# Article

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Developing an Expert System for Identifying Optimal Pumping Lift Based on Technical, Financial and Components Levels

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#### Abstract

Selection of optimum artificial lift system depends basically on reservoir characteristics, fluid properties, well location and geometry, surface facilities, available logistics and feasibility studies. Insightful evaluation of these criteria improves the quality of the decision and its implications. For this large number of conflicting criteria, multi criteria decision making (MCDM) methods are used to clearly show the problem, analyze its dimensions and make optimal decisions. This paper introduces a comprehensive expert system for optimal selection of pumping lift systems based on technical, operational and financial criteria. ES includes four phases; screening inappropriate pumps, determination the components for the acceptable pumps, feasibility analysis and decision optimization. Selection is performed by using technique for order preference by similarity to ideal solution. This ES was developed specifically for the General Petroleum Company, Egypt. It can be considered as a prototype that can be developed to include comprehensively the other artificial lift techniques.

Keywords: TOPSIS; pumping lift selection; expert system; financial evaluation.

### 1. Introduction

Downhole pump is used to overcome the pressure losses through the conduit of the fluid from its intake to the storage facilities. It is fed by an external source of energy either mechanical, hydraulic or electrical to raise the oil to surface. Positive displacement pump captures a fixed fluid volume and force it to discharge acquiring the required pressure to be raised. While, the dynamic pumps supplies the fluid with kinetic energy which in turn turns into pressure when fluid exits the pump. The evolved pressure raises liquid to surface. Reciprocating rod pump (RRP) and progressive cavity pump (PCP) are of the most common types of downhole positive displacement pumps, while electric submersible pump (ESP) is the most common downhole dynamic pump [1].

### 2. Selection criteria

Reservoir characteristics	Reservoir pressure, temperature, porosity, permeability, skin factor, drainage area, driving mechanism
Well conditions	Well location, geometry, tubular sizes, depth
Fluid properties	Fluid density, viscosity, composition, content of erosive materials, content of corrosive fluids.
Available logistics	Power sources, servicing equipment, technical support and experienced personnel
Production parameters	Wellhead pressure, surface-facilities pressure, pipelines geometry and condition
Financials	Outflows, including capital expenditure, maintenance, and operating costs, represent expenditures. Inflows, including sold oil revenues and equipment salvage rates, this represent returns.

Table 1. Selection criteria [1]

Selection criteria are classified into reservoir characteristics, well conditions, fluid properties, production parameters, available logistics and financials. Table 1 represents the factors included in each of selection criteria considered in the developed ES <sup>[1]</sup>.

### 3. Previous expert systems for artificial lift selection procedures

The ES is a computer program that mimics the ability of individuals for decision-making based on their acquired knowledge from the previous experiences. It is composed of two parts; knowledge base and inference engine. The knowledge base is a complex set of experts' knowledge and is represented in the form of "if-then" rules. The inference engine in the ES represents the perception and learning of human-being. The entered data are processed by the inference engine compared to stored knowledge to generate conclusions using logical issues <sup>[2]</sup>.

Valentin *et al.* <sup>[2]</sup> developed optimal pumping unit system (OPUS). In first stage, the user is asked some questions and based on the answers. Suitability coefficients (SC) are set for each ALS option according to the knowledge base. Suitability coefficients varies between -1 (definitely eliminated option), and 1 (definitely suited option). By using the inference engine, suitability coefficients are compiled to a final result at which the pumping lift system is ranked. Then, technical and financial assessment are performed <sup>[2]</sup>.

In 1994, Espin *et al.* <sup>[3]</sup> developed a software called SEDLA. It composed of three modules. Module I is a knowledge base including expertise; calculations and theoretical knowledge. Module II is specified for complete design of pump; completion and facility components. Module III provides a financial evaluation based on cost database. SEDLA simulates the experts in evaluating quantitative, qualitative parameters and production problems. Suitability coefficients are set, multiplied by weight of the criteria according to its importance and summed to be ranked.

