Artificial Lift Selection Methods in Conventional and Unconventional Wells: A Summary and Review from Old Techniques to Machine Learning Applications

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Abstract:- Artificial lift (AL) selection is an important process in enhancing oil and gas production from reservoirs. This article explores the old and current states of AL selection in conventional and unconventional wells, identifying the challenges faced in the process. The role of various factors such as production and reservoir data and economic and environmental considerations is highlighted. The article also examines the use of machine learning (ML) techniques in the AL selection process, emphasising their potential to increase the accuracy of selection and reduce data analysis time. The findings of this article provide valuable insights for researchers and practitioners in the oil and gas industry, as well as for those interested in the development of AL selection methods.

Keywords:- *Artificial Lift, Selection, Conventionals, Unconventionals, Machine Learning.*

I. INTRODUCTION

The selection of the optimum Artificial Lift (AL) to achieve the highest recovery is a real challenge in the petroleum industry. Optimal selection is a requirement for obtaining the maximum profit from an oil well (Bucaram and Patterson 1994). Several factors determine the selection process: depth, rates, reservoir and fluid properties, initial and operating cost, and geographical and environmental aspects. Special AL selection techniques are required to cope with different reservoir, well, and field conditions, for instance: high-viscosity oil, high water cut, sand, gas, low reservoir pressures, high temperatures, low-productivity wells, surface facilities, as well as human interference. Historically, the AL selection process generally begins by studying the advantages and disadvantages of each method. Then the elimination depends on the engineers' decision based on their analysis of the AL record, field data availability, and failure history. Since these factors change over time, the AL design for current production conditions without considering future production results in high inconstancy rates and fluctuations in lifting selection (JPT staff 2014; Lea and Nickens 1999). The following sections explore old and recent selection criteria in conventional and unconventional wells (conventionals and unconventionals) from the literature and the various techniques used by the engineers and factors considered.

II. AL SELECTION IN CONVENTIONALS

At the early 1980s, Neely et al. (1981) summarised the criteria for selecting four methods of lifting, namely gas lift (GL), sucker rod pump (SRP), electrical submersible pump (ESP), and hydraulic pump (HP), by examining their advantages and disadvantages in relation to reservoir and well properties. They found that SRPs are suitable for low volumes but not recommended for offshore or residential areas, or wells prone to sand production. Continuous gas lift (CGL) is suitable for high volumes, high bottom hole pressure (BHP), and handling solids and sand; however, it is limited by back pressure and high costs. Intermittent gas lift (IGL) is less expensive than continuous gas lift (CGL) but yields lower volumes. ESP is suitable for high volumes and confined spaces, such as offshore platforms, and can tolerate deviations of up to 80°. However, major drawbacks of ESP include sand production, workover costs, and inefficiency at rates below 150 B/D. HPs (piston pump (HPP) and jet pump (HJP)) are suitable for deep wells and can deliver up to 17,000 B/D. HJPs are effective for sand production due to their lack of moving parts, while HPPs are efficient with highly viscous fluids; however, they require more maintenance and have a shorter lifespan compared to jets and submersibles. HJP cannot operate at BHP below 1000 psi, whereas HPP can operate at 0 psi. The aforementioned criteria and findings bear resemblance to the AL selection decision tree outlined by Heinze et al. (1995), where 50% of the tree's selection criteria relied on productivity index (PI) and the Inflow performance relationship (IPR). Brown (1982) introduced a selection methodology aligned with AL to aid engineers in their AL selection process. In 1986, Blais (1986) developed selection charts in 1986 to delineate the operational parameters for AL methods. These charts served as a prominent reference for selection during that period, alongside elementary computer programs employed as supplementary tools. **Table 1** provides a concise overview of AL selection methodologies documented in the literature.

It is notable that inadequate selection of AL selection can lead to frequent replacements within a short timeframe, resulting in reduced profits and heightened operational costs. It was not until Clegg et al., (1993) unveiled comprehensive reference selection tables and design considerations, which compared seven methods: SRP, PCP, ESP, HPP, HJP, GL and Plunger, across 31 parameters. These tables represent a comprehensive selection framework that has been

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consistently utilised by numerous researchers to date, albeit with minor adjustments and the integration of software tools. They serve as the cornerstone of many contemporary AL selection methodologies. Bucaram and Patterson (1994) proposed a selection criterion that accounted for factors such as well location, capital expenditures (CAPEX), operating expenditures (OPEX), production rates, run life, and failure rates, in addition to fundamental well and reservoir characteristics including depth, bottom hole pressure (BHP), gas presence, sand, and solids content. They also highlighted the significance of considering laterally drilled wells in mature fields. When selecting an AL method for a new well, it is crucial to ensure compatibility with existing surface production facilities to avoid additional expenses associated with installing new flowlines and wellhead fittings. Furthermore, they provided an illustrative example of the selection process for SRPs and outlined various factors to be taken into account. It became evident that SRPs were unsuitable for use in gassy and deep wells. The paramount selection criterion revolves around striking a balance between AL reliability, the desired production rate, and current constraints to ensure smooth operation of the pump over an extended period.

