Field Development and Economic Analysis using Decline Curve

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Data

I will be using single set of data, containing all the production data of the well in the vincity.

Permian Basin - Data Dump

About this file

- Well Name: Name of the wells within Permian Basin
- Prod Date: Production Date
- Monthly Oil Volume: Monthly cumulative oil
- Well Spacing: Well spacing, ft
- Fluid bb/ft: Fluid in barrels pumped per feet
- Proppants lbs/ft: Proppants in pounds pumped per feet

Importing Libraries

In [1]:

```
import pandas as pd # library for data analsysis
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

import numpy as np # library to handle data in a vectorized manner


# Matplotlib and associated plotting modules
import matplotlib.pyplot as plt

# backend for rendering plots within the browser
%matplotlib inline
%config InlineBackend.figure_format = "svg"

from datetime import datetime

from scipy.optimize import curve_fit

from statsmodels.tsa.stattools import adfuller, acf, pacf
from statsmodels.tsa.arima_model import ARIMA

import pmdarima as pm

print('Libraries imported')
```

```
Libraries imported
```

Next, we will import Permian Basin - Data Dump file

In [2]:

```
df_Permian = pd.read_excel(r"C:\Users\apoor\Desktop\Matt - Tall City\Permian_Basin_Data Dump.xlsx", hea
der=0)

# Let us visualize the first 5 rows of the dataframe
df_Permian.head()
```

Out[2]:

	Well Name	Prod Date	Monthly Oil Volumes	Well Spacing, ft	Fluid bb/ft	Proppant lbs/ft
0	Juggernaut	2021-01-01	12545.894960	1043.49	68.397212	3457.549049
1	Juggernaut	2021-02-28	23550.457169	1043.49	68.397212	3457.549049
2	Juggernaut	2021-03-31	33206.903943	1043.49	68.397212	3457.549049
3	Juggernaut	2021-04-30	44284.133100	1043.49	68.397212	3457.549049
4	Juggernaut	2021-05-31	51640.976921	1043.49	68.397212	3457.549049

Data Pre-Processing

Let us filter df_Permian dataframe and We will only be using Beast well data since it's the closest to the Tall City Lease.

In [3]:

```
df_Beast = df_Permian[df_Permian['Well Name']=='Beast']
```

Decline Curve Analysis

Once we have pre-processed our data, we will perform decline curve analysis on Beast well

