

# MCMC Production Data Analysis with Arps, THM and Jacobi Theta Function Model

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## Step 0: Import the basic packages

```
In [1]: import pandas
import numpy as np
import matplotlib.pyplot as plt
from scipy import optimize
plt.style.use('ggplot')
%matplotlib inline
```

## Step 1: Read production data from CSV file (Drillinginfo output)

```
In [2]: #Extract api, monthly_oil and date from Drillinginfo File
df = pandas.read_csv('Monthly_Production.CSV')
oil = np.array(df['Monthly Oil'].values)
api_well = np.array(df['API/UWI'].values)
pro_month = np.array(df['Monthly Production Date'].values)
unique_ids=len(np.unique(api_well))
# Confirming all 153 wells are read into memory
print('Total number of wells are: {}'.format (unique_ids))
```

Total number of wells are: 153

## Read each individual well's production data into an array

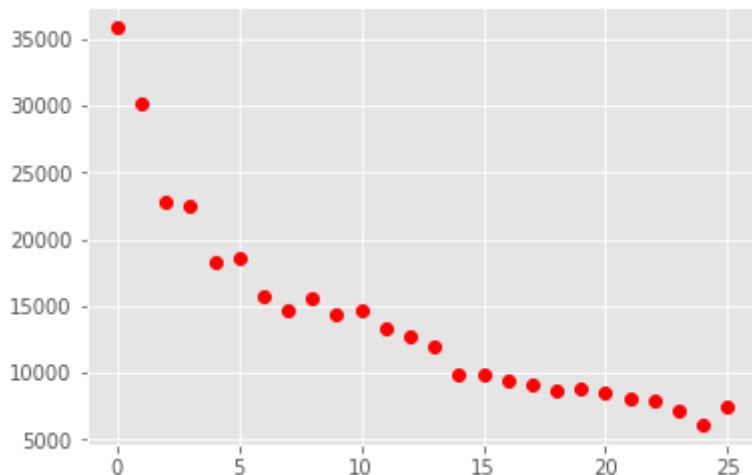
- Chose a well, and plot the original production data
- Take first 12 month of log(oil rate) as training data

```
In [3]: ID_0 = api_well[0]
i=0
j=0
k=0
oil_array=np.zeros((unique_ids,36),dtype=int)
for ID in api_well:
    if ID==ID_0:
        oil_array[i,j]=oil[k]
        j=j+1
    else:
        ID_0=ID
        i=i+1
        j=0
        k=k+1
```

In this case, we chose well #150, the user can choose any random well

```
In [4]: cur = oil_array[7]
rec_month = np.count_nonzero(cur)
plt.plot(cur[:rec_month], 'ro')
```

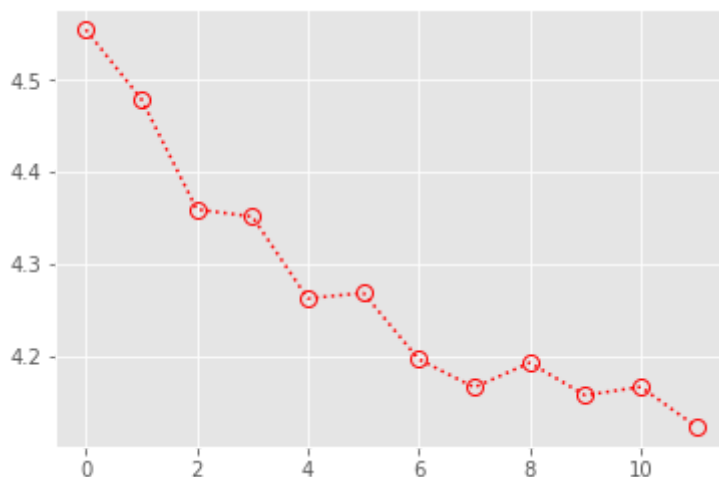
```
Out[4]: [matplotlib.lines.Line2D at 0x106113518]
```



plot the first 12 month as training data

```
In [5]: data = np.log10(cur[0:12])
marker_style = dict(color='r', linestyle=':', marker='o',
                    markersize=8, markerfacecoloralt='gray')
plt.plot(data, fillstyle='none', **marker_style)
```

```
Out[5]: [matplotlib.lines.Line2D at 0x1018eb3f28]
```