Table 1: AL Selection Techniques in the Literature

References	Selection Criteria	No of Screened AL	Analysed Parameters	Remarks
Neely et al. 1981	Limitations, IPR	4 (SRP, GL, ESP, HP)	Location, flowrate, reservoir and fluid properties, gas, sand, paraffin, scale, cost, deviation, skilled operators	Efficiency is the most important factor to consider. Cost for GL. ESP not adoptable for rate < 150B/D
Brown 1982	Advantages and disadvantages tables, elimination guidelines, IPR vs TPR	6 (SRP, GL, ESP, HPP, HJP, Plunger)	Flow rate, depth limitations, reservoir and fluid properties, pressure loss across the system, location, sand, gas, paraffin, corrosion, scale, cost, run life.	Flow rate is the most important factor to consider
Blais 1986	Operating range charts	7 (SRP, PCP, GL, ESP, HPP, HJP, Plunger)	Depth vs. flow rate	-
Clegg et al. 1993	Comprehensive advantages and disadvantages tables, design considerations	7 (SRP, PCP, GL, ESP, HPP, HJP, Plunger)	31 factors among these attributes (location, reservoir and fluid properties, flow rate, depth limitations, CAPEX, OPEX, temperature limitations, completion, efficiency, reliability, flexibility, system, salvage value, usage, intake, noise, surveillance, life cycle, gas, sand/solids, paraffin, corrosion, scale, deviation)	The crucial consideration is to sustain the desired rate over AL life cycle at the minimum OPEX. Field personnel must be trained for successful operation.
Bucaram and Patterson 1994	Guidelines	1 (SRP)	Location, CAPEX, OPEX, reliability, flow rate, operating conditions (casing size, depth, intake capability, BHP), gas, sand, paraffin, corrosion, scale	Flow rate and reliability are the most critical factors
Espin et al. 1994 Heinze et al. 1989 Valentin and Hofmann 1988	Expert systems (computer programs for ranking and eliminating AL from least to most recommended)	10 (Espin) (SRP, ESP, PCP, HP, Plunger, CGL, IGL, IGL with Plunger, constant slug injection GL, chamber GL) 4 (Heinze) (SRP, GL, HP, ESP) 6 (Valentin) (SRP, PCP, ESP, GL, HPP, HJP)	Espin [(Quantitative data (well and reservoir props), qualitative data (engineer experience and well geographic), production problems (corrosion, paraffin, sand, gas) and economic evaluation)] Heinze (flow rate, casing size, deviation, sand, paraffin, scale, corrosion) Valentin [well data (location, depth, deviation, P/T gradient flow rate), technical data (pump type, viscosity), economic data]	Espin (some high-ranked AL eliminated because they were not economically feasible), (SEDLA software used) Valentin (no economic data provided for GL), (OPUS software used)

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Heinze et al. 1995	Decision tree	7 (SRP, PCP, ESP, GL, HPP, HJP, Plunger)	Economics [CAPEX, OPEX (repair, maintenance, replacement, energy, personnel)], depth vs. rate, reservoir characteristics, location	IPR eliminates 50% of AL. Important considerations are CAPEX and OPEX
Lea and Nickens 1999	Advantages and disadvantages, Blais charts, selection by net present value (NPV) and feasibility map	5 (SRP, GL, ESP, ESPCP, HP)	Location, reservoir and fluid properties, flow rate, depth limitations, AL and equipment run life, economics (NPV, total cost)	ESPCP is offshore recommended for feasible pulling out of failed wire-lined pump.
Naguib et al. 2000	Reservoir simulation, well performance analysis, economic evaluation	4 (SRP, ESP, GL, HJP)	Reservoir and fluid properties (WC%, GOR, wax content), flow rate, CAPEX, OPEX, run life, failure rate and workover.	Economic evaluation is the primary elimination factor
Lanier and Mahoney 2009 Williams et al. 2008	Ranking matrix (high, medium, to low recommended)	6 (Lanier) (GL, ESP, SRP, PCP, HJP, long-stroke RP) 5 (William) (ESP, PCP, GL, HJP, SRP)	Lanier screening for thermal EOR [reservoir and fluid properties (temperature, viscosity, API°, WC%, GOR), flow rate, CAPEX, OPEX, maintenance, surveillance]. William (flow rate, depth, BHP, casing size, deviation, gas, sand/solids)	Lanier (SRP selected with attached sinker bars to reduce rod buckling) William (flow rate is the primary elimination factor)
Mali and Al-Jasmi 2014	Company selection tables	7 (PCP, SRP, ESP, ESPCP, MTMPCP, HJP, GL)	Screening for CHOPS and thermal EOR (reservoir and fluid properties, depth, flow rate, gas, sand, high temperature, efficiency, CAPEX, OPEX, run life in vertical and horizontal wells)	CAPEX and OPEX are the critical consideration
Kaplan and Duygu 2014	Analysis of axial and radial shear stress, and the torque on the required power	4 (SRP, PCP, ESP, ESPCP)	Screening for heavy oil with CO2 injection (viscosity, temperature, fluid velocity, rod string length, number of strokes, stroke length, rod radius, rotation speed, tubing size, power consumption, pump size)	Blending light oil with heavy oil reduces the power required. PCP is more efficient and require less horsepower than SRP for emulsified heavy oil
Caicedo et al. 2015	Preliminary screening, nodal analysis, reservoir simulation	6 (SRP, PCP, GL, ESP, HJP, Nitrogen lift)	Screening for high uncertainty reservoir [location, flow rate, depth, reservoir and fluid properties (PI, bubble point pressure, pressure, temperature, GOR, WC%, viscosity), casing and tubing size, high H2S and CO2, corrosion, power source, economics, environmental aspects.	Environmental aspects determine the selection if the field is close to urban areas. High uncertainty and complex reservoirs complicate AL selection
Kefford and Gaurav 2016	Nodal analysis	7 (SRP, PCP, GL, ESP, HPP, HJP, HSP)	Consistency, audibility, efficiency, technical rigour, vendor independence.	Designed flow rate is the primary selection factor
Ounsakul et al. 2019	Machine Learning	4 (SRP, PCP, ESP, GL)	17 out of 50 factors in these attributes (reservoir and fluid properties, pressures and temperatures, depth, flow rate, API°, GOR, gas, sand, cost, run life)	The selected AL has low cost per barrel.
Hoy et al. 2020	Assessment matrix	6 (GL, SRP, ESP, PCP, ESPCP, HJP)	Screening for polymer EOR (reservoir and fluid properties, PI, depth, deviation, flow rate, polymer concentration, sand, corrosion,	500 ppm polymer concentration is a constraint for ESP.

