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Automation of Gas Lift Opportunity Identification Using Well-Test Trend Analysis

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ABSTRACT

Gas lift is widely applied to sustain oil production from wells experiencing declining natural flow performance; however, identifying suitable gas lift candidates from large volumes of well-test data remains a repetitive and time-consuming engineering task. This study developed an automated gas lift opportunity identification system to process well-test data, capture predefined engineering decision criteria, improve the consistency and speed of candidate identification, and standardize gas lift initiation evaluation. Historical well-test data from 76 wells were analysed using basic sediment and water (BS&W), net oil rate, gas-liquid ratio (GLR), tubing pressure, flowline pressure and choke size. Candidate screening focused on increasing BS&W, declining net oil rate and declining GLR. Mann-Kendall trend analysis and the Theil-Sen slope estimator were used to determine trend direction and trend magnitude. Trend scores were ranked for each parameter, normalized, weighted, and combined to generate a composite score for candidate prioritization. The system identified 69 wells (90.8%) as potential gas lift candidates, while 7 wells (9.2%) exhibited none of the predefined trends and were excluded. Increasing BS&W, declining net oil rate and declining GLR occurred in 49 (64.5%), 47 (61.8%) and 45 (59.2%) wells, respectively. Final composite scores ranged from 0.14 to 0.82, with XY-TD23 ranked highest at 0.82. The results demonstrate that routine well-test data can be transformed into a consistent, quantitative and prioritized candidate list. The developed automation provides a standardized screening framework that can reduce repetitive manual analysis and support faster engineering review of wells requiring further gas lift evaluation.

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INTRODUCTION

Artificial lift is an important production technique used to sustain hydrocarbon production when reservoir energy is no longer sufficient to maintain the desired natural flow performance. Gas lift is particularly attractive because high-pressure gas can be injected into the production tubing to reduce the effective density of the fluid column and improve the pressure conditions for flow to surface (Brown, 1984; Takács, 2005; Economides et al., 2013). The method is adaptable to changing well conditions and is widely used in mature production assets.

An important engineering activity preceding gas lift implementation is the identification of wells that are likely to benefit from artificial lift. In conventional practice, production engineers review historical well-test data, production trends, flowing pressures and operating conditions to determine whether declining well performance is associated with insufficient lifting energy, increasing water production, changing gas-liquid behaviour or surface constraints. When many wells and repeated well-test records must be assessed, this workflow becomes repetitive and can produce differences in screening outcomes arising from

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individual judgement and available engineering time.

Digitalization and automation have created opportunities to transfer repetitive engineering workflows into structured decision-support systems. Existing automation and intelligent gas-lift studies have largely emphasized gas allocation, operational optimization, monitoring and artificial-lift selection. The engineering stage that precedes gas lift implementation—particularly the systematic screening and prioritization of candidate wells from routine well-test data—has received comparatively less attention in the research considered in this study.

The present work addresses this gap through the development of an automated gas lift opportunity identification system. The system translates selected engineering screening criteria into statistical trend logic and combines trend direction, trend strength, parameter ranking, normalization and user-defined weighting to produce a prioritized candidate list. The objectives are to automate the processing of well-test data, capture selected engineering decision criteria, improve the consistency and speed of opportunity identification, and standardize preliminary gas lift candidate evaluation.

MATERIALS AND METHODS

Study data and engineering screening parameters

The evaluation used historical well-test data comprising 76 wells. The dataset contained production and operating parameters including BS&W, net oil rate, GLR, tubing pressure, flowline pressure and choke size. The principal screening indicators used to determine gas lift opportunity were increasing BS&W, declining net oil rate and declining GLR. Tubing pressure, flowline pressure and choke size were retained as supporting operating-condition variables used to provide engineering context.

BS&W was selected because an increasing water fraction can indicate deteriorating production behaviour and increased fluid-handling requirements. Net oil rate was selected because sustained decline is a direct indicator of reducing well productivity. GLR was selected to represent gas behaviour relative to the total produced liquid stream and to provide additional information on changing well performance. The system therefore evaluates the parameters as time series rather than relying on a single well-test observation.