Define Functions

Let us define some functions that will help us perform decline curve analysis

In [4]:

```
def hyperbolic_equation(t, qi, b, di):
    """
    Hyperbolic decline curve equation

    Arguments:
        t: Float. Time since the well first came online, can be in various units
        (days, months, etc) so long as they are consistent.
        qi: Float. Initial production rate when well first came online.
        b: Float. Hyperbolic decline constant
        di: Float. Nominal decline rate at time t=0

    Output:
        Returns q, or the expected production rate at time t. Float.
    """
    return qi/((1.0+b*di*t)**(1.0/b))

def exponential_equation(t, qi, di):
    """
    Exponential decline curve equation

    Arguments:
        t: Float. Time since the well first came online, can be in various units
        (days, months, etc) so long as they are consistent.
        qi: Float. Initial production rate when well first came online.
        di: Float. Nominal decline rate (constant)

    Output:
        Returns q, or the expected production rate at time t. Float.
    """
    return qi*np.exp(-di*t)

def get_max_initial_production(df, number_first_months, variable_column, date_column):
    """
    This function allows you to look at the first X months of production, and selects
    the highest production month as max initial production

    Arguments:
        df: Pandas dataframe.
        number_first_months: float. Number of months from the point the well comes online
        to compare to get the max initial production rate qi (this looks at multiple months
        in case there is a production ramp-up)
        variable_column: String. Column name for the column where we're attempting to get
        the max volume from (can be either 'Gas' or 'Oil' in this script)
        date_column: String. Column name for the date that the data was taken at
    """
    #First, sort the data frame from earliest to most recent prod date
    df=df.sort_values(by=date_column)

    #Pull out the first x months of production, where number_first_months is x
    df_beginning_production=df.head(number_first_months)

    #Return the max value in the selected variable column from the newly created
    #df_beginning_production df
    return df_beginning_production[variable_column].max()

def Convert_DailyDecline_to_MonthlyDecline(qi,daily_decline):
    """
    This function converts daily decline rate
    to monthly

    Arguments:
        qi: Float. Initial flow rate (B/D or SCF/D or B/M or SCF/M)
            calculated from max_initial_production function
            or initial production rate when well first came online
        daily_decline: Float. Exponential or nominal decline rate
            (in days).

    Output:
        Monthly decline rate. Float.
    """
    return np.log(qi/(qi*np.exp(-daily_decline*30.417)))

def EUR_Time(model,qi,q_limit,b,declineRate):
    """
    This function calculates Economic Ultimate Recovery and time

    Arguments:
        model: String. Hyperbolic or Exponential
        qi: Float. Initial flow rate (B/D or SCF/D or B/M or SCF/M)
            calculated from max_initial_production function
            or initial production rate when well first came online
        q_limit: Float. Economic limit production rate (B/D or SCF/D)
        b: Float. Hyperbolic Exponent
        declineRate: Float. Exponential or nominal decline rate
            (in days, months, year so long as they are consistent).

    Output:
        Returns EUR (Barrels or SCF)
        and time (in days, months, year
        so long as they are consistent). Float.
    """
    if model == 'Exponential':
        return (qi-q_limit)/declineRate, round(np.log(qi/q_limit)/declineRate)
    elif model == 'Hyperbolic':
        num = (qi**b)*((qi**(1-b))-(q_limit**(1-b)))
        den = (1-b)*declineRate
        return num/den
    else:
        print('Incorrect Model Name')

def Forecast_DeclineRate(model,qi,q_limit,b,declineRate_Daily):
    """
    This function forecasts monthly cumulative production and calculates
    time in months.

    Arguments:
        model: String. Hyperbolic or Exponential
        qi: Float. Initial flow rate (B/D or SCF/D or B/M or SCF/M)
            calculated from max_initial_production function
            or initial production rate when well first came online
        q_limit: Float. Economic limit production rate (B/D or SCF/D or
                B/M or SCF/M)
        b: Float. Hyperbolic Exponent
        declineRate: Float. Exponential or nominal decline rate (in days).

    Output:
        Returns a dataframe with time in months, oil rate
        per month and cumulative production for every month.
    """
    d_PerMonth = Convert_DailyDecline_to_MonthlyDecline(qi,declineRate_Daily)
    time = [] # Time in months
```

```
    q_calc = [] # Rate in BBLS per day or per month
    Np = [] # Monthly Cumulative oil production in BBLS

    if model == 'Exponential':
        for i in np.arange(EUR_Time(model,qi,q_limit,b,d_PerMonth)[1]):
            q = qi * np.exp(-d_PerMonth*i)
            Np_calc = 30.417*((qi - q)/d_PerMonth)

            if q >= q_limit:
                time.append(i+1)
                q_calc.append(q)
                Np.append(Np_calc)

            else:
                break

    return pd.DataFrame({'Time_Month':time, 'OilRate_BBL_Month':q_calc,'Cumulative_Oil_BBL':Np})
```

Performing Decline Curve Analysis

Let's take Beast dataframe and create a copy to Well_Data and visualize first five rows of the dataframe

In [5]:

```
Well_Data = df_Beast.copy()
Well_Data.head()
```

Out[5]:

	Well Name	Prod Date	Monthly Oil Volumes	Well Spacing, ft	Fluid bb/ft	Proppant lbs/ft
162	Beast	2021-01-01	11268.712902	523.725	70.961317	3388.189688
163	Beast	2021-02-28	19783.701439	523.725	70.961317	3388.189688
164	Beast	2021-03-31	26394.345873	523.725	70.961317	3388.189688
165	Beast	2021-04-30	32914.151816	523.725	70.961317	3388.189688
166	Beast	2021-05-31	40444.966695	523.725	70.961317	3388.189688

