Constructing IPR for a Well Using Python

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ABSTRACT

Using Python, a significant and reliable approach for constructing the Inflow Performance Relationship (IPR) is presented in this paper. Predicting production rate of a well as a function of its flowing bottom-hole pressure by using a fundamental tool in petroleum engineering known as IPR. Python is used in this paper to automate the process of building IPR curves through fitting mathematical models to well data. By applying our approach to well data and comparing the resulting IPR curves using Vogel's equation with those obtained using traditional methods, will show its effectiveness. Our Python-based approach is accurate, efficient, and provides a powerful tool for IPR analysis, as shown by our results. By providing a tool that can enhance the accuracy and speed of IPR estimation, the study will contribute to the field of petroleum engineering and enable more informed decision-making in oil and gas production operations.

Keywords: inflow performance relationship, python, mathematical models

INTRODUCTION

For many years, the oil and gas sector has relied on the inflow performance relationship (IPR) concept to assess the efficiency of oil wells. IPR is a mathematical or graphical representation of the correlation between the inflow rate of fluid and the pressure at wellbore. It is crucial for well testing, reservoir management, and determining the production capacity of the well.

The Inflow Performance Relationship is among the diagnostic tool utilized by Petroleum engineers to assess the effectiveness of a flowing well. It is essential to precisely predict well IPR to estimate the best production plan for company, designing production equipment required, and artificial lift system. Consequently, there is a requirement for a fast and dependable technique to forecast well IPR.

Understanding the productivity of a well is essential when evaluating its performance, designing it, and solving production issues. The inflow performance relationship (IPR) curve shows the correlation of production rates and the bottom-hole pressures at which they are produced. This curve helps determine a well's productivity and can be estimated using production tests or empirical correlations.

The oil and gas sector has widely embraced the utilization of Python programming language for carrying out data analysis and modelling in recent years. An ideal choice for oil and gas engineers is Python, which provides a flexible and powerful platform for constructing IPRs.

Using Python, we will construct the Inflow Performance Relationship using vogel's equation in this paper. An overview of the concept of IPR and its significance in analyzing well performance will be provided.

Next, we will introduce the code used in constructing IPRs using Python. We will then provide a step-by-step guide on how to implement the IPR construction process using Python.

LITERATURE REVIEW

During the year 1968, Vogel exhibited a practical inflow performance correlation for reservoirs driven by solution gas. This was formulated by taking into consideration the outcomes of computer simulations and a broad spectrum of fluid and rock characteristics. His well-known non-dimensional IPR was created for the transfer of unsaturated oil from a solution gas drive reservoir having some parameters into the well, while ignoring the impact of skin effects (Vogel, J. V,1968).

Jahanbani and S.R. Shadizadeh proposed techniques for calculating IPR curves, which are limited to specific scenarios and may not be universally applicable. Additionally, these methods often lack mathematical derivation. Their research introduced a general method for generating IPR curves by utilizing well-test analysis and incorporating reservoir parameter values into inflow equations. This approach enables the prediction of future IPR curves. Among distinctive techniques evaluated on this work, Vogel's IPR equation is suitable matched work; however, it isn't always specific and ignores the flow rates. Though it is widely used, empirical methods are not applicable for all cases. In this study, they have examined their application to an oil well in a having fractured reservoir. Therefore, it is very important to use empirical relationships within their range of validity (Jahanbani, A, & Shadizadeh, S. R , 2009).

Ayowole Onoopemipo Ogunleye created a model in 2012 by utilizing Vogel and base case parameters as inputs in a Reservoir Simulator (Eclipse). The model was initially configured as a vertical well and the simulation outcomes were verified against the Vogel Reference curve. Once the validation was successful, the model was altered to a horizontal well configuration. With this modification, a Vogel type IPR intended for horizontal wells was generated. Furthermore, the equation produced took into account the skin effect, which is a crucial element that affects well productivity (Ogunleye, A. O, 2012).

In 2020 Del Pino Fiorillo, M. A. Developed a model applying machine learning for creating multivariate IPR models from high frequency streaming data. The developed code was able to successfully deal with the high frequency data generated from the asset SCADA (Del Pino Fiorillo, M. A , 2020).