## Section 1

In this section, we implement the MCMC Arps model

## 1. Define Arps equation and get best estimate using least square residual.

- Plot data, initial guess and best estimate

```
In [6]: def Arps(t,Di,logQi,b):
        Qt = logQi - 1/b*np.log10(1+b*Di*t)
        return Qt
```

```
In [7]: Di = 0.5
        logQi = 4
        b = 0.5
        t = np.linspace(0,11,12)
        y_init = Arps(t,Di,logQi,b)
        params, params_covariance = optimize.curve_fit(Arps, t, data,
                                                        p0=[0.22,4.3,2])
        y_hat = Arps(t,params[0],params[1],params[2])
        sigma = np.sqrt(np.sum(np.power(data-y_hat,2))/(len(data)-3))

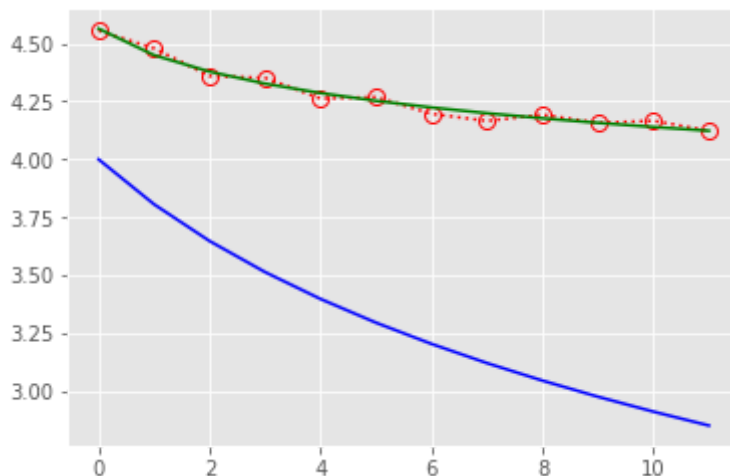
        print('The best estimate are: \n Di = {}\n log(Qi) = {}\n b = {}'.format(pa
        print('Variance is {}'.format(sigma))
```

```
The best estimate are:
Di = 0.360589738558525
log(Qi) = 4.563803782420842
b = 2.270570505844425
Variance is 0.02487316937430861
```

The plot below shows the initial guess (blue line) is random, which is far away from best (least square) estimate

```
In [8]: plt.plot(y_init,'b-') # initial guess
        plt.plot(data,fillstyle='none',**marker_style)
        plt.plot(y_hat,'g-')
```

```
Out[8]: [<matplotlib.lines.Line2D at 0x10615b898>]
```



## 2. MCMC for parameter estimation

- Define posterior function
- Initialize the chain
- Sampling from posterior distribution

```
In [9]: def post(Di,logQi,b,sigma,t,data):  
        like = np.prod(np.exp(-np.power(Arps(t,Di,logQi,b)-data, 2)/sigma**2))  
        return like # because constant uniform prior
```

```
In [10]: logQi = data[0]  
        Niter = 100000  
        chain = np.zeros((Niter,3))  
        chain[0,0] = Di # Initialize the chain with first guess  
        chain[0,1] = logQi  
        chain[0,2] = b
```

```

In [11]: for ii in np.arange(Niter-1):
            if ii%10000 ==0:
                print('iteration {}'.format(ii))
            Di = chain[ii,0]
            logQi = chain[ii,1]
            b = chain[ii,2]
            #sigma = chain[ii,3]
            Di_p = Di + np.random.normal(loc=0.0,scale=0.1,size=1)
            logQi_p = logQi + np.random.normal(loc=0.0,scale=0.1,size=1)
            b_p = b + np.random.normal(loc=0.0,scale=0.1,size=1)

            if Di_p < 0.1 or Di_p>50 or b_p<0 or b_p>=2 or logQi > 1000000 or 1
                chain[ii+1,:] = chain[ii,:]
            elif (post(Di_p,logQi_p,b_p,sigma,t,data) / post(Di,logQi,b,sigma,t
                chain[ii+1,0] = Di_p
                chain[ii+1,1] = logQi_p
                chain[ii+1,2] = b_p
            else:
                chain[ii+1,:] = chain[ii,:]
print('Sampling finished at iteration {}'.format(Niter))

```

iteration 0

/Users/weibing/anaconda3/lib/python3.6/site-packages/ipykernel\_launcher.p  
y:14: RuntimeWarning: invalid value encountered in double\_scalars

/Users/weibing/anaconda3/lib/python3.6/site-packages/ipykernel\_launcher.p  
y:14: RuntimeWarning: divide by zero encountered in double\_scalars

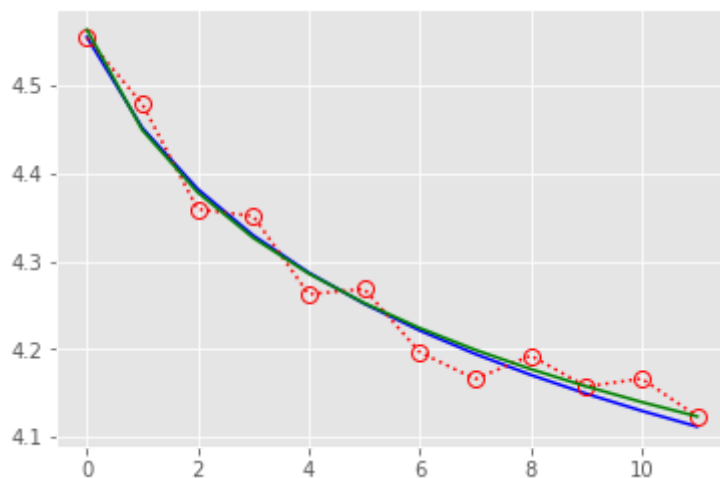
```

iteration 10000
iteration 20000
iteration 30000
iteration 40000
iteration 50000
iteration 60000
iteration 70000
iteration 80000
iteration 90000
Sampling finished at iteration 100000

```

```
In [12]: y_theta = Arps(t,Di,logQi,b)
plt.plot(y_theta,'b-')
plt.plot(data,'ro',fillstyle='none',**marker_style)
plt.plot(y_hat,'g-')
```

