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MODELLING APPROACH FOR MULTI-CRITERIA DECISION-MAKING SELECTION PROCESS FOR ARTIFICIAL LIFT SYSTEMS IN CRUDE OIL PRODUCTION.

MODELAMIENTO DEL PROCESO DE SELECCIÓN DE SISTEMAS DE LEVANTAMIENTO ARTIFICIAL EN PRODUCCIÓN DE PETRÓLEO POR MEDIO DE METODOLOGÍAS MULTICRITERIO PARA TOMA DE DECISIONES.

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ABSTRACT

Artificial Lift system selection is a key factor in enhancing energy efficiency, increasing profit and expanding asset life in any oil-producing well. Theoretically, this selection has to consider an extensive number of variables, making hard to select the optimal Artificial Lift System. However, in practice, a limited number of variables and empirical knowledge are used in this selection process. The latter increases system failure probability due to pump – well incompatibility.

The multi-criteria decision-making methods present mathematical modelling for selection processes with finite alternatives and high number of criteria. These methodologies make it feasible to reach a final decision considering all variables involved.

In this paper, we present a software application based on a sequential mathematical analysis of hierarchies for variables, a numerical validation of input data and, finally, an implementation of Multi-Criteria Decision Making (MCDM) methods (SAW, ELECTRE and VIKOR) to select the most adequate artificial lift system for crude oil production in Colombia. Its novel algorithm is designed to rank seven Artificial Lift Systems, considering diverse variables in order to make the decision. The results are validated with field data in a Case study relating to a Colombian oilfield, with the aim of reducing the Artificial Lift Failure Rate.

RESUMEN

La selección del sistema de levantamiento artificial es un factor clave para mejorar la eficiencia energética, aumentar los beneficios y ampliar la vida útil de los activos en cualquier pozo productor de petróleo. Teóricamente, esta selección debe tener en cuenta un gran número de variables, lo que dificulta la elección del sistema óptimo. Sin embargo, en la práctica, este proceso involucra un número limitado de variables y conocimiento empírico lo cual aumenta la probabilidad de falla del sistema debido a la incompatibilidad entre la bomba y el pozo.

Los métodos de toma de decisiones multicriterio presentan modelos matemáticos para procesos de selección con alternativas finitas y un alto número de criterios. Estas metodologías hacen factible tomar una decisión considerando todas las variables involucradas.

En este artículo, presentamos una aplicación software basada en un análisis matemático secuencial jerárquico de variables, una validación numérica de datos de entrada y una implementación de métodos multicriterio para toma de decisiones (MCDM, por sus siglas en inglés): SAW, ELECTRE y VIKOR. Esto con el fin de seleccionar el sistema de levantamiento artificial más adecuado. Su novedoso algoritmo está diseñado para clasificar siete sistemas, considerando diversas variables en la toma de decisión. Los resultados se validan con datos de un campo colombiano, enfocándose en reducir el índice de falla de los pozos de dicho campo.

KEYWORDS / PALABRAS CLAVE

Artificial lift | Oilfield production | AHP | SAW | ELECTRE VIKOR.
Levantamiento artificial | Producción de petróleo | AHP | SAW ELECTRE | VIKOR

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1. INTRODUCTION

In some cases, Artificial Lift System (ALS) selection for crude oil production is mostly based on operator experience, on analogy or comparison with similar cases, on required flow rates, or well depths and bottomhole pressure, among other things. Although these variables can be good criteria in some cases, they do not have a strong analytical / mathematical basis and they use a set of criterions with little or no application of the scientific method. Despite of the fact that application of many of these criteria result in acceptable performance in ALS, it's worth noting that there is a big opportunity for developing an automated process based on algorithms that model mathematical procedures used for decision-making processes. Software applications reduce time-consuming processes, standardize procedures, decrease the likelihood of errors in selection, optimize downhole pump performance, and increase asset life.

This paper presents an algorithm and a software application developed to perform the selection of artificial lift systems for crude oil production in Colombia. The process is based on three MCDM methods with a prior Analytic Hierarchy Process (AHP) setup. Subsequently, its results are evaluated with a brief case study using a Colombian field's well sample, with the intention of selecting the most suitable ALS, hence reducing the current failure rate.