VOGEL'S EQUATION

Since 1968, the Vogel formula has been widely and effectively employed to analyze the inflow performance correlation (IPR) of streaming oil wells under solution-gas drive. By utilizing the Vogel IPR curvature and the seepage efficiency of the well, the oil well efficiency can be promptly estimated. However, the Vogel curve was initially created for traditional vertical wells and might not be applicable for inclined and parallel wells. To address this, IPR models have been developed for inclined and parallel wells by utilizing a vertical/horizontal/slanted well. The generalized Vogel's IPR model can be employed to portray well inflow from multi-layered reservoirs where the reservoir pressures are higher than the oil bubble-point pressures, and the wellbore pressure is lower. Vogel's formula is an empirical equation utilized in petroleum engineering to model the inflow performance correlation (IPR) of a well. The IPR demonstrates the relationship between the pressure at the wellbore and the rate of fluid (oil or gas) that can be produced from a reservoir. Vogel's equation is particularly useful for predicting the flow rate from a well under various operating conditions, and for optimizing the production rate by adjusting the well pressure. However, it should be noted that this equation is based on simplifying assumptions and may not be accurate in all cases.

The computation of flow capacity in oil wells needs knowledge of the relationship between well inflow performance and productivity. In simpler terms, the inflow performance relationship (IPR) describes how the bottomhole pressure (BHP) of a well relates to its flow rate (q) at a stable reservoir pressure. There are various methods to prepare an IPR, such as using Darcy's equation, an empirical formula, or a reservoir simulator. In the oil industry, the most commonly used method for generating an IPR curve quickly and accurately is the empirical Vogel equation, which was developed in 1968.

In current analysis of well productivity performance in advanced nodal systems, the Vogel equation has become a customary instrument for making the IPR for a specific well. The Vogel equation is remarkably uncomplicated, requiring only one set of stabilized well flow test data (Pwf, qo) to produce the IPR for that particular well.

Vogel's Equation $\longrightarrow$ $$\frac{Q}{Qmax} = 1 - 0.2\left(\frac{Pwf}{\bar{P}}\right) - 0.8\left(\frac{Pwf}{\bar{P}}\right)^2$$

Maximum Flowrate $\longrightarrow$ $$q_{\max} = \frac{J^*\bar{p}}{1.8}$$

Productivity Index $\longrightarrow$ $$J^* = \frac{kh}{141.2B\mu\left(\ln\frac{r_e}{r_w} - \frac{3}{4} + S\right)}$$

METHODOLOGY

(A) PYTHON CODE

At the start of the code (Figure A), the packages required, namely ctypes, math, numpy, and matplotlib.pyplot, are imported.

To encapsulate the entire process of calculating the IPR and plotting the curve the Vogel () function is defined(Image A).

```
from ctypes import Array
import math
import numpy
import matplotlib.pyplot as plt
def vogel():
```

(Image A)

User input is taken for various reservoir and well parameters including porosity, permeability, pay zone thickness, viscosity, formation volume factor, skin factor, reservoir pressure, bubble point pressure, compressibility factor, drainage area, and wellbore radius at the start of the function (Image B).

```python
poro = float(input("Enter Porosity: "))
ko = float(input("Enter perm(mD): "))
h = float(input("Enter payzone thickness(ft): "))
muo = float(input("Enter the viscosity(cp): "))
Bo = float(input("Enter the formation volume factor: "))
s = float(input("Enter the skin factor: "))
pr = float(input("Enter the reservoir pressure(psia): "))
pb = float(input("Enter the bubble point pressure(psia): "))
ct = float(input("Enter the compressibility factor (psi^-): "))
A = float(input("Enter Drainage area(acres): "))
rw = float(input("Enter the wellbore radius(ft): "))
```

(Image B)

The drainage radius (re) is calculated from the input drainage area(Figure C).

```python
re =  np.sqrt(43560*A/np.pi)
```

(Image C)

The input parameters are used in Vogel's equation to determine the well's productivity index (J). (0.00708koh)/(muoBo(np.log(re/rw)-0.75+s)) is the formula for J. Then, the console displays the calculated value of J.(Image D).

```python
J = (0.00708*ko*h)/(muo*Bo*(np.log(re/rw)-0.75+s))
print(f"Productivity Index is {J}")
```

(Image D)

Using the calculated value of J and the input reservoir pressure, the maximum production rate (qmax) is determine J*pr/1.8. Then, the console prints the calculated value of qmax (Image E).

```python
qmax = J*pr/1.8
print(f"The maximum production is {qmax}")
```

(Image E)

A range of pressure values, starting from 0 psi up to the input reservoir pressure (pr), is generated in increments of 500 psi. The array is then reversed and appended with the input reservoir pressure to create an array of flowing bottomhole pressure (pwf) values(Figure F). numpy. arange (0, pr, 500) generates an array a with elements ranging from 0 to pr in steps of 500.numpy.append(a, pr) appends the value of pr at the end of array a and generates a new array b.b[::-1] reverses the order of elements in the array b and makes a new array pwf(Image F).

```python
a = np.arange(0, pr, 500)
b = np.append(a, pr)
pwf = b[::-1]
flowrate = []
for i in pwf:
  q = qmax*(1-0.2*(i/pr)-0.8*((i/pr)**2))
  flowrate.append(q)
```