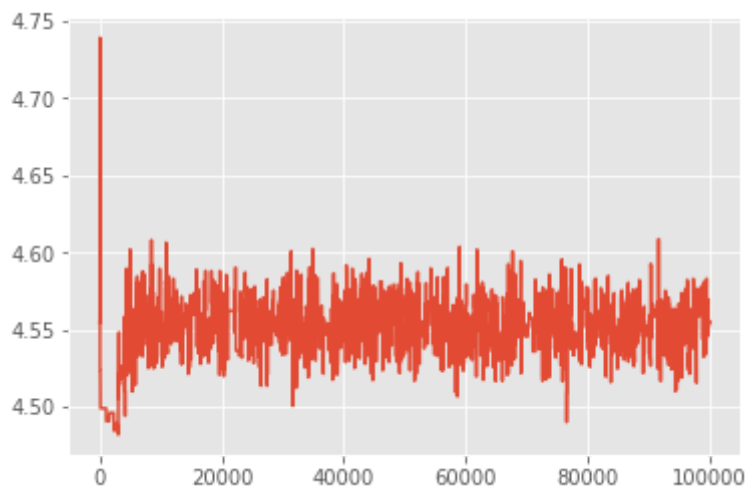
```
Out[12]: [matplotlib.lines.Line2D at 0x1019088d68]
```



**Check Mixing of the chain, it shows good convergence**

```
In [13]: plt.plot(chain[:,1])
chain.shape
```

```
Out[13]: (100000, 3)
```



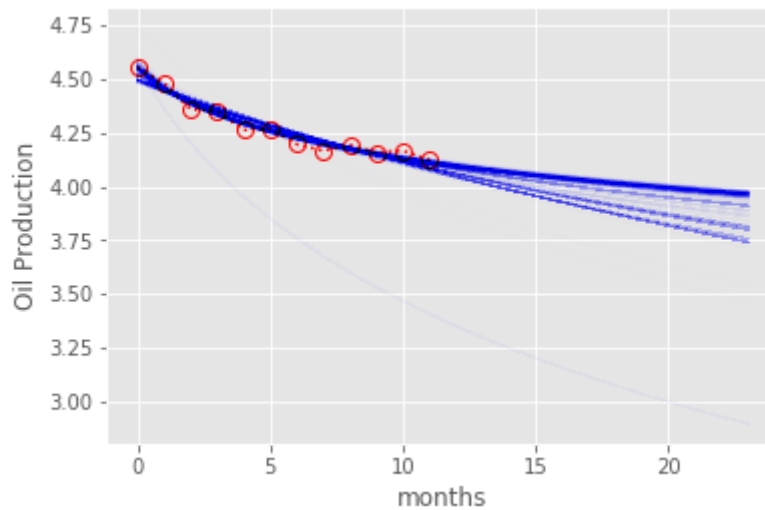
**Plot the last 1000 samples from the posteriors**

```

In [14]: t_test = np.linspace(0,23,24)
chains_to_plot=np.arange(1000)*9

fig = plt.figure()
aa = plt.axes()
aa.plot(data,'ro',fillstyle='none',**marker_style)
#aa.plot(y_hat,'g-')
kk=0
qq=np.zeros([len(chains_to_plot),24])
for ii in chains_to_plot:
    qq[kk,:]=Arps(t_test,chain[ii,0],chain[ii,1],chain[ii,2])
    aa.plot(qq[kk,:],color='blue',alpha=0.002)
    kk+=1
aa.set(xlabel='months', ylabel='Oil Production')