			maturity, robustness (efficiency), reliability)	
Zein El Din Shoukry et al. 2020	Weatherford selection tables	8 (SRP, PCP, GL, ESP, HPP, HJP, Plunger, Foam Lift)	Max flow rate, max depth, max temperature, API°, gas, solids, corrosion, maintenance, power source, location, efficiency.	PCP can handle viscosity up to 100000 cp. Have lower CAPEX and OPEX. Simple to operate
Crnogorac et al. 2020	Fuzzy logic	5 (SRP, PCP, GL, ESP, HJP)	14 factors (power source, automation, maintenance, flow rate, depth, temperature, fluid density and viscosity, deviation, corrosion, solids, paraffin, GOR, WC%)	AL of a new well is the one that best matched to AL database
Adam et al. 2022 Alemi et al. 2010, 2011 Fatahi et al. 2011, 2012	Decision-making approaches (TOPSIS model, ELECTRE model) mathematical models for ranking and elimination	5 (Adam) (SRP, PCP, GL, ESP, HJP) 5 (Fatahi and Alemi) (SRP, PCP, GL, ESP, HJP)	Adam 15 factors among these attributes (reservoir and fluid properties, flow rate, depth, flow line pressure and temperature, sand, corrosion, contaminants, recovery, location, power source) Fatahi and Alemi 25 factors among these attributes (reservoir and fluid properties, flow rate, depth, completion, casing size, deviation, sand, corrosion, contaminants, recovery, stability, location, power source, service, stimulation)	Adam (flow rate and depth are the essential consideration) Fatahi compared their results with Schlumberger standard AL selection tables
Mahdi et al. 2023	Machine learning	4 (SRP, PCP, GL, ESP) + natural flow	9 production parameters	Gas and cumulative production are the critical factors
Unconventionals				
Khan et al. 2014 Oyewole 2016 Valbuena et al. 2016 Liu and Zerpa 2016 Kefford and Gaurav 2016 Escobar Patron et al. 2018 Chow et al. 2020 Lane and Chokshi 2016 Temizel et al. 2020	Selection in unconventional by analysing field conditions using simulation, IPR, nodal analysis, NPV	GL, PCP, ESP, ESPCP, SRP, Jets, Plunger, Foam, Compression, Velocity Strings	Drilling conditions, depth, casing size, reservoir and fluid properties (porosity, permeability, saturation, GOR, GLR, pressures, temperatures), flow rate, depletion period, gas, sand, solids, surface facilities, pump size, CAPEX, OPEX, well-integrity, run life.	Economic evaluation is the critical selection factor in unconventionals

A. Computer Programming and Nodal Analysis Applications

The advent of computer programming and simulation tools for AL selection emerged during the late 1980s and early 1990s. Espin et al., (1994) pioneered the development of a coding program designed to assist engineers in selecting the appropriate AL method from a pool of 10 lifting techniques. This program utilised field data categorised into three main groups: (1) quantitative data encompassing well and reservoir properties, (2) qualitative data including engineer expertise and well geographical considerations, and (3) production challenges such as corrosion, paraffin deposition, sand influx, and gas interference, alongside

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economic evaluations. The program ranked lifting methods on a scale ranging from 1 (least recommended) to 5 (most recommended). Despite some lifting methods receiving high scores, they were disregarded due to their lack of economic feasibility, and instead, lower-ranked methods were adopted. The same methodology was employed by (Heinze et al. 1989; Valentin and Hofmann 1988). Other ranking computer programs and mathematical models were also applied by (Alemi et al. 2010, 2011; Fatahi et al. 2011, 2012). Lanier and Mahoney (2009) employed a ranking matrix to assess six lifting methods: GL, ESP, SRP, PCP, HJP, and long-stroke pump. They scrutinized technical and operational constraints associated with AL, along with CAPEX and OPEX, within the context of a thermally recovered heavy oil reservoir situated in Oman, aiming to enhance production rates. Notably, the study revealed that elevated temperatures posed significant challenges for both GL and ESP methods. GL was found unsatisfactory due to the costly gas supply and low GOR. Meanwhile, the high operational and capital expenses rendered HJP and ESP unfeasible options. Although Metal-to-Metal PCP (MTMPCP) boasted economical operational costs, it was disqualified due to design rate limitations, susceptibility to sand production, and a history of failures, much like the long-stroke pump. Furthermore, Jet was excluded due to its substantial power requirement for lifting fluids with a density below 14 API, coupled with limited historical data on pump performance in the field. Ultimately, all attempts to introduce new AL alternatives proved unsuccessful, prompting the continued utilization of the primary SRP, albeit with modifications such as attached sinker bars to mitigate rod buckling. Similarly, Williams et al. (2008) employed a matrix screening approach to optimise five lifting methods: ESP, PCP, GL, HJP, and SRP in a Colombian oil field, addressing prevalent challenges such as depth, gas presence, and solid content, each of which influences the efficacy of the method. The selection process was refined by utilizing flow rates spanning from 0 to 750 B/D as a discriminating factor. Their findings indicated GL as suitable across all flow rate ranges, whereas PCP was deemed effective for productions up to 300 B/D. SRP and ESP were identified as optimal choices for flow rates ranging between 300 and 750 B/D, while GL and ESP were preferred for flow rates exceeding 750 B/D. Another investigation conducted by Naguib et al. (2000) focused on four AL methods; SRP, ESP, GL, and HJP in an Egyptian oil field. The study entailed reservoir simulation and well performance analysis to ascertain the optimal AL method. SRP and HJP were discounted due to their incompatibility with high reservoir volumes and wax content. Ultimately, GL was selected due to the convenience of gas supply availability from a nearby company, while ESP was chosen to regulate flow rates, particularly concerning the presence of high associated gas, albeit with the intention of installing a downhole gas separator. Subsequently, a further evaluation was conducted between the two remaining candidates. GL exhibited lower CAPEX and OPEX compared to ESP, alongside a superior recovery factor. However, ESP demonstrated advantages in scenarios involving high production rates, increasing water cut, and inadequate gas supply.