(Image F)

The plot will have a size of 6 inches by 6 inches.(Image G)
The data for the plot is assumed to be stored in two arrays or lists, "flowrate" and "pwf", representing flowrate in stock tank barrels per day (stb/day) and bottomhole flowing pressure in pounds per square inch (psia), respectively.
To plot the data points on the graph, you can use the command plt.plot(flowrate, pwf).
Respectively, the x-axis and y-axis are labeled using the commands plt.xlabel and plt.ylabel.
To give the plot a title, use the command plt.title.
Adding a grid to the plot using the plt.grid() command can make it easier to read.
In this case, the fivethirtyeight style, which is known for its modern and bold design, is applied to the plot using the plt.style.use command.

```
  plt.figure(figsize = (6,6))
  plt.plot(flowrate, pwf)
  plt.xlabel("flowrate(stb/day)")
  plt.ylabel("Pwf(psia)")
  plt.title("Vogel's IPR for reservoir")
  plt.grid()
  plt.style.use("fivethirtyeight")
vogel()
```

(Image G)

Finally, the vogel() function is called to execute the code.

(B) RESERVOIR MODEL DESCRIPTION

The combination of favorable reservoir and fluid properties coupled with the parameters of vertical well, presents a promising scenario for optimal oil production. The reservoir porosity of 0.19 indicates the presence of interconnected pores spaces within the rock, allowing for the storage and flow of hydrocarbon. Additionally, the effective horizontal permeability of 8.2 millidarcies suggests that the reservoir rock has sufficient pathway to enable the moment of fluid through the formation. The substantial pay zone, thickness of 53 feet indicates a considerable reservoir interval containing economically viable oil. This provides a significant reservoir volume to tapped in and extracted enhancing the potential for high production rates and long-term profitability. The fact that both reservoir pressure and the bubble point pressure are equal at 5651 indicates that reservoir is fully saturated with oil, ensuring maximum oil recovery potential. The fluid formation volume factor of 1.1 indicates that the volume of oil will expand by 10% when it is produced from the reservoir. This property is crucial for estimating the actual volume of oil that will be obtained during the production operation. Additionally, the fluid viscosity of 1.7 centipoise implies that the oil has moderate resistance to flow. This viscosity value suggests that the oil will likely to flow relatively easily through the reservoir and wellbore, felicitating efficient extraction. The total compressibility factor of the reservoir at 0.000129 PSI^-1 indicates the responsiveness of the reservoir to pressure changes. This parameter helps to assess the reservoir's ability to accommodate pressure depletion during production, allowing for sustained oil recovery without the significant changes in the reservoir volume. Considering a well parameter, the large drainage area of 640 acres indicates a considerable area from which the oil can be drained towards the well. This wide drainage area enhances the potential for high production rate and increase ultimate recovery. The distance from the well to the edge of the drainage area (re) at a 2980 feet, provides insight into the extent of a reservoir that will be influenced by well’s production. It helps to estimate the radial extent of pressure drawdown and it’s impact on oil recovery. The wellbore radius of 0.328 feet affects the flow dynamics near the wellbore region. A larger wellbore radius can enhance the productivity by reducing the pressure drop and improving the contact area between the well and the reservoir. In this case, the absence of skin suggests that there is no additional flow restrictions or enhancement due to the drilling or completion operations, indicating a favorable condition for productivity.

OUTPUT USING PYTHON

```
Enter Porosity: 0.19
Enter perm(mD): 8.2
Enter payzone thickness(ft): 53
Enter the viscosity(cp): 1.7
Enter the formation volume factor: 1.1
Enter the skin factor: 0
Enter the reservoir pressure(psia): 5651
Enter the bubble point pressure(psia): 5651
Enter the compressibility factor (psi^-): 0.0000129
Enter Drainage area(acres): 640
Enter the wellbore radius(ft): 0.328
Productivity Index is 0.19672716432884102
The maximum production is 617.6140031234892
```