2. THEORETICAL FRAME

MULTI-CRITERIA DECISION ANALYSIS METHODOLOGY

Multi-Criteria Decision Making (MCDM) forms part of advanced analytical methods developed to improve efficiency and reduce time-consuming processes, and make better decisions [1]. MCDM methodologies confront conflicting criteria or Input Variables (*Iv*) and generate matrix systems that consider possible solutions to a specific situation, sorting and ranking them quantitatively according to its relevance as possible solutions to the given situation. [2]

Usually, MCDM methodologies are preferred when there is not a clear *Iv* that affects the output of a decision-making analysis. Instead, the change in any *Iv* leads to a variation of the matrix systems, hence leading to a different set of alternatives [2]. This behaviour is referred to as non-dominated.

There are many different MCDM methods and all of them differ in the quantitative result and usually the ranking of alternatives. For this study, three different methods were chosen (SAW, VIKOR and ELECTRE) according to the differences in their mathematical treatment in order to see which would provide the best accuracy in relation to empirical field data and on an engineering basis.

ANALYTIC HIERARCHY PROCESS (AHP)

Besides the three MCDM methods already mentioned, the AHP process was used to define a priority vector that contains normalized values of the n input variables that pre-determine weights (W_i) of any *Iv*. The procedure used is shown below [1]:

1. Create an $n \times n$ matrix (pair-wise comparison matrix) comparing all *Iv* against each other *Iv*, this matrix will be referred as $M_{(nxn)}$. This comparison is based on a scale predefined before AHP is used. For any correlation of *Iv* a numerical value (n_{ij}) that represents how important it is in regard to the other *Ivs* is required.

2. Add up all resulting values for every column N_j (see *Equation 1*). Then, divide every n_{ij} by N_j to normalize them (see *Equation 2*); the resulting matrix is $\bar{M}_{(nxn)}$:

$$Nj = \sum_{1}^{n} n_{ij} \quad i=1,\ldots n \; j=1,\ldots n \tag{1}$$

$$n_{ij} = \frac{n_{ij}}{N_j} \quad i=1,\ldots n \; j=1,\ldots n \tag{2}$$

3. Add up all n_{ij} values for every row of $\bar{M}_{(nxn)}$ (see *Equation 3*) to determine the priority vector ($\vec{W}$)

$$W_i = \sum_{1}^{n} n_{ij} \quad i=1,\ldots n \; j=1,\ldots n \tag{3}$$

A consistent verification of the *Iv* is recommended at this point. "To ensure that the judgments of decision makers are consistent" [3] a consistency ratio (*CR*) is introduced. If *CR* exceeds 0.1, this means that one or more of the scale values used before AHP application needs to be redefined [1].

For all three MCDM methods a matrix X_{mxn} is required:

Once the set of alternatives (possible solution to the situation) is defined, construct a matrix $X_{(mxn)}$ of alternatives(A_i) against criteria (Iv_i):

$$X_{mxn} \begin{bmatrix} & Iv_1 & Iv_2 & Iv_3 & Iv_4 & \cdots & Iv_n \\ A_1 & X_{1,1} & X_{1,2} & X_{1,3} & X_{1,4} & \cdots & X_{1,n} \\ A_2 & X_{2,1} & X_{2,2} & X_{2,3} & X_{2,4} & \cdots & X_{2,n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & X_{m,1} & X_{m,2} & X_{m,3} & X_{m,4} & \cdots & X_{m,n} \end{bmatrix} \tag{4}$$

The process shown above is performed before SAW, ELECTRE or VIKOR methods are applied in order to define one primary input for all of these methods.

SIMPLE ADDITIVE WEIGHTING (SAW) METHOD

SAW is a method for the linear combination of weights that were given to all input variables according to their supposed influence in each possible alternative. This is the most often used method due to its relative simplicity [3].

The procedure to determine a set of alternatives for a specified situation with SAW consists of the following steps [1]:

1. Multiply $X_{(mxn)}$ to every factor of $\vec{W}$ and the result will be a vector $\overrightarrow{SAW}$, where every element of the vector is a A_j *(j=1…m)* alternative.

$$A_j=\sum_{i=1}^{n} W_j \cdot X_{j,i} \quad i=1,\ldots n \quad j = 1,\ldots m \tag{5}$$

2. Ranking $\overrightarrow{SAW}$ vector will provide the most suitable solution for the given situation (The higher the A_j the nearer to a unanimous decision).

THE "VISEKRITERIJUMSKA OPTIMIZACIJA I KOOMPROMISNO RESENJE" (VIKOR) METHOD

This is a MCDM method that gives a maximum point of "group utility" for the "majority" of decision makers, providing minimum regret to the "opponent" according to the authors [4] [5].

