex and multi-attribute problems. By this integration, limitations of one method can be offset by strengths of the other method.

2.11.2 Combined MCDA and fuzzy logic method

MCDA methods can be categorized into two types of crisp and fuzzy models (Shafiee, 2015a). The crisp MCDA models express the importance weights of criteria using crisp numbers. However, it is sometimes difficult to provide precise numerical values for evaluation criteria due to the uncertainty and vagueness in real-life decision-making processes. The fuzzy MCDA models express the preferences of relative importance between criteria by linguistic terms and then set them into fuzzy numbers such as triangular or trapezoidal fuzzy numbers. A triangular fuzzy number is a fuzzy number whose membership function is defined by three real numbers, expressed as (l, m, u), where the function is first linearly increasing form point [l, 0] to [m, 1] and then linearly decreasing to [u, 0]. m is called the modal value, and l and u denote the right and left boundary respectively.

3. Review methodology and classification framework

In order to identify the available literature regarding the application of different DMS methods in the upstream oil and gas industry, a systematic review was conducted. The literature review covered all the studies published by scholars and practitioners throughout the world in relevant journals and conference proceedings in English language between the years 1977 and 2016.

The literature was identified from different databases such as Scopus, Web of Science, Onepetrol, Knovel, IEEE Xplore, American Society of Mechanical Engineers (ASME) digital collection and Google scholar, and the related articles were selected based on a set of inclusion criteria. The above indexing databases were selected due to their broad coverage of scientific peer-reviewed journal articles as well as conference papers. Several keywords and phrases such as "decision-making", "upstream petroleum", "oil and gas", "decision analysis", "methods", "techniques" in different combinations were used to identify the existing literature. The keyword search resulted in a total of 129 papers. The title and abstract of each paper were then reviewed to assess their relevance to the topic. After reviewing the titles and abstracts, 19 papers were discarded due to their irrelevance to the subject area and eventually, 110 papers were selected for inclusion in this study. These papers are: Korn *et al.* (1978); Sprowso *et al.* (1979); Jentsch Jr and Marrs (1988); Balen *et al.* (1988); Methven (1993); Roosmalen *et al.* (1993); Songhurst and Kingsley (1993); Dear *et al.* (1995); Heinze *et al.* (1995); Smith and Celant (1995); Lassen and Syvertsen (1996); Harding (1996); Winkel (1996); Cheldi *et al.* (1997); Smith *et al.* (1997); Iyer *et al.* (1998); Joshi *et al.* (1998); Poremski (1998); Denney (1999); Gatta (1999); Mudford (2000); Tague and Hollman (2000); Aycaguer *et al.* (2001); Erdogan *et al.* (2001); Gerbacia and Al-Shammari (2001); Goldsmith *et al.* (2001); Paula *et al.* (2001); Suslick and Furtado (2001); Suslick *et al.* (2001); Begg *et al.* (2002); Castro *et al.* (2002); Denney (2002); Finch *et al.* (2002); Balch *et al.* (2003); Cullick *et al.* (2003); El-Reedy (2003); Joshi (2003); Chitwood *et al.* (2004); Ferreira *et al.* (2004); Vorarat *et al.* (2004); Hegstad *et al.* (2005); Islam and Powell (2005); Brainard

(2006); Cullick *et al.* (2007); Lev and Murphy (2007); Moan (2007); Bahmannia (2008); Ghazi *et al.* (2008); Kayrbekova and Markeset (2008); Liu and Ford (2008); Orimo *et al.* (2008); Virine (2008); Zhu and Arcos (2008); Abhulimen (2009); Bybee (2009); Gomez *et al.* (2009); Jafarizadeh and Bratvold (2009); Li *et al.* (2009); Verre *et al.* (2009); Kayrbekova and Markeset (2010); Ratnayaka and Markeset (2010); Pinturier *et al.* (2010); Angert *et al.* (2011); Chen *et al.* (2011); Gong *et al.* (2011); Kayrbekova *et al.* (2011); Nam *et al.* (2011); Ortiz-Volcan and Iskandar (2011); Stephenson *et al.* (2011); Streeter and Moody (2011); Burnham *et al.* (2012); Goodwin *et al.* (2012); Grosse-Sommer *et al.* (2012); Schulze *et al.* (2012); Shrivastva *et al.* (2012); Weber and Clavin (2012); Zoveidavianpoor *et al.* (2012); Burlini and Araruna (2013); Hernandez *et al.* (2013); Lopes and Almeida (2013); Pettersen *et al.* (2013); Pierce and Wills (2013); Sheremetov *et al.* (2013); Trujillo *et al.* (2013); Fergestad *et al.* (2014); Fowler *et al.* (2014); Jeong *et al.* (2014); Kullawan *et al.* (2014); Lilien *et al.* (2014); Maddah *et al.* (2014); Marten and Gatzen (2014); Sandler *et al.* (2014); Siveter *et al.* (2014); Wright *et al.* (2014); Chilukuri *et al.* (2015); Chun *et al.* (2015); de Wardt and Peterson (2015); Ghani *et al.* (2015); Oruganti *et al.* (2015); Silitonga (2015); Zavala-Araiza *et al.* (2015); Adam and Ghosh (2016); Bello *et al.* (2016); Guedes and Santos (2016); Johannknecht *et al.* (2016a); Johannknecht *et al.* (2016b); Ortiz-Volcan *et al.* (2016); Seo *et al.* (2016); Shafiee *et al.* (2016); Steuten and Onna (2016).

The full text of each paper was reviewed carefully and a classification framework was presented to categorize the existing literature. As shown in Figure 1, the state-of-the-art of methods used to support decision-making in the upstream oil and gas industry can be classified according to the following attributes:

****Figure 1****

Figure 1. Classification framework for decision-making support methods applied to the upstream oil and gas sector.

- Year of publications (1977–1986, 1987–1996, 1997–2006, 2007–2016);
- Distribution of publications (type of publication, source of publication);
- Types of fossil fuel sources (conventional, non-conventional);
- Oil and gas field's lifecycle phases (exploration, development, production, life extension, abandonment/decommission);
- Data collection techniques (survey, direct measurement or observation, monitoring and data acquisition systems, others);
- Decision support methods (OR, CBA, ROA, LCC, ELCA, MCS, DTA, MCDA, FLA, AI, and Hybrid methods);
- Geographical distribution of case studies and their locations (Asia, South America, North America, Europe, Africa).

4. Review findings and classification results

In this section, the observation and findings of the review classification process are reported in details.

4.1 Distribution of studies based on year of publication

We divided the period of study into four equal decades of ten years each—1977 to 1986, 1987 to 1996, 1997 to 2006, and 2007 to 2016. Figure 2 depicts a bar chart representing the number of papers published about the application of DMS methods to upstream oil and gas operations during the past four decades.

**** Figure 2****

Figure 2. The number of publications during the past four decades.

As can be seen, there is a significant increase in the number of papers over the period of study. However, more than 60 percent of the studies have been published in the past ten years (2007-2016), which implies the increasing importance and usefulness of DMS methods in the upstream oil and gas sector.

4.2 Distribution of studies based on type of source of publications

Out of the 110 identified papers, there were thirty-two journal articles (~ 29%) (Jentsch Jr and Marrs (1988); Dear *et al.* (1995); Iyer *et al.* (1998); Denney (1999); Aycaguer *et al.* (2001); Suslick and Furtado (2001); Denney (2002); Finch *et al.* (2002); Ferreira *et al.* (2004); Moan (2007); Bybee (2009); Li *et al.* (2009); Ratnayaka and Markeset (2010); Kayrbekova *et al.* (2011); Nam *et al.* (2011); Stephenson *et al.* (2011); Burnham *et al.* (2012); Goodwin *et al.* (2012); Weber and Clavin (2012); Zoveidavianpoor *et al.* (2012); Lopes and Almeida (2013); Sheremetov *et al.* (2013); Fowler *et al.* (2014); Maddah *et al.* (2014); Marten and Gatzen (2014); Sandler *et al.* (2014); Ghani *et al.* (2015); Silitonga (2015); Zavala-Araiza *et al.* (2015); Guedes and Santos (2016); Johannknecht *et al.* (2016b); Shafiee *et al.* (2016)) and seventy-eight conference papers (~ 71%) (Korn *et al.* (1978); Sprowso *et al.* (1979); Balen *et al.* (1988); Methven (1993); Roosmalen *et al.* (1993); Songhurst and Kingsley (1993); Heinze *et al.* (1995); Smith and Celant (1995); Lassen and Syvertsen (1996); Harding (1996); Winkel (1996); Cheldi *et al.* (1997); Smith *et al.* (1997); Joshi *et al.* (1998); Poremski (1998); Gatta (1999); Mudford (2000); Tague and Hollman (2000); Erdogan *et al.* (2001); Gerbacia and Al-Shammari (2001); Goldsmith *et al.* (2001); Paula *et al.* (2001); Suslick *et al.* (2001); Begg *et al.* (2002); Castro *et al.* (2002); Balch *et al.* (2003); Cullick *et al.* (2003); El-Reedy (2003); Joshi (2003); Chitwood *et al.* (2004); Vorarat *et al.* (2004); Hegstad *et al.* (2005); Islam and Powell (2005); Brainard (2006); Cullick *et al.* (2007); Lev and Murphy (2007); Bahmannia (2008); Ghazi *et al.* (2008); Kayrbekova and Markeset (2008); Liu and Ford (2008); Orimo *et al.* (2008); Virine (2008); Zhu and Arcos (2008); Abhulimen (2009); Gomez *et al.* (2009); Jafarizadeh and Bratvold (2009); Verre *et* *al.* (2009); Kayrbekova and Markeset (2010); Pinturier *et al.* (2010); Angert *et al.* (2011); Chen *et al.* (2011); Gong *et al.* (2011); Ortiz-Volcan and Iskandar (2011); Streeter and Moody (2011); Grosse-Sommer *et al.* (2012);; Schulze *et al.* (2012); Shrivastva *et al.* (2012); Burlini and Araruna (2013); Hernandez *et al.* (2013); Pettersen *et al.* (2013); Pierce and Wills (2013); Trujillo *et al.* (2013); Fergestad *et al.* (2014); Jeong *et al.* (2014); Kullawan *et al.* (2014); Lilien *et al.* (2014); Siveter *et al.* (2014); Wright *et al.* (2014); Chilukuri *et al.* (2015); Chun *et al.* (2015); de Wardt and Peterson (2015); Oruganti *et al.* (2015); Adam and Ghosh (2016); Bello *et al.* (2016); Johannknecht *et al.* (2016a); Ortiz-Volcan *et al.* (2016); Seo *et al.* (2016); Steuten and Onna (2016)).

We also identified the sources of journals and conference proceedings in which the papers were published. It was found that the literature has been scattered among twenty-seven academic journals and thirty-eight conference proceedings. Among the journals, the "Journal of Petroleum Technology" – which is published by the Society of Petroleum Engineers (SPE) – contained the largest number of papers on the topic (4 papers). Furthermore, about 60 percent of the conference papers have been published in proceedings for the SPE oil and gas energy conferences, amongst which the SPE Annual Technical Conference and Exhibition with 8 papers is the most dominant event.