In 1995, Heinze *et al.* <sup>[4]</sup> introduced a decision tree to select ALS concentrated on the financial evaluation. The decision tree eliminates the unaccepted options. Then, a technical evaluation is performed for the accepted options. In the last step, a financial evaluation is done to compare among the candidates by determining the net present value (NPV) <sup>[4]</sup>. Another decision tree was developed by Han-Young Park <sup>[5]</sup> to screen out the remedial unloading options for gas wells. Ratings are given depending upon a built-in table on the basis of (if) rule. Ratings are got by weight sum model (WSM) and ranked descendingly. Finally, NPV analysis is done for each pump to be ranked <sup>[5]</sup>.

Alemi *et al.* <sup>[6]</sup> developed an ES for optimal artificial lift selection using a decision-making model called technique for order preference by similarity to ideal solution (TOPSIS). It is based on developing a decision matrix which includes criteria and alternatives. Ratings are filled through the cells presenting the behavior of each alternative against the criterion. The ratings are normalized by TOPSIS model and ideal solution is determined. The ideal solution is an imaginary solution that involves the best values for whole selection criteria. Separation distance of each alternative from the ideal solution is determined. Ranking is performed based on the separation distance from the ideal solution representing the optimal selection. Fatahi *et al.* <sup>[7]</sup> compared these results to those got by another MCDM method; ELECTRE <sup>[7]</sup>.

Ounsakl *et al.* <sup>[8]</sup> use machine learning technology to develop a promising tool furnishing the artificial lift selection to adopt the dynamic conditions of matured oil fields. The model is constructed on the patterns and relationships between the inputs, field data, and the outputs (ALS selection). Around 30,000 samples of different production systems were used to build the model. Seventeen attributes are considered in selections <sup>[8]</sup>.

## 4. Developed multi criteria decision making (MCDM)

As mentioned before, decision-making is a cognitive process resulting in selecting a certain way for action or statement towards situation among several possible options considering desired goals and beliefs appropriate to the decision makers' minds. Critical and complex problems involves both multiple conflicting criteria presented in different units of measurements, and several alternatives to review and take a decision among them. For problems involving uncertainty, complexity and high risk consequences, multi-criteria decision-making (MCDM) methods are developed. MCDM methods are classified into three groups. The priority method is based on simple numerical analysis for the alternatives depending mainly on the priorities of this criteria while selection, such as weighted sum method (WSM). The distance methods are based on determination of the nearest alternative to the ideal solution, such as technique for order preference by similarity to an ideal solution (TOPSIS). The outranking methods are based on pairwise comparisons among alternatives, such as Elimination Et Choix Traduisant La REalite (ELECTRE) <sup>[6-7]</sup>.

# 4.1. Technique for order preference by similarity to an ideal solution (TOPSIS)

TOPSIS is based on building a  $(m \times n)$  matrix in which rows are the alternatives (m) and columns are the criteria (n). It is based on the following steps to determine the best alternative:

1. Normalize each value in the matrix. Find squared alternative responses towards the different criteria  $(a_{ij})$ . Then, find the sum of the squared responses for all alternatives for the same criterion. At that juncture, find the square root for this sum, roughly "Xj" for each criterion, Eq. (1). Finally, find the division of each alternative response by "Xj", Eq.(2).

$$X_{j} = \sqrt{\sum_{i=1}^{m} (a_{ij})^{2}}$$
(1)  
$$r_{ij} = \frac{a_{ij}}{X_{i}}, for \ i = 1, 2, 3, ..., m$$
(2)

2. Find  $t_{ij}$  using Eq. (3).

$$t_{ij} = r_{ij} * w_j \tag{3}$$

- 3. Identify the negative-ideal and positive-ideal solutions. For each criterion, the negativeideal solution  $t_{\text{worst}}$  is the one with the worst value of  $(t_{ij})$  for all alternatives. While, the ideal solution  $t_{\text{best}}$  is the one with the best value of  $(t_{ij})$  for all alternatives.
- 4. For each alternative, find the separation measures between its response and both ideal  $(S_i^*)$  and negative-ideal  $(S_i^-)$  solutions by Eq. (4 and 5):

$$S_{i}^{*} = \sqrt{\sum_{j=1}^{n} (t_{ij} - t_{best})^{2}}$$

$$S_{i}^{*} = \sqrt{\sum_{j=1}^{n} (t_{ij} - t_{best})^{2}}$$
(4)
(5)

5. Find for each alternative the relative closeness,  $C_i$ , to the ideal solution by Eq. (6 :

$$C_{i} = \frac{S_{i}}{S_{i} + S_{i}}^{*}$$
(6)

6. As  $C_i$  closes to 0, alternative closes to the positive-ideal solution. Rank the alternatives according to  $C_i$ , from the smaller value to the largest one <sup>[6]</sup>.