```

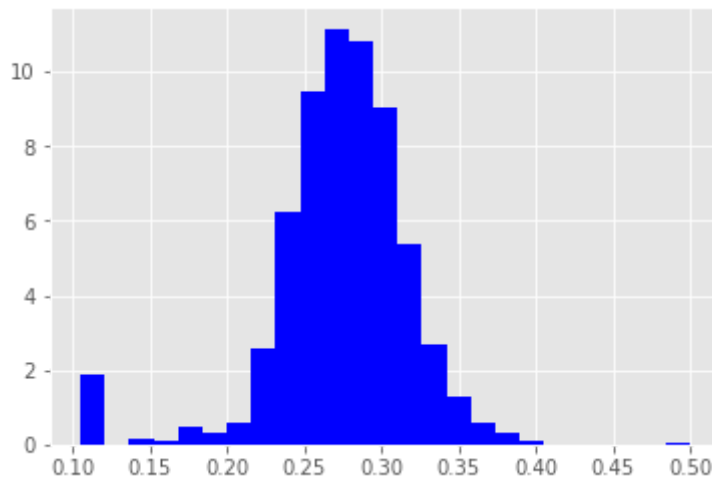


### Posterior Summary, the $D_i$ , $\log(Q_i)$ , and $b$ parameters

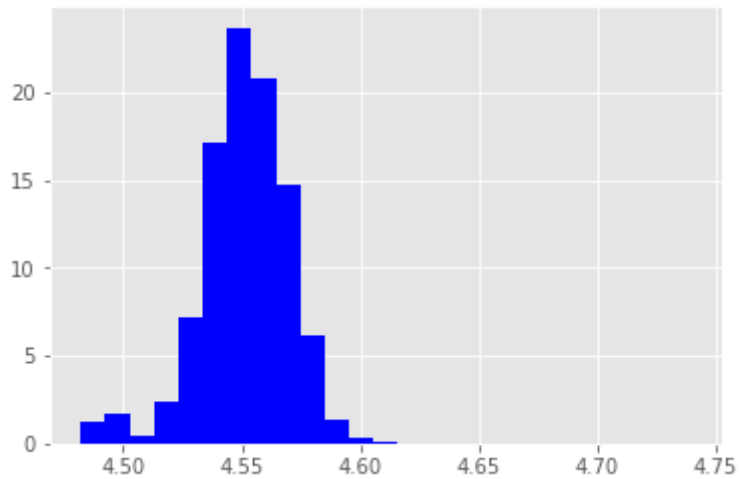
```

In [15]: fig = plt.figure()
ax = plt.axes()
rectangles = ax.hist(chain[:,0],25,density=True,color='blue')

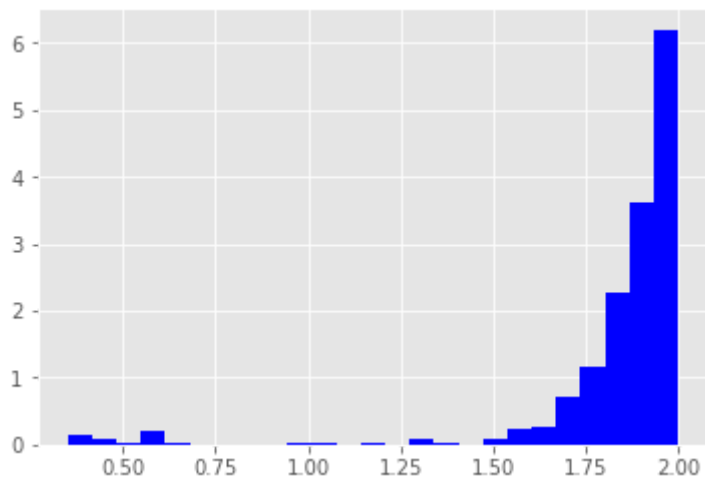
```



```
In [16]: fig = plt.figure()
ax = plt.axes()
rectangles = ax.hist(chain[:,1],25,density=True,color='blue')
```



```
In [17]: fig = plt.figure()
ax = plt.axes()
rectangles = ax.hist(chain[:,2],25,density=True,color='blue')
```



### 3. Plot of 12month training data, 12-24 month testing data and p10-p90 interval



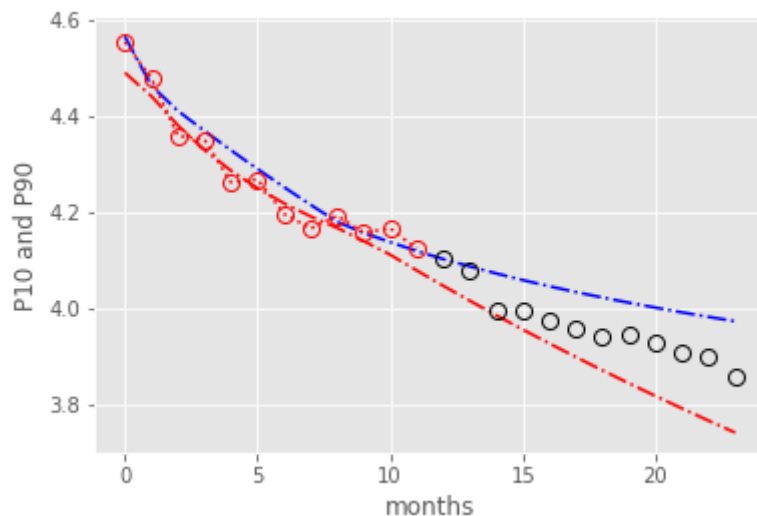
```

In [37]: qq_p10=np.zeros(24)
qq_p90=np.zeros(24)
for tt in np.arange(0,24):
    sorted_qq=np.sort(qq[:,tt])
    ixL = np.floor(np.size(sorted_qq)*0.1).astype(int) ## lower index
    ixU = np.floor(np.size(sorted_qq)*0.9).astype(int) ## upper index
    qq_p10[tt]=sorted_qq[ixL]
    qq_p90[tt]=sorted_qq[ixU]

fig = plt.figure()
aa = plt.axes()
aa.plot(qq_p10,'r-.')
aa.plot(qq_p90,'b-.')
aa.set(xlabel='months', ylabel='P10 and P90');
aa.plot(data,'ro',fillstyle='none',**marker_style)
aa.plot(np.linspace(12,23,12),np.log10(cur[12:24]),'ko',fillstyle='none',ma

```

Out[37]: [matplotlib.lines.Line2D at 0x101acec5f8>]