4.3 Distribution of studies based on fossil fuel sources

The upstream oil and gas sector involves the exploration and development of conventional fossil fuel reserves as well as unconventional fossil fuel deposits such as shale oil and gas. The U.S. Energy Information Administration (EIA) (https://www.eia.gov/) projected that shale gas production is expected to reach 90 billion cubic feet per day (Bcf/d) in 2040, which is more than twice current levels. However, the geological and technical approaches employed in the exploration and development of shale gas differ from those of the conventional oil and gas. Some of the important issues in the shale oil and gas sector that may require the use of DMS methods include the evaluation of cost of exploration, development and production, estimation of revenues, and the examination of the environmental impact of shale oil and gas production over the life span of a field.

Those studies that have discussed or applied different DMS methods to support the development of both conventional and unconventional fossil fuel sources in the upstream oil and gas sector were identified and reviewed. Out of 110 studies included in this review, only five papers (representing around 4.5 percent of all studies) addressed the decision-making processes regarding shale gas production and GHG emission effects, while the rest of the studies focused on decision-making aspects of the conventional fossil fuel sources. These five studies about the shale gas production and GHG footprint assessment are highlighted below:

Gong *et al.* (2011) presented a decline-curve-based reservoir model with a decision model to determine optimal development strategies in shale reservoirs by incorporating uncertainty in production forecasts. Stephenson *et al.* (2011) modelled the relative GHG emissions from both shale gas and conventional natural gas production. One of the key findings of the study was that the well-to-wire (WtW) emissions from conventional natural gas production were estimated to be approximately 1.8%-2.4% less than that of shale gas. Burnham *et al.* (2012) synthesized the current scientific knowledge on methane emissions from shale gas, conventional oil and gas as well as coal to estimate GHG emissions from different fossil fuel sources. The study further indicated that the combustion of natural gas produces significantly less GHG as compared to conventional coal and oil sources. In Weber and Clavin (2012), the upstream carbon footprint from both shale and conventional natural gas production was assessed and compared. The results showed that there was no significant difference in the upstream carbon footprint from these two types of natural gas production. Zavala-Araiza *et al.* (2015) used a life-cycle allocation method to assign methane emissions to natural gas and oil production from shale formations.

4.4 Distribution of studies based on oil and gas field's lifecycle phases

In this Section, the reviewed papers are classified according to the phases of oil and gas field lifecycle. The lifecycle, as shown in Figure 3, is divided into five phases of exploration, development, production, life extension, and abandonment/decommission. These lifecycle phases are briefly explained in the followings:

**** Figure 3****

Figure 3. The lifecycle phases of an oil and gas field.

- Exploration phase: This phase involves the search for economic and recoverable oil and natural gas deposits (either onshore or offshore) and includes detailed surface exploration, drilling and well testing.
- Development phase: The development phase occurs after exploration. The main activities during this phase include construction of production facilities, water injection and abandonment wells, an FPSO, subsea structures, etc., laying of flow lines and umbilicals, and installation of subsea systems for subsequent commencement of oil and gas production.
- Production phase: This phase employs various skills, advanced technologies and professionals to extract oil and gas products and subsequently separate two- or three-phase products into oil, gas, produced water and solid particles. The oil and natural gas products are then transported to the agreed delivery points either through the use of export lines or shuttle tankers in the case of offshore production. This phase also involves workover operations of production wells and maintenance of oil and gas production facilities which is carried out to ensure effective and efficient production.
- Life extension phase: This phase begins when oil and gas production facilities reach end of their original design lifetimes and the process of life extension is economically and

technically viable. Also, in some countries due to highly restrictive regulations on construction of new fields, companies use life extension as means to avoid phasing out existing fields. Life extension of oil and gas facilities delivers some benefits such as increased production, reduced capital expenditures (CAPEX) associated with constructing new facility, increased job creation, reduced CO_2 emissions, and lowered financial risk compared to risk of investing in greenfield project (Shafiee and Animah, 2017).

- Abandonment/Decommission: This phase represents the final stage of oil and gas field's lifecycle, taking place when production facilities are no longer safe or cannot produce economic quantities of oil and gas products. Oil and gas field abandonment is a critical and complex decision-making process which involves the use of DMS methods in terms of risk analysis, cost estimation, health and safety, and environmental assessment (Kaiser and Pulsipher, 2004). Typical decommissioning activities include well plugging, full removal of platforms, partial removal platforms, trenching and burial of pipelines, etc. (Koroma *et al.*, 2018).

Table 1 shows a detailed distribution of the published papers on the application of DMS methods in upstream oil and gas industry according to the phases of oil and gas field's lifecycle taken into consideration. Those publications which did not report the phase of lifecycle in the decision-making process were excluded from the table. As can be seen, the DMS methods have received the most attention during the development phase, followed by the production and exploration phases.

****Table 1****

Table 1. Distribution of studies according to the oil and gas field's lifecycle phases.

4.5 Distribution of studies based on data collection techniques

Decision-making in relation to the upstream oil and gas activities should be reliant on accurate data for the analysis. This means that the outcomes of a decision are dependent upon the quality of input data, hence making data collection an essential step of decision-making process in the upstream oil and gas sector. Applying the DMS methods to make effective decisions usually requires a database of cost information (e.g. cost of design, operation and maintenance (O&M), decommissioning, etc.), equipment failure mechanisms and root causes, degradation rates, environmental data (e.g. CO_{2eq} as a results of production and operation of equipment) as well as experts' opinions about the evaluating criteria. Without using high quality data, the results of decision-making may lead to inaccurate conclusions. In a study, Vorarat *et al.* (2004) discussed the data requirements for LCC analysis of oil and gas field projects.

Generally, the use of survey methods (including questionnaires, face-to-face or telephone interviews, or a combination of these) to obtain experts' judgement and knowledge is one of common data collection techniques in the oil and gas sector (Virine, 2008). Many researchers often consider survey techniques more subjective and, thus, less accurate than experimentally acquired data. Nevertheless, it still remains one of the popular ways of data collection for decision-making in the upstream oil and gas sector. Another means of obtaining data for decision-making is through direct measurement or observation (such as close visual inspection (CVI)). The data stored in monitoring databases or data acquisition systems is also another source for decision makers in the upstream oil and gas industry. Additionally, information from other primary/original sources such as published literature, company's reports, legislations of regulators, suppliers' databases, etc. is also used for decision analysis in the upstream sector.

Among the reviewed papers, Aycaguer *et al.* (2001) used data generated from the continuous monitoring of a process safety system to perform ELCA, in order to assess the benefits obtained from storing CO_2 in active reservoirs and its corresponding environmental impact over the process lifetime. Eight studies, including Gatta (1999), Bahmannia (2008), Abhulimen (2009), Pinturier *et al.* (2010), Nam *et al.* (2011), Kullawan *et al.* (2014), Sandler *et al.* (2014) and Ghani *et al.* (2015) have utilized data from published literature and handbooks.

In Jentsch Jr and Marrs (1988), Dear *et al.* (1995), Smith and Celant (1995), Gerbacia and Al-Shammari (2001), Islam and Powell (2005), Goodwin *et al.* (2012), Wright *et al.* (2014) and Shafiee *et al.* (2016), the information from industry was used as input to support ELCA and CBA analyses. Studies conducted by Johannknecht *et al.* (2016a) and Johannknecht *et al.* (2016b) collected data from previously commercialized products to develop a LCC toolkit. Ghazi *et al.* (2008) and Ratnayaka and Markeset (2010) combined different data collection techniques in their respective studies. Eight studies of Joshi *et al.* (1998), Suslick and Furtado (2001), Suslick *et al.* (2001), Li *et al.* (2009), Verre *et al.* (2009), Ortiz-Volcan and Iskandar (2011), Streeter and Moody (2011) and Sandler *et al.* (2014) applied data acquired from other projects/fields to support decision-making in the upstream oil and gas sector.

The rest of the publications failed to indicate the type of techniques used for collecting the data and hence were excluded from our analysis.

4.6 Distribution of studies based on DMS methods

In terms of the decision-making methods employed in the upstream oil and gas sector, all the one-hundred and ten identified publications were analysed and classified into various categories as follows:

- Operational research (OR)
- Cost-benefit analysis (CBA)

- Real options analysis (ROA)
- Life cycle costing (LCC)
- Environmental life cycle assessment (ELCA)
- Monte-Carlo simulation (MCS)
- Decision tree analysis (DTA)
- MCDA (WSM, AHP/ANP, MAUT, TOPSIS, PROMETHEE, ECLECTRE, VIKOR)
- Hybrid MCDA (when a study combines two or more MCDA methods);
- Fuzzy logic analysis (FLA)
- Others (when a decision-making method different from those mentioned above is used).

The distribution of the publications based on the method used to support decision-making in the upstream oil and gas is shown in Table 2. As can be seen, LCC method with 39 papers has received the most attention in the literature, followed by ELCA with 18 papers, CBA with 14 papers, DTA with 10 papers and MCDA methods with 10 papers. Another interesting observation from Table 2 is that the classical MAUT and AHP/ANP methods are the most popular MCDA methods to support decision-making in the upstream sector, whereas other MCDA methods such as WSM, TOPSIS, PROMETHEE, ELECTRE and VIKOR have not been extensively utilized. Moreover, our search revealed that only one study in the literature has used the fuzzy set theory approach.

****Table 2****

Table 2. Classification of studies based on decision-making methods.

Figure 4 shows a detailed distribution of various DMS methods applied to the upstream oil and gas sector during the past four decades.

****Figure 4****

Figure 4. Distribution of DMS methods applied to the upstream sector during the past four decades.

4.7 Distribution of studies based on geographical location of case studies

The results of our content analysis indicate that 38 out of 110 publications (i.e. about 34.5 percent of the total number of publications) have reported a case example of the application of DMS methods to the upstream oil and gas sector. Out of these 38 published works, 27 studies have mentioned the geographical location of the case study. Table 3 presents the aim and the geographical location and of the identified case studies around the world.

****Table 3****

Table 3. Distribution of studies based on geographical location of case studies.

As can be seen, the continents of North and South America have reported the largest number of case studies, accounting for 41 percent of the total number of publications. This is followed by the Middle East region and Asia with 30 percent of the publications. The North Sea which comprises the UK Continental Shelf (UKCS) and Norwegian Continental Shelf (NCS) account for 15 percent of the publications. Mediterranean Sea and West Africa regions also have been studied each in 7% of the case studies.

5. Concluding remarks and future research directions

Over the past four decades, a wide range of qualitative and quantitative decision-making support (DMS) methods have been developed in the literature to assist upstream oil and gas industry stakeholders to better understand reservoir characteristics, simulate field operations, develop low carbon production technologies, and make justifiable business decisions regarding field exploration, development and production activities. In this paper, we reviewed one hundred and ten studies (including 32 journal articles and 78 conference papers) about the use of different DMS methods in the upstream oil and gas industry. These studies were published by many scholars and practitioners throughout the world in twenty-seven academic journals and thirty-eight conference proceedings in English language between the years 1977 and 2016. The key issues of the subject area, including the type of DMS methods applied to support the decision-makers, the phases of oil and gas field's lifecycle considered in the analysis, data collection techniques, case study regions that have utilised DMS methods to solve the problem, etc. were highlighted and discussed.