Image (a) Input parameters and Output for PI and qmax

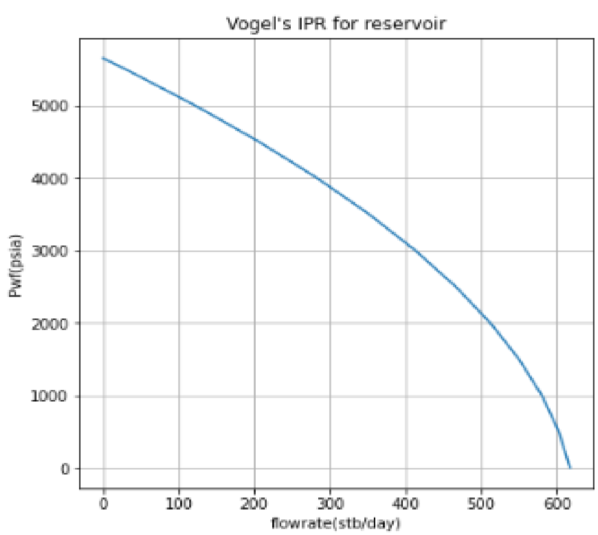

Image (b) Results obtained using python

In the above Image (a) and (b) we can see after inputting the reservoir parameters we have got an output for productivity index is 0.1967 and maximum production is 617.61 stb/day.

OUTPUT USING A TRADITIONAL APPROACH

$$J^* = \frac{kh}{141.2B\mu(\ln\frac{re}{rw} - \frac{3}{4} + S)}$$

$$= \frac{(8.2)(53)}{141.2(1.1)(1.7)(\ln\frac{2980}{0.328} - \frac{3}{4} + 0)}$$

$= 0.1968$ STB/day

$$q_{max} = \frac{J*\bar{P}}{1.8}$$

$$= \frac{(0.1968)(5651)}{1.8}$$

$= 618$ STB/day

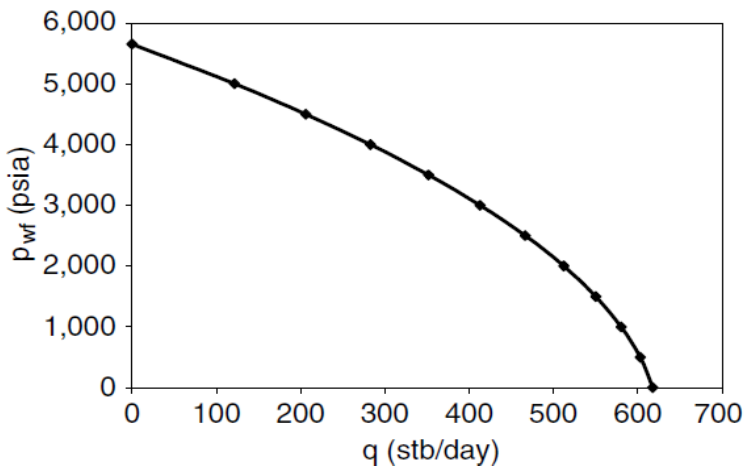

Image (1) Results obtained using traditional approach

The overall shape and characteristics of the curves in the IPR graphs produced by Python and the traditional method were similar, as both methods yielded the same output from Image (a),(b) and Image (1).As the flowing bottom hole pressure increased, the flow rate exhibited a decreasing trend in both graphs, with the well's productivity index being represented by the slope of the line or curve. The presentation of the Python graph was more detailed and visually appealing, featuring a color-coded legend and markers that indicate the location of each data point. They both showed identical information and had the same objective, which was to approximate the productivity of the well and offer understanding into the correlation between the well's flow rate and flowing bottomhole pressure.

Using Python for IPR curve construction offers more flexibility and automation in data processing, potentially saving time and reducing the risk of human error.A more suitable option for large- scale operations is Python, which can handle larger datasets and more complex reservoir models.

Both the graphs generated by respective methods have the same output which proves that the python can be used to estimate the IPR and can be a reliable tool for estimating the flow rate accurately.

ADVANTAGES

1. Faster computation times: Python is known for being a fast language, and when used correctly, it can significantly reduce the time it takes to create an IPR. Traditional or conventional method consumes lot of time for constructing IPR.
2. Improved accuracy: Python allows for accurate calculations, which can lead to accurate IPRs. Python can help reduce the possibility of human error during calculations. Human error can make a loss of the company a single mistake can lead to huge loss of company therefore considering accuracy is important factor.
3. Better visualization capabilities: Python has many visualization libraries, such as Matplotlib, that can easily visualize complex datasets. This can help the user better understand their IPR calculations and make more informed decisions rather than the traditional approach.
4. Flexibility : Using Python the user can make easy changes during the calculation which offers an advantage over a traditional approach
5. Better reproducibility: By using Python to create IPRs, engineers can ensure their calculations are reproducible and transparent. This is especially important where regulatory compliance is required.
6. Better accessibility: Python is a widely used programming language supported by a large number of developer and active developer’s community. This indicates engineers can easily access a variety of resources, including documentation, tutorials, and code samples, to help them build IPR using Python.
7. Lower cost: Python is a free, open-source language, which means that using it is less expensive than traditional commercial software for IPR building which can save the company’s cost to invest in the software which are used to construct the IPR.
8. Engineers can continuously improve their IPR models over time using Python's modular design and flexibility, resulting in better decisions and increased productivity over the long term.

