



Ontology Knowledge-Based Decision Support System

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ABSTRACT

Since the inception of making decisions, one or more forms of decision support systems have been applied to a number of areas as a system that has the capability to help decision makers in decision making. Decision support systems has also been designed using a number of knowledge representation techniques. This paper uses an ontology knowledge representation technique for a decision support system design. The important terms taxonomy of the domain serves as the knowledge base and this was combined with Java rules (as the data management model) connected together using the web ontology language application programming interface (OWL-API). Subsea multiphase pump used in the oil and gas industry was used as the case study to build the decision support system. The result shows the tool ability in recommending prospective technologies based on the match algorithm and percentage comparator; this aid in refining the applicable suggested technologies by showing the percentage match. This contribution of this paper is an ontology knowledge-based system that serves as the knowledge-base, that is built on linguistic terms which can influence decision makers approval of knowledge-based decision making which is usually done manually in this domain. The validation by domain experts between the Ontology knowledge-based tool and the Pugh matrix shows that the tool was 20% better in recommending suitable technology to suit a particular oil and gas field scenario for an appropriate technology assessment and selection.

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INTRODUCTION

Decision support process involves a number of steps which usually goes through series of iteration. Using the case study of the oil and gas field subsea processing technology selection in this paper, from the literature, the oil and gas field development requires a working knowledge of the offshore facilities used around the world [1,2]. Huge capital investment costs and operational expenditures is involved in this industry, these makes its profitability dependent upon the reliability, availability and maintainability (RAM) of the equipment's [3]. The task involved in the decision making in the subsea domain has been tagged as risky and is by no means an easy task because many important issues have to be considered because of the subsea domain the technology will be deployed in. Costs of lost production/downtime due to failure of these technologies will greatly exceed the cost of

procuring the technology in the first place [4,5,6]. Decision support for technologies for use in this industry can help lower the risk of inappropriate technology selection, failure reduction, cost reduction and optimum oil and gas recovery increment. The rate of growth in different decision scenarios in the oil and gas industry kept increasing at an alarming rate [7,8,9]. The various decision scenarios can be from subsea processing systems to the entire subsea production systems. The subsea processing systems core technologies includes: the subsea multiphase pump, subsea separation, gas compression, water injection and storage technologies. The subsea multiphase pump, which is currently the heart of subsea processing [10,11,12,13] is the focus of this paper. Authors [1,14], argues that an integrated decision making tool can help during the process of making an informed decisions. Therefore, there is need for a tool that can

integrate all the important parameters together with an easy-to-use interface that can add knowledge to the system as information becomes available for future decision making.

In the domain of interest (oil and gas) industry, many activities are needed to be performed, efficient access to information is an issue [1,14,15] which is also primarily due to the fact that when changes are made in some certain aspect of the operation, passing across to relevant information repository is a major issue [7]. This was corroborated by [16] in reporting a project results research in Netherlands which revealed that the major reason for project failure cost is lack of insufficient information exchange and communication within projects. They also reported that a workshop outcome shows that project leaders and engineers are not proficient in a simple to use modeling method that is close to human semantics and suggested that proficiency in this modeling skills can improve interoperability and consequently, efficient communication among project teams. This was also corroborated by [7,14] that the use of decision and risk analysis tools in this industry is still limited, they attributed this to tools complexity and suggests that selection of software tools is a critical aspect of decision making process.

RELATED WORK

Decision support systems, which is also an assessment and selection process has been widely accepted in a number of domains such as in Medicine [17,18], Aviation [19,20], oil and gas [21, 22] and Emergency management during pandemic [23]. Combinations of different approaches have also been reported in [24] for Bayesian network in combination with expert system. Decision making (in oil and gas) have employed: general guidelines, heuristics, intuition, analytical information, traditional financial management (such as discounted cash flow/decision trees) and information provided by vendors for selecting equipment [1,6,25,26,27]. Besides, the selection is usually done manually [7,26,28, 29]. Other approach found in the literature are: Blockchain [30,31], qualitative model [13], Multi criteria decision making methods [8,32,33,34,35], guidelines based on the mechanical strength of the equipment [4,26], statistical estimates such as

Bayesian network analysis [5,36]; Reliability, availability and maintainability analysis [37], Parameter mappings [6], Cost estimates such as net present value calculations, life cycle cost [38], and decision matrix [33]. The use of different types of model in the assessment and selection of oil and gas technologies have been reported in the literature such as the use of integrated production model (IPM) or integrated asset model (IAM) [13] and Multi-criteria decision making (MCDM) models such as: Analytical Hierarchy process (AHP) model, Multi-attribute utility (MAUT) model, Simple multi-attribute rating technique (SMART), Technique for Order Preference by Similarity to ideal situation (TOPSIS) and Elimination Et Choix Traduisant la REalite (ELECTRE) [32,34,35,39]. According to [32], with Blockchain technology, exchange and transmission of data can be more efficient, thus improving the correctness of decision-making.