# 5. Methodology

The ES is developed to determine the optimal pumping-lift system by analyzing user's inputs according to a pre-configured database. The research methodology consists of three main parts:

# 5.1. Optimization problem model

In mathematics, an optimization problem is the problem of finding the best solution from all feasible solutions. The problem model consists of three parts; the design variables, the objective function and the set of constraints. Thus, in order to select pump lift system, design variables used are the criteria that influence selection. Furthermore, it was decided that the objective function is the TOPSIS model and the set of constraints would be the mechanical limits for all pump lift systems (PLSs). Pumping-lift selection is classified as a multiple objectives optimization problem. This is because multiple criteria are contributed to the selection of optimal PLS. It is challenging to choose a system that satisfies all the criteria. Therefore, TOPSIS decision making method is nominated to reformulate this multiple objectives problem into a single objective problem. TOPSIS-single objective model-is used to determine the closest alternative to the best solution

Twenty-four discrete design variables influence optimal pump selection are given I n Table 2. The objective function is TOPSIS alternative closeness to the ideal solution ( $C_i$ ), Eq. (6. Optimal selection is achieved based on the results of the objective function, where the closest to the positive-ideal solution is the most appropriate choice. The set of constraints for pumps are shown in Table 2.

Tuble 2. Design variables innacheng i Es optimization problem	Table 2. Design	variables	influencing	PLS	optimization problem	
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1. Well Location	2. Gas Liquid Ratio	3. Paraffin Production
4. Measured Pump Depth	5. Aromatics Production	6. Staff Experience
7. Well Deviation	8. Emulsion Production	9. Available Prime Mover
10. Casing Diameter	11. Scale Production	12. Available Servicing Type
13. Dogleg Severity	14. Corrosive Fluid Production	15. PLS Flexibility
16. Desired Gross Rate	17. Fluid Viscosity	18. PLS Reliability
19. Productivity Index	20. Oil Gravity	21. System Efficiency
22. Bottomhole Temperature	23. Abrasives Production	24. Net Present Value

Table 3. PLS screening criteria & mechanical limits

Criteria	RRP	PCP	ESP
Operating vertical depth (ft.)	100 - 16000	2000 - 6000	1000 - 15000
Typical operating rate (BPD)	5 – 5000	5 – 4500	200 - 30000
Operating temperature (° F)	100 – 550	75 – 250	100 - 400
Corrosion handling	Good to Excellent	Fair	Good
Gas handling	Fair to good	Good	Poor to Fair
Solids handling	Fair to Good	Excellent	Poor to Fair
Oil Gravity (°API)	> 8	< 35	> 10
Prime mover	Gas or Electricity	Gas or Electricity	Electricity
Offshore application	Limited	Good	Excellent
Overall system efficiency (%)	45 - 60	45 - 70	35 - 60

## 5.2. Developed algorithm calculations and database

Developed ES utilizes the basic API calculations, rules of thumb and practice recommendations by GPC engineers to determine the PLSs' equipment. Database is divided into two main parts; experts' pump recommendations towards each criteria and equipment list. The entered equipment list is that of current contracts between GPC and vendors. Both experts' recommendations and equipment list can be modified according to any new developments.

## 5.3. Phases of the developed ES

Developed ES includes four phases; screening, components selection, financial analysis and PLS optimization decision. Developed ES flowchart is shown in Fig.1.

Technical screening has two stages. The first stage is categorization of the inputs according to Table 4. Categories were determined by taking into account the pumps' mechanical limits, the experts' recommendations of choosing PLS and the opinions of the engineers at the GPC. The second stage is to evaluate the performance of each pump for each criterion and rate it from 1 to 5. Pump preferences ratings can be modified according to the admin-users.