The procedure to determine the maximum group utility in a given situation through VIKOR is as follows [6]:

1. Determine the best value (f_i^*) and the worst value (f_i) in every *Iv* in X_{mxn} (see *Equation 4*) matrix:

$$f_i^*=\max\left|X_{j,i}\right| \quad i = 1,\ldots n \quad j = 1,\ldots m \tag{6}$$

$$f_i^-= \min\left|X_{j,i}\right| \quad i = 1,\ldots n \quad j = 1,\ldots m \tag{7}$$

Where, *i* stands for *Iv* (Input variable) index and *j* for *A* (alternative) index.

2. At this step, it is necessary to obtain the distance to the ideal positive solution.

$$S_j=\sum_{i=1}^{n} \frac{Wi\ (f_i^*-X_{j,i})}{(f_i^*-f_i^-)} \quad i=1,\ldots n \quad j=1,\ldots m \tag{8}$$

$$R_j=\max_i \left[\frac{Wi\ (f_i^*-X_{j,i})}{(f_i^*-f_i^-)}\right] i=1,\ldots n \quad j=1,\ldots m \tag{9}$$

Where, S_i is the distance of the *i* th alternative to the "positive ideal solution (best combination)", R_i is the distance of the *i* th alternative to the "negative ideal solution (worst combination)" [7].

3. Calculate Q_j by the following equation

$$Q_j=v\left[\frac{S_j - S^*}{S^- - S^*}\right] + (1 - v)\left[\frac{R_j - R^*}{R^- - R^*}\right] j=1,\ldots m \tag{10}$$

Where, S^* is the Minimum value of S_j, S^- is the Maximum value of S_j, R^* is the Minimum value of R_j, R^- is the Maximum value of R_j and *v* ranges between 0 to 1. When *v* is 1, this means that the selected alternative is selected by unanimity (with regard to which *Iv* affects the selection more) and 0 means that there is no consensus between the decision makers [8].

4. Rank Q_j , S_j and R_j from the lowest value to the highest. The lowest Q_j value is the best decision to be taken in the given situation. In addition, the selected *Alternative* must satisfy two conditions:

   a. Condition one ("Acceptable advantage") [6]:

$$Q(A^2) - Q(A^1) \geq DQ \tag{11}$$

$$DQ= \frac{1}{m - 1} \quad m=number\ of\ Alternatives \tag{12}$$

   Where: A^1 and A^2 are the first and the second best options in Q rank, respectively.

   b. Condition two ("Acceptable stability in decision making"): A^1 must be ranked the best option (the lowest value) in either S_j or R_j ranks or in both of them at the same time [6].

THE ELECTRE METHOD (ELIMINATION ET CHOIX TRADUISANT LA RÉALITÉ):

Developed by French scientists [9] based on the idea that is better to accept a less accurate result than to overwhelm the decision makers with mathematical hypotheses that are too complex [10]. Since the development of this method, more have been created (ELECTRE II, ELECTRE III, ELECTRE IV and ELECTRE TRI). For this paper ELECTRE I was the method used and will be referred to as "ELECTRE". The steps for applying ELECTRE are as follows [11].

1. From X_{mxn} (see *Equation 4*) calculate the Standard Decision Matrix (X^*_{mxn}):

$$x_{j,i}^* = \frac{x_{j,i}}{\sqrt{\sum_{k=1}^{m} x_{k,j}^*}} \tag{13}$$

Where, $x_{j,i}^*$ is an element located in row *j (j=1,2,3….m)* and column *i (i=1,2,3…n)* in the X^*_{mxn} matrix and k is an alternative row index in X^*_{mxn} matrix.

2. Generate Standard Decision Matrix *(Y_{mxn})* from step 1 and *Equation 3*:

$$y_{j,i}=x_{j,i}{}^* \ w_i \tag{14}$$

Where, $y_{j,i}$ is an element located in row *j* and column *i* in the matrix y_{mxn}. w_i is the weight vector (see *Equation 3*).

3. Determine Nonconformity (D_{kl}) and Conformity (C_{kl}) sets. Conformity set results from comparing every element of Y_{mxn} according to its j and i indexes and $y_{j,i}$ values, therefore, nonconformity set elements are the *i* indexes that are not present in C_{kl}:

$$C_{k,l}=\{i,y_{k,i}\geq y_{l,i}\} \tag{15}$$

Equation 14 defines that every element of $C_{k,l}$ is equal to its i index provided that the demonstrated inequality is fulfilled.