We shall perform data cleaning on this data set

In [6]:

```
# Perform some data cleaning to get the columns as the right data type
Well_Data['Prod Date']=pd.to_datetime(Well_Data['Prod Date'])

# Dropping columns
Well_Data = Well_Data.drop(columns=['Well Spacing, ft','Fluid bb/ft','Proppant lbs/ft'])

#Renaming Columns
Well_Data = Well_Data.rename(columns={"Well Name": "Well_Name",
                                       'Prod Date': 'Prod_Date',
                                      'Monthly Oil Volumes':'Monthly_OilVolumes_BBL'})

#Declare the desired product that we want to curve fit for--it can either by 'Gas' or 'Oil'
desired_product_type='Monthly_OilVolumes_BBL'

#Remove all rows with null values in the desired time series column
Well_Data = Well_Data[(Well_Data[desired_product_type].notnull()) & (Well_Data[desired_product_type]>0
)]
Well_Data=Well_Data[(Well_Data['Prod_Date'].notnull())].reset_index(drop=True)


#Generate column for time online delta
Well_Data['Days_Online']=(Well_Data['Prod_Date']-Well_Data['Prod_Date'][0]).dt.days
```

Let's visualize the first 5 dataset

In [7]:

```
Well_Data.head()
```

Out[7]:

	Well_Name	Prod_Date	Monthly_OilVolumes_BBL	Days_Online
0	Beast	2021-01-01	11268.712902	0
1	Beast	2021-02-28	19783.701439	58
2	Beast	2021-03-31	26394.345873	89
3	Beast	2021-04-30	32914.151816	119
4	Beast	2021-05-31	40444.966695	150

Curve fitting

Once the data has been processed, we will move towards curve fitting

In [8]:

```
production_time_series=Well_Data

# Get the highest value of production, to use as qi value
total_days = production_time_series.Prod_Date.count()
qi=get_max_initial_production(production_time_series, total_days, desired_product_type, 'Prod_Date')

# Exponential curve fit the data to get best fit equation
popt_exp, pcov_exp=curve_fit(exponential_equation, production_time_series['Days_Online'],
                              production_time_series[desired_product_type],bounds=(0, [qi,0.1]))
print('Exponential Fit Curve-fitted Variables: qi='+str(popt_exp[0])+', Nominal Decline per day (di)='+
str(popt_exp[1]))

# Hyperbolic curve fit the data to get best fit equation
popt_hyp, pcov_hyp=curve_fit(hyperbolic_equation, production_time_series['Days_Online'],
                              production_time_series[desired_product_type],bounds=(0, [qi,2,20]))
print('Hyperbolic Fit Curve-fitted Variables: qi='+str(popt_hyp[0])+', b='+str(popt_hyp[1])+', Decline
 per day (di)='+str(popt_hyp[2]))

# Exponential fit results
production_time_series.loc[:,'Exponential_Predicted']=exponential_equation(production_time_series['Days
_Online'],
                           *popt_exp)
# Hyperbolic fit results
production_time_series.loc[:,'Hyperbolic_Predicted']=hyperbolic_equation(production_time_series['Days_O
nline'],
                           *popt_hyp)
production_time_series.loc[:,'Hyperbolic_Predicted']=hyperbolic_equation(production_time_series['Days_O
nline'],
                           50417.69,(1.919*10**-10),0.00157)
```

```
Exponential Fit Curve-fitted Variables: qi=35787.636742218165, Nominal Decline per day (di)=0.0019484
088539942915
Hyperbolic Fit Curve-fitted Variables: qi=35778.36444607826, b=1.7966090344709504e-16, Decline per da
y (di)=0.0019466271863687148
```