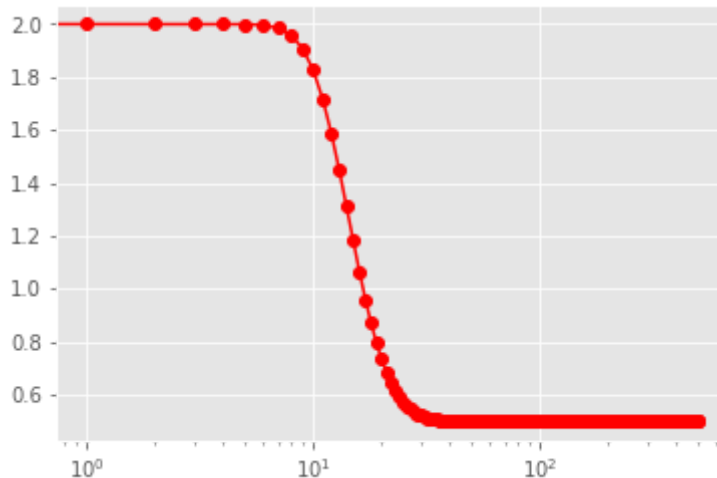


## Section 2

**In this section, we implement MCMC parameter estimation for the Transient Hyperbolic Model proposed by David Fulfor and Dr. Blasingame**

```
In [38]: # First we plot one example of THM model to see its behavior
t_elf = 12
bf = 0.5
t_test = np.linspace(0,1000,500)
c = np.exp(0.57722)/(1.175*t_elf)
b = 2-(2-bf)*np.exp(-np.exp(-c*(t_test-t_elf)+np.exp(0.57722)))
plt.semilogx(b, 'ro-')
```

Out[38]: [matplotlib.lines.Line2D at 0x101ad4f8d0>]



**We define the posterior probability function based on changing b parameter**

```
In [39]: def post(Di,logQi,bf,t_elf,sigma,t,data):
c = np.exp(0.57722)/(1.175*t_elf)
b = 2-(2-bf)*np.exp(-np.exp(-c*(t-t_elf)+np.exp(0.57722)))
like = np.prod(np.exp(-np.power(Arps(t,Di,logQi,b)-data, 2)/sigma**2))
return like # because constant uniform prior
```

```
In [40]: logQi = data[0]
bf = 0.5
t_elf = 24
Niter = 100000
chain = np.zeros((Niter,4))
chain[0,0] = Di # Initialize the chain with first guess
chain[0,1] = logQi
chain[0,2] = bf
chain[0,3] = t_elf
```

```

In [41]: for ii in np.arange(Niter-1):
            if ii%10000 ==0:
                print('iteration {}'.format(ii))
            Di = chain[ii,0]
            logQi = chain[ii,1]
            bf = chain[ii,2]
            t_elf = chain[ii,3]
            Di_p = Di + np.random.normal(loc=0.0,scale=0.1,size=1)
            logQi_p = logQi + np.random.normal(loc=0.0,scale=0.1,size=1)
            bf_p = bf + np.random.normal(loc=0.0,scale=0.1,size=1)
            t_elf_p = t_elf + np.random.normal(loc=0.0,scale=0.1,size=1)

            if Di_p < 0.1 or Di_p>50 or bf_p<0 or bf_p>1 or t_elf_p<0 or logQi
                chain[ii+1,:] = chain[ii,:]
            elif (post(Di_p,logQi_p,bf_p,t_elf_p,sigma,t,data) / post(Di,logQi,
                chain[ii+1,0] = Di_p
                chain[ii+1,1] = logQi_p
                chain[ii+1,2] = bf_p
                chain[ii+1,3] = t_elf_p
            else:
                chain[ii+1,:] = chain[ii,:]
print('Sampling finished at iteration {}'.format(Niter))

```

```

iteration 0
iteration 10000
iteration 20000
iteration 30000
iteration 40000
iteration 50000
iteration 60000
iteration 70000
iteration 80000
iteration 90000
Sampling finished at iteration 100000

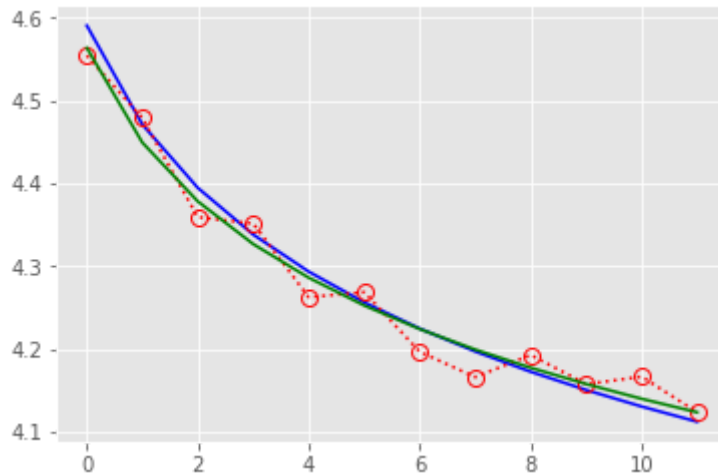
```