4. Calculate Conformity *(C^*_{mxm})* and Nonconformity *(D^*_{mxm})* matrices. Where, *m* is the total number of Alternatives and *k=l* places are empty. C^*_{mxm} elements are calculated as follows:

$$C^*_{k,l} =\sum_{i\in C_{kl}} w_i \tag{16}$$

Elements of Nonconformity matrix are determined with *Equation 16*.

$$d_{k,l}=\frac{\max\left|y_{k,i}-y_{l,i}\right|_{i\in D_{k,l}}}{\max\left|y_{k,i}-y_{l,i}\right|} \quad (17)$$

Where, max[ ] is the maximum value in a set of numbers.

5. Obtain conformity threshold ($\underline{c}$) and Nonconformity threshold ($\underline{d}$) by means of the formulas:

$$\underline{c}=\frac{1}{m(m-1)}\sum_{k=1}^{m}\sum_{l=1}^{m}c^{*}_{k,l} \quad (18)$$

$$\underline{d}=\frac{1}{m(m-1)}\sum_{k=1}^{m}\sum_{l=1}^{m}d_{k,l} \quad (19)$$

6. From the thresholds calculated in *Equation 17* and *Equation 18*, determine Conformity Supremacy F_{mxm} and Nonconformity Supremacy G_{mxm} matrices. All elements of F_{mxm} $(f_{k,l})$ and G_{mxm} $(g_{k,l})$ take the value of $C^{*}_{k,l}$ and d_{kl}, respectively, if a condition is fulfilled (See *Equation 19* and *Equation 20*) and the main diagonal is empty due to its derivation from C^{*}_{mxm} and D^{*}_{mxm}.

$$f_{k,l}=\begin{cases}\text{if } C^{*}_{k,l}>\underline{c}\Rightarrow f_{k,l}=C^{*}_{k,l}\\ \text{if } C^{*}_{k,l}\leq\underline{c}\Rightarrow f_{k,l}=0\end{cases} \quad (20)$$

$$g_{k,l}=\begin{cases}\text{if } d_{k,l}>\underline{d}\Rightarrow g_{k,l}=d_{k,l}\\ \text{if } d_{k,l}\leq\underline{d}\Rightarrow g_{k,l}=0\end{cases} \quad (21)$$

7. Formation of Total Dominance Matrix (E_{mxm}). All elements $(e_{k,l})$ of this matrix are calculated based on $f_{k,l}$ and $g_{k,l}$:

$$e_{k,l}=f_{k,l}*g_{k,l} \quad (22)$$

8. Add up all elements in every E_{mxm} row to calculate a total for every *Alternative* (A_j). Rank all A_j values from highest to lowest (the highest *Alternative's value* is the best option for the given situation).

ARTIFICIAL LIFT SYSTEM SELECTION

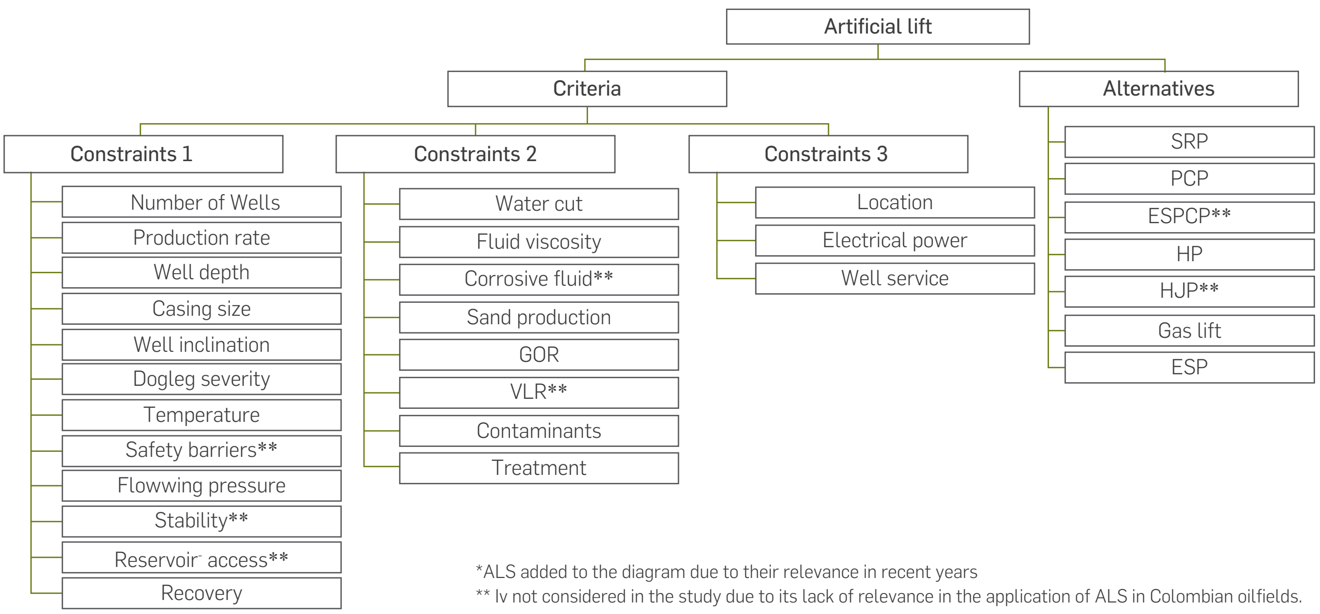
There are five types of basic Artificial Lift System (ALS) that are used in oil wells. They are classified according to their mechanical and operational differences (some of these types are sub divided into other ALS). The major ALS for oil production are Electro submersible Pump (ESP), Sucker-Rod Pump (SRP), Gas lift (GL), Hydraulic Piston Pump (HP), Hydraulic Jet Pump (HJP), Progressing Cavity Pumps (PCP) [12]and one more that is a combination of the former systems and is worth mentioning, due to the advantages it offers. This is the Electrical Submersible Progressing Cavity Pump (ESPCP).