As this study revealed, the number of publications related to the application of DMS methods in the upstream oil and gas industry have grown significantly over the past four decades. The analysis of the studies based on decision-making methods indicated that the operational research (OR) methods such as mixed integer programming (MIP), economic analysis methods such as cost-benefit analysis (CBA), real options analysis (ROA) and life cycle costing (LCC), statistical methods such as Monte Carlo simulation (MCS) and decision tree analysis (DTA); and environmental assessment methods such as environmental life cycle assessment (ELCA) have received the most attention in the literature. However, the use of multi-criteria decision analysis (MCDA) methods such as analytic hierarchy process (AHP) and analytic network process (ANP) have been gaining momentum in recent years. Such methods are able to consider simultaneously multiple technical, economic, social, legal and environmental attributes of decision-making problems in the upstream sector. Moreover, in order to account for uncertainties associated with practitioners' subjective perception and experience in decision-making, soft computing methods such as fuzzy set theory, rough set theory, artificial intelligence (AI), and neural networks (NN) have become popular.

The findings of this literature review and the results of the proposed classification scheme offer interesting conclusions that could be useful to field owners, asset managers, service providers, policy makers, environmentalist, financial analyst, and regulatory agencies to gain better insight about their business activities with well-informed decision-making processes, find out how to determine the most effective DMS method for each problem, and to identify real-life applications and case studies. However, there is still large scope of research on the use of decision analytics modelling in the upstream, midstream and downstream oil and gas sectors. Some of the potential directions for future research are listed below:

1. When comparing the number of studies that have used DMS methods to support decision analysis of exploration, development and production activities of conventional and unconventional fossil fuel sources, it was realised that unconventional fossil fuel (such as shale oil and gas) has received very little attention in the literature. Hence, further research works can be conducted on various aspects of decision-making for the exploration, development and production of shale oil and gas.
2. It was found from this review that all the studies in relation to unconventional fossil fuel sources utilized ELCA method to estimate GHG footprint of shale gas production. Nevertheless, the development and production of shale gas present huge economic opportunities and it will be of great interest if future research work can use other decision analytics methods to estimate the economic potential of shale gas projects.
3. The majority of the DMS methods identified in this study were data-driven and required good quality data so that decisions could be made with high degree of confidence. However, the paucity of good quality data is still considered as a challenge in the upstream oil and gas sector. In order to overcome this challenge, there is an essential need for the stakeholders to define measures, procedures, and data collection platforms capable of providing decision makers with appropriate information to make suitable decisions.
4. Our findings indicated that decision-making tools such as LCC, ELCA, CBA, DTA, MCS and ROA have received good attention in industrial case studies. However, MCDA methods and also hybrid decision analysis methods have rarely been reported to be applied to real-case projects in the upstream oil and gas sector.
5. Despite the wide application of AHP/ANP methods to solve decision-making problems in the upstream oil and gas industry, the literature on the use of other MCDA methods such as TOPSIS, PROMETHEE, ELECTRE, VIKOR and fuzzy MCDA techniques is very limited.
6. Life extension and field abandonment/decommission are the current challenges facing the upstream oil and gas sector. This is because significant number of facilities supporting operations in the upstream oil and gas sector are approaching or have already exceeded their original design lifetimes and asset managers have to make a decision between life extension and decommissioning. However, very few research studies have used DMS methods to address the challenges of life extension and/or decommissioning

decision-making in the oil and gas industry (Shafiee and Animah, 2017). Therefore, future work must direct efforts at applying DMS to address the challenges during life extension and decommission phase of asset life cycle in the upstream oil and gas sector.

7. This review revealed that the West Africa region, though produces a sizeable amount of the crude oil and natural gas, has reported the least number of case studies about the application of DMS method to provide robust solutions for exploration, development and production activities. Therefore, further researches can be conducted about this region in the future.

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Decision Support Methods and Applications in the Upstream Oil and Gas Sector

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Abstract

Decision-making support (DMS) methods are widely used for technical, economic, social and environmental assessments within different energy sectors, including upstream oil and gas, refining and distribution, petrochemical, power generation, nuclear power, solar, biofuels, and wind. The main aim of this paper is to present a comprehensive literature review and classification framework for the latest scholarly research on the application of DMS methods in the upstream oil and gas industry. To achieve this aim, a systematic review is conducted on the current state-of-the-art and future perspectives of various DMS methods applied to different upstream operations (such as exploration, development and production) which take place prior to shipping of crude oil and natural gas to the refineries for processing. Journal and conference proceeding sources that contain literature on the subject are identified, and based on a set of inclusion criteria the related papers are selected and reviewed carefully. A framework is then proposed to classify the literature according to the year and source of publications, type of fossil fuel sources, oil and gas field's lifecycle phases, data collection techniques, decision-making methods, and geographical distribution and location of case studies. The proposed literature classification and content analysis can help upstream oil and gas industry stakeholders such as field owners, asset managers, service providers, policy makers, environmentalist, financial analyst, and regulatory agencies to gain better insight about their business activities with well-informed decision-making processes.

Keywords

Decision-making; Asset management; Decision support system (DSS); Upstream Oil and gas.

1. Introduction

Despite the unprecedented increase in the use of renewables - wind, solar, biofuels, hydro, waste, geothermal and tidal energy - to support electricity generation in the last decade, many countries still produce significant amount of energy from burning fossil fuels, mainly crude oil, coal, and natural gas. According to a recent report published by the World Energy Council (2017), oil remains the world's leading fuel, accounting for about one-third of global energy consumption, followed by coal and natural gas with around %29 and %24 respectively. The oil and gas industry is divided into three major sectors of upstream, midstream, and downstream. The upstream sector is the most capital-intensive and important segment of the three in the oil and gas business, as this is where crude oil and natural gas are produced. The upstream oil and gas includes all activities related to the exploration and extraction of crude oil and natural gas which take place prior to shipping products to the refineries for processing.

Over the past four decades, the upstream oil and gas industries have applied various ways of well-informed business decision-making to increase production volume, reduce costs, improve safety, enhance operational performance, and protect the environment. Many of the decision-making problems in upstream oil and gas sector are complex in nature, involve uncertainties and risks, and require significant input from practitioners and policy-makers. The concept of decision analysis was first applied in the 1960s to solve oil and gas 'exploration' problems in the upstream sector (Huang *et al.*, 1995). Since then, the concept has been used in decision-making for a number of other important areas such as field development, production, maintenance of wells and facilities, life extension and decommissioning, etc. (Animah and Shafiee, 2018).

In recent years, a spectrum of qualitative and quantitative decision-making support (DMS) methods has been proposed in the literature to assist stakeholders in the upstream oil and gas sector to better understand reservoir characteristics, simulate field operations, develop low carbon production technologies, and make justifiable business decisions regarding exploration and development of both green and brown fields. As stated in Bratvold *et al.* (2009), DMS methods can help practitioners not only in performing technical and diagnostic tests of equipment but also in complying with regulatory and risk management requirements. Typical DMS methods used within the upstream sector include: operational research methods such as linear programming, integer programming, and goal programming; economic analysis methods such as cost-benefit analysis (CBA), real options analysis (ROA), and life cycle costing (LCC); statistical methods such as probabilistic approaches, simulation-based methods, and decision tree analysis (DTA); and environmental assessment methods such as environmental life cycle assessment (ELCA).

Strantzali and Aravossis (2016) indicated that the use of single-criterion approaches have historically dominated decision-making in the upstream oil and gas sector. However, given the complexity and conflicting interests of involved actors in the decision making process, the use of multi-criteria evaluation techniques is gaining momentum. Such techniques are able to consider simultaneously multiple attributes of different decision-making problems in the upstream sector (such as selecting the best drilling techniques and vessels, choosing the most appropriate maintenance strategies for different systems and components on oil and gas platforms, determining the most environmentally friendly end-of-life strategies for wells, identifying the most viable decommissioning processes for facilities, etc.). Moreover, in order to account for uncertainties associated with practitioners' subjective perception and experience in decision-making, soft computing methods such as fuzzy set theory, rough set theory, artificial intelligence (AI), and neural networks (NN) are increasingly becoming popular.

Despite the growing use of decision analytics approaches in upstream, midstream, and downstream oil and gas sectors in recent years, the literature on classification of the methods employed to support the decision-making processes in these sectors has been very limited (Deore, 2012). This paper aims to conduct a systematic review on the current state-of-the-art and future perspectives of the application of various DMS methods in the upstream oil and gas industry. The review is based on an exhaustive assessment of the studies identified in relation to the topic, including scholarly articles in refereed academic journals and conference proceedings between the years 1977 and 2016. A framework is also proposed to classify the literature according to the year and source of publication, type of fossil fuel source, oil and gas field development phase, data collection technique, decision-making method, and geographical location of the case studies. The findings of this review can be very useful to upstream oil and gas industry stakeholders, including field owners, asset managers, service providers, policy makers, environmentalist, financial analyst, and regulatory agencies to gain current state-of-the-art knowledge about well-informed decision-making, find out how to determine the most effective DMS method for each problem, and to identify real-life applications and case studies.

The structure of the paper is organized as follows. In Section 2, the most commonly used decision-making support methods in the oil and gas industry, and in particular the upstream sector, are introduced. The review methodology as well as the classification framework are presented in Section 3, and the observation and findings of the classification process are reported in details in Section 4. Finally, the concluding remarks and future research directions are given in Section 5.

2. Decision-making support (DMS) methods

The most commonly used decision-making support (DMS) methods in the oil and gas industries include operational research (OR), cost-benefit analysis (CBA), real options analysis (ROA), life cycle costing (LCC), environmental life cycle assessment (ELCA), Monte-Carlo simulation (MCS), decision tree analysis (DTA), multi-criteria decision analysis (MCDA), fuzzy logic analysis (FLA) and artificial intelligence (AI). In what follows, a brief description of these methods and their application to the upstream sector are presented.

2.1 Operational research (OR)

OR models include a model representing the logical and mathematical relationships between variables, an objective function with which alternative solutions are evaluated, and constraints that restrict solutions to feasible values. This mathematical model can be either a linear programming (LP) or a non-linear programming (NLP) problem. In LP, all objectives and constraints are linear functions, however, in NLP, at least one of constraints or the objective function is a non-linear function. The decision variables of an OR model can be continuous, or integer, or a mixture of both. Integer programming (LP) is a model whose all variables are constrained to take integer values, whereas in mixed-integer programming (MIP) only some of the decision variables are required to have integer values.

Goal programming (GP) is a relatively new OR model that has been proposed as an approach for the analysis of problems involving multiple, conflicting objectives. The basic approach of GP is to specify an aspiration level for each of the objectives and then seek a solution that minimizes the weighted sum of deviations of these objective functions from their respective goals. GP problems, depending on the type of their mathematical model, can be solved by either LP, NLP, IP or MILP.

2.2 Cost-benefit analysis (CBA)

CBA concept offers decision-makers the opportunity to evaluate the economic viability of different technologies, projects and policies. A key strength of this approach is that it provides results that are compatible to market mechanisms. CBA evaluation process involves summing up the equivalent money value of present costs of a project or policy and compare the result with the present value of benefits in order to ascertain if the project or policy is worthwhile. A project or policy is considered beneficial if the sum of its benefits becomes greater than the sum of its costs or when the benefit to cost ratio is greater than one.