Integrated production model or integrated asset model are models that combines reservoir simulation models with production facility models for assessment and selection of oil and gas assets. Reference [40] combined transient reservoir behaviour, artificial lifting efficiency, equipment reliability and economics in their IPM model to select artificial lift system. [13] built an integrated production model which combines reservoir, production and processing facility model to economically compare which artificial lift (AL) technologies (basically, subsea gas liquid separation and gas lift) is most suitable. They employed two case studies for the comparison between gas liquid separation and gas lift. Their model was able to estimate the incremental recovery factors for each of the technology under study. Also, [60], focused on offshore assets, they used IPM to deduced the best strategy for development combining new and undersized assets into existing production fields. They stressed that to derive maximum benefits from IPM, there is need for the model to be continually measured and superised over a number of time. This type of models also requires a lot of field data which might be difficult to obtain [14].

Multi-criteria decision making (MCDM) models or Multi-criteria decision analysis (MCDA) are process that can aid organizations to input and evaluate known

factors and outcomes that are associated with a particular decision [32,33,34,41]. The process ranges with interviewing experts on their corporate decision-making policy to reviewing historical making policy data or guideline which aid in identifying and quantifying each organization's objectives and preferences. According to [41], the general approach for MCDA includes: defining decision objectives; establishing selection criteria that reflects the objectives; identifying alternative options; evaluating the performance for each criteria; weighing criteria according to their importance; combining criteria evaluations and weights into overall performance estimate for each option; selecting options based on the overall performance. In [8], an approach based on the system was used for quantifying risk factors and the use of different approaches for the development and positioning of possible production assets of the arctic offshore MCDA.

MCDM models that have been adopted are Bow-Tie model and simulation [33], Elimination Et Choix Traduisant la REalite (ELECTRE) [35] and Technique for Order Preference by Similarity to ideal situation (TOPSIS) [39,42]. These models can select from a number of criteria based on a comparative analysis of data sets. Bow-Tie analysis has been used to quantify risk and its impacts while the simulation model works on the information about the systems and their interactions [33]. The selection process takes the chosen artificial lift based on the one that has the shortest Euclidean distance from the ideal solution and the farthest from the non-ideal solution to select a suitable artificial lift technique for a particular field. They developed a software in visual basic.net with the models to aid in assessment and selection [35,39]. The work by [42] combined failure mode and effect analysis with TOPSIS to develop a model to select maintenance policies for artificial lift. Multi-attribute decision model with multi-attribute utility function was used by [27] to assess ways for selecting development projects in the oil and gas industry. Multi-attribute utility theory (MAUT), was used to model uncertainty and multiple criteria. The recommended chosen model is the model that has the highest multi-attribute utility which is a combination of options interaction among alternatives and the multi-attribute value of the project. They argued that

in the industry, all important and critical factors should be taken into consideration during selections. The work by [34] was centered about finding the best decommissioning method for subsea oil and gas equipment's using analytical hierarchical model (AHP) while [32] used MCDM to select suppliers for the oil and gas industry. They used delphi method to select critical success factors utility function and for each critical success factors, they use complex proportional approach to rank suppliers and use the step-wise weight assessment ratio analysis to generate criteria weight, for the fuzziness of the preferences of the experts, they employed Z-numbers. They further reiterated that assessment and selection help decrease cost and raise revenue.

Statistical tools that have been used include: Risk analysis (RA), Life cycle costing (LCC), Decision tree, Reliability availability and maintainability (RAM) analysis [3,37,43], Bayesian network (BN) analysis [5,36]. RAM analysis, a probability simulation model is one of the key tools for technology assessment and selection in this industry as it can reveal the expected performance required. It can also evaluate development scenarios and give assessment of each option under consideration [43]. In [3], a mathematical model was developed as a guide to understand and present uncertainties in production assurance analysis (arrangement and measures decision making for production availability) of subsea gas production system using Monte Carlo simulation. They reported that their result shows that the total production unavailability to be 4.6%. In [37], RAM analysis was used to choose technology from the trend/comparison analysis to aid in the selection process of oil and gas facilities. While [43], developed a guideline that combines reliability, performance simulation and technology qualification for decision support (based on other field information and data analysis) when considering new technologies. RAM analysis has been shown to be effective [43] but a drawback is there is need for failure and maintenance data which are often difficult to obtain.