**From the converged Markov Chain, we plot one sample THM decline curve vs the least square estimate**

- it shows the "end of linear flow time" is about 25 month

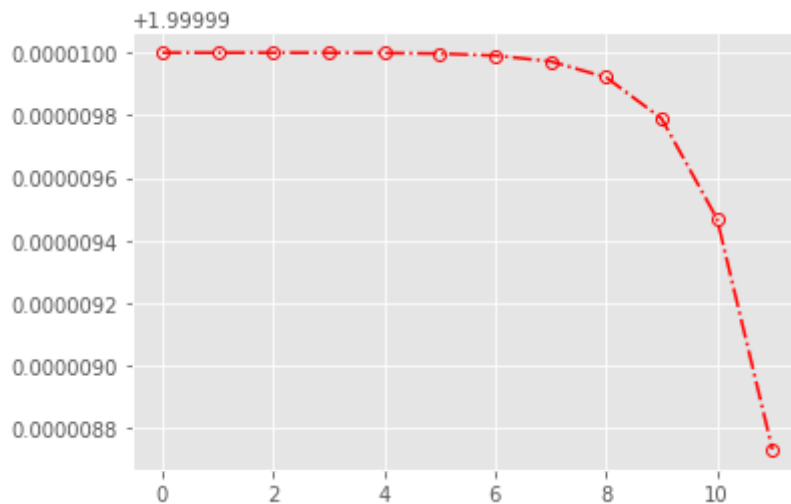
```
In [42]: c = np.exp(0.57722)/(1.175*t_elf)
b = 2-(2-bf)*np.exp(-np.exp(-c*(t-t_elf)+np.exp(0.57722)))
y_theta = Arps(t,Di,logQi,b)
plt.plot(y_theta,'b-')
plt.plot(data,'ro',fillstyle='none',**marker_style)
plt.plot(y_hat,'g-');
print('bf is: {} \nt_elf is: {}'.format(bf,t_elf))
```

```
bf is: 0.05149126671846663
t_elf is: 25.26660614137497
```



```
In [55]: # plot the b parameter
plt.plot(b,'ro-.', fillstyle='none')
```

```
Out[55]: [<matplotlib.lines.Line2D at 0x101a21a438>]
```

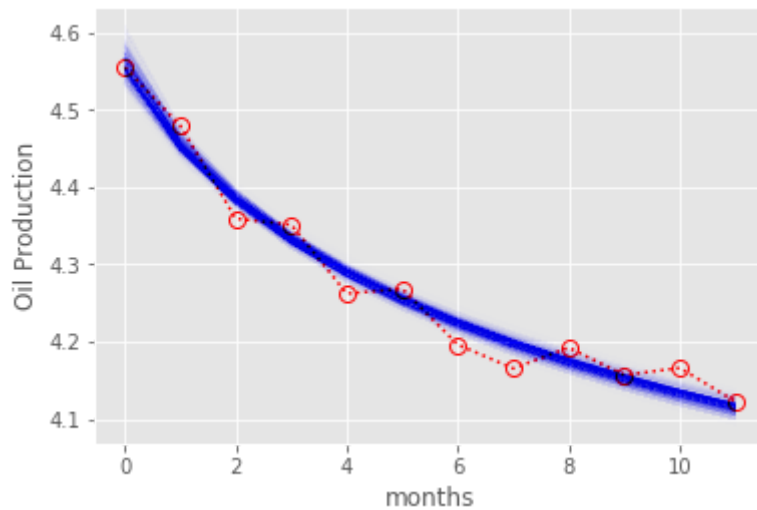


```

In [44]: chains_to_plot=np.arange(1000)*9

fig = plt.figure()
aa = plt.axes()
aa.plot(data,'ro',fillstyle='none',**marker_style)
#aa.plot(y_hat,'g-')
kk=0
qq=np.zeros([len(chains_to_plot),len(t)])
for ii in chains_to_plot:
    b = 2-(2-chain[ii,2])*np.exp(-np.exp(-c*(t-chain[ii,3])+np.exp(0.57722))
    qq[kk,:]=Arps(t,chain[ii,0],chain[ii,1],b)
    aa.plot(qq[kk,:],color='blue',alpha=0.002)
    kk+=1
aa.set(xlabel='months', ylabel='Oil Production')

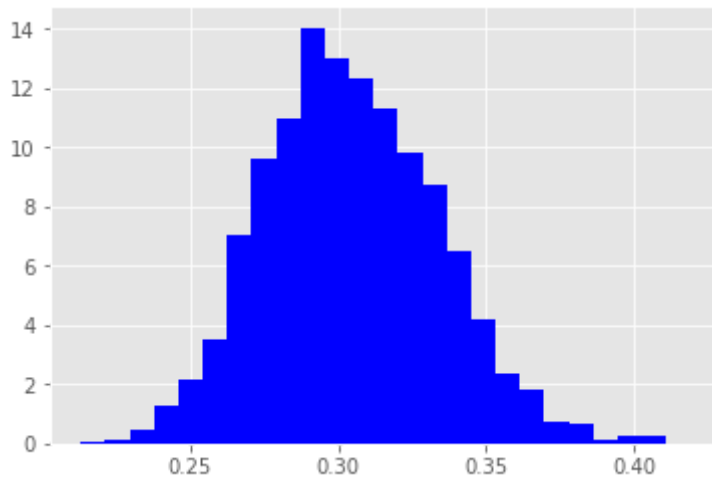
```



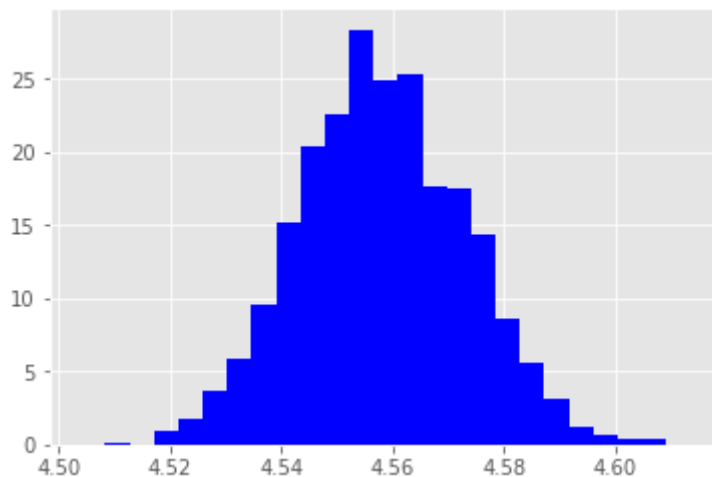
### Posterior parameter distribution of

- $D_i$
- $\log(Q_i)$
- $b_{\text{final}}$
- end of linear flow time ( $t_{\text{elf}}$ )

```
In [46]: fig = plt.figure()
ax = plt.axes()
rectangles = ax.hist(chain[:,0],25,density=True,color='blue')
```