2.3 Real options analysis (ROA)

One of the limitations of the CBA approach is that not all costs or benefits (e.g. cost of human injury/death) of a project or policy can be expressed in monetary equivalents (Hammond, 1966). For this reason, those decision-making outcomes that cannot be easily assigned a monetary value may introduce a level of uncertainty into cost or benefit calculations, hence restricting the applicability of the CBA method. ROA, also termed as real options valuation (ROV), is an extension of CBA approach that can be used for evaluating the value of options associated with a decision under uncertainty. The tool can help stakeholders decide on investments that might be delayed, expanded, abandoned, or repositioned. ROA is useful for the analysis of investment projects in the upstream sector, such as the development of oil fields (Jafarizadeh and Bratvold, 2009; Silitonga, 2015). Oil field development projects are an example of multiyear investment that is subject to many uncertainties during the whole lifetime of the project. The ROA approach involves the following steps: (1) create the structure for the problem, (2) develop a model of the decisions, uncertainties, and outcomes over time, (3) gather data for estimating outcome values in each scenario, and (4) perform analysis comparing alternatives and identifying action plans.

2.4 Life cycle costing (LCC)

The LCC analysis concept was originally introduced by the U.S. Department of Defence (DoD) in the 1970s (Ghosh *et al.*, 2018) to assist stakeholders and decision makers in conducting systematic assessment of costs of a project or policy. Since then, it has been applied to a wide variety of projects in different industries including oil and gas energy (Fuller and Peterson, 1996). This approach has helped upstream oil and gas stakeholders improve systems/components design, prioritize capital-intensive exploration activities, support comparative assessment of two or more investment projects, optimize operation and maintenance (O&M) strategies, determine whether life-extension is a viable consideration when production equipment reach end of their lives, etc.

In contrast to CBA, the LCC method calculates all direct costs associated with a project or a policy without taking indirect costs (or benefits) into account. The evaluation process involves the summation of discounted cash flows that accrue cost elements over the life cycle of a project/asset/policy with an appropriate discount rate. Over the last few years, the LCC method has evolved with life cycle cost-benefit (LCCB) and activity-based life cycle costing (AB-LCC) analysis approaches (for more see Thoft-Christensen, 2012; Animah *et al.*, 2018). The disadvantage of the LCC approach is similar to those associated with the CBA method. Thoft-christensen (2008) indicated the high discount rate set by different countries may render this approach inaccurate.

2.5 Environmental life cycle assessment (ELCA)

ELCA is a holistic and integrated approach for overall assessment of environmental compatibility of a project, policy, an activity or a product over its whole life cycle. The ELCA of a product comprises a "cradle-to-grave" assessment by considering the environmental consequences of various phases of the product life cycle, including: raw material acquisition phase, design/development phase, manufacturing phase, distribution phase, O&M phase, and end-of-life phase (Jacquemin *et al.*, 2012).

Conducting a ELCA study in the upstream oil and gas industry can help field owners better understand the material usage as well as environmental performance (such as emission of greenhouse gases, including CO_2, CH_4, N_2O, H_2S, etc.) of various upstream operations (exploration and production). For more details on ELCA applications in the upstream oil and gas sector, readers can refer to the following references: Aycaguer *et al.* (2001); Goodwin *et al.* (2012); Garg *et al.* (2013).

2.6 Monte-Carlo simulation (MCS)

MCS is a computerized mathematical method that relies on repeated random sampling and statistical analysis to obtain numerical results. In this method, the likelihood of occurrence of events are sampled at random from a probability distribution which is chosen based upon the type of problem under investigation. Each discrete sample set is referred to as an iteration and the resulting outcome from the calculations for that sample is recorded. This process will be repeated hundreds or thousands of times to obtain an estimate of mean probability of occurrence of the event. The accuracy of the estimate is dependent on the number of iterations performed. MCS has been vastly used in many applications within the upstream oil and gas The applications include risk assessment, reservoir evaluation, hydraulic fracturing of wells, and enhanced recovery processes (Macmillan, 2000).

2.7 Decision Tree analysis (DTA)

DTA uses graphical models to represent the sequence of decisions, events and their anticipated outcomes (Dey, 2002). The analysis is structured in a form of a tree with branches representing the possible action-event combinations. The conditional payoffs are obtained for each decision by considering various action-event combinations. The DTA method is appropriate when decision-making procedures are multi-stage, e.g. when an event takes place over a sequence of stages. This makes the DTA method logically structured and suitable for decision-making problems (Dey, 2012). According to Cheldi *et al.* (1997), DTA is used in the oil and gas industry mainly for quantitative risk assessment. One important feature of the DTA method is the calculation of expected monetary value (EMV), which is used as the basis to compare different decision options and choose the best one.

2.8 Multi-criteria decision analysis (MCDA)

MCDA method is one of the popular and commonly used DMS methods in the oil and gas energy industry. This method is increasingly becoming popular for decision-making in the upstream sector because the conventional single-criterion decision-making approaches cannot deliver appropriate results considering the complexity of field exploration and development activities. The MCDA method provides a flexible approach to solve complex problems with multiple attributes (e.g. technical, economic, social, legal and environmental) by helping stakeholders to make clear and consistence decisions.

Up to date, several MCDA methods have been developed for solving complex decision-making problems in the oil and gas industry. The most widely used MCDA methods include: Weighted Sum Model (WSM), Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Multi-Attribute Utility Theory (MAUT), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Preference Ranking Organization Method Of

Enrichment Evaluation (PROMETHEE), Elimination and Choice Expressing Reality (ELECTRE), Vlsekriterijumska Optimizacija I KOmpromisno Resenje (VIKOR). A brief discussion of each of these methods, with an attempt to highlight advantages and disadvantages, follows.

2.8.1 Weighted sum model (WSM)

This is the best known and simplest MCDA method (Shafiee, 2015a). WSM is also referred to as the simple addictive weighting (SAW) in the literature as it is suitable for handling single dimensional problems. The fundamental principle behind this method is to determine weighted sum of rating for each alternative considered in decision analysis. According to Kabir *et al.* (2014), to apply WSM correctly, all criteria should be single dimensional, i.e. cost-type or benefit-type. For this reason, Caterino *et al.* (2009) suggested that WSM is not efficient for solving complex decision-making problems which involve different types of criteria and decision variables.

2.8.2 Analytic hierarchy process (AHP)

The analytical hierarchy process (AHP) was developed by Saaty (1980) and since then this method has been applied to solve complex problems in various industries including oil and gas. The method helps decision makers to break down complex decision-making problems into hierarchical structure with goal at the top, followed by criteria, sub-criteria and alternatives (Zio, 1996). In AHP, to select the best alternative, decision-maker performs pairwise comparison of evaluation criteria and alternatives and then test the consistency of the pairwise comparison by computing an index called consistency ratio (CR). The weight for pairwise comparison is obtained using Saaty's fundamental scale of 1-9, where 1 indicates equal importance, 3 moderate importance, 5 strong importance, 7 very strong importance, and 9 indicates extreme importance. The values of 2, 4, 6, and 8 are assigned to indicate compromise values of importance.

2.8.3 Analytic network process (ANP)

The analytical network process (ANP) is a generalized form of the AHP method, but the difference is that in contact to AHP, the basic structures of ANP are networks. This is because AHP has been criticized for structuring the decision-making problems in hierarchical manner (Meade and Presley, 2002; Shafiee, 2015b). Also, Saaty (1996) suggested the use of ANP for solving the problems in which there is dependence between alternatives or criteria.

2.8.4 Multi-Attribute Utility Theory (MAUT)

This MCDA method takes into account the decision makers' preferences as a utility function for a set of possible attributes associated with alternatives. The best alternative is the one that maximizes the decision-makers' expected utility function. With respect to single attribute utility, the utility function can either be separated additively or multiplicatively (Pohekar and Ramachandran, 2004).

2.8.5 Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS is a useful MCDA method for ranking and selection of alternatives based on distance measures. The basic concept of this method is that the selected alternative should have the shortest geometric distance from the positive ideal solution and the longest geometric distance from the negative ideal solution. The TOPSIS method ranks alternatives in ascending or descending order of preference, which makes it easier to identify the best solution. Thus, decision makers' preference order of alternatives is obtained through comparison of Euclidean distances (Pohekar and Ramachandran, 2004).

2.8.6 Preference Ranking Organization Method Of Enrichment Evaluation (PROMETHEE)

PROMETHEE was developed by Brans and Vincke (1985) to outrank a set of finite alternatives with respect to conflicting criteria and then select the best alternative. The PROMETHEE method uses positive and negative preference flows for different alternatives in order to produce ranking in relation to decision weights (Kabir *et al.*, 2014). There are different methods of PROMETHEE described in the literature, including PROMETHEE I (partial ranking), PROMETHEE II (complete ranking), PROMETHEE III (ranking based on intervals), PROMETHEE IV (continuous case), PROMETHEE V (PROMETHEE II and integer linear programming), PROMETHEE VI (weights of criteria are intervals) and PROMETHEE GAIA (graphical representation of PROMETHEE) (Silva *et al.*, 2010). The most popular and commonly used techniques among the family of PROMETHEE methods include PROMETHEE I and PROMETHEE II & II (Emovon *et al.*, 2018). According to Vinodh and Jeya Girubha (2012) PROMETHEE II is applied to rank alternatives because it establishes a complete ranking or pre-order of alternatives.

2.8.7 Elimination and Choice Expressing Reality (ELECTRE)

ELECTRE uses an indirect method to rank alternatives by means of pair comparison under each criteria (Cheng *et al.*, 2002). Several versions of the ELECTRE method have been developed since its conception in the mid-1960s (Kabir *et al.*, 2014), with ELECTRE TRI and ELECTRE III being the most popular and commonly used methods among the family of ELECTRE methods. One of the key strength of ELECTRE is its applicability even when there is missing information.

2.8.8 VIsekriterijumska Optimizacija I KOmpromisno Resenje (VIKOR)

VIKOR is a compromising MCDA method that determines compromise ranking of alternatives (Zeleny and Cochrane, 1982). The main objective of using this method is to select a suitable alternative that is possibly close to the ideal solution. It introduces a multi-criteria ranking index based on the particular measure of 'closeness' to the 'ideal' solution

(Sayadi *et al.*, 2009). The distance measure used in the VIKOR method is a family of L_p-metrics that is used as an aggregation function in a compromise programming.

2.9 Fuzzy logic analysis (FLA)

FLA is a powerful methodology which was introduced by Zadeh (1965) to deal with uncertainties in human judgments during decision-making. In FLA, fuzzy sets rather than crisp sets are used to determine the membership of a variable. Fuzzy sets are often presented by linguistic terms such as ‘low temperature’, ‘high pressure’, etc. In general, the output of a FLA is a fuzzy set expressed as a distribution of possibilities. FLA has been successfully applied in many different areas of upstream oil and gas sector, including reservoir characterization, drilling, permeability and rock type estimation, petroleum separation, and hydraulic fracturing (see Zoveidavianpoor *et al.*, 2012).

2.10 Artificial intelligence (AI)

AI is defined as the theory and development of computer systems able to support decision-making processes that normally require human intelligence. In other words, AI is the use of computer algorithms to attempt to replicate the human ability to learn, reason and make decisions. AI includes a wide range of techniques such as artificial neural networks (ANN), generic algorithm (GA), support vector machine (SVM), etc. Applications of AI tools in various operations of the upstream oil and gas sector can be found in the literature (see Mohaghegh and Khazaeni, 2011). For instance, for drilling decision-making the readers can refer to Bello *et al.* (2016), and for further details about oil production forecasting the readers are recommended to read Sheremetov *et al.* (2013).