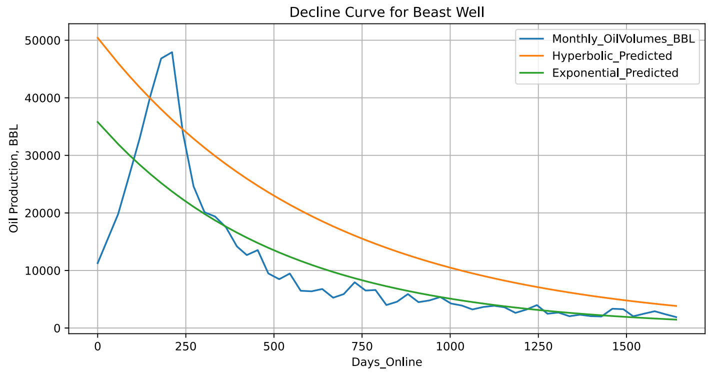
For Exponential Fit we got qi (max initial production) = 35787 BBL/Month and nominal decline per day = 0.0019

For Hyperbolic Fit we got qi (max initial production) = 35778 BBL/Month, b = 1.79e-16 and daily decline rate = 0.0019

Plotting the data to visualize the equation fit

In [9]:

```
# Declare the x- and y- variables that we want to plot against each other

y_variables=[desired_product_type, "Hyperbolic_Predicted", "Exponential_Predicted"]
x_variable='Days_Online'

# Figure Size
fig_size=(10,5)

# Create the plot title
plot_title='Decline Curve for Beast Well'

# Plot the data to visualize the equation fit
production_time_series.plot(x=x_variable, y=y_variables, title=plot_title,figsize=fig_size, grid=True)
plt.ylabel('Oil Production, BBL')
# plt.savefig('Decline Curve for Beast Well.jpeg',dpi=200,quality=95,optimize=True)
plt.show()
```



We can clearly see from the plot that Hyperbolic Curve will give you good fit. Let's see what is our EUR for Magneto Well. We will use the function 'EUR_Time' to get the results. Let us assume economic limit to be 30 BBL/Month

In [10]:

```
oil_ecn = 30 # STB/Month
monthly_decline = Convert_DailyDecline_to_MonthlyDecline(popt_exp[0],popt_exp[1])

print('EUR = {} MSTB. It will take {} months to reach economic rate of {} STB/Month'.format(round(EUR_T
ime('Exponential',popt_exp[0],oil_ecn,0,monthly_decline)[0]/1000),round(EUR_Time('Exponential',popt_exp
[0],oil_ecn,0,monthly_decline)[1]),oil_ecn))

# Remaining Reserves
remaining_reserves = EUR_Time('Exponential',popt_exp[0],oil_ecn,0,monthly_decline)[0] - production_time
_series.Monthly_OilVolumes_BBL[production_time_series.shape[0]-1]
print(round(remaining_reserves/1000),'MSTB')
```

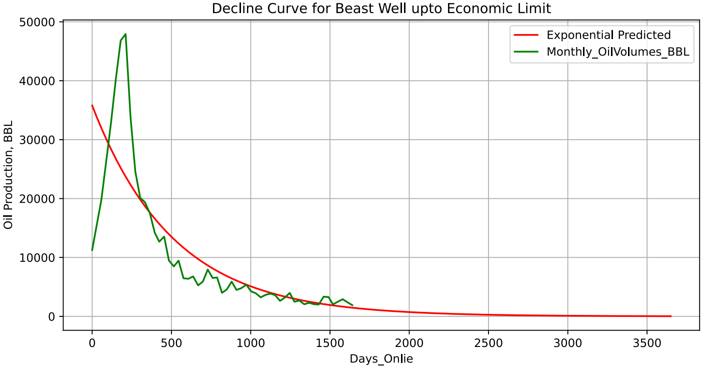
```
EUR = 603 MSTB. It will take 120 months to reach economic rate of 30 STB/Month
601 MSTB
```

EUR = 603 MSTB. It will take 120 months to reach economic rate of 30 STB/Month. Remaining recoverable reserves are 601 MSTB.