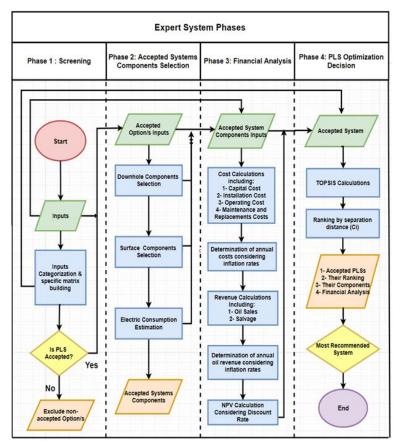


Fig. 1. Developed ES flow diagram

Table 4. Criteria and categories

Criteria	Sub-criteria	
1)	Well location	Onshore, offshore, urban
2)	Well measured depth	Shallow well (<4500 ft.), Intermediate well (4500-6000 ft.), Deep
		well (6000 to 10000 ft.), Extremely Deep well (>10000 ft.)
3)	Production casing diameter	Conventional, Slim (<6 in.)
4)	Well profile	Vertical (0-20o), Deviated (20-50o), Highly deviated (50-80o), Hor-
		izontal (80-90o), Extended reach (80-90o)
5)	Productivity Index	<0.5 bpd/psi, >0.5 bpd/psi
6)	Anticipated gross rate	<200 bpd, 200-1500 bpd, 1500-4500 bpd, >4500 bpd
7)	Dogleg severity	<6 deg. /100 ft., 6-15 deg. /100 ft.
8)	Well temp.	<150 F deg., 150-250 F deg., 250-400 F deg., >400 F deg.
9)	Fluid Viscosity	<200 cp, 200-500 cp, >500 cp
10)	Abrasive solids Production	No or Minor prod. (<0.01%), Moderate (0.01 - 0.1%), Severe (0.1
		- 3%), Extremely severe (>3%)
11)	Corrosives production	No Production, Minor, Moderate, Severe
12)	Aromatics production	No or minor production, Moderate, Severe
13)	Emulsion Production	Yes, No
14)	Scale Production	Yes, No
15)	Paraffin production	Yes, No
16)	Fluid API	<15 deg., 15-35 deg., >35 deg.
17)	Gas Liquid Ratio	<500 scf/stb, 500-2000 scf/stb, 2000-3000 scf/stb
18)	Prime mover	Gas engine, Diesel engine, Electric motor or feeder
19)	Staff Experience	Poor, Intermediate, Expertise
20)	Servicing availability	Pulling Unit, Workover Rig, Both

The PLS flexibility, reliability and system efficiency are constants and set according to Table 5. Consequently, any ratings of 1 for any criterion are reflected of pump refusal and screened out the evaluation.

Criteria	ESP	PCP	ESPCP	RRP
PLS Flexibility	3	4	3	5
PLS Reliability	3	3	3	5
System Efficiency	55%	60%	60%	50%

Table 5. PLS flexibility, reliability and system efficiency ratings [9]

Next, both surface and downhole components for acceptable pumps are selected from the database previously entered from GPC's current contract catalogs. The database of pump components are flexibly modified according to available contracts. Financially, revenues and expenditures are determined through the evaluation period and are restored to present to find the net present value (NPV) for each of the accepted pumps.

A specific-case matrix is built which dimensions are m x n, where m is the specified categories by phase 1-step 1, and n is the accepted pumps ratings for each criterion. NPV is also added to the built matrix. TOPSIS is performed to determine the most optimal alternative according to both technical and financial criteria. The rankings of accepted pumps are determined according to the relative separation from the positive ideal solution ( $C_i$ ).

Two windows are built; one for the admin and the other for the user. The admin's window includes the database of pumps components, experts' preferences and criteria of selection. The user's window is a friendly interface asking the user to enter the required inputs to proceed the ES phases.