2.11 Hybrid decision analysis methods

Hybrid decision analysis methods such as hybrid MCDA methods, combined MCDA and fuzzy logic methods, etc. are a powerful group of DMS methods which can assist decision-makers in handling miscellaneous information, divergence in stakeholders’ preferences, interconnected or contradicting criteria, and uncertain environments (Dinmohammadi and Shafiee, 2017).

2.11.1 Hybrid MCDA methods

Majority of the classical MCDA methods have practical limitations. In order to improve their strengths and eliminate their weaknesses, some hybrid MCDA models have been developed in the literature, e.g. SWM-AHP, ANP-TOPSIS. A hybrid MCDA method is an effective decision-making method which involves the integration of two or more appropriate MCDA methods for solving complex and multi-attribute problems. By this integration, limitations of one method can be offset by strengths of the other method.

2.11.2 Combined MCDA and fuzzy logic method

MCDA methods can be categorized into two types of crisp and fuzzy models (Shafiee, 2015a). The crisp MCDA models express the importance weights of criteria using crisp numbers. However, it is sometimes difficult to provide precise numerical values for evaluation criteria due to the uncertainty and vagueness in real-life decision-making processes. The fuzzy MCDA models express the preferences of relative importance between criteria by linguistic terms and then set them into fuzzy numbers such as triangular or trapezoidal fuzzy numbers. A triangular fuzzy number is a fuzzy number whose membership function is defined by three real numbers, expressed as (l, m, u), where the function is first linearly increasing form point [l, 0] to [m, 1] and then linearly decreasing to [u, 0]. m is called the modal value, and l and u denote the right and left boundary respectively.

3. Review methodology and classification framework

In order to identify the available literature regarding the application of different DMS methods in the upstream oil and gas industry, a systematic review was conducted. The literature review covered all the studies published by scholars and practitioners throughout the world in relevant journals and conference proceedings in English language between the years 1977 and 2016.

The literature was identified from different databases such as Scopus, Web of Science, Onepetrol, Knovel, IEEE Xplore, American Society of Mechanical Engineers (ASME) digital collection and Google scholar, and the related articles were selected based on a set of inclusion criteria. The above indexing databases were selected due to their broad coverage of scientific peer-reviewed journal articles as well as conference papers. Several keywords and phrases such as “decision-making”, “upstream petroleum”, “oil and gas”, “decision analysis”, “methods”, “techniques” in different combinations were used to identify the existing literature. The keyword search resulted in a total of 129 papers. The title and abstract of each paper were then reviewed to assess their relevance to the topic. After reviewing the titles and abstracts, 19 papers were discarded due to their irrelevance to the subject area and eventually, 110 papers were selected for inclusion in this study. These papers are: Korn *et al.* (1978); Sprowso *et al.* (1979); Jentsch Jr and Marrs (1988); Balen *et al.* (1988); Methven (1993); Roosmalen *et al.* (1993); Songhurst and Kingsley (1993); Dear *et al.* (1995); Heinze *et al.* (1995); Smith and Celant (1995); Lassen and Syvertsen (1996); Harding (1996); Winkel (1996); Cheldi *et al.* (1997); Smith *et al.* (1997); Iyer *et al.* (1998); Joshi *et al.* (1998); Poremski (1998); Denney (1999); Gatta (1999); Mudford (2000); Tague and Hollman (2000); Aycaguer *et al.* (2001); Erdogan *et al.* (2001); Gerbacia and Al-Shammari (2001); Goldsmith *et al.* (2001); Paula *et al.* (2001); Suslick and Furtado (2001); Suslick *et al.* (2001); Begg *et al.* (2002); Castro *et al.* (2002); Denney (2002); Finch *et al.* (2002); Balch *et al.* (2003); Cullick *et al.* (2003); El-Reedy (2003); Joshi (2003); Chitwood *et al.* (2004); Ferreira *et al.* (2004); Vorarat *et al.* (2004); Hegstad *et al.* (2005); Islam and Powell (2005); Brainard

(2006); Cullick *et al.* (2007); Lev and Murphy (2007); Moan (2007); Bahmannia (2008); Ghazi *et al.* (2008); Kayrbekova and Markeset (2008); Liu and Ford (2008); Orimo *et al.* (2008); Virine (2008); Zhu and Arcos (2008); Abhulimen (2009); Bybee (2009); Gomez *et al.* (2009); Jafarizadeh and Bratvold (2009); Li *et al.* (2009); Verre *et al.* (2009); Kayrbekova and Markeset (2010); Ratnayaka and Markeset (2010); Pinturier *et al.* (2010); Angert *et al.* (2011); Chen *et al.* (2011); Gong *et al.* (2011); Kayrbekova *et al.* (2011); Nam *et al.* (2011); Ortiz-Volcan and Iskandar (2011); Stephenson *et al.* (2011); Streeter and Moody (2011); Burnham *et al.* (2012); Goodwin *et al.* (2012); Grosse-Sommer *et al.* (2012); Schulze *et al.* (2012); Shrivastva *et al.* (2012); Weber and Clavin (2012); Zoveidavianpoor *et al.* (2012); Burlini and Araruna (2013); Hernandez *et al.* (2013); Lopes and Almeida (2013); Pettersen *et al.* (2013); Pierce and Wills (2013); Sheremetov *et al.* (2013); Trujillo *et al.* (2013); Fergestad *et al.* (2014); Fowler *et al.* (2014); Jeong *et al.* (2014); Kullawan *et al.* (2014); Lilien *et al.* (2014); Maddah *et al.* (2014); Marten and Gatzen (2014); Sandler *et al.* (2014); Siveter *et al.* (2014); Wright *et al.* (2014); Chilukuri *et al.* (2015); Chun *et al.* (2015); de Wardt and Peterson (2015); Ghani *et al.* (2015); Oruganti *et al.* (2015); Silitonga (2015); Zavala-Araiza *et al.* (2015); Adam and Ghosh (2016); Bello *et al.* (2016); Guedes and Santos (2016); Johannknecht *et al.* (2016a); Johannknecht *et al.* (2016b); Ortiz-Volcan *et al.* (2016); Seo *et al.* (2016); Shafiee *et al.* (2016); Steuten and Onna (2016).

The full text of each paper was reviewed carefully and a classification framework was presented to categorize the existing literature. As shown in Figure 1, the state-of-the-art of methods used to support decision-making in the upstream oil and gas industry can be classified according to the following attributes:

****Figure 1****

Figure 1. Classification framework for decision-making support methods applied to the upstream oil and gas sector.

- Year of publications (1977–1986, 1987–1996, 1997–2006, 2007–2016);
- Distribution of publications (type of publication, source of publication);
- Types of fossil fuel sources (conventional, non-conventional);
- Oil and gas field's lifecycle phases (exploration, development, production, life extension, abandonment/decommission);
- Data collection techniques (survey, direct measurement or observation, monitoring and data acquisition systems, others);
- Decision support methods (OR, CBA, ROA, LCC, ELCA, MCS, DTA, MCDA, FLA, AI, and Hybrid methods);
- Geographical distribution of case studies and their locations (Asia, South America, North America, Europe, Africa).

4. Review findings and classification results

In this section, the observation and findings of the review classification process are reported in details.

4.1 Distribution of studies based on year of publication

We divided the period of study into four equal decades of ten years each—1977 to 1986, 1987 to 1996, 1997 to 2006, and 2007 to 2016. Figure 2 depicts a bar chart representing the number of papers published about the application of DMS methods to upstream oil and gas operations during the past four decades.

**** Figure 2****

Figure 2. The number of publications during the past four decades.

As can be seen, there is a significant increase in the number of papers over the period of study. However, more than 60 percent of the studies have been published in the past ten years (2007-2016), which implies the increasing importance and usefulness of DMS methods in the upstream oil and gas sector.

4.2 Distribution of studies based on type of source of publications

Out of the 110 identified papers, there were thirty-two journal articles (~ 29%) (Jentsch Jr and Marrs (1988); Dear *et al.* (1995); Iyer *et al.* (1998); Denney (1999); Aycaguer *et al.* (2001); Suslick and Furtado (2001); Denney (2002); Finch *et al.* (2002); Ferreira *et al.* (2004); Moan (2007); Bybee (2009); Li *et al.* (2009); Ratnayaka and Markeset (2010); Kayrbekova *et al.* (2011); Nam *et al.* (2011); Stephenson *et al.* (2011); Burnham *et al.* (2012); Goodwin *et al.* (2012); Weber and Clavin (2012); Zoveidavianpoor *et al.* (2012); Lopes and Almeida (2013); Sheremetov *et al.* (2013); Fowler *et al.* (2014); Maddah *et al.* (2014); Marten and Gatzen (2014); Sandler *et al.* (2014); Ghani *et al.* (2015); Silitonga (2015); Zavala-Araiza *et al.* (2015); Guedes and Santos (2016); Johannknecht *et al.* (2016b); Shafiee *et al.* (2016)) and seventy-eight conference papers (~ 71%) (Korn *et al.* (1978); Sprowso *et al.* (1979); Balen *et al.* (1988); Methven (1993); Roosmalen *et al.* (1993); Songhurst and Kingsley (1993); Heinze *et al.* (1995); Smith and Celant (1995); Lassen and Syvertsen (1996); Harding (1996); Winkel (1996); Cheldi *et al.* (1997); Smith *et al.* (1997); Joshi *et al.* (1998); Poremski (1998); Gatta (1999); Mudford (2000); Tague and Hollman (2000); Erdogan *et al.* (2001); Gerbacia and Al-Shammari (2001); Goldsmith *et al.* (2001); Paula *et al.* (2001); Suslick *et al.* (2001); Begg *et al.* (2002); Castro *et al.* (2002); Balch *et al.* (2003); Cullick *et al.* (2003); El-Reedy (2003); Joshi (2003); Chitwood *et al.* (2004); Vorarat *et al.* (2004); Hegstad *et al.* (2005); Islam and Powell (2005); Brainard (2006); Cullick *et al.* (2007); Lev and Murphy (2007); Bahmannia (2008); Ghazi *et al.* (2008); Kayrbekova and Markeset (2008); Liu and Ford (2008); Orimo *et al.* (2008); Virine (2008); Zhu and Arcos (2008); Abhulimen (2009); Gomez *et al.* (2009); Jafarizadeh and Bratvold (2009); Verre *et* *al.* (2009); Kayrbekova and Markeset (2010); Pinturier *et al.* (2010); Angert *et al.* (2011); Chen *et al.* (2011); Gong *et al.* (2011); Ortiz-Volcan and Iskandar (2011); Streeter and Moody (2011); Grosse-Sommer *et al.* (2012);; Schulze *et al.* (2012); Shrivastva *et al.* (2012); Burlini and Araruna (2013); Hernandez *et al.* (2013); Pettersen *et al.* (2013); Pierce and Wills (2013); Trujillo *et al.* (2013); Fergestad *et al.* (2014); Jeong *et al.* (2014); Kullawan *et al.* (2014); Lilien *et al.* (2014); Siveter *et al.* (2014); Wright *et al.* (2014); Chilukuri *et al.* (2015); Chun *et al.* (2015); de Wardt and Peterson (2015); Oruganti *et al.* (2015); Adam and Ghosh (2016); Bello *et al.* (2016); Johannknecht *et al.* (2016a); Ortiz-Volcan *et al.* (2016); Seo *et al.* (2016); Steuten and Onna (2016)).