Let us next plot the decline curve upto the economic limit

In [11]:

```
#Plot the fitted function

days = range(round(EUR_Time('Exponential',popt_exp[0],oil_ecn,0,monthly_decline)[1]*30.4167))
y_exp_pred = exponential_equation(days, *popt_exp)

plt.figure(figsize = (10,5)) # Figure Size

plt.plot(days, y_exp_pred, color='red', label='Exponential Predicted')
plt.plot(production_time_series.Days_Online, production_time_series.Monthly_OilVolumes_BBL, 'g', label=
'Monthly_OilVolumes_BBL')
plt.grid()
plt.title('Decline Curve for Beast Well upto Economic Limit')
plt.xlabel('Days_Onlie')
plt.ylabel('Oil Production, BBL')
plt.legend()
# plt.savefig('Decline Curve EUR for Beast Well.jpeg',dpi=200,quality=95,optimize=True)
plt.show()
```



Let's get the Forecasted results and pre-process the data.

We will forecast the data using the function Forecast_Decline which we had defined earlier

In [12]:

```python
df_DCA_MonthlyForecast = Forecast_DeclineRate('Exponential',popt_exp[0],oil_ecn,0,popt_exp[1])
```

In [13]:

```python
# Adding gas and water production to our forecast dataframe. We have fixed our GOR and WOR at 3MSCF/BBL
 and 70% respectively

df_DCA_MonthlyForecast['GasProduction_MSCF'] = df_DCA_MonthlyForecast['OilRate_BBL_Month']*3
df_DCA_MonthlyForecast['WaterProduction_BBLS'] = df_DCA_MonthlyForecast['OilRate_BBL_Month']*(0.7/(1-0.
4))

# Let us visualize the first 5 rows of forecast data
df_DCA_MonthlyForecast.head()
```

Out[13]:

	Time_Month	OilRate_BBL_Month	Cumulative_Oil_BBL	GasProduction_MSCF	WaterProduction_BBLS
0	1	35787.636742	0.000000e+00	107362.910227	41752.242866
1	2	33728.316584	1.056924e+06	101184.949751	39349.702681
2	3	31787.495435	2.053030e+06	95362.486305	37085.411341
3	4	29958.354534	2.991817e+06	89875.063601	34951.413622
4	5	28234.467487	3.876583e+06	84703.402461	32940.212068

Since our forecasted data is in months, we will convert it into years

In [14]:

```python
# Exracting data at every 12th month
df_DCA_YearlyForecast = df_DCA_MonthlyForecast[df_DCA_MonthlyForecast['Time_Month']%12==0].reset_index
(drop=True)

# Renaming Columns
df_DCA_YearlyForecast = df_DCA_YearlyForecast.rename(columns={'Time_Month':'Time_Years',
                                                               'OilRate_BBL_Month':'OilRate_BBL_Year'
                                                              })
# Converting Time from months to year
df_DCA_YearlyForecast['Time_Years'] = df_DCA_YearlyForecast['Time_Years']/12
df_DCA_YearlyForecast['Time_Years'] = df_DCA_YearlyForecast['Time_Years'].astype('int32')

# Visualize the dataframe
df_DCA_YearlyForecast

# Exporting Forecasting dataframe to excel
# df_DCA_YearlyForecast.to_excel('DCA_Forecast_Results.xlsx',index=None)
```

Out[14]:

	Time_Years	OilRate_BBL_Year	Cumulative_Oil_BBL	GasProduction_MSCF	WaterProduction_BBLS
0	1	18647.092170	8.797201e+06	55941.276511	21754.940865
1	2	9156.950357	1.366791e+07	27470.851071	10683.108750
2	3	4496.665704	1.605976e+07	13489.997112	5246.109988
3	4	2208.159012	1.723431e+07	6624.477036	2576.185514
4	5	1084.351505	1.781109e+07	3253.054514	1265.076755
5	6	532.488004	1.809433e+07	1597.464013	621.236005
6	7	261.486680	1.823342e+07	784.460040	305.067793
7	8	128.407181	1.830172e+07	385.221544	149.808378
8	9	63.056383	1.833526e+07	189.169149	73.565780
9	10	30.964837	1.835173e+07	92.894511	36.125643

There, you saw how we calculated EUR for Beast well. The same concept can be applied for any given wells and we will get the EUR for that respective wells.