Semantic technologies use is now being explored in the oil and gas industry as a tool for decision support due to the fact that it gives a broad view of a domain [15] due to its expressive representation of different data

source which is a way to deal with information management issues. The key technology of the semantic web is OWL [15,17,44,45,46]. OWL models the domain concepts and this gives rise to a knowledge base that forms the central repository of the individual (instance) data of the system. The semantic web technologies give rise to intuitive and simple data modeling, which can further be processed for distributed and collaborative use with other tools and thus has the capability to perform useful inference by inferring facts from the user provided data [18]. The semantic web ontologies are generally accepted as an alternative to relational database [45]. This was also corroborated by [44,46,47,48,49] that ontology is predicted as a viable tool of describing and representing domain knowledge which has a potential application as a decision and knowledge management tool. According to [15]; semantic modeling can form the backbone of oil field applications to facilitate information integration and knowledge representation. They further reiterated that the approach in assessment and selection in this industry is labour intensive due

to its time consumption and it has scalability issues owing primarily to the large number of criteria's.

A number of researchers [15,21,50,51] have enumerated the important role ontology as a tool can play in the information retrieval of information in the oil and gas industry. Other assessment and selection that has also been reported includes: Parameter mapping [6], developed algorithm [51,52], mechanical strength [4,26] and concept selection [28]. According to [41], decisions will most probably need to be made in the next decade without sufficient empirical data due to the fact that there will be large knowledge gaps and as such tools needs to be developed which can integrate data as it becomes available.

Decision Support systems

Decision support systems that have been widely used is depicted in Table 1. Basically, DSS is built on a graphical user interface, knowledge based and a management system that works to manipulate the model.

Table 1. Different Types of Decision Support system [53,54]

Decision Support System (DSS)	Description
Data-driven DSS	Concern with data manipulations. Types includes: Data warehouse, Online analytical processing (OLAP)
Model-driven DSS	They are used as: Numerical models for possible alternatives evaluation via simulation, risk analysis and optimization
Knowledge-driven DSS	They are intelligent DSS for knowledge management
Communication-driven DSS	Type includes web-based DSS. Used for interchange of data and information for cooperative decision making
Document-driven DSS	Types includes: analytics-based and business intelligence systems. It is suited for unstructured data such as multimedia documents and web pages

METHODOLOGY

The methodology flowchart is depicted in Figure 1. The web ontology language application programming interface (OWL-API) library consisting of nine libraries files that is referenced in the java classes such as the OntMain.java class, MainOWLOntology.java and the rest of java class files that is used to develop the decision support system.

This facilitates the communication between the OWL Ontology and the Java codes. The Pallet reasoner is also another library that is used to infer assertions in the

ontology. Inference only happens when this reasoner is called, if the reasoner is not called, there won't be any assertion as such, no instance (technologies) or properties/attributes (data on the technologies) can be retrieved from the ontology. The Ontology database system is the designed Ontology for the domain. It defines the basic three ontology building blocks which are the classes, the properties and the individual (instance). Relationships connect all the three building blocks together. Instances are the technologies that recommendations will be made on with their respective required data on the classes and properties.

Basically, the ontology knowledge base designed for this system comprises of : Classes (Class Tab is depicted Figure 2). This Tab shows the subsea multiphase concept in an hierarchical form. The Individual/Instance (instance Tab is depicted in Figure 3). Individuals or instance are the main object of

concern in the ontology, in this research, individuals such as ESP1, TSP1, HAP1 and so on are variants of the subclass electrical submersible pump, twin screw pump and helico axial pump respectively which are all members of the class subsea multiphase pump.