We also identified the sources of journals and conference proceedings in which the papers were published. It was found that the literature has been scattered among twenty-seven academic journals and thirty-eight conference proceedings. Among the journals, the "Journal of Petroleum Technology" – which is published by the Society of Petroleum Engineers (SPE) – contained the largest number of papers on the topic (4 papers). Furthermore, about 60 percent of the conference papers have been published in proceedings for the SPE oil and gas energy conferences, amongst which the SPE Annual Technical Conference and Exhibition with 8 papers is the most dominant event.

4.3 Distribution of studies based on fossil fuel sources

The upstream oil and gas sector involves the exploration and development of conventional fossil fuel reserves as well as unconventional fossil fuel deposits such as shale oil and gas. The U.S. Energy Information Administration (EIA) (https://www.eia.gov/) projected that shale gas production is expected to reach 90 billion cubic feet per day (Bcf/d) in 2040, which is more than twice current levels. However, the geological and technical approaches employed in the exploration and development of shale gas differ from those of the conventional oil and gas. Some of the important issues in the shale oil and gas sector that may require the use of DMS methods include the evaluation of cost of exploration, development and production, estimation of revenues, and the examination of the environmental impact of shale oil and gas production over the life span of a field.

Those studies that have discussed or applied different DMS methods to support the development of both conventional and unconventional fossil fuel sources in the upstream oil and gas sector were identified and reviewed. Out of 110 studies included in this review, only five papers (representing around 4.5 percent of all studies) addressed the decision-making processes regarding shale gas production and GHG emission effects, while the rest of the studies focused on decision-making aspects of the conventional fossil fuel sources. These five studies about the shale gas production and GHG footprint assessment are highlighted below:

Gong *et al.* (2011) presented a decline-curve-based reservoir model with a decision model to determine optimal development strategies in shale reservoirs by incorporating uncertainty in production forecasts. Stephenson *et al.* (2011) modelled the relative GHG emissions from both shale gas and conventional natural gas production. One of the key findings of the study was that the well-to-wire (WtW) emissions from conventional natural gas production were estimated to be approximately 1.8%-2.4% less than that of shale gas. Burnham *et al.* (2012) synthesized the current scientific knowledge on methane emissions from shale gas, conventional oil and gas as well as coal to estimate GHG emissions from different fossil fuel sources. The study further indicated that the combustion of natural gas produces significantly less GHG as compared to conventional coal and oil sources. In Weber and Clavin (2012), the upstream carbon footprint from both shale and conventional natural gas production was assessed and compared. The results showed that there was no significant difference in the upstream carbon footprint from these two types of natural gas production. Zavala-Araiza *et al.* (2015) used a life-cycle allocation method to assign methane emissions to natural gas and oil production from shale formations.

4.4 Distribution of studies based on oil and gas field's lifecycle phases

In this Section, the reviewed papers are classified according to the phases of oil and gas field lifecycle. The lifecycle, as shown in Figure 3, is divided into five phases of exploration, development, production, life extension, and abandonment/decommission. These lifecycle phases are briefly explained in the followings:

**** Figure 3****

Figure 3. The lifecycle phases of an oil and gas field.

- Exploration phase: This phase involves the search for economic and recoverable oil and natural gas deposits (either onshore or offshore) and includes detailed surface exploration, drilling and well testing.
- Development phase: The development phase occurs after exploration. The main activities during this phase include construction of production facilities, water injection and abandonment wells, an FPSO, subsea structures, etc., laying of flow lines and umbilicals, and installation of subsea systems for subsequent commencement of oil and gas production.
- Production phase: This phase employs various skills, advanced technologies and professionals to extract oil and gas products and subsequently separate two- or three-phase products into oil, gas, produced water and solid particles. The oil and natural gas products are then transported to the agreed delivery points either through the use of export lines or shuttle tankers in the case of offshore production. This phase also involves workover operations of production wells and maintenance of oil and gas production facilities which is carried out to ensure effective and efficient production.
- Life extension phase: This phase begins when oil and gas production facilities reach end of their original design lifetimes and the process of life extension is economically and

technically viable. Also, in some countries due to highly restrictive regulations on construction of new fields, companies use life extension as means to avoid phasing out existing fields. Life extension of oil and gas facilities delivers some benefits such as increased production, reduced capital expenditures (CAPEX) associated with constructing new facility, increased job creation, reduced CO_2 emissions, and lowered financial risk compared to risk of investing in greenfield project (Shafiee and Animah, 2017).

- Abandonment/Decommission: This phase represents the final stage of oil and gas field's lifecycle, taking place when production facilities are no longer safe or cannot produce economic quantities of oil and gas products. Oil and gas field abandonment is a critical and complex decision-making process which involves the use of DMS methods in terms of risk analysis, cost estimation, health and safety, and environmental assessment (Kaiser and Pulsipher, 2004). Typical decommissioning activities include well plugging, full removal of platforms, partial removal platforms, trenching and burial of pipelines, etc. (Koroma *et al.*, 2018).

Table 1 shows a detailed distribution of the published papers on the application of DMS methods in upstream oil and gas industry according to the phases of oil and gas field's lifecycle taken into consideration. Those publications which did not report the phase of lifecycle in the decision-making process were excluded from the table. As can be seen, the DMS methods have received the most attention during the development phase, followed by the production and exploration phases.

Table 1

Table 1. Distribution of studies according to the oil and gas field's lifecycle phases.

4.5 Distribution of studies based on data collection techniques

Decision-making in relation to the upstream oil and gas activities should be reliant on accurate data for the analysis. This means that the outcomes of a decision are dependent upon the quality of input data, hence making data collection an essential step of decision-making process in the upstream oil and gas sector. Applying the DMS methods to make effective decisions usually requires a database of cost information (e.g. cost of design, operation and maintenance (O&M), decommissioning, etc.), equipment failure mechanisms and root causes, degradation rates, environmental data (e.g. CO_{2eq} as a results of production and operation of equipment) as well as experts' opinions about the evaluating criteria. Without using high quality data, the results of decision-making may lead to inaccurate conclusions. In a study, Vorarat *et al.* (2004) discussed the data requirements for LCC analysis of oil and gas field projects.

Generally, the use of survey methods (including questionnaires, face-to-face or telephone interviews, or a combination of these) to obtain experts' judgement and knowledge is one of common data collection techniques in the oil and gas sector (Virine, 2008). Many researchers often consider survey techniques more subjective and, thus, less accurate than experimentally acquired data. Nevertheless, it still remains one of the popular ways of data collection for decision-making in the upstream oil and gas sector. Another means of obtaining data for decision-making is through direct measurement or observation (such as close visual inspection (CVI)). The data stored in monitoring databases or data acquisition systems is also another source for decision makers in the upstream oil and gas industry. Additionally, information from other primary/original sources such as published literature, company's reports, legislations of regulators, suppliers' databases, etc. is also used for decision analysis in the upstream sector.

Among the reviewed papers, Aycaguer *et al.* (2001) used data generated from the continuous monitoring of a process safety system to perform ELCA, in order to assess the benefits obtained from storing CO_2 in active reservoirs and its corresponding environmental impact over the process lifetime. Eight studies, including Gatta (1999), Bahmannia (2008), Abhulimen (2009), Pinturier *et al.* (2010), Nam *et al.* (2011), Kullawan *et al.* (2014), Sandler *et al.* (2014) and Ghani *et al.* (2015) have utilized data from published literature and handbooks.

In Jentsch Jr and Marrs (1988), Dear *et al.* (1995), Smith and Celant (1995), Gerbacia and Al-Shammari (2001), Islam and Powell (2005), Goodwin *et al.* (2012), Wright *et al.* (2014) and Shafiee *et al.* (2016), the information from industry was used as input to support ELCA and CBA analyses. Studies conducted by Johannknecht *et al.* (2016a) and Johannknecht *et al.* (2016b) collected data from previously commercialized products to develop a LCC toolkit. Ghazi *et al.* (2008) and Ratnayaka and Markeset (2010) combined different data collection techniques in their respective studies. Eight studies of Joshi *et al.* (1998), Suslick and Furtado (2001), Suslick *et al.* (2001), Li *et al.* (2009), Verre *et al.* (2009), Ortiz-Volcan and Iskandar (2011), Streeter and Moody (2011) and Sandler *et al.* (2014) applied data acquired from other projects/fields to support decision-making in the upstream oil and gas sector.

The rest of the publications failed to indicate the type of techniques used for collecting the data and hence were excluded from our analysis.

4.6 Distribution of studies based on DMS methods

In terms of the decision-making methods employed in the upstream oil and gas sector, all the one-hundred and ten identified publications were analysed and classified into various categories as follows:

- Operational research (OR)
- Cost-benefit analysis (CBA)

- Real options analysis (ROA)
- Life cycle costing (LCC)
- Environmental life cycle assessment (ELCA)
- Monte-Carlo simulation (MCS)
- Decision tree analysis (DTA)
- MCDA (WSM, AHP/ANP, MAUT, TOPSIS, PROMETHEE, ECLECTRE, VIKOR)
- Hybrid MCDA (when a study combines two or more MCDA methods);
- Fuzzy logic analysis (FLA)
- Others (when a decision-making method different from those mentioned above is used).

The distribution of the publications based on the method used to support decision-making in the upstream oil and gas is shown in Table 2. As can be seen, LCC method with 39 papers has received the most attention in the literature, followed by ELCA with 18 papers, CBA with 14 papers, DTA with 10 papers and MCDA methods with 10 papers. Another interesting observation from Table 2 is that the classical MAUT and AHP/ANP methods are the most popular MCDA methods to support decision-making in the upstream sector, whereas other MCDA methods such as WSM, TOPSIS, PROMETHEE, ELECTRE and VIKOR have not been extensively utilized. Moreover, our search revealed that only one study in the literature has used the fuzzy set theory approach.

****Table 2****

Table 2. Classification of studies based on decision-making methods.

Figure 4 shows a detailed distribution of various DMS methods applied to the upstream oil and gas sector during the past four decades.

****Figure 4****

Figure 4. Distribution of DMS methods applied to the upstream sector during the past four decades.

4.7 Distribution of studies based on geographical location of case studies

The results of our content analysis indicate that 38 out of 110 publications (i.e. about 34.5 percent of the total number of publications) have reported a case example of the application of DMS methods to the upstream oil and gas sector. Out of these 38 published works, 27 studies have mentioned the geographical location of the case study. Table 3 presents the aim and the geographical location and of the identified case studies around the world.

****Table 3****

Table 3. Distribution of studies based on geographical location of case studies.

As can be seen, the continents of North and South America have reported the largest number of case studies, accounting for 41 percent of the total number of publications. This is followed by the Middle East region and Asia with 30 percent of the publications. The North Sea which comprises the UK Continental Shelf (UKCS) and Norwegian Continental Shelf (NCS) account for 15 percent of the publications. Mediterranean Sea and West Africa regions also have been studied each in 7% of the case studies.