Automated data preparation

The system was implemented within Microsoft Excel using Visual Basic for Applications (VBA) for workflow automation and Python in Excel for the analytical component. The workflow begins with data import and validation. The system checks that the dataset is populated and that a valid well identifier is available. It then maps alternative column names to standardized analytical parameters, verifies the presence of required fields, removes records associated with wells already operating under gas lift, and retains accepted well-test records. Dates are converted to a consistent date format and numerical parameters are standardized for computation. The user can define an analysis timeline in months or years and can also specify a maximum number of historical data points. These controls allow the screening window to reflect the current engineering objective rather than necessarily using the complete historical record.

Trend-direction analysis using the Mann-Kendall statistic

The Mann-Kendall approach was used to convert the visual interpretation of an increasing or decreasing production trend into a repeatable numerical procedure. For a time series $x1, x2, ..., xn$, the Mann-Kendall statistic is calculated by comparing each observation with all subsequent observations and assigning +1 when the later observation is greater, −1 when it is smaller and 0 when the observations are equal. The resulting statistic S indicates the dominant direction of the series: $S > 0$ indicates an upward trend, $S < 0$ indicates a downward trend, and $S = 0$ indicates no net directional trend.

This logic was applied independently to BS&W, net oil rate and GLR for each well. It therefore reproduces the directional component of

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the engineering workflow in which production engineers inspect historical plots and determine whether the dominant behaviour is increasing, decreasing or approximately stable.

Data		20	59	56	56	59	61	50	50	50	49	42	40	64	69	72
20	20															
59	59	1														
56	56	1	-1													
56	56	1	-1	0												
59	59	1	0	1	1											
61	61	1	1	1	1	1										
50	50	1	-1	-1	-1	-1	-1									
50	50	1	-1	-1	-1	-1	-1	0								
50	50	1	-1	-1	-1	-1	-1	0	0							
49	49	1	-1	-1	-1	-1	-1	-1	-1	-1						
42	42	1	-1	-1	-1	-1	-1	-1	-1	-1	-1					
40	40	1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1				
64	64	1	1	1	1	1	1	1	1	1	1	1	1			
69	69	1	1	1	1	1	1	1	1	1	1	1	1	1		
72	72	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
67	67	1	1	1	1	1	1	1	1	1	1	1	1	1	-1	-1
					5		23									

Figure 1- Mann-Kendall statistic

Trend-strength analysis using the Theil-Sen estimator

Trend direction alone does not indicate how strongly a parameter is changing. The Theil-Sen estimator was therefore used to quantify trend magnitude. The method calculates the slope between pairs of observations and uses the median of the resulting slopes as the representative trend slope. Its non-parametric nature and resistance to outliers make it appropriate for well-test data containing operational disturbances, unstable flow and abnormal measurements.

For each well and each principal screening parameter, the system stores both the Mann-Kendall statistic and the Theil-Sen slope. The two measures provide complementary information: the Mann-Kendall statistic captures the consistency and direction of the trend, while the Theil-Sen slope captures its magnitude.

Date	GLR	Slope Between Points
42309	0.35	
42339	0.34	-0.000333333
42370	0.28	-0.001935484
42401	0.35	0.002258065
42430	0.35	0
42491	0.23	-0.001967213
42552	0.27	0.000655738
42583	0.29	0.000645161
42614	0.11	-0.005806452
42644	0.115	0.000166667
42675	0.105	-0.000322581
42705	0.1	-0.000166667
42736	0.11	0.000322581
42795	0.105	-8.47458E-05
42826	0.01	-0.003064516
42856	0.275	0.008833333
42948	0.025	-0.002717391
43009	0.05	0.000409836
43040	0.045	-0.00016129
	-0.0001230	

Figure 2- Theil sen slope estimator

Trend scoring, ranking and weighting

The system combines the Mann-Kendall statistic and Theil-Sen slope to produce a trend score for each principal parameter. The trend score is then ranked across the evaluated wells. Because the numerical ranges of the individual parameters can differ, the ranked values are normalized to a common scale. User-defined

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weights are subsequently applied to the normalized parameter rankings.