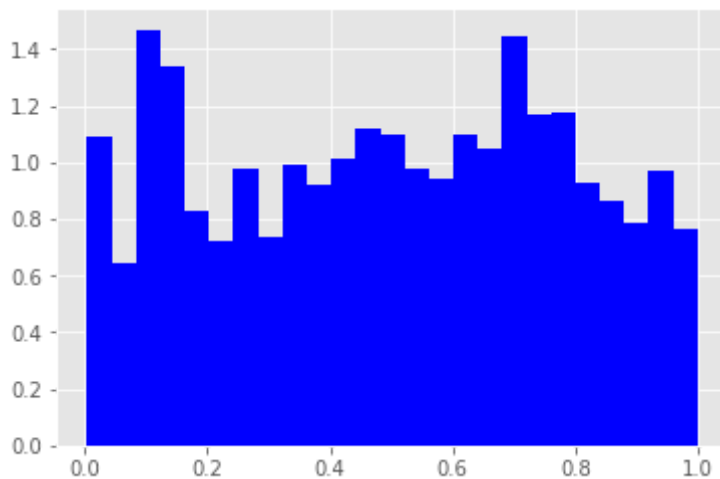


```
In [48]: fig = plt.figure()
ax = plt.axes()
rectangles = ax.hist(chain[:,1],25,density=True,color='blue')
```

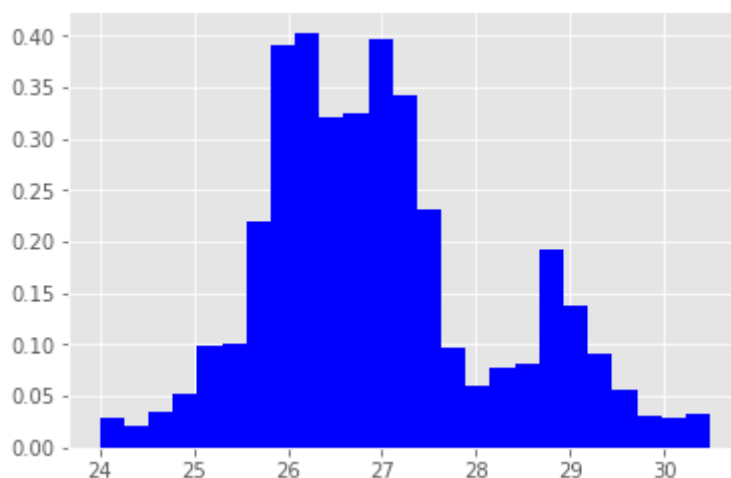


**It shows below that  $b_{\text{final}}$  is evenly possible for any value between 0-1. This is because the production data is only 12 month, it didn't reach end of linear flow yet. So no estimation on the  $b_{\text{final}}$**

```
In [49]: fig = plt.figure()
ax = plt.axes()
rectangles = ax.hist(chain[:,2],25,density=True,color='blue')
```



```
In [50]: fig = plt.figure()
ax = plt.axes()
rectangles = ax.hist(chain[:,3],25,density=True,color='blue')
```



## Section 3

**In this section, we implement the MCMC parameter estimation of Jacobi Theta Function decline curve proposed**

```
In [51]: #import the special function library
import mpmath as mp
```

**Define Jacobi Theta Function**

```
In [56]: def Jacobi_theta(t,logQi,chi,eta):
          Qt = np.zeros(len(t))
          for i in range(len(t)):
              Qt[i] = logQi + np.log10(float(mp.jtheta(2,chi,np.exp(-eta*t[i]))))
          return Qt
```

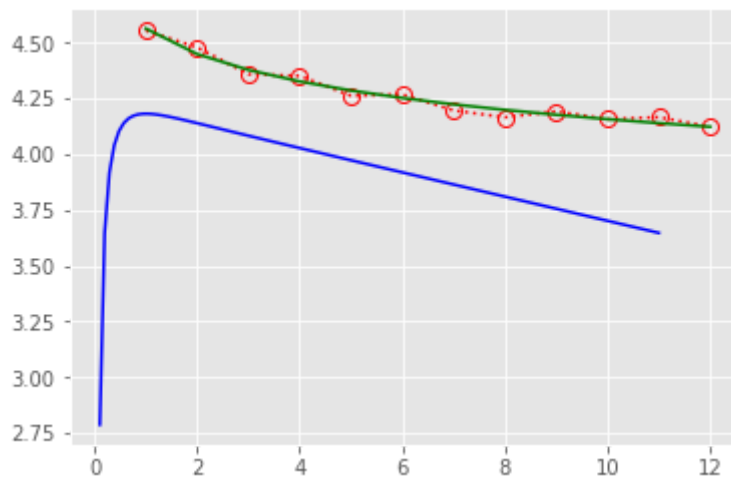
```
In [105]: logQi = 4
          chi = 0.5
          eta = 0.5
          t_fine = np.linspace(0.01,11,119)
          t = np.linspace(1,12,12)
```