Matondang et al. (2011) introduced an alternative method for AL selection combining GL mandrels and ESP. Initially, this approach aimed to alleviate gas-related issues affecting the pump by venting gas through the casing and subsequently reducing water cut (WC%). The implementation proved successful, with gas released through the mandrels merging with the gas expelled from the ESP gas separator, resulting in a production increase from 350 to 500 B/D and a reduction in water production. This technique facilitated the adoption of ESP in high GOR wells, contingent upon the suitability of well completion for this hybrid application. In a separate study, Zulkapli et al. (2014) assessed ESP production in the Bokor offshore field in Malaysia following the replacement of a dual string GL system, prompted by escalating water production and inadequate gas supply. They employed nodal analysis using the commercial simulator PIPESIM to simulate performance. Despite the theoretical feasibility of GL, their findings revealed deficiencies in gas supply from a nearby field and complications with compressor functionality, impairing the efficiency of GL. Additionally, discrepancies in real-time measurements impeded the optimization process, leading to misinterpretation—a widespread issue globally. Consequently, ESP was chosen due to the low GOR of the wells and absence of historical sand production. Rather than discontinuing GL, Alshmakhy et al. (2020, 2019) pursued a novel approach to enhance its efficiency. They introduced digital optimization techniques for both single and dual-string GL systems within an onshore field in the UAE, aiming to mitigate common challenges such as casing pressure instability, temperature fluctuations, and injection rate control issues. The implementation involved deploying a Digital Intelligent Artificial Lift (DIAL) system, featuring up to six injection orifices and an electric cable connected to the mandrels, enabling remote control of GL orifice operations from the surface. Additionally, the system facilitated real-time monitoring of pressure and temperature, with an anticipated 20% increase in oil production. The potential efficacy of this technology appears promising, particularly if deployed offshore, where the cost associated with workovers is substantially higher. In a similar vein, Caicedo et al. (2015) conducted nodal analysis to ascertain the most suitable AL method for a high-uncertainty, large reserve field in Abu Dhabi, presuming no natural flow. Given the presence of H_2S and the proximity to residential areas, safety considerations predominated the selection process to avert potential leaks that could jeopardize human safety. Following analysis accounting for various GOR, Water Cut (WC%), and reservoir pressure values, it was determined that AL would be necessary if the reservoir pressure dipped below 2500 psi, WC% exceeded 90%, and GOR remained below 3000 scf/STB. SRP and PCP were eliminated due to the risk of stuffing box leakage, while GL was not feasible due to inadequate gas supply. Finally, ESP was selected, with particular attention to ensuring that GOR did not surpass 1500 scf/STB. Kefford and Gaurav (2016) undertook an assessment of multiple lifting methods, employing adjusted correlations and iterative calculations. Their study encompassed an analysis of specific reservoir attributes and operational factors across three fields, including unconventional reservoirs, with the aim of estimating

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production rates and assessing AL capacity to manage associated gas. The objective was to broaden the selection methodology and introduce a novel criterion instead of the conventional Blais method. Nodal analysis was utilised to compute well performance, determining the AL methods capable of achieving both maximum and targeted production rates, while considering factors such as gas handling, wellhead pressure, and power requirements. Alferov et al. (2015) and Khabibullin and Krasnov (2015) explored the impact of varying parameters: reservoir pressure, BHP, WC%, PI, GOR, and flowline pressure on the CAPEX and OPEX of AL methods in Russian fields. Alferov et al. (2015) argued against the practicality of relying on outdated selection technical tables, asserting that such tables are primarily derived from the operational history of AL under diverse field conditions. Their case study examined the field implementation of Simultaneous Water Alternating Gas (WAG) in a low-permeability, heterogeneous reservoir characterized by paraffin, salt, and corrosion. SRP, PCP and HJP were eliminated due to inadequate equipment availability. The most viable and cost-effective AL options identified for the field development plan (FDP) were ESP and GL, owing to their respective capabilities in managing fluctuations in WC% and GOR, respectively. Khabibullin and Krasnov (2015) AL selection map for a new field revealed comparable results for ESP and GL at BHP of 100 atm BHP, highlighting a preference for 40 atm for optimal applicability.

B. Other AL Selection Experiments

Fraga et al. (2020) introduced a new pump system, termed the progressive vortex pump (PVP), which combines PCP and ESP mechanisms. Developed by Petrobras, the PVP aims to optimize production and address the challenges posed by high temperatures in cyclic steam stimulation (CSS) and steam flooding (SF) operations, while also accommodating varying flow rates. Comprising a rotor, stator, and diffuser with multiple stages to convert kinetic energy into potential energy, the PVP exhibited an efficiency approximately 50% lower than ESP, reaching up to 33%. However, it demonstrated superior performance in handling additional head compared to ESP. Performance tests of the PVP indicated that a single stage operating at 60Hz could generate a head of 75.5, equivalent to 32.7 psi. Following installation for a pilot test onshore, the pump achieved a positive efficiency of 6-8% after four months of operation, determined by the difference between consumed and delivered power.

In a distinct approach, Kaplan and Duygu (2014) investigated a selection strategy in a Turkish heavy oil field undergoing CO_2 injection for enhanced oil recovery (EOR). Their analysis focused on axial and radial shear stress, as well as torque requirements for two AL methods: Beam Pumping Unit (BPU) and PCP. Due to elevated temperatures, ESP was deemed unsuitable. Although BPU had been effectively producing oil, issues such as emulsion formation and high viscosity led to rod failures and restricted oil production volumes. Comparative analysis revealed that the power required to handle radial shear stress and torque for PCP was lower than that required to manage axial shear stress for BPU. This reduction in power could be attained by adjusting the RPM and employing a larger pump. Consequently, PCP was selected to replace the SRP in the field. Mali and Al-Jasmi (2014) implemented a selection screening process for cold heavy oil production with sand (CHOPS) and CSS thermal recovery techniques in a Kuwaiti oil field. The FDP targeted a maximum production of 300 B/D for cold oil and 1000 B/D for hot oil, under conditions of 12 API density, GOR, and well depths up to 3000 ft. Seven AL candidates were assessed, including SRP, ESP, Electrical Submersible PCP (ESPCP), GL, HJP, PCP, and MTMPCP. Selection criteria are detailed in **Table 2**. Ultimately, PCP and MTMPCP were chosen for their lower CAPEX and OPEX.

Table 2: AL Comparison for Heavy Oil Production (Mali and Al-Jasmi 2014)

Parameters	**SRP**	**ESP**	**PCP**	**Jet**	**ESPCP**	**GL**
Capital Cost	Low	High	Low	High	Moderate	High
Operating Cost	Low	Moderate	Low	High	Moderate	Moderate
Run life in vertical wells	Average	Average	Average	High	Average	High
Run life in horizontal wells	Low	Average	Low	High	Average	High
Ability to handle sand content	Average	Low	Average	Good	Average	Average
Efficiency	Average	Low	Average	Low	Average	Average
Suitability for thermal production	Applicable	Applicable	Applicable	Applicable	Not Applicable	Applicable
Operational Flexibility	Average	Good	Good	Low	Average	Good
Ability to handle gas content	Average	Good	Good	Good	Good	Good
Production Handling Capacity	Good	Average	Good	Average	Average	Good

Hoy et al. (2020) conducted an evaluation of existing lifting methods with the aim of selecting an appropriate system for a polymer EOR application within an Austrian oil field. Their investigation focused on assessing the impact of viscosity changes and head column variations on GL, SRP, ESP, and PCP, aiming to determine their reliability in achieving the desired flow rate. Their findings indicated that ESP and SRP emerged as the optimal lifting methods. However, while ESP demonstrated capability in managing fluid head, it proved inadequate in handling a polymer

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concentration of 500 ppm. Conversely, SRP exhibited some friction-related issues. In a complementary study, Zein El Din Shoukry et al. (2020) delineated a set of parameters crucial for achieving optimal AL selection (**Table 3**) with the main goal of extending run life and maximising revenue.