	Pump						
	Pro	ope	rties				
A)		+ 1d	= Name	- Description	E Note	= Unit Type	Choice Type
1. T		103	W_NPV	Nel Present Value	Percentage	percentage	text_tex
		562	RDR	Reservoir Depletion Rate, (decimal)			test_box
	8	561	ODTEP	Average downtime for downhole			test_box
	10		Bashboard	Acmin Users	Pumps F	Properties C	ommests Da
	Pump	rs					
	ADMIN		Tabs				
	ADMIN	P)	Tabs	Properties			

Fig. 2. Admin's window, (A) properties tab & (B) pump preferences

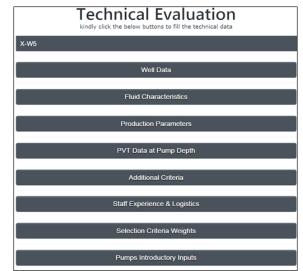


Fig. 3. User's window

Full Assessment	For Pump in 2019	-		tems fo	or X-47
Phase one : Techn	ical Scree	ening			
	Abb.	ESPCP	ESP	RRP	PCP
Well Location	WL	5	5	5	5
Measured Pump Well	MD_pum	4	4	4	4
Well Deviation	WD	5	5	3	1
Casing Diameter	CSG_ND	5	5	5	5
Dogleg Severity	DS	5	5	5	5
Desired Gross Rate	GQ	4	5	5	4
Productivity Index	J	5	5	5	5

Surface E quipment :							
Pumping Unit Designation	С	320	256	144			
NEMA D Motor	150	HP					
Downhole Equipment :							
1-Rod-Characteristics							
Rod Size :	77						
NO. Rods for each size :							
6/8 "	0						
7/8 "	205						
1 "	0						
1 1/8"	0						
Rod Type (Weatherford Nomenclature):	KD						
2-Downhole Pump -Characteristics							
Pump Designation :	30	375	Т	HC	20	6	0
Pump Service Material :	Corrosive Se	ervice					

### Fig. 4. Sample of phase 1 results

Years	0-1	1-2	2-3	3-4	4-5
Cashflows	1	2	3	4	5
Capital Cost	65684	0	0	0	0
Installation Cost	14500	0	0	0	0
M. & R. Costs per Cashflow	24634				
M.& R. Costs Change Rate (%)	10				
M. & R. Costs After Change Rate	24634	27097	29807	32787	36066
Anuual M. & R. After Change Rate	30078				
Operating Cost	1195898				
Operating Cost Change Rate (%)	7				
Operating Cost After Change Rate	1195898	1279611	1369184	1465027	1567578
Anuual Operating Cost After Change Rate	1375460				
Salvage Cost After Project Assessment	0	0	0	0	47726
Oil Production Sales	21732000				
Reservoir Depletion Rate (%)	2				
Oil Prices Change Rate (%)	3				
Oil Production Sales After Change Rate	21732000	21936281	22142482	22350622	22560718
Inflow After Rates Of Change	21732000	21936281	22142482	22350622	22608443

#### Fig. 5. Sample of phase 2 results

Phase 4 : Decision Optimization						
	Abb.	ESPCP	ESP	RRP		
Well Location	WL	5	5	5		
Measured Pump Well Depth	MD_pump	4	4	4		
Well Deviation	WD	5	5	3		
Casing Diameter	CSG_ND	5	5	5		
Dogleg Severity	DS	5	5	5		
Desired Gross Rate	GQ	4	5	5		
Productivity Index	J	5	5	5		
Bottomhole Temperature	T_bh	4	5	5		
Fluid Viscosity	meo_m	5	5	5		
Oil Gravity	API	5	5	5		
Abrasives Production	AP	5	3	3		
Corrosive Fluid Production	CP	3	4	5		
Aromatics Production	ArP	5	5	5		
Emulsion Production	EP	5	5	5		
Scale Production	SP	5	5	5		
Paraffin Production	PP	5	5	5		
Gas Liquid Ratio	GLR	5	5	5		
Available Prime mover	APM	5	5	5		
Staff Experience	SE	2	4	5		
Available Servicing type	AST	5	5	5		
PLS Flexibility	PF	3	3	5		
PLS Reliability	PR	3	3	5		
System Efficiency	SE	5	4	3		
Net Present Value	NPV	93166021	93871488	89309730		
Positive Separation	positiveSep	0.021	0.019	0.022		
Negative Separation	negativeSep	0.021	0.019	0.021		
ci	ci	0.507	0.501	0.490		
The most optimized	l PLS is : F	RRP				

#### Fig. 6. Sample of phase 3 results

Fig. 7	7. Sample	of phase 4	results
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#### 6. Results validation and discussion

Validating the results of the developed ES takes two main axes. The first is for phase 2, where the results were compared with the results of another approved PLS programs provided by the contracted vendors. The second is for phase 4, where the results are compared with the selections done by GPC for well-designed cases.