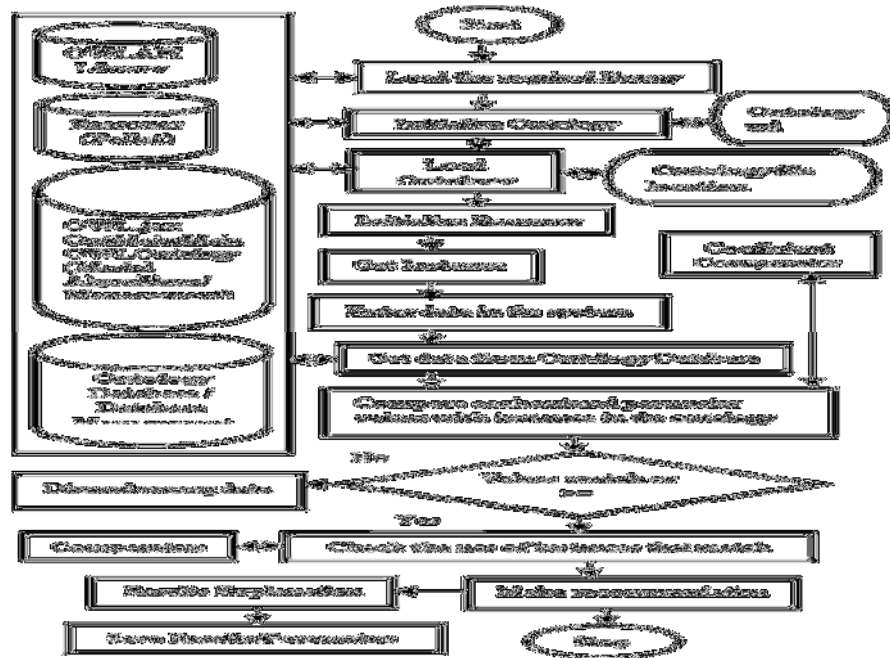


Figure 1. Methodology flow chart

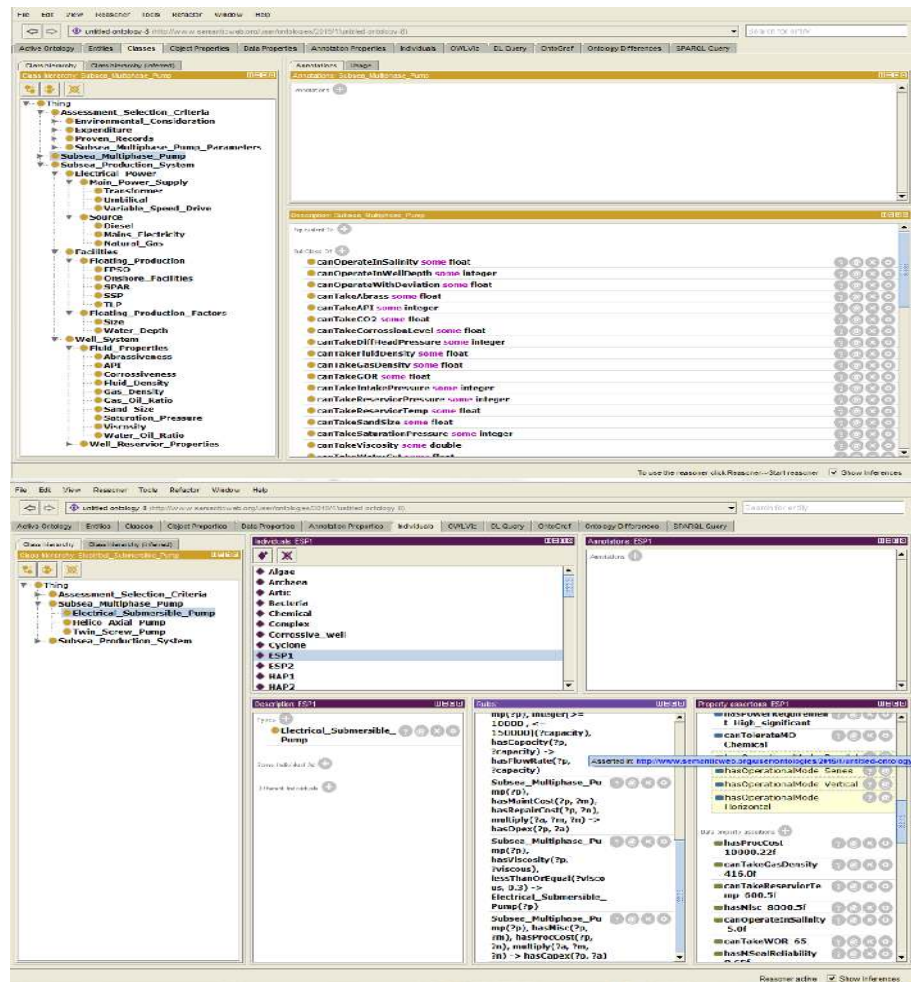


Figure 2. Classes, its hierarchies and properties assertions

Also on this tab, the individual object and property assertions of each individual can be seen (i.e Property assertions ESP1 and the rest of the individual when they are clicked). It also houses the semantic web rule language (SWRL) tab, which is a rule that complements the ontology development for some properties that needs to be calculated. Figure 3 also shows the inference that is made for object properties, data properties and SWRL when the reasoner is invoked on the reasoner tab (this is Shown in the property assertion tab in light yellow shade). Object Properties (the object property tab also in Figure 2) is used to define non numeric properties of an instance. Example the object property “canOperateInWell” is used to denote