Table 3: AL Selection Parameters (Zein El Din Shoukry et al. 2020)

AL	Gas Lift	Foam Lift	Plunger	Rod Lift	PCP	ESP	HJP	HPP
Max Depth	18,000 ft	22,000 ft	19,000 ft	16,000 ft	<9,000 ft	15,000 ft	20,000 ft	17,000 ft
Max Volume	75,000 B/D	500 B/D	200 B/D	6,000 B/D	5,000 B/D	60,000 B/D	35000 B/D	8,000 B/D
Max Temp	450˚F	400˚F	550˚F	550˚F	302˚F	482˚F	550˚F	550˚F
Corrosion Handling	Good to excellent	Excellent	Excellen t	Good to excellent	Good	Good	Excellent	Good
Gas Handling	Excellent	Excellent	Excellen t	Fair to good	Good	Fair	Good	Fair
Solids Handling	Good	Good	Fair	Fair to good	Excellent	Sand<40ppm	Good	Fair
Fluid Gravity (°API)	>15°	>8°	>15°	>8°	8°<API<45 °	Viscosity<400 cp	≥6°	>8°
Servicing	Wireline or workover rig	Capillary unit	Wellhea d catcher or wireline	Workover or pulling rig	Wireline or workover rig	Wireline or workover rig	Hydraulic or wireline	Hydraulic or wireline
Prime Mover	Compresso r	Well natural energy	Well natural energy	Gas or electric	Gas or electric	Electric	Gas or electric	Gas or electric
Offshore	Excellent	Good	N/A	Limited	Good	Excellent	Excellent	Good
System Efficiency	10% to 30%	N/A	N/A	45% to 60%	55% to 75%	35% to 60%	10% to 30%	45% to 55%

Crnogorac et al. (2020) presented a study aimed at selecting the optimal AL method through the application of fuzzy logic and mathematical models. The model's effectiveness is contingent upon a predefined dataset encompassing five lifting methods and may not be universally applicable when different input parameters or alternative AL techniques are utilised. The selection of AL for a new well is based on aligning the characteristics of the prospective AL with those stored in the AL database. (Adam et al., 2022) introduced a novel selection methodology tailored for Sudanese oil fields. Their decision-making model adapted the approach proposed by (Alemi et al., 2010), incorporating TOPSIS (Technique for Order Preference by Similarity to the Ideal Solution) and integrating Analytic Hierarchy Process (AHP) for parameter weighting, with the aim of facilitating informed decision-making. By considering the desired flow rate and other pertinent parameters, the model ranked the most suitable AL method. However, the study suggests that incorporating economic evaluations into the decision-making process could enhance the robustness of the results.

III. AL SELECTION IN UNCONVENTIONALS

In unconventionals application, the most used ALs are ESP, GL, SRP, Jets, and Plunger lift (Table 4). The installation of AL occurs either subsequent to the decline in natural well flow or at the onset of production (Chow et al. 2020). The typical operational lifespan of ESP systems ranges between 6 to 9 months. An essential consideration for SRP pertains to maintaining side loads within the range of 200 lbf/25 ft; deviations beyond this limit necessitate exploring alternative AL methods. GL systems are suitable for use within deviations of up to 75°. Jets, distinguished by their absence of moving components, exhibit an adeptness in handling solids. Conversely, Plunger Lift systems are deployed to manage lower production rates, typically around 200 STB/D (Kolawole et al. 2019; Pankaj et al. 2018).

Table 4: AL used in Unconventionals (Kolawole et al. 2019)

AL	Percentage of Application
GL	40%
ESP	36%
SRP	13%
Jets	4%
Plunger	7%

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The rapid decline in production rates observed in unconventionals over a short span of time, often spanning just a few years or even months, poses a significant challenge necessitating the replacement of AL and an increase in OPEX. In the context of unconventional reservoirs, the size of the casing plays a pivotal role in the design and selection of AL systems. A larger casing diameter results in higher gas production through the annulus to the surface, thereby influencing the performance of AL (Parshall 2013). Recent advancements in AL technology aim to enhance performance in unconventionals. Notable developments include the integration of permanent magnet motors and optimized stage designs for ESP, the implementation of controlled valves in GL, tailpipe designs tailored to manage slugging, and the introduction of the Geared Centrifugal Pump (GCP), which operates akin to an ESP albeit with surface-driven rods powered by hydraulic and electric sources, offering enhanced suitability for gas-rich environments compared to conventional ESPs (Parshall 2013; Stephenson 2020). Valbuena et al. (2016) introduced a methodological framework for selecting suitable AL systems in horizontal gas wells, incorporating technical and economic considerations. The technical screening process evaluated the constraints of various lifting methods in terms of production rates, depth versus rate, reservoir/fluid properties, and gas handling, drawing upon standard selection tables and charts. Subsequently, the feasibility of lifting methods was assessed through Net Present Value (NPV) calculations. In addition to conventional selection criteria employed across the oil and gas industry (OGI), the authors categorized selection factors into three distinct groups: weighting factors, representing the significance of each factor in the selection process and rated on a scale of 1 to 10; suitability factors, determined through mathematical equations; and economic factors, quantified through NPV analysis. This methodology was applied in a field case study. Ultimately, the study underscored the paramount importance of economic evaluation in guiding the AL selection process. Oyewole (2016 presented a field case study aimed at selecting an appropriate AL system capable of managing the rapid decline in production. The selection process was structured into four distinct categories: (1) technical considerations, encompassing production rates and associated gas production to ascertain depletion periods; (2) reservoir/fluid properties and drilling conditions; (3) surface facilities; and (4) economic evaluation. Regardless of the recommended AL methods, economic factors emerged as the primary selection criterion. In a separate study, Liu and Zerpa (2016) conducted a cost analysis of AL methods (**Table 5**) to identify a suitable approach for a hydrate reservoir in Alaska characterized by low pressure, low Gas-Liquid Ratio (GLR), low reservoir and surface temperatures, and sand production issues. The authors determined PCP to be a viable option; however, its inability to manage sand production led to premature failure. Moreover, the high CAPEX associated with ESP and the low GLR posed challenges for GL suitability. In addition to CAPEX, (Khan et al. 2014) incorporated various factors, including workover costs, OPEX, oil prices, oil treatment and transportation expenses, along with maximum NPV, into their selection strategy for four AL methods; GL, ESP, ESPCP, SRP for Shale play horizontal wells. Their analysis also considered natural flow conditions and the optimal interval for transitioning to alternative lifting methods. The results indicated that using ESP followed by SRP after a two-year period yielded greater profitability compared to employing a single or multiple lifting methods. While using a single lifting method resulted in reduced efficiency, employing three methods significantly increased the CAPEX of production.