Developed ES is applied on 38 wells. Only 13 wells are operating with the optimal PLS. In addition, 16 wells are operated by one of the recommended PLS, but not the most optimal one. Five wells were modified their PLSs. Economically, operating costs were reduced slightly, but the mean time between failures increased which reduced the costs for reproducing the well.

The remaining 9 wells are operating with non-recommended PLSs according to the developed ES. Actually, these 9 wells were nominated to change their PLSs. Changing their PLSs contributes significantly in reducing the well interventions and in magnifying the wells' productivities.

### 7. Conclusions

Developed ES shows reliable PLS selections when compared to real applications which are well designed. Some wells have very close ES results for multiple PLSs. By practice, it is concluded that we can use any of these alternatives with no issues according to availability and the NPV of each PLS when comparing.

Developed ES show single alternative to be used in some cases from phase 1. Only phase 2 should be performed to determine the components of this system. Using of the developed ES can replace buying of expensive PLS design software licenses and can eliminate probable human errors associated hand calculations.

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#### Nomenclature

ALS	Artificial lift system
API	American petroleum institute
BPD	Barrels per day
C <sub>i</sub>	Relative closeness
ELECTRE	Elimination Et Choix Traduisant La REalite
ES	Expert system
ESP	Electric submersible pump
°F	Degree Fahrenheit
MCDM	Multiple criteria decision making
NPV	Net present value
OPUS	Optimal pumping unit system
PCP	Progressive cavity pump
PLS	Pumping lift system
RRP	Reciprocating rod pump
SC	Suitability coefficient
SC	Suitability coefficient
TOPSIS	Technique for order preference by similarity to an ideal solution
WSM	Weighted sum method
	Weighted Sum method

#### References

- [1] Lake LW, and Clegg JD. Petroleum Engineering Handbook, Vol. 4, Production Operations Engineering, Texas: Society of Petroleum Engineers, 2007.
- [2] Valentin EP, and Hoffman FC. OPUS: An Expert Advisor for Artificial Lift. in 63rd Annual Technical Conference and Exhibition of SPE, Houston, 1988.
- [3] Espin DA, Gasbarri S, and Chacin JE. Expert System for Selection of Optimum Artificial Lift Method. in Latin American/ Caribbean Petroleum Engineering Conference, Buenos Aires, 1994.
- [4] Heinze LR, and Winkler HW. Decision Tree for Selection of Artificial Lift Method. SPE 29510, in Production Operations Symposium, Oklahoma, 1995.
- [5] Park HY. Decision Matrix for Liquid Loading in Gas Wells for Cost/Benefit Analysis of Lifting Options. Texas: Texas A&M University, 2008.
- [6] Alemi M, Jalalifar H, Kamali G, and Kalbasi M. A prediction to the best artificial lift method selection on the basis of TOPSIS model. Journal of Petroleum and Gas Engineering, 2010; 1(1): 009-015, 2010.
- [7] Fatahi E, Jalalifar H, Pourafshari P, and Moradi B. Selection of the Best Artificial Lift Method for One of the Iranian Oil Field Using Multiple Attribute Decision Making Methods. International Journal of Engineering and Technology, 2012; 2(2): 188-193.
- [8] Ounsakul T, Sirirattanachatchawan T, Pattarachupong W, Yokart Y, and Ekkawong P. Artificial Lift Selection Using Machine Learning. IPTC-19423-MS, in International Petroleum Technology Conference, Beijing, 2019.
- [9] Morsy MA. Developing an Expert System for Identifying Optimal Pumping Lift Based on Technical, Financial and Components Levels, Cairo: Cairo University, 2020.

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