Figure 3. Individual Tab with property assertions

a particular instance can operate in one or more of different well types. Data properties are used to denote the numeric properties of an instance. For example the data property “canOperateInWellDepth” is used to denote each individuals suitability for a particular oil well depth such as ESP1 can operate in well depth of 1000m. It denotes each individuals suitability for a particular oil well.

Typically, an application programming interface (API) work together with relevant functions by which programs (could be through a third-party application) on the designed knowledge base and can be used to provide additional functionality to delete, add,

retrieve, modify classes, properties, individuals / instances and assertions of the knowledge base. The reasoning function in OWL-API is done separately. The Pallet reasoner is also another library that is used to infer assertions in the ontology. Inference only happens when this reasoner is called, if the reasoner is not called, there won't be any assertion as such, no instance (technologies) or properties/attributes (data on the technologies) can be retrieved from the ontology. The Ontology database system is the designed Ontology for the domain. It defines the basic three ontology building blocks which are the classes, the properties and the individual (instance). Relationships connect all the three building blocks together. Instances are the technologies that recommendations will be made on with their respective required data on the classes and properties.

The OWL-API gives the data structure representing the OWL ontology with the ability to reason, parse, create, manipulate and render the ontology. The domain ontology consists of the concepts in the domain. It is loaded from OWL file whose location is specified. The ontology model is used together with a reasoner

(Pallet) to output instances of interest from the ontology. For the knowledge acquisition module, see [21]

This decision support flowchart (Figure 1) accepts data inputs for the important parameters that influence the assessment and selection of subsea multiphase pump technologies and make recommendations on the best technologies match that will best fit the user's requirements based on existing and newly added individuals (instance) to the ontology knowledge base. The match algorithm which is embedded in the system includes six comparators and the results explanation is built in the MainOWLontology class while, all the parameters initialization and assignments are done in the OntMain class.

RESULTS

The case study data for a subsea field for exploration is presented in Table 2. At the beginning of the decision to start exploration for a field, usually the parameters available are first used for the assessment and selection of technologies for that field.

Table 2. Case Study data

Parameters	Value
Flowrate (bbl/d)	50,000
Water Depth (m)	2,900
Differential Pressure (psi)	4206
Oil Density (API-degree)	23
Wellhead Pressure (psi)	14,000
Viscosity (cp)	100
Gas Volume Fraction (%)	10
Reservoir Temperature (degree C)	180