5. Concluding remarks and future research directions

Over the past four decades, a wide range of qualitative and quantitative decision-making support (DMS) methods have been developed in the literature to assist upstream oil and gas industry stakeholders to better understand reservoir characteristics, simulate field operations, develop low carbon production technologies, and make justifiable business decisions regarding field exploration, development and production activities. In this paper, we reviewed one hundred and ten studies (including 32 journal articles and 78 conference papers) about the use of different DMS methods in the upstream oil and gas industry. These studies were published by many scholars and practitioners throughout the world in twenty-seven academic journals and thirty-eight conference proceedings in English language between the years 1977 and 2016. The key issues of the subject area, including the type of DMS methods applied to support the decision-makers, the phases of oil and gas field's lifecycle considered in the analysis, data collection techniques, case study regions that have utilised DMS methods to solve the problem, etc. were highlighted and discussed.

As this study revealed, the number of publications related to the application of DMS methods in the upstream oil and gas industry have grown significantly over the past four decades. The analysis of the studies based on decision-making methods indicated that the operational research (OR) methods such as mixed integer programming (MIP), economic analysis methods such as cost-benefit analysis (CBA), real options analysis (ROA) and life cycle costing (LCC), statistical methods such as Monte Carlo simulation (MCS) and decision tree analysis (DTA); and environmental assessment methods such as environmental life cycle assessment (ELCA) have received the most attention in the literature. However, the use of multi-criteria decision analysis (MCDA) methods such as analytic hierarchy process (AHP) and analytic network process (ANP) have been gaining momentum in recent years. Such methods are able to consider simultaneously multiple technical, economic, social, legal and environmental attributes of decision-making problems in the upstream sector. Moreover, in order to account for uncertainties associated with practitioners' subjective perception and experience in decision-making, soft computing methods such as fuzzy set theory, rough set theory, artificial intelligence (AI), and neural networks (NN) have become popular.

The findings of this literature review and the results of the proposed classification scheme offer interesting conclusions that could be useful to field owners, asset managers, service providers, policy makers, environmentalist, financial analyst, and regulatory agencies to gain better insight about their business activities with well-informed decision-making processes, find out how to determine the most effective DMS method for each problem, and to identify real-life applications and case studies. However, there is still large scope of research on the use of decision analytics modelling in the upstream, midstream and downstream oil and gas sectors. Some of the potential directions for future research are listed below:

1. When comparing the number of studies that have used DMS methods to support decision analysis of exploration, development and production activities of conventional and unconventional fossil fuel sources, it was realised that unconventional fossil fuel (such as shale oil and gas) has received very little attention in the literature. Hence, further research works can be conducted on various aspects of decision-making for the exploration, development and production of shale oil and gas.
2. It was found from this review that all the studies in relation to unconventional fossil fuel sources utilized ELCA method to estimate GHG footprint of shale gas production. Nevertheless, the development and production of shale gas present huge economic opportunities and it will be of great interest if future research work can use other decision analytics methods to estimate the economic potential of shale gas projects.
3. The majority of the DMS methods identified in this study were data-driven and required good quality data so that decisions could be made with high degree of confidence. However, the paucity of good quality data is still considered as a challenge in the upstream oil and gas sector. In order to overcome this challenge, there is an essential need for the stakeholders to define measures, procedures, and data collection platforms capable of providing decision makers with appropriate information to make suitable decisions.
4. Our findings indicated that decision-making tools such as LCC, ELCA, CBA, DTA, MCS and ROA have received good attention in industrial case studies. However, MCDA methods and also hybrid decision analysis methods have rarely been reported to be applied to real-case projects in the upstream oil and gas sector.
5. Despite the wide application of AHP/ANP methods to solve decision-making problems in the upstream oil and gas industry, the literature on the use of other MCDA methods such as TOPSIS, PROMETHEE, ELECTRE, VIKOR and fuzzy MCDA techniques is very limited.
6. Life extension and field abandonment/decommission are the current challenges facing the upstream oil and gas sector. This is because significant number of facilities supporting operations in the upstream oil and gas sector are approaching or have already exceeded their original design lifetimes and asset managers have to make a decision between life extension and decommissioning. However, very few research studies have used DMS methods to address the challenges of life extension and/or decommissioning

decision-making in the oil and gas industry (Shafiee and Animah, 2017). Therefore, future work must direct efforts at applying DMS to address the challenges during life extension and decommission phase of asset life cycle in the upstream oil and gas sector.

7. This review revealed that the West Africa region, though produces a sizeable amount of the crude oil and natural gas, has reported the least number of case studies about the application of DMS method to provide robust solutions for exploration, development and production activities. Therefore, further researches can be conducted about this region in the future.

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RESEARCH HIGHLIGHTS

- Systematic review on the current state-of the-art and future perspectives of various decision-making support methods applied to the upstream oil and gas sector;
- To identify publication sources that contain literature on the topic;
- To propose a framework to classify the literature according to a set of assessment criteria;
- To identify the most commonly used decision analytics methods for upstream oil and gas operations, e.g. exploration, development and production;
- To gain better insight about upstream oil and gas business activities with well-informed decision-making.

Figure

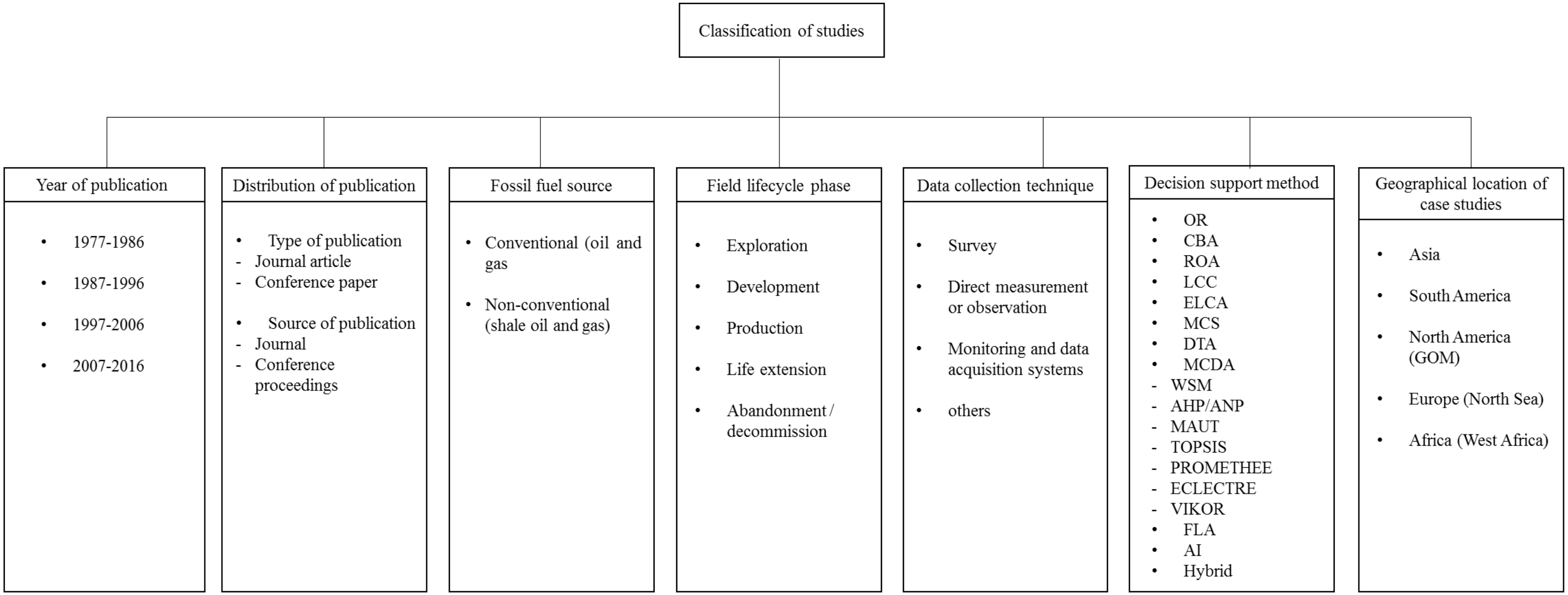


Figure 1. Classification framework for decision-making support methods applied to the upstream oil and gas sector.

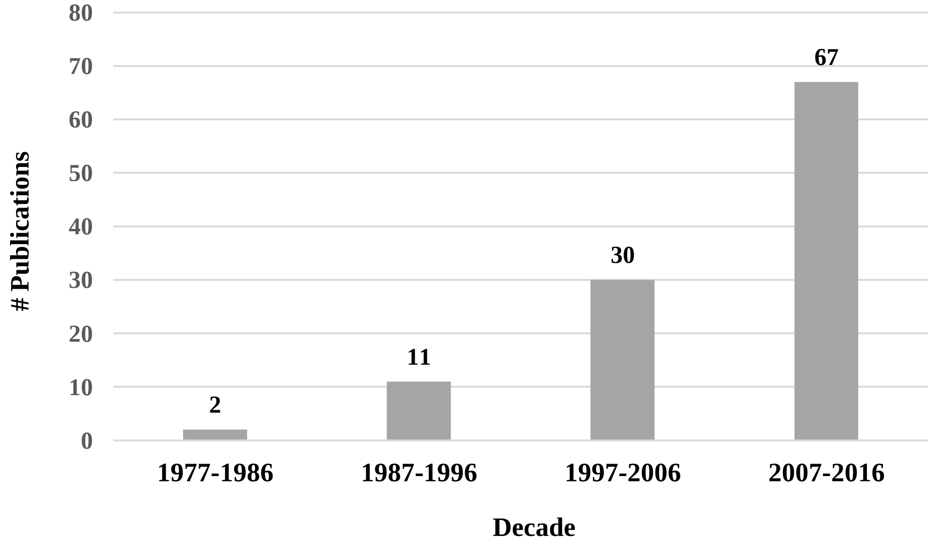
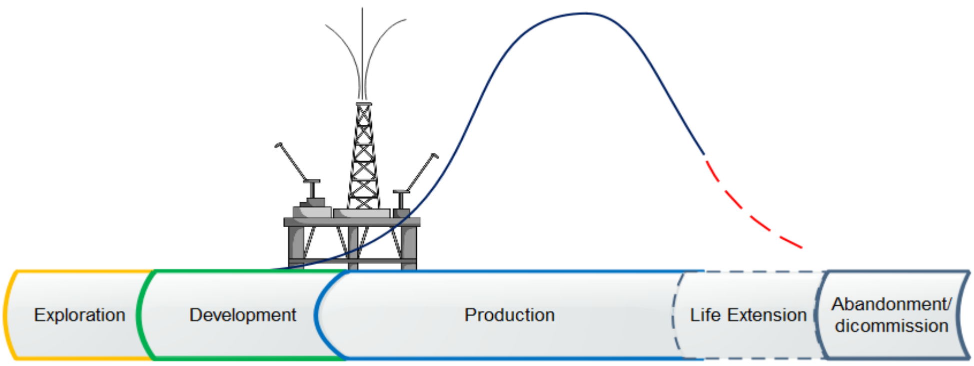


Figure 1. Number of publications during the past four decades.



**** Figure 3****

Figure 3. The lifecycle phases of an oil and gas field.