In some fields, ALS selection is mostly based on operator experience [12], analogy with similar cases, required flow rates, well depths and bottom hole pressure etc. which are good criteria but do not have a strong analytical / mathematical basis that considers other properties or characteristics, leaving out of the analysis variables such as:

- The field's stage of production (newly discovered, mature etc.): due to fluid production pressure drops and new conditions arising in the wells.
- The implementation of future or current recovery methods.
- Supply chain constraints.
- Surface facility capacity and availability.
- Well service equipment availability.
- Energy availability/energy costs.

INPUT VARIABLES (CRITERIA) FOR ALS SELECTION

In order to define the scope of this study, an onshore scenario in the Colombian Oil & Gas industry was chosen to constrain the number of input variables for the MCDM methods. Based on Alemi M. *et al* [12] (see **Figure 1**) a number of input variables were selected (See **Table 1**).



*ALS added to the diagram due to their relevance in recent years

** Iv not considered in the study due to its lack of relevance in the application of ALS in Colombian oilfields.

Figure 1. Alternatives and criteria for ALS selection, Source: Alemi M. et al [12]

Table 1. Selected Ivs for the MDCM procedure

Input Variables	Description
Flowing pressure (pwf)	Expected average pressure at pump intake. Expressed in psi.
GOR (Gas to Oil ratio)	Volume of gas per oil barrel. Expressed in scf/stb.
Water Cut	Volume of water per total liquid (oil + water) volume. Expressed in percentage (%).
Well Depth	Measured depth (MD) to pump intake. Expressed in Feet (ft).
Fluid production	Total fluid production (Oil + Water). Barrels per Day (BPD).
Casing Size	Inner diameter of the smallest casing to pump intake interval. Expressed in Nominal size in inches (in).
Well inclination	The maximum well deviation from vertical. Expressed in degrees.
Viscosity	Emulsion dynamic viscosity of at downhole conditions. Expressed in centipoise.
Sand production	Sand content in produced fluids. Expressed in ppm.
Location	Distance to pump supplier production centre. Qualitative variable.
Well Completion	Production completion type: Simple or Multiple Completed well. Qualitative variable.
Recovery method	Recovery method applied in adjacent oilfield zones. Qualitative variable.
Dogleg severity	Turn, bend or change in well three-dimensional trajectory. Expressed in degrees per 100 ft.
Temperature	Downhole fluid temperature. Expressed in Fahrenheit degrees (F).
Well service	Available Well service equipment for ALS installation. Qualitative variable.
Number of wells	Amount of potential wells where the selected ALS would be installed. Expressed in units.
Contaminants	Chemical substances considered contaminants in produced fluids. Qualitative variable.
Treatment	Downhole Chemical treatment injected in the well. Qualitative variable.
Electrical power	Electricity generation: In situ (electric portable power generator) or national electric grid. Qualitative variable.
Space	Available surface space. Qualitative variable.