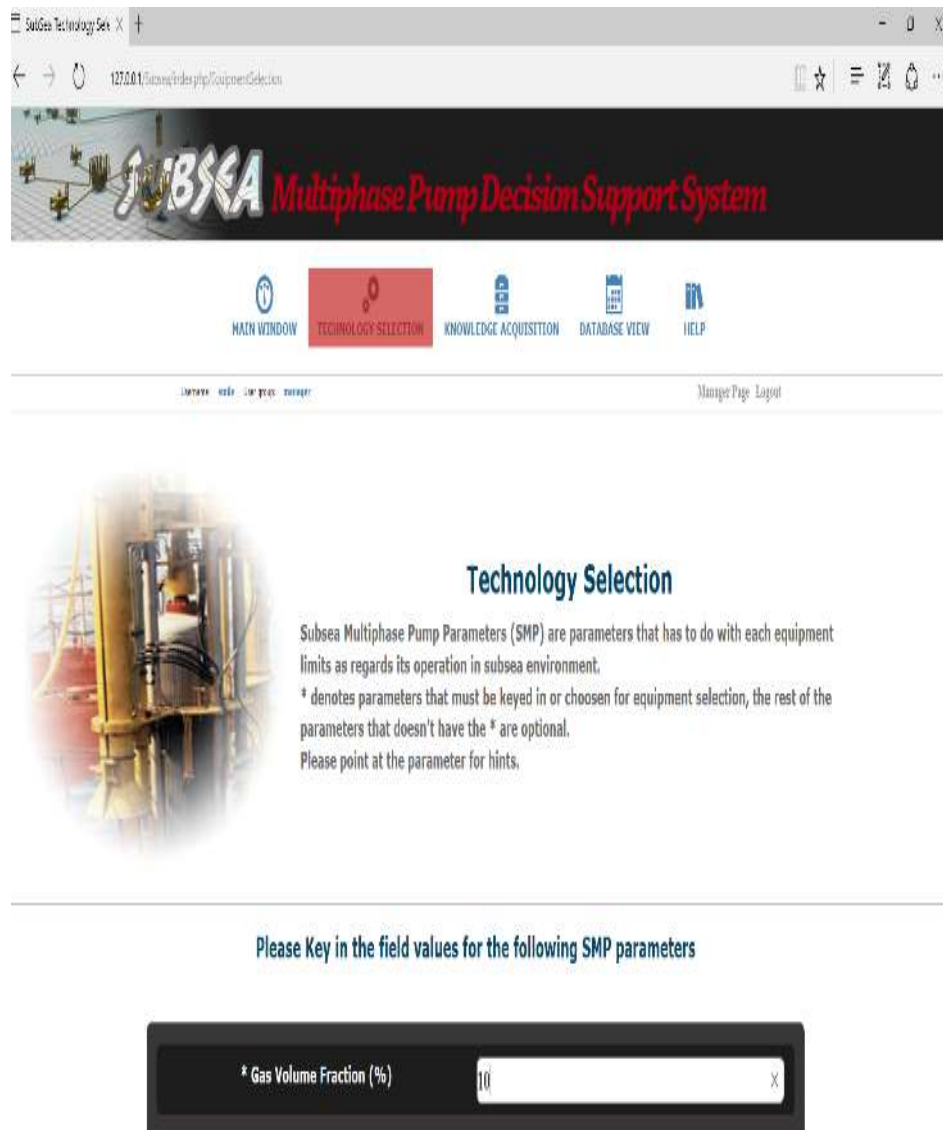



Figure 4. Decision screen 1



Technology Selection

Subsea Multiphase Pump Parameters (SMP) are parameters that has to do with each equipment limits as regards its operation in subsea environment.
* denotes parameters that must be keyed in or chosen for equipment selection, the rest of the parameters that doesn't have the * are optional.
Please point at the parameter for hints.

Please Key in the field values for the following fluid properties

* What is the level of viscosity (cp) in your fluid ?	100
What is the API(degree API) of your fluid ?	23
What is the fluid density(kg/m3) of your fluid ?	
What is the Gas Oil Ratio in your fluid (scf/bbl) ?	
What is the sand size (µm) in your fluid ?	
What is the saturation pressure (psi) of your fluid ?	
What is the gas density (kg/m3) of your fluid ?	
What is the water oil ratio of your fluid ?	

Please Key in the field values for the following well parameters

* What is your differential head pressure (psi) ?	4206
* What is your flow rate (bbl/d) ?	50000
* What is your reservoir pressure (psi) ?	
* What is your reservoir temperature (degree C) ?	180
* What is your water depth at TVD (meters) ?	2900
What is your wellhead pressure (psi) ?	14000
What is your well deviation (degree) ?	
What is your intake pressure at seabed (psi) ?	
What is your well type ?	<div> Viscous_crude_well High_gas_oil_ratio_well Solid_sand_well Variable_speed_well </div>

Figure 5. Decision screen 2

Figure 6. Decision screen 3

Data (Table 2) on a subsea field was used in testing the decision support system. Usually at this stage in decision making only a few data are supplied to get a view of the likely technology that can be deployed in the field.

The screenshot of the technology selection interfaces is shown in Figures 4-6. The recommendations outputted are shown in Figure 7 and Figure 8. In these Figures, comparison is made with the user's parameters against the data in the knowledge base. This

shows the percentage match of the recommendations. Using the case study data parameters, after entering the desired parameters and clicking on select button, the system scans through the database to check the equipment that closely fits these criteria. The parameters entered and the generated results can be saved in 4 different file formats which are: Excel, PDF, word and text. The system has the capability to suggest the most matched equipment technologies; this makes it



easy as a guide for the user to do a comparison among the suggested technologies.

Screenshot of the "Equipment Match Result" web application interface.

Equipment Match Result

In this page, user can save entered parameter and selection result into text, word, excel, pdf, power point.
Select document type option and click either of below buttons.
Default option is text.