The final composite score is calculated as the weighted combination of the normalized BS&W, net oil-rate and GLR ranking scores. This creates two distinct decision stages. First, screening determines whether a well exhibits at least one of the predefined trends. Second, prioritization differentiates retained candidates according to the relative strength of their trends and the selected parameter weights. A well with three positive screening indicators therefore does not necessarily have to rank first; its final position depends on the relative severity and ranking of its trends.

System integration and validation

The user-facing workflow is implemented through an Excel template containing a column-mapping section, data-preview section and well-trend-analysis section. The final ranked candidates are displayed in a result sheet. VBA buttons automate common user actions, while backend worksheets store imported data, intermediate calculations and analytical outputs. This separation allows engineers to interact with the system without directly modifying the analytical code.

Validation was performed by comparing system-generated candidates with production behaviour and engineering expectations. Trend plots were reviewed to confirm that higher-ranked wells exhibited characteristics consistent with declining natural-flow performance, including declining oil rate, increasing BS&W and declining GLR. The validation also assessed whether the combined statistical and weighting procedures produced rankings that were reasonable from an engineering perspective.

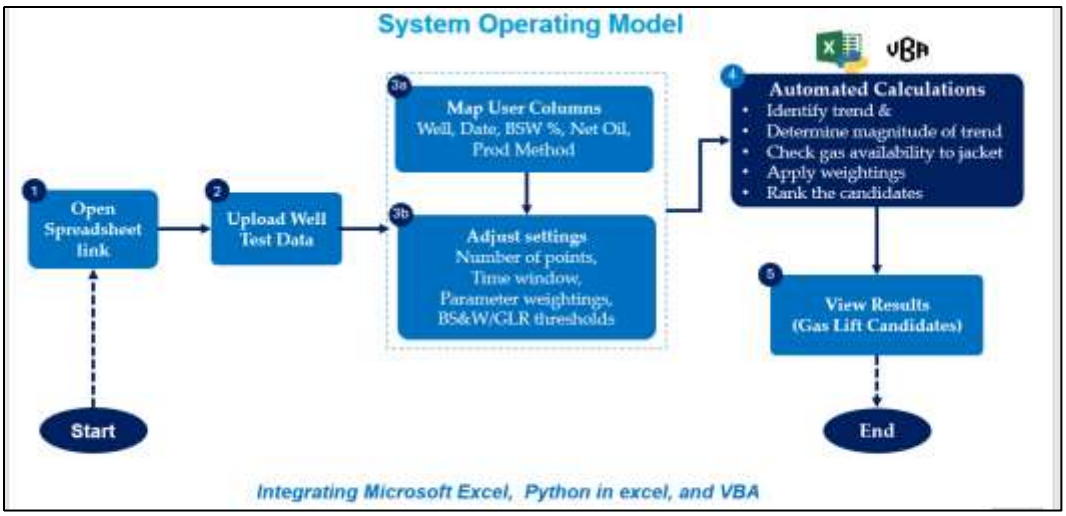

Figure 3- System Operating Model

RESULTS

Candidate screening results

Application of the automated screening workflow to the 76-well dataset identified 69 potential gas lift candidates, corresponding to 90.8% of the evaluated wells. Seven wells (9.2%) were excluded because none of the three predefined screening trends was identified.

Table 1. Summary of automated gas lift candidate identification.

Classification	Number of wells	Percentage
Identified candidates	69	90.8%
Excluded wells	7	9.2%
Total	76	100%

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Distribution of screening indicators

Increasing BS&W was identified in 49 wells (64.5%), declining net oil rate in 47 wells (61.8%), and declining GLR in 45 wells (59.2%). The relatively similar occurrence of the three indicators indicates that candidate identification was not controlled by a single parameter. Instead, different combinations of production behaviour contributed to the candidate population.

This result is important because gas lift opportunity identification is inherently multi-parameter. A decline in oil rate may be accompanied by increasing water production, while changes in GLR may provide additional evidence of changing lifting conditions. The automated workflow preserves this multi-parameter interpretation rather than reducing candidate selection to a single production metric.