Table 5: Summary of AL Method Feasibility for Hydrate Reservoir (Liu and Zerpa 2016)

AL	ESP	PCP	SRP	HP	GL	Plunger	Compress	Foam	Vel String
Shallow depth	Well suited	Well suited	Well suited	Well suited	Well suited	V. well suited	Well suited	Well suited	V. well suited
Offshore	Maybe	Maybe	Poorly suited	Poorly suited	V. well suited	Well suited	Maybe	Maybe	V. well suited
Permafrost	Well suited	Well suited	Well suited	Well suited	Well suited	V. well suited	Well suited	Well suited	Well suited
Low production	Poorly suited	Maybe	Well suited	Maybe	Maybe	V. well suited	V. well suited	V. well suited	Maybe
Low GLR	Well suited	Well suited	Well suited	Well suited	Poorly suited	Poorly suited	V. poorly suited	V. Poorly suited	Poorly suited
Low BHP	Maybe	Maybe	V.well suited	Maybe	Poorly suited	Well suited	Well suited	Well suited	Maybe
Viscous production	Poorly suited	Maybe	Poorly suited	Poorly suited	Poorly suited	V.Poorly suited	Poorly suited	V.Poorly suited	V.Poorly suited
Sandy production	Poorly suited	Maybe	Poorly suited	Poorly suited	Maybe	V.poorly suited	Poorly suited	Well suited	Well suited
Secondary hydrate	Poorly suited	Maybe	Poorly suited	Poorly suited	Maybe	V.poorly suited	Poorly suited	Well suited	Well suited
Ice	Poorly suited	Maybe	Poorly suited	Poorly suited	Maybe	V.poorly suited	Poorly suited	Well suited	Well suited

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Slow pressure building up	Well suited	Well suited	Well suited	Well suited	Maybe	Poorly suited	Maybe	Maybe	Poorly suited
Low reservoir temperature	Well suited	V. well suited	Well suited	Well suited	Well suited	Well suited	Well suited	Well suited	Well suited
CAPEX	115,000	35,000	45,000	45,000	25,000	10,000	20,000	7,500	10,000

Pankaj et al. (2018) conducted an analysis of reservoir characteristics, including porosity, permeability, saturation, geological structures, and GORs, alongside varying production rates ranging from 500 to 2500 STB/D, employing simulators to identify suitable AL for deep horizontal shale wells. Their findings identified GL and Jets as the most suitable options, although Jets proved unsuitable for low-rate operations. Similarly, Escobar Patron et al. (2018) utilised simulators to ascertain the optimal AL methods for addressing production decline challenges in unconventionals within the US. The software analysed input parameters such as well depth, reservoir and fluid properties, and solids content to screen out AL methods based on known constraints. Subsequently, nodal analysis and NPV calculations were employed for forecasting purposes, identifying AL systems capable of achieving the desired production rate at minimal expense. Simulation scenarios spanning 1, 3, and 6 years were considered, revealing that the well could naturally flow for 3 months in all scenarios, after which ESPs and Jets were identified as suitable for higher flow rates, followed by SRPs as production declined. Chow et al. (2020) devised a selection tool for determining the most viable lifting method for offshore unconventionals. Analyses of well and fluid properties were conducted, and well performance was validated independently for the selected method. Pump feasibility was evaluated in three stages: firstly, assessing the pump's capacity to handle Gas Volume Fraction (GVF); secondly, ensuring compatibility between pump and casing sizes; and finally, aligning reservoir deliverability with pump size. Subsequent calculations and plots were employed to validate these steps, followed by consideration of company specifications pertaining to temperature, pressure, and production rates. Furthermore, additional analysis encompassed various aspects such as well integrity and a comparison between qualitative and quantitative well parameters that may limit the application of AL techniques, culminating in the ranking of each lifting method based on its applicability. Lane and Chokshi (2016) and Temizel et al. (2020) summarised the use of AL in unconventionals into four production stages (Fig. 1):

- High rates Jet is used for cleaning operations to remove hydraulic fracturing fluids and this continues until production declines.
- GL, Plunger, and Foam Lift are to handle gas slug flow.
- GL, Jet, and ESP are used in early production, and an amalgamation of GL and Jet/Foam could be applied depending on completion.
- SRP is used in the later production period after the decline occurs.

➢ *Additional Selection Considerations Recommended by the Authors are:*

- Integrated planning for well completion, considering several future AL.
- AL life cycle estimation to reduce workover cost.
- Continuous well parameters surveillance for production optimisation.