All conventional ALS were included in the analysis, while twenty (20) *Ivs* were selected and reordered according to their relevance and data availability for the intended case study.

ALGORITHM AND SOFTWARE APPLICATION DEVELOPMENT:

The software application developed was based on an algorithm derived from the procedure, methods, ALS and *Iv* described in previous sections. This software is a standalone windows app with monolithic architecture in visual basic (VB.NET®), with a local Database.

Figure 2 shows the flow diagram developed and used for this study. It has three main stages (from Start to End): System/methodology setup, real variable weights definition and MCDM application.

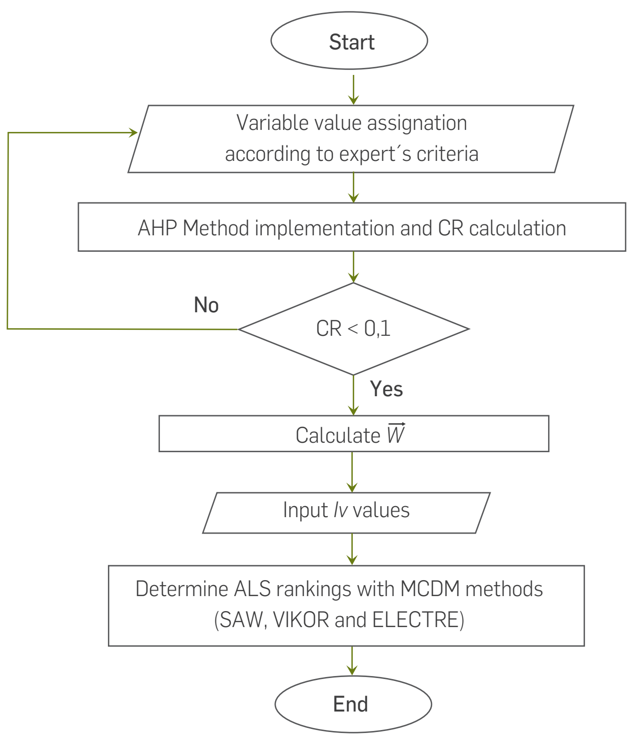


Figure 2. Algorithm's Pseudocode

CASE STUDY IN A COLOMBIAN FIELD:

The Casabe oilfield is located in Middle Magdalena Valley basin. Currently, this field produces approximately 15,000 BOPD of 14.8 to 23.3 API oil (upper sands) and 15.4 to 24.8 API oil (lower sands) [13] with a low Gas to Oil Ratio (lower than 100 scf/STB on average), oil average viscosity of 40 cP and diverse water cuts per well with a water flooding process ongoing. Its lithology is not consolidated [14], and for that reason, high quantities of sand are produced.

WELL SAMPLE SELECTION

In order to evaluate the results of the methodology, a group of 30 wells using PCP as the ALS were chosen. This group represents

13% of the total wells that use PCP in the field and it represents the Pareto group for failure rate (44% of all failures comes from 15% of the total PCP wells). Every well failed between two to eight times in a time period of one year.

VARIABLE VALUE ASSIGNMENT

The variable values (relative weights) for AHP analysis were defined in accordance with engineering field experience and ALS historical data application in Colombian oil fields (See **Table 2**). For the distribution shown in **Table 2**, the CR obtained was 0.0981 and the defined VIKOR coefficient was 0.5.

These values affect all the subsequent calculations and vary according to the particular conditions of each Well / Oilfield (e.g. for this application, Flowing Pressure is considered a critical criteria. In other applications this will most likely vary).

Table 2. Variable values for AHP analysis

Input Variables	Value (dimensionless)
Flowing pressure	9.0
GOR	6.9
Water Cut	6.6
Well Depth	6.0
Fluid production	8.0
Casing Diameter	6.0
Well inclination	7.6
Viscosity	5.6
Sand production	9.0
Location	5.2
Well Completion	5.0
Recovery method	4.8
Dogleg severity	8.0
Temperature	4.4
Well service	4.2
Number of wells	3.0
Contaminants	2.5
Treatment	3.5
Electrical power	1.5
Space	1.0

3. RESULTS ANALYSIS

SIMILAR APPLICATION FOR MCDM METHODS

Previous works that use MCDM methods for ALS selection [12,15,17,19] were used as a base for the study presented in this paper. In these cases *Alemi et al* use five ALS with 25 variables, some of them applied to similar but not equal offshore scenarios for Iranian oilfields.