Candidate prioritization

The final composite scores of the retained candidates ranged from 0.14 to 0.82. XY-TD23 achieved the highest composite score of 0.82 and was ranked first. The ten highest-ranked wells were XY-TD23, XX-DUNNE 18, DA-JCP1-E, XX-JCP13-T, DA-D29, AC-TDC04406717, XZ-JCP5-T, AB-DS3975-16-21-1FH, XX-TDC044067B3 and XY-TD31.

Table 2. Ten highest-ranked gas lift candidates generated by the system.

Rank	Well	Composite score
1	XY-TD23	0.82
2	XX-DUNNE 18	0.79
3	DA-JCP1-E	0.79
4	XX-JCP13-T	0.77
5	DA-D29	0.72
6	AC-TDC04406717	0.72
7	XZ-JCP5-T	0.68
8	AB-DS3975-16-21-1FH	0.67
9	XX-TDC044067B3	0.67
10	XY-TD31	0.66

Screening versus prioritization

The results demonstrate a distinction between candidate eligibility and candidate priority. A well that records a positive screening outcome for BS&W, net oil rate and GLR satisfies the predefined trend criteria, but the final rank is determined by the relative magnitude of its calculated trend scores after ranking, normalization and weighting. Consequently, two wells with the same screening classification can receive different composite scores.

This distinction provides an advantage over a simple Yes/No screening approach. The screening stage answers whether a well exhibits relevant production behaviour, while the prioritization stage identifies which retained wells exhibit the strongest relative combination of indicators. The result is therefore a decision-support list that can direct detailed engineering evaluation towards the highest-priority wells.

Engineering interpretation and validation

The automated outputs were reviewed against expected production behaviour. Higher-ranked candidates were expected to show stronger evidence of declining natural-flow performance, whereas stable wells or wells without the predefined trends were expected to be excluded or ranked lower. Trend plots generated by the system provided a visual means of checking the statistical interpretation. The validation indicates that the system can reproduce important elements of conventional engineering screening while applying the same analytical procedure across the well population. This is particularly valuable where large numbers of well-test records must be reviewed repeatedly. However, the output should be interpreted as a preliminary candidate ranking rather than a final gas lift design decision.

Practical implications

The principal practical contribution of the system is the transfer of a repetitive engineering screening task into a structured digital workflow. Instead of manually inspecting individual production histories and compiling candidate lists, the engineer can upload well-test

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data, map the required parameters, define the analysis window and obtain a ranked candidate list. The workflow also retains an interactive trend-analysis capability, allowing the engineer to interrogate individual wells before proceeding to more detailed engineering studies.

The system is therefore positioned as a screening and decision-support layer before detailed gas lift design. Candidate wells identified by the system can subsequently be evaluated using well modelling, nodal analysis, injection-gas requirements, facility constraints and economic considerations. Such downstream analyses were outside the scope of the present study.

CONCLUSIONS

An automated gas lift opportunity identification system was developed to transform routine well-test data into a structured and prioritized candidate list. The system integrates Excel, VBA and Python in Excel to automate data preparation, trend analysis, screening, ranking and presentation. The Mann-Kendall statistic provided a repeatable method for identifying the direction of BS&W, net oil-rate and GLR trends, while the Theil-Sen estimator quantified trend magnitude. Combining these measures with parameter ranking, normalization and user-defined weighting enabled the system to distinguish candidate screening from candidate prioritization.

Evaluation of 76 wells and 954 observations identified 69 wells (90.8%) as potential gas lift candidates. Increasing BS&W, declining net oil rate and declining GLR occurred in 49, 47 and 45 wells, respectively. The final composite scores ranged from 0.14 to 0.82, with XY-TD23 ranked first at 0.82. The study demonstrates that automation can improve the consistency, repeatability and efficiency of preliminary gas lift opportunity identification. The system is not intended to replace production engineering judgement; rather, it provides a standardized first-stage screening tool that allows engineering attention to be focused on higher-priority wells.

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