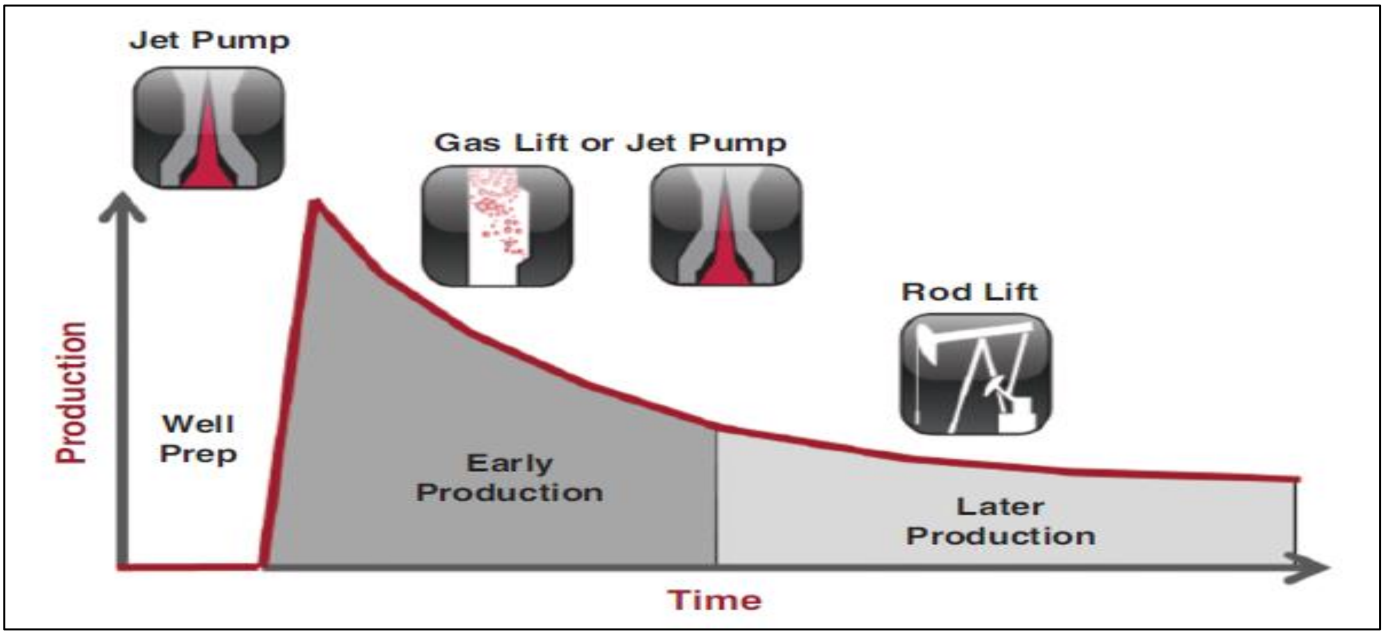

Fig. 1: AL Life Stages in Unconventionals (Lane and Chokshi 2016)

IV. ML APPLICATION IN OIL AND GAS

Over the past decade, the utilisation of ML in the OGI has experienced a steady increase across various domains. Fig. 2 illustrates the recent applications of ML in the OGI, as evidenced by data obtained from Google Scholar (Pandey et al. 2020).

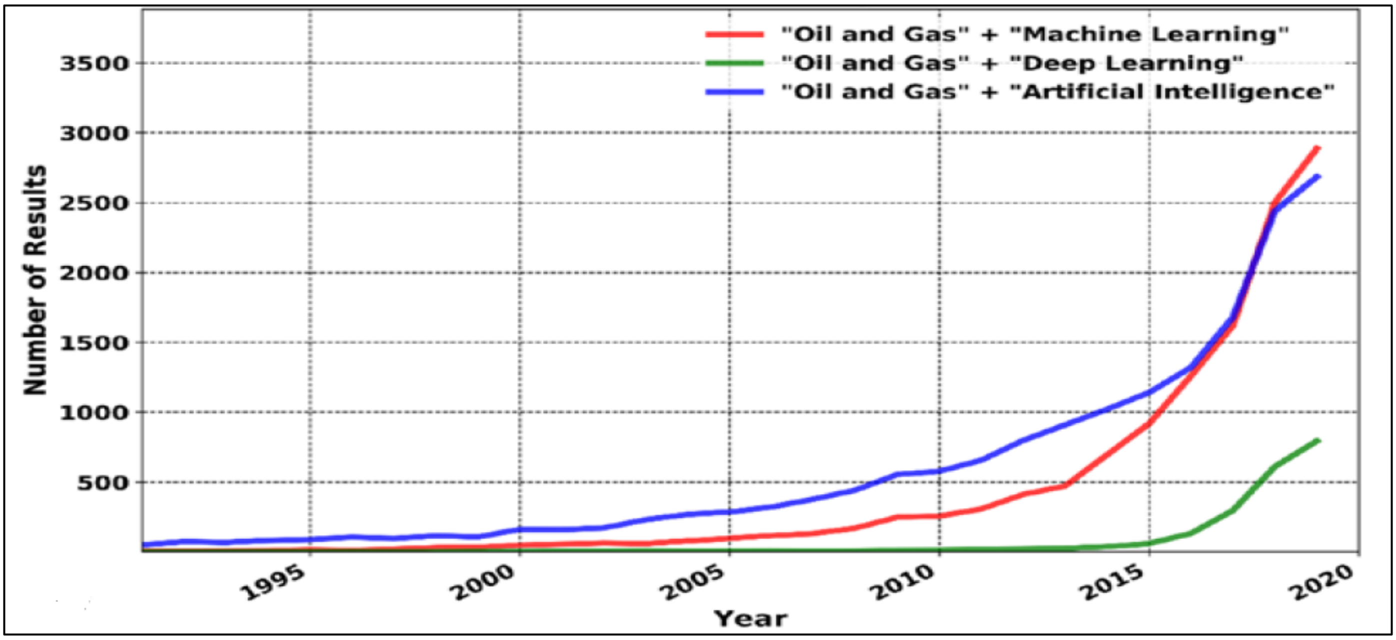

Fig. 2: Keywords Search on Google Scholar (Pandey et al. 2020)

In the OGI, ML has been applied to achieve significant advancements in big-data analysis, often compared with traditional correlations and commercial software solutions. Theoretical and empirical correlations are at times deemed impractical and limited to specific properties and datasets (Khan et al. 2019). Elichev et al. (2019) contended that ML algorithms may lack accuracy when confronted with inadequate or uncertain data, highlighting the necessity to mitigate noise stemming from errors to ensure robust outputs. Conversely, several studies (Andrianova et al. 2018; Daigle and Griffith 2018; Shoeibi Omrani et al. 2019) contradicted (Elichev et al. 2019) prospective by demonstrating the accuracy and adaptability of ML algorithms in accommodating data anomalies within petroleum engineering. It is acknowledged that data collected in this field is susceptible to errors, stemming from factors such as sensor inaccuracies or human oversight during data collection. The emphasis lies in training the ML models to effectively handle such anomalies and derive approximate or semi-corrected data through problem-solving approaches. Over 500 papers addressing ML applications in the oil and gas industry have been published on OnePetro (Hajizadeh, 2019). **Table 7** provides examples of ML applications within the oil and gas sector.