Economic Analysis

Let us find the optimum number of wells required

We will create a function which will give us the optimum number of wells for greater NPV returns

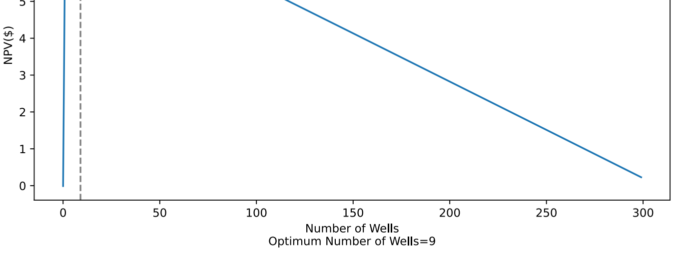
In [15]:

```python
def Optimum_wells(time,intrest_rate,C,V,q,Np,Z,show_plot=False,save_fig=False):
    """
    Calculates and plots optimum number of wells

    Arguments:
        time: String. monthly or yearly
        intrest_rate: Percentage. Interest rate or discount rate
        (annually)
        C: Float. Drilling/Completion costs
        V: Float. Price of oil($) or gas($)
        q: Float. Given oil rate(BOPD)
        Np: Float. Total cumulative production
        Z: Float. the present value of other investments not
        dependent on the number of wells after income
        tax's effect ($)
        save_fig: Boolean. Save the plot if set True. Default is False
        show_plot: Boolean. Show the plot if set True. Default is False

    Output:
        Returns a tuple consisting of number of optimum wells and
        maximum NPV. If set True for save plot or show plot will
        show and save plot respectively.
    """
    W = np.zeros(300)
    NPV = np.zeros(300)

    if time == 'yearly':
        time = 365
        intrest_rate = intrest_rate/(100)

    elif time == 'monthly':
        time = 30
        intrest_rate = intrest_rate/(time*100)

    for i in range(300):
        W[i] = i
        npv = (time*W[i]*q*V) / [(time*W[i]*q/(Np))+np.log(1+intrest_rate)] - (C*W[i]) - Z
        NPV[i] = npv

    df = pd.DataFrame()
    df['Wells'] = W
    df['NPV'] = NPV

    if show_plot == True:
        plt.figure(figsize=(10,5))
        plt.plot(df.Wells,df.NPV)
        plt.axvline(x=df[df['NPV']==df.NPV.max()].iloc[0,0], linestyle='--', color='grey')
        plt.title('NPV vs Number of Wells')
        plt.xlabel('Number of Wells\nOptimum Number of Wells={}'.format(str(int(df[df['NPV']==df.NPV.ma
x()].iloc[0,0]))))
        plt.ylabel('NPV($)')
        if save_fig == True:
            plt.savefig('NPV vs Number of Wells.jpeg',dpi=200,quality=95,optimize=True)
        plt.show()

    return df[df['NPV']==df.NPV.max()].iloc[0,0] , round(df.NPV.max())
```

Let us see with the given economic parameters, what is our maximum optimum number of wells

In [16]:

```python
max_well,max_Npv = Optimum_wells('yearly',
                                intrest_rate=20,
                                C=2325000+300000,
                                V=42+2.11, q=popt_exp[0],
                                Np=df_DCA_YearlyForecast['Cumulative_Oil_BBL'].max(),
                                Z=1000000,show_plot=True,save_fig=False)
```



Closing Remarks

NPV calculations has been done on the excel. All in all, I hope I was able to convey my thought process in the form of this particular exercise.