This paper shows an application of MCDM methods to a Colombian Onshore Oilfield. For this study, 20 variables with seven ALS were considered. In addition, a novel sequential mathematical approach is made: First, an analytical hierarchy process (AHP) is used for variable values, followed by a numerical validation of input data and, finally, MCDM application to the sample of 30 wells to make the results of the three methods comparable. The first two steps of the mathematical process were not used in any of the referenced studies for MCDM in ALS selection.

VARIABLE WEIGHT AFTER AHP IMPLEMENTATION:

After implementation of the AHP methodology with initial relative variable values (see **Table 2**), a W vector of variable weights was calculated (see **Figure 3**). The five variables with the highest weights relate to hydraulic flow, well geometry and fluids / solids produced. These results are in accordance with the most common causes of failure in downhole equipment in the selected well sample. They represent the most important parameters in ALS design in the studied field: downhole pressure for ALS integrity, rod and pipe failure due to well deviation (wearing of rotating rod surface with the inner surface of the pipe) and peaks of sand production, due to unconsolidated reservoir sandstones, which causes ALS failure.

MCDM METHODS RESULTS:

After software implementation and ranking definition for every well, all of the numerical values were consolidated in a global distribution of all ALS for the three methods. **Figures 4** to **6** show the percentage suitability (number of wells that should use that specific ALS out of the 30 wells) of the alternatives in the well sample considering particular values for the parameters and wells.