Table 7: ML Application Examples in Oil and Gas

Work	Application
Andrianova et al. 2018	PVT analysis
Anifowose et al. 2017	Reservoir characterisation uncertainty
Ahmadi and Chen 2019; Elichev et al. 2019; Alakbari et al. 2017; Onwuchekwa 2018; Ramirez et al. 2017	Reservoir and fluid properties
Al-Alwani et al. 2019; Al Selaiti et al. 2020; Boguslawski et al. 2019; Bowie 2018; Cao et al. 2016; Han et al. 2019; Herve et al. 2020; Khan et al. 2019; Luo et al. 2018; Pennel et al. 2018; Saghir et al. 2020	Well performance, production optimisation and forecast
Noshi and Schubert 2018; Pollock et al. 2018	Drilling and directional drilling optimisation
Pankaj et al. 2018; Prosper and West 2018	Completion design in unconventionals
Chiroma et al. 2016	Oil prices estimation
Hajizadeh 2019	Strategic planning and development projects

V. ML APPLICATION IN AL SELECTION

As previously discussed, the selection of AL methods predominantly relies on the expertise of engineers and the historical performance of mature wells. Engineers typically conduct well performance and nodal analyses to assess well deliverability and forecast production, thereby identifying an appropriate lifting method capable of achieving the desired flow rate. Traditional approaches have often involved the use of commercial simulators to design lifting methods, a process that can be repetitive and tedious over time (Kefford and Gaurav 2016). In recent years, several researchers have

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turned to ML techniques to analyse well performance and reservoir/fluid properties. However, the application of ML as a selection technique for AL methods remains relatively underexplored. Ounsakul et al. (2019) applied supervised ML to determine the optimal lifting method from ESP, PCP, GL, and SRP. Their model utilises field data upon which algorithms are trained to analyse for AL selection. The objective was to enhance the selection criteria by minimising human errors. Three distinct algorithms, namely Naive Bayes, decision tree, and neural network, were employed to assess 30,000 samples encompassing reservoir, fluid, and economic factors. Their findings demonstrated the capability of ML to identify optimal pumps and reduce the lifecycle costs of producing wells compared to human decision-making processes. The author of this article recently conducted AL selection research in a Sudanese oil field using ML techniques (Mahdi et al. 2023). The analysis involved several production parameters of four lifting methods along with natural flow deployed across 24 wells over a period of 16 years, comprising a dataset of over 450,000 samples. Key factors influencing AL selection were identified as gas content, wellhead pressure, and cumulative fluid production. Production performance and economic analyses were conducted to compare the actual AL performance in the field with the predictions generated by ML. The results revealed that the ML-predicted AL exhibited superior production performance compared to the actual implementations. Syed et al. (2020) conducted AL system optimisation using ML techniques to facilitate the selection and monitoring of AL systems within shale gas fields. Diverging from conventional ML approaches, their study incorporated the consideration of the optimal timing for replacing the current AL systems, aiming to prevent pump failures and enhance profitability. This aspect of AL replacement during ongoing operations may encounter resistance from oil companies, given the potential reluctance to replace operative AL systems. Additionally, the researchers investigated monitoring and maintenance practices, which are deemed essential within the OGI to ensure operational efficiency and equipment integrity. In a related study, Ranjan et al., (2015) employed an Artificial Neural Network (ANN) to optimise GL operations in an offshore field situated in India. They developed a simplistic model consisting of 10 neurons representing reservoir and well parameters, with a single hidden layer employed as input to determine the optimal gas injection rate required to achieve maximum oil production. The ML model served to validate nodal analysis outcomes and provided engineers with a time-saving alternative to laborious calculations.

VI. DISCUSSION

The traditional methods of AL selection, relying on selection tables and flow rate and depth limitations, possess several drawbacks. These methods often lack flexibility, as they rely on predefined tables that may not accurately reflect the unique characteristics of each well. Additionally, they may have limitations in terms of the range of flow rates and depths they can effectively handle. While these methods have the advantage of simplicity and ease of use, they can also be time-consuming, requiring engineers to manually screen through data and compare various parameters. In contrast, the application of ML techniques offers a promising solution to the complexities of AL selection. Mahdi et al. (2023) demonstrates how ML models can significantly streamline the selection process by analysing large datasets and identifying patterns that may not be immediately apparent to human analysts. By leveraging ML algorithms, engineers can make more informed decisions about the most suitable AL method for a given well, potentially leading to improvements in production and revenue. Overall, while traditional selection techniques have their advantages, they are often limited by their rigidity and reliance on manual analysis. In contrast, ML-based approaches offer the potential to revolutionize AL selection by automating data analysis and providing more accurate predictions.

VII. CONCLUSION

The same AL have been used for decades with some modernisations. Most AL selection in the literature played around the prevalent selection criteria focusing on studying and analysing reservoir parameters, fluid properties, well productivity, surface facilities, power requirements, environmental aspects, corrosion, solids, paraffin handling, gas handling, well completion and design, and economic factors, including workover and maintenance. The approaches applied in the literature might look the same, however, every field has its peculiar circumstances and reservoir/fluid properties. Few applications of ML and AI in AL selection are found in the literature, and the area is still fertile for more research. The current state of the art in AL is not fully optimised to meet the demands of the industry, especially in unconventional reservoirs. To address this gap, future research in AL should focus on developing innovative technologies, improving the understanding of the failure mechanisms, reinforcing ML applications, and enhancing the design and operation practices of the existing systems. Despite some innovations in gas handling and pump designs, problems still exist, and long-lasting AL seems to be the inevitable challenge in the petroleum industry.

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ABBREVIATION

AL	Artificial lift	MTMPCP	Metal to metal PCP
SRP	Sucker rod pump	ML	Machine learning
GL	Gas lift	CAPEX	Capital expenditure
PCP	Progressive cavity pump	OPEX	Operational expenditures
ESP	Electrical submersible pump	GOR	Gas oil ratio
HJP	Hydraulic jet pump	IPR	Inflow performance relationship
HPP	Hydraulic piston pump	WC%	Water cut
ESPCP	Electrical submersible progressive cavity pump	PI	Productivity index
Conventionals	Conventional wells	Unconventionals	Unconventional wells

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