### Plot the initial guess using data, Jacobi Theta Function and Least Square Estimate

```
In [106]: y_init = Jacobi_theta(t_fine,logQi,chi,eta)
          plt.plot(t_fine,y_init,'b-') # initial guess
          plt.plot(t, data,fillstyle='none',**marker_style)
          plt.plot(t, y_hat,'g-')
```

/Users/weibing/anaconda3/lib/python3.6/site-packages/ipykernel\_launcher.p  
y:4: RuntimeWarning: invalid value encountered in log10  
after removing the cwd from sys.path.

```
Out[106]: [<matplotlib.lines.Line2D at 0x101f531588>]
```



```
In [64]: ##### Define posterior probability function, and run MCMC to sample the para
```

```
In [60]: def post(logQi,chi,eta,sigma,t,data):
          like = np.prod(np.exp(-np.power(Jacobi_theta(t,logQi,chi,eta)-data, 2)/
          return like # because constant uniform prior
```



```
In [62]: logQi = data[0]
Niter = 30000
chain = np.zeros((Niter,3))
chain[0,0] = logQi# Initialize the chain with first guess
chain[0,1] = chi
chain[0,2] = eta
```

```
In [108]: for ii in np.arange(Niter-1):
            if ii%10000 ==0:
                print('iteration {}'.format(ii))
            logQi = chain[ii,0]
            chi = chain[ii,1]
            eta = chain[ii,2]
            chi_p = float(chi + np.random.normal(loc=0.0,scale=0.1,size=1))
            logQi_p = float(logQi + np.random.normal(loc=0.0,scale=0.1,size=1))
            eta_p = float(eta + np.random.normal(loc=0.0,scale=0.1,size=1))

            if chi_p < 0 or eta_p<0 or logQi_p > 7 or logQi_p< -2:
                chain[ii+1,:] = chain[ii,:]
            elif (post(logQi_p,chi_p,eta_p,sigma,t,data) / post(logQi,chi,eta,s
                chain[ii+1,0] = logQi_p
                chain[ii+1,1] = chi_p
                chain[ii+1,2] = eta_p
            else:
                chain[ii+1,:] = chain[ii,:]
print('Sampling finished at iteration {}'.format(Niter))
```

iteration 0

/Users/weibing/anaconda3/lib/python3.6/site-packages/ipykernel\_launcher.p  
y:4: RuntimeWarning: invalid value encountered in log10  
after removing the cwd from sys.path.

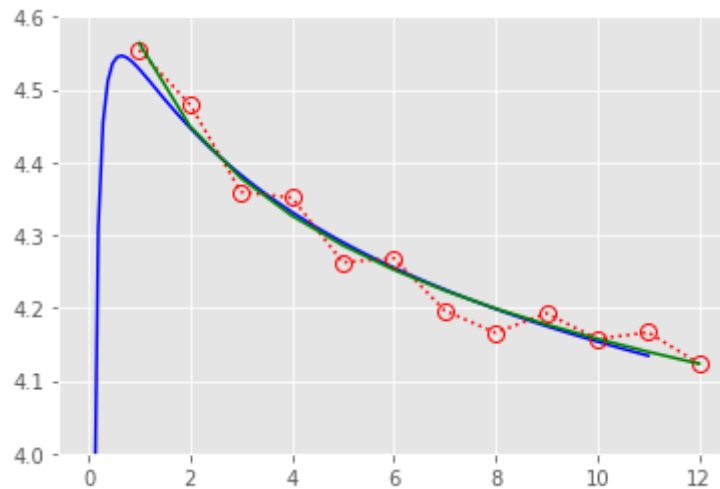
iteration 10000

iteration 20000

Sampling finished at iteration 30000

```
In [109]: y_theta = Jacobi_theta(t_fine,logQi,chi,eta)
fig = plt.figure()
aa = plt.axes()
plt.plot(t_fine,y_theta,'b-')
plt.plot(t,data,'ro',fillstyle='none',**marker_style)
plt.plot(t,y_hat,'g-')
aa.set(ylim = (4,4.6))
```

Out[109]: [(4, 4.6)]



```

In [119]: chains_to_plot=np.arange(1000)*9
fig = plt.figure()
aa = plt.axes()
aa.plot(t,data,'ro',fillstyle='none',**marker_style)
#aa.plot(y_hat,'g-')
kk=0
qq=np.zeros([len(chains_to_plot),len(t_fine)])
for ii in chains_to_plot-1:
    qq[kk,:]=Jacobi_theta(t_fine,chain[ii,0] ,chain[ii,1] ,chain[ii,2] )
    aa.plot(t_fine,qq[kk,:],color='blue',alpha=0.02)
    kk+=1
aa.set(ylim= (3.5,4.8), xlabel='months', ylabel='Oil Production')

/Users/weibing/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.p
y:4: RuntimeWarning: invalid value encountered in log10
after removing the cwd from sys.path.

```

```

Out[119]: [(3.5, 4.8), Text(0, 0.5, 'Oil Production'), Text(0.5, 0, 'months')]

```