FUTURE SCOPE

IPR models based on Python can be utilized for the optimization and analysis of reservoir performance. By integrating parameters like pressure, permeability, and thickness into the IPR, engineers can anticipate the pressure behavior and flow rate of a well. This data can aid in the management of reservoirs, optimization of production, and analysis of well testing.

Python-based IPR models can be integrated into workflows for production optimization. By simulating different production strategies and operating scenarios, engineers can identify the most efficient techniques for maximizing production rates while minimizing expenses. This allows for real-time decision-making, forecasting of well performance, and production forecasting.

Python can be used for the analysis of well testing data and the creation of IPR curves. By fitting the flow rate and pressure data obtained from well testing, engineers can develop precise

IPR models to estimate the productivity and performance characteristics of the well. This information is crucial for the assessment of reservoir properties, identification of potential production problems, and optimization of production strategies.

Python provides robust libraries and tools for data visualization. Engineers can use these capabilities to create interactive graphs and plots that showcase production-related data like pressure profiles, flow rate trends, and IPR curves. Visualization of this information facilitates the interpretation of data, analysis of trends, and effective communication of results to stakeholders.

Python's extensive libraries for machine learning allow for the development of advanced models to enhance IPR predictions. Engineers can train machine learning algorithms using historical data to improve IPR accuracy. Machine learning can also be utilized for the automated detection of anomalies, predictive maintenance, and real-time production optimization.

Python-based IPR models can be incorporated into reservoir simulation software to improve reservoir modeling and prediction capabilities. By coupling IPR models with numerical reservoir simulators, engineers can simulate fluid flow and pressure behavior across intricate reservoir geometries, leading to enhanced reservoir characterization, production forecasting, and field development planning.

The creation of an IPR for a well using Python offers numerous opportunities for advancements in reservoir engineering, optimization of production, analysis of well testing, data visualization, integration of machine learning, development of digital twins, and reservoir simulation. These advancements can result lead to improved decision making, enhanced production efficiency and optimized reservoir management in the petroleum industry.

APPLICATIONS

1. Forecasting : IPR models built using Python can be used to predict the inflow performance of a well, which is critical for optimizing well production and predicting future productivity.
2. Reservoir Management: IPR models built using Python can be used to optimize reservoir management by identifying underperforming wells and implementing appropriate strategies to increase production.
3. Production optimization: IPR models can be used to optimize production rates and maximize recovery by identifying the bottom hole pressure and flow rate.
4. Python-based IPR models can be used to identify potential flow assurance issues
5. By predicting the expected production rates and estimating the associated costs and revenues, economic analysis can be performed using Python-based IPR models.

CONCLUSION

1. Estimating the well's productivity is equally valid using both the traditional approach and constructing the IPR curve using Python and computational methods. Although the results are the same using Python for computational still offers many Advantages over the traditional method.
2. Because they can handle large datasets and automate repetitive tasks, reducing the overall time required for analysis, Python-based approaches are generally faster and

more efficient than traditional approaches.

3. Moreover, by utilizing Python-based computational techniques, one can achieve greater flexibility in choosing the appropriate curve to match the data, leading to a more accurate and comprehensive understanding of the well's behavior.
4. Python is being widely used in petroleum engineering for data analysis and visualization, with numerous companies and organizations making it their primary tool. Using Python to build IPR curves can enhance communication and teamwork among team members.
5. Although achieving identical outcomes with conventional and Python-based methods is commendable, the latter still provides numerous benefits that can enhance the analysis's efficiency and precision. It is recommended that petroleum engineers consider using Python-based approaches for constructing IPR curves, especially as the technology continues to advance and become more widely adopted.

NOMENCLATURE

Q = Flowrate (stb/day)

qmax = Maximum Flowrate (stb/day)

J* = Productivity Index

$\bar{P}$ = Reservori Pressure (Psia)

k = Permeability(md)

h = Payzone thickness(ft)

B = Formation volume factor

μ = Viscosity(cp)

ln = Log

re = Effective radius(ft)

rw = Wellbore radius(ft)

S = Skin

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