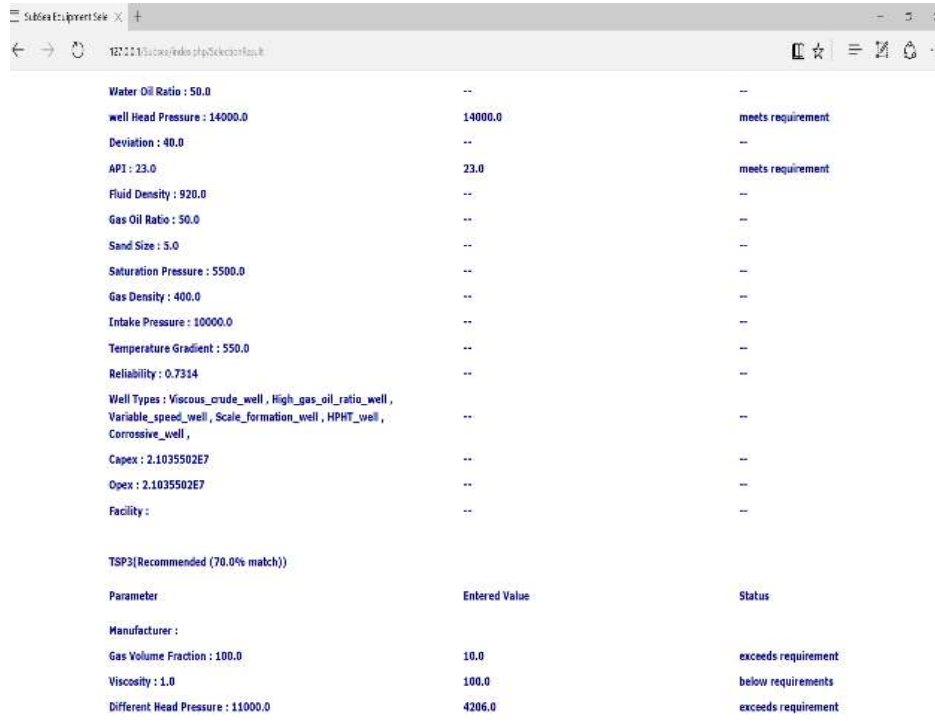
Buttons: Save Parameters, Save Results

Document Type Selection: ☒ Excel, ☐ PDF, ☐ Word, ☐ Text

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TSP2(Recommended (70.0% match))

Parameter	Entered Value	Status
Manufacturer :		
Gas Volume Fraction : 100.0	10.0	exceeds requirement
Viscosity : 1.0	100.0	below requirements
Different Head Pressure : 10500.0	4206.0	exceeds requirement
Flow Rate : 450000.0	50000.0	exceeds requirement
Reservoir Pressure : 8000.0	15000.0	below requirements
Reservoir Temperature : 630.0	180.0	exceeds requirement



Parameter	Entered Value	Status
Water Oil Ratio : 50.0	--	--
well Head Pressure : 14000.0	14000.0	meets requirement
Deviation : 40.0	--	--
API : 23.0	23.0	meets requirement
Fluid Density : 920.0	--	--
Gas Oil Ratio : 50.0	--	--
Sand Size : 5.0	--	--
Saturation Pressure : 5500.0	--	--
Gas Density : 400.0	--	--
Intake Pressure : 10000.0	--	--
Temperature Gradient : 550.0	--	--
Reliability : 0.7314	--	--
Well Types : Viscous_crude_well , High_gas_oil_ratio_well , Variable_speed_well , Scale_formation_well , HPHT_well , Corrosive_well ,	--	--
Capex : 2.1035502E7	--	--
Opex : 2.1035502E7	--	--
Facility :	--	--
TSP3(Recommended (70.0% match))		
Manufacturer :		
Gas Volume Fraction : 100.0	10.0	exceeds requirement
Viscosity : 1.0	100.0	below requirements
Different Head Pressure : 11000.0	4206.0	exceeds requirement

Figure 7. Decision screen 4

Figure 8. Decision screen 5

Validation

The validation methodology is depicted in Figure 9. Pugh Matrix is a well-known and typically used in the oil and gas for technology assessment and selection [28,29, 55] and it was developed by Stuart Pugh. Table 2 shows the Pugh matrix template. The score of each technology to be compared is used for comparison to determine the most suitable option. technologies to be compared are on the horizontal axis while vertical axis is for the criteria's to be used for the comparison. Scores of each considered technologies are assigned weight relative to the criteria for measurement of the best alternative. The strengths and weaknesses of each technology is compared against a chosen base concept (datum). the best matrix iteration concept gives the datum. At each iteration level, the technology that does not meet the criteria is eliminated, finally, the result of the last iteration could be a tie of more than 2 technologies. Decision makers usually find it time consuming due to work pressures [55].