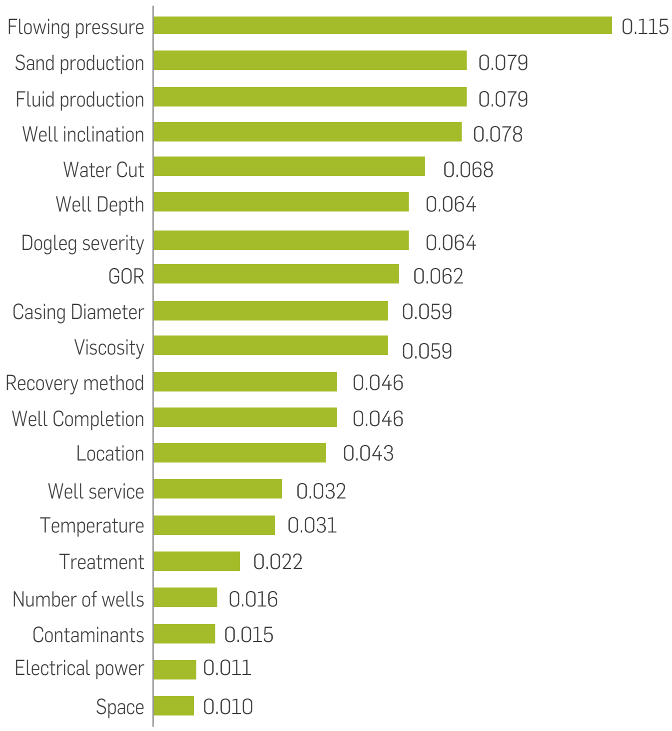


Figure 3. Variable weight after AHP implementation

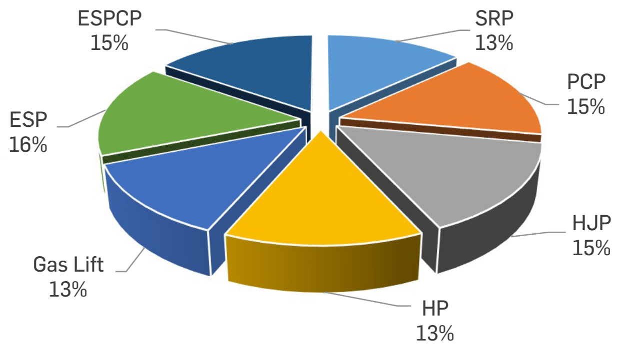


Figure 4. ALS distribution with the SAW method

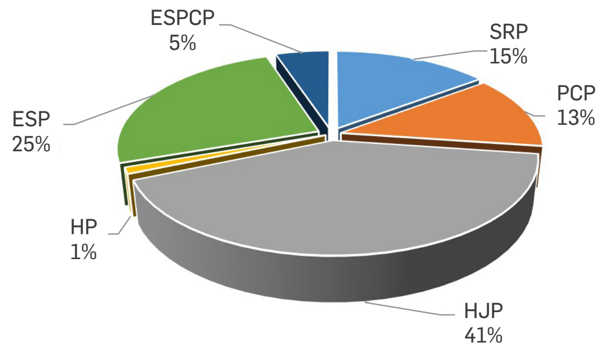


Figure 5. ALS distribution with the ELECTRE method

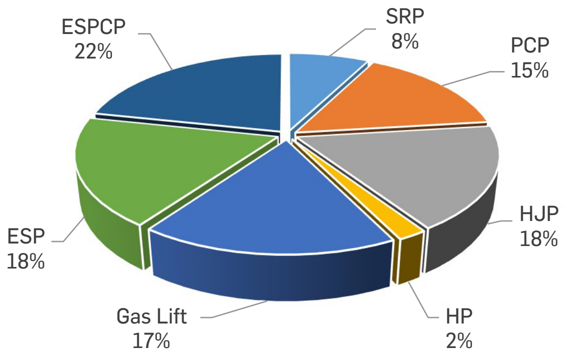


Figure 6. ALS distribution with the VIKOR method

According to field experience, the most important constraint in the field studied for an ALS is the high content of sand. It can cause consistent damage to the downhole pump, hence the necessity for a system capable of managing elevated solids concentrations. For this purpose, the most suitable ALS are PCP and ESPCP, while the others require a second system (i.e.: Gravel Packs) to control the effects of sand production.

In Figures 4 to 6, the distribution obtained for the three methods shows a trend towards HJP, ESP and ESPCP being the most suitable Artificial Lift Systems for the wells sample. This is due to the following main reasons:

- Hydraulic Jet Pump, Electrical Submersible Progressing Cavity Pump and Electro submersible Pump are the best solution for deviated wells due to the absence of rotary or reciprocating parts from surface to downhole (These ALS transform electricity/hydraulic energy into movement in downhole systems).
- Electrical Submersible Pump (ESP) is one of the best options for high water cuts. A characteristic parameter in mature fields with a long history of water injection projects.
- ESPCP along with PCP are the best ALS for handling high sand production.
- For the remaining parameters, all ALS exhibit similar behaviour for this specific well sample of the field studied.

Despite the fact that the sample analysed is constituted only by wells with PCP installed due to its good performance in handling fluids with a high solids content, and good to acceptable performance in the other parameters, in the MCDM final distribution this ALS is not present among the top places in the three rankings. This highlights the need for exclusive variables or Max/Min constraints (if a specific ALS does not fulfil a requirement, it is discarded) and the fact that instead of PCP, ESPCP is present (as one of the most suitable options) in two out of three distributions for the same capacity for handling high volumes of sand.

CONCLUSIONS

Mathematical modelling for decision-making in artificial lift systems selection is an excellent way of reducing time consuming processes, standardizing procedures, decreasing the likelihood of errors, optimizing performance, and increasing asset life. However, the proposed algorithm and software is not a complete replacement for the engineering ALS selection process due to the quantity and complexity of the parameters involved; both methodologies complement one another.

Every Oilfield can be divided into sectors or an individual well; each one of them has an analysis model. Any of these models could differ radically from one another or, on the contrary, be very similar in their parameters. Those differences in the input variables could result in significantly different rankings in every MCDM method after the software's implementation. Consequently, every field, sector, group or individual well has to assign specific lv weights separately, considering that every application is different.

The results interpretation for the selected Colombian field shows an optimal selection trend towards the hydraulic jet pump (HJP) as an artificial lift system. Despite the fact that HJP does not have good performance for sand production greater than 500 ppm, the rest of the variables considered make this system one of the best, with optimal theoretical performance. By implementing supplementary sand control technologies not included in the methodology described, hydraulic jet pumping could see its performance improved for most of the 30 wells analyzed.

The order of priority for the artificial lift systems to be implemented was established for each of the mathematical models reviewed, obtaining the following potential solutions in order of priority:

- Hydraulic Jet Pump, with a sand control system included (bottomhole filters, unconventional pump designs, etc.).
- Electro-submersible Pump, with additional technology that can tolerate high contents of sand.
- Progressing Cavity Pump, with a bottomhole bottom motor, along with the additional advantages of combining two lifting systems. This is considered a good option for deviated wells.
- Conventional Progressing Cavity Pumps. This poses an additional advantage due to the handling capacity for fluids with high sand content.

In this paper, an innovative algorithm for artificial lift selection and subsequent software development in Visual basic. NET® code was created based on MCDM methods (SAW, ELECTRE and VIKOR) and validated as an efficient mechanism for ALS selection.

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