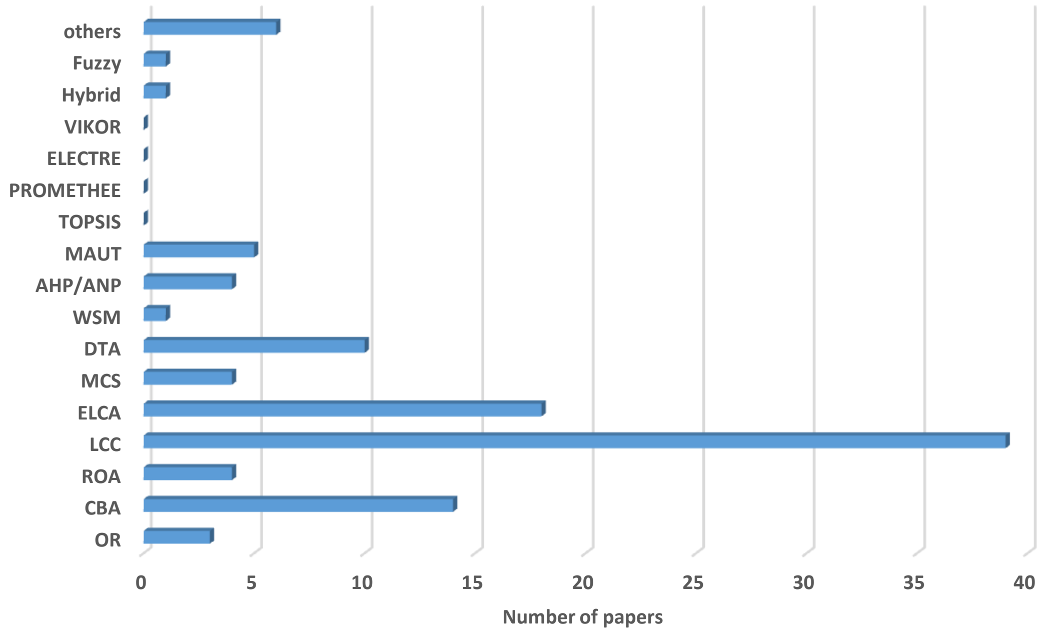


Figure 4. Distribution of decision-making methods applied to the upstream sector during the past four decades.

Table 1. Distribution of studies based on oil and gas field's lifecycle phases.

developmental phase	# of papers	References
Exploration	13	Sprowso *et al.* (1979); Erdogan *et al.* (2001); Suslick and Furtado (2001); Abhulimen (2009); Gomez *et al.* (2009); Jafarizadeh and Bratvold (2009); Verre *et al.* (2009); Shrivastva *et al.* (2012); Zoveidavianpoor *et al.* (2012); Burlini and Araruna (2013); Lopes and Almeida (2013); Bello *et al.* (2016); Guedes and Santos (2016);
Development	19	Methven (1993); Dear *et al.* (1995); Iyer *et al.* (1998); Denney (1999); Mudford (2000); Gerbacia and Al-Shammari (2001); Goldsmith *et al.* (2001); Begg *et al.* (2002); Denney (2002); Finch *et al.* (2002); Ferreira *et al.* (2004); Brainard (2006); Cullick *et al.* (2007); Ghazi *et al.* (2008); Zhu and Arcos (2008); Angert *et al.* (2011); Gong *et al.* (2011); Streeter and Moody (2011); Adam and Ghosh (2016);
Production	17	Jentsch Jr and Marrs (1988); Cheldi *et al.* (1997); Aycaguer *et al.* (2001); Castro *et al.* (2002); Cullick *et al.* (2003); Hegstad *et al.* (2005); Islam and Powell (2005); Kayrbekova and Markeset (2008); Abhulimen (2009); Li *et al.* (2009); Verre *et al.* (2009); Kayrbekova and Markeset (2010); Chen *et al.* (2011); Nam *et al.* (2011); Ortiz-Volcan and Iskandar (2011); Hernandez *et al.* (2013); Ghani *et al.* (2015);
Life extension	2	Chitwood *et al.* (2004); Shafiee *et al.* (2016)
Abandonment / Decomission	2	Poremski (1998); Fowler *et al.* (2014).

Table 2. Classification of studies based on decision-making methods.

Reference	OR	CBA	ROA	LCC	ELCA	MCS	DTA	WSM	AHP /ANP	MAUT	TOPSIS	PROMETHEE	ECLECTRE	VIKOR	Hybrid	FLA	Others
Korn *et al.* (1978)		√															
Sprowso *et al.* (1979)							√										
Jentsch Jr and Marrs (1988)		√															
Balen *et al.* (1988)				√													
Methven (1993)				√													
Roosmalen *et al.* (1993)				√													
Songhurst and Kingsley (1993)				√													
Dear *et al.* (1995)							√										
Heinze *et al.* (1995)							√										
Smith and Celant (1995)				√													
Lassen and Syvertsen (1996)				√													
Harding (1996)				√													
Winkel (1996)				√													
Cheldi *et al.* (1997)							√										
Smith *et al.* (1997)		√															
Iyer *et al.* (1998)	√																
Joshi *et al.* (1998)				√													
Poremski (1998)					√												
Gatta (1999)							√										
Denney (1999)				√													
Mudford (2000)							√										
Tague and Hollman (2000)		√															
Aycaguer *et al.* (2001)					√												
Erdogan *et al.* (2001)							√										
Gerbacia and Al-Shammari (2001)									√								
Goldsmith *et al.* (2001)				√													
Paula *et al.* (2001)				√													
Suslick and Furtado (2001)										√							
Suslick *et al.* (2001)										√							
Begg *et al.* (2002)			√														
Castro *et al.* (2002)										√							
Denney (2002)									√								
Finch *et al.* (2002)						√											
Balch *et al.* (2003)		√															
Cullick *et al.* (2003)						√											
El-Reedy (2003)				√													

Joshi (2003)		√							
Chitwood *et al.* (2004)				√					
Ferreira *et al.* (2004)								√	
Vorarat *et al.* (2004)				√					
Hegstad *et al.* (2005)						√			
Islam and Powell (2005)		√							
Brainard (2006)		√							
Cullick *et al.* (2007)	√								
Lev and Murphy (2007)							√		
Moan (2007)					√				
Bahmannia (2008)					√				
Ghazi *et al.* (2008)					√				
Kayrbekova and Markeset (2008)				√					
Liu and Ford (2008)		√							
Orimo *et al.* (2008)		√							
Virine (2008)									√
Zhu and Arcos (2008)				√					
Abhulimen (2009)					√				
Bybee (2009)									√
Gomez *et al.* (2009)									√
Jafarizadeh and Bratvold (2009)			√						
Li *et al.* (2009)				√					
Verre *et al.* (2009)				√					
Kayrbekova and Markeset (2010)				√					
Ratnayaka and Markese (2010)							√		
Pinturier *et al.* (2010)		√							
Angert *et al.* (2011)				√					
Chen *et al.* (2011)				√					
Gong *et al.* (2011)						√			
Kayrbekova *et al.* (2011)				√					
Nam *et al.* (2011)				√					
Ortiz-Volcan and Iskandar (2011)				√					
Stephenson *et al.* (2011)					√				
Streeter and Moody (2011)				√					
Burnham *et al.* (2012)					√				
Goodwin *et al.* (2012)					√				
Grosse-Sommer *et al.* (2012)					√				

Schulze *et al.* (2012)							√										
Shrivastva *et al.* (2012)							√										
Weber and Clavin (2012)					√												
Zoveidavianpoor *et al.* (2012)																√	
Burlini and Araruna (2013)				√													
Hernandez *et al.* (2013)				√													
Lopes and Almeida (2013)										√							
Pettersen *et al.* (2013)					√												
Pierce and Wills (2013)															√		
Sheremetov *et al.* (2013)																	√
Trujillo *et al.* (2013)							√										
Fergestad *et al.* (2014)					√												
Fowler *et al.* (2014)																	√
Jeong *et al.* (2014)				√													
Kullawan *et al.* (2014)								√									
Lilien *et al.* (2014)					√												
Maddah *et al.* (2014)	√																
Marten and Gatzen (2014)				√													
Sandler *et al.* (2014)					√												
Siveter *et al.* (2014)					√												
Wright *et al.* (2014)		√															
Chilukuri *et al.* (2015)				√													
Chun *et al.* (2015)					√												
de Wardt and Peterson (2015)				√													
Ghani *et al.* (2015)				√													
Oruganti *et al.* (2015)				√													
Silitonga (2015)			√														
Zavala-Araiza *et al.* (2015)					√												
Adam and Ghosh (2016)				√													
Bello *et al.* (2016)																	√
Guedes and Santos (2016)			√														
Johannknecht *et al.* (2016a)				√													
Johannknecht *et al.* (2016b)				√													
Ortiz-Volcan *et al.* (2016)				√													
Seo *et al.* (2016)		√															
Shafiee *et al.* (2016)		√															
Steuten and Onna (2016)				√													
Total number of papers	3	14	4	39	18	4	10	1	4	5	0	0	0	0	1	1	6
Percentage of papers (%)	2.7	12.7	3.6	35.5	16.4	3.6	9.1	0.9	3.6	4.5	0	0	0	0	0.9	0.9	5.5

Table 3. Distribution of studies based on geographical location of case studies.

Reference	Aim of study	Case study location
Songhurst and Kingsley (1993)	LCC reduction through design for maintenance	North Sea
Dear *et al.* (1995)	Mud system selection	Nigeria
Lassen and Syvertsen (1996)	Fatigue reliability and LCC analysis of mooring chains	North Sea
Winkel (1996)	Material selection	North Sea
Cheldi *et al.* (1997)	Material selection	Mediterranean Sea
Tague and Hollman (2000)	CBA of downhole video	USA
Aycaguer *et al.* (2001)	EOR with injection of CO_2 feasibility analysis	USA
Gerbacia and Al-Shammari (2001)	Selection of strategic reservoir planning option	Kuwait
Suslick and Furtado (2001)	Decision models for offshore oil exploration	Brazil
Chitwood *et al.* (2004)	Evaluations of deepwater marginal field developments	GOM
Islam and Powell (2005)	CBA of flowline replacement	Middle East
Lev and Murphy (2007)	Project portfolio selection	Canada
Orimo *et al.* (2008)	CBA to determine the design of FLNG storage size	Indonesia
Bahmannia (2008)	ELCA of gas treatment plant	Iran
Li *et al.* (2009)	Minimize expected LCC for ice-resistance platforms	China
Ortiz-Volcan and Iskandar (2011)	LCC analysis for production technologies in heavy oil well construction	Venezuela
Streeter and Moody (2011)	Maximizing NPV of uneconomical fields using shallow water subsea systems	GOM
Grosse-Sommer *et al.* (2012)	Evaluating the sustainability of completion fluid	North Sea
Shrivastva *et al.* (2012)	Optimizing borehole imaging for tight gas exploration	Oman
Hernandez *et al.* (2013)	LCC analysis for a nitrogen over hydraulic pumping unit	Colombia
Lopes and Almeida (2013)	Selecting a portfolio of oil and gas exploration projects	Brazil
Pierce and Wills (2013)	Assessing risk for Permian Basin tank battery	USA
Maddah *et al.* (2014);	An optimization model to define a production sharing contract between the government and oil companies	Mediterranean Sea
Chun *et al.* (2015)	Reservoir management through ELCA	Peru
Adam and Ghosh (2016)	Material selection	Brunei
Ortiz-Volcan *et al.* (2016)	Cost optimization of a thermal recovery project	Kuwait
Shafiee *et al.* (2016)	CBA of water deluge system for life extension	W/A

Note: The abbreviation W/A means West Africa, GoM means Gulf of Mexico, and FLNG means Floating Liquefied Natural Gas, EOR means Enhanced Oil Recovery, and NPV means Net Present Value.