In the ISO/IEC 9126, the internal quality, external quality and the quality in use express quality model. The internal attributes of the software such as the design and compliance with standards are used to evaluate the internal quality. During testing, when the software is run, then the external quality is evaluated while, the user's assessment of the software quality when it is used in a particular situation denotes the quality in use. Typically, when the software is installed for real time usage only then is quality in use evaluated. A wide range of respondents were given the decision-making tool and the Pugh matrix template together with the case study (Table 2) and any other case study of their choice related to the domain to test. The respondents include experts from the subsea field and academicians that are proficient in software tools/development. A total of 10 respondents were able to fill the survey. Some metrics that is used in the evaluation is the ISO/IEC 9126 software quality model evaluation metrics. 40% of the respondents have about 5 years working experience, 20% has between 10

years to 15 years working experience while 40% has about 15 years. 40% are in engineering, 10% in management while 50% are in information systems. 50% have PhD degree, 40% have master's degree while 10% has BSc. 10% are from oil and gas company while 90% are from the academia. The metrics are in

Table 3, these metrics that generally be adopted to measure software quality. Some Authors argue that generally, the reliability metrics cover the performance of functions of software and specified environment for software product [56-59].

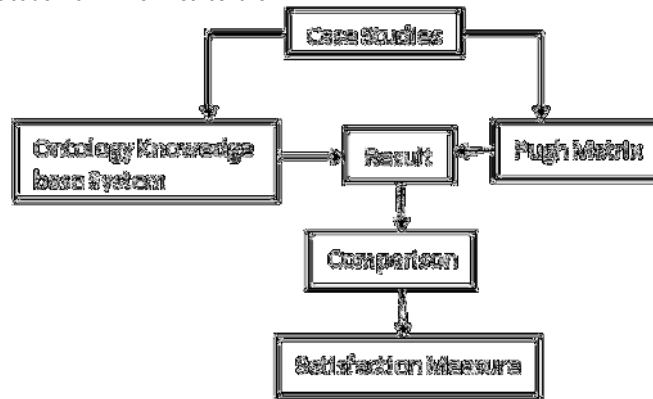


Figure 9: Comparison for validation

Table 2. Pugh Matrix Computation

Criteria Selection	for Weight	Datum	Helico-axial pump	Electrical pump	Sub. pump	Twin pump	Screw pump
Flow rate	a						
Water depth	b						
.....	c						
Score							
Rank							

Table 3. Validation Result

	Pugh Matrix Outstanding	Good	Satisfactory	Ontology KBS Outstanding	Good	Satisfactory
Ease of use	20%	80%	0%	40%	60%	0%
Accuracy	30%	70%	0%	30%	70%	0%
Decision reliability	40%	60%	0%	30%	70%	0%
Operation reliability	20%	80%	0%	20%	80%	0%
Organization	10%	80%	10%	30%	70%	0%
Effectiveness	10%	90%	0%	10%	90%	0%
Time response	0%	80%	20%	50%	50%	0%
Resource consumption	30%	70%	0%	50%	50%	0%
Explanation adequacy	40%	60%	0%	40%	60%	0%
Usefulness	30%	70%	0%	30%	70%	0%
Stability	10%	90%	0%	20%	80%	0%

CONCLUSION

In this paper, a method for developing an ontology decision support system has been described. The basic components of the method are: the OWL ontology as the knowledge base, the OWL-API (to link the knowledge base with the data management model) and the java parts as the data management model for subsea multiphase pump decision support system and which can also be applicable to other complex oil and gas technology decisions support. The strengths of these three software languages has been merged together to provide a robust tool that gets more better as data is added via the graphical user interface that is deployed on java which is automatically sent to the OWL ontology knowledge based, whose semantics is close to human language through the OWL-API and the java modules. The OWL ontology is an alternative to relational databases that is sometimes used in the knowledge base systems development of decision support systems as it is functional and easier to design and develop. It is also easier to use as the graphical user interface makes it easy for persons who are not proficient in the software language to use the decision support system effortlessly. The validation of the decision support tools by oil and gas field experts and academia shows the applicability of the ontology knowledge-based tool.

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