Monte Carlo Simulation:

What is Monte Carlo simulation?

In forecasting and decision-making, the Monte Carlo approach is a computerised mathematical tool that enables humans to quantitatively account for risk. The Monte Carlo method, at its heart, is a technique for investigating the behaviour of complicated systems using random samples of parameter values. To comprehend the effects of risk and uncertainty, a Monte Carlo simulation is used to address a wide range of problems in a variety of different domains.

Monte Carlo vs. Other Predictive Models

The impact of risk has been evaluated using Monte Carlo simulations in a variety of real-world situations, including project management, AI, and stock prices. The Monte Carlo method has a number of advantages over predictive models with fixed inputs, including the capacity to perform sensitivity analysis and determine the correlation of inputs.

Applications of Monte Carlo Simulations:

Finance & Banking
Energy & Utilities
Manufacturing & Consumer Goods
Construction & Engineering
Insurance & Reinsurance
Logistics & Transportation
Environmental Conservation
Aerospace & Defense
Healthcare & Pharmaceuticals
Agriculture & Food Safety
Consulting & Legal
Entertainment, Sports & Media
Mining & Minerals
Technology & Telecommunication

How Monte Carlo Simulation Works?

By creating models of potential outcomes and replacing every factor that has intrinsic uncertainty with a range of values (referred to as a probability distribution), Monte Carlo simulation does risk analysis. Then, using a new set of random values drawn from the input probability distributions, it repeatedly calculates the outcomes. Before it is finished, a Monte Carlo simulation may require thousands or even tens of thousands of recalculations, depending on the number of uncertainty and the ranges assigned to them. A Monte Carlo simulation yields a distribution, or range, of potential outcome values. You can use this information on potential outcomes to determine the likelihood of various outcomes in your projections and to carry out a variety of other analysis.

We can describe the various possible values for these variables along with their likelihood of occurring by using probability distributions for unknown inputs. In comparison to traditional "best guess" or "best/worst/most likely" analyses, probability distributions are a far more realistic way to describe uncertainty in variables in a risk analysis.

In this case we have used Normal Distribution for simulating Percentage Change Values.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
temp_ongc = pd.read_csv("ONGC new.csv")
temp_ntpc = pd.read_csv("NTPC new.csv")
temp_gail = pd.read_csv("GAIL new.csv")
data_ongc = temp_ongc.iloc[:501,-1:]
data_ntpc = temp_ntpc.iloc[:501,-1:]
data_gail = temp_gail.iloc[:501,-1:]
```

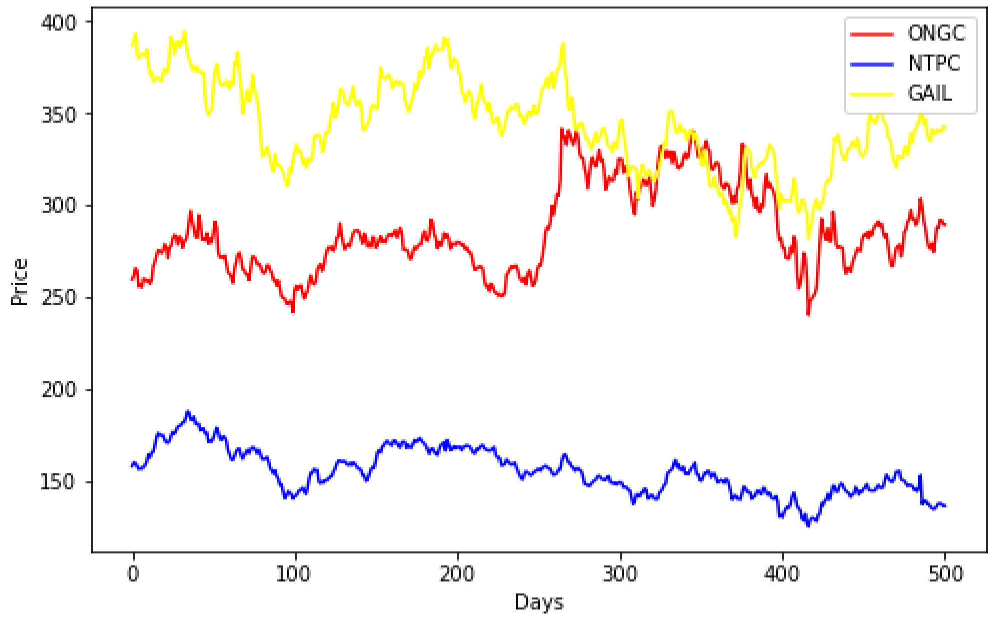
In [3]:
```
data = pd.concat([data_ongc, data_ntpc, data_gail], axis = 1, ignore_index=True)
data.columns=['ONGC', 'NTPC', 'GAIL']
data
```

Out[3]:

	ONGC	NTPC	GAIL
0	259.82	158.32	386.67
1	261.71	160.31	390.24
2	265.74	159.77	393.56
3	264.53	158.42	381.71
4	255.79	156.61	379.77
...	...	...	...
496	287.75	137.92	340.40
497	292.14	137.99	340.50
498	291.84	137.63	340.09
499	289.69	136.55	343.11
500	289.55	136.70	342.64

501 rows × 3 columns

In [4]:
```
plt.figure(figsize=(8,5))
plt.plot(data['ONGC'], color = 'red')
plt.plot(data['NTPC'], color = 'blue')
plt.plot(data['GAIL'], color = 'yellow')
plt.xlabel('Days')
plt.ylabel('Price')
plt.legend(['ONGC','NTPC','GAIL'])
plt.show()
```



In [5]:
```
# calculating pct change and mean pct change
pct_change = data[["ONGC", "NTPC", "GAIL"]].pct_change()
mean_pct_change = pct_change.mean()
mean_pct_change
```

Out[5]:
```
ONGC     0.000353
NTPC    -0.000196
GAIL    -0.000140
dtype: float64
```

ONGC simulation for different initial values

In [6]:
```
starting_prices = np.random.normal(259.82,1,1000) # randomly generating values between with 148 mean and SD=1 for start
total_days = 501
ONGC_pct_change = pct_change['ONGC']

arr = np.full((len(starting_prices), total_days), 1.0) #array to store new prices

for i in range(len(starting_prices)):
    for j in range(total_days):
        if j==0:
            arr[i][j]=starting_prices[i]  #using initial starting price to compute first value
        else:
            arr[i][j]=arr[i][j-1] + arr[i][j-1] * ONGC_pct_change[j]  #computing using just previous value


ONGC = pd.DataFrame(arr)
ONGC.set_axis(labels = [x for x in starting_prices], axis = 0, inplace=True)
ONGC
```

Out[6]:

	0	1	2	3	4	5	6	7	8	9	...	
258.411527	258.411527	260.291281	264.299435	263.095994	254.403373	255.129416	254.134837	258.719846	258.491093	257.327436	...	274.9
261.311083	261.311083	263.211930	267.265058	266.048114	257.257956	257.992145	256.986406	261.622863	261.391543	260.214828	...	278.0
259.515393	259.515393	261.403177	265.428452	264.219871	255.490117	256.219262	255.220434	259.825029	259.595299	258.426671	...	276.0
258.478422	258.478422	260.358663	264.367854	263.164102	254.469231	255.195461	254.200625	258.786821	258.558009	257.394050	...	274.9
260.709169	260.709169	262.605637	266.649429	265.435288	256.665377	257.397876	256.394453	261.020230	260.789443	259.615439	...	277.3
...	...	...	...	...	...	...	...	...	...	...	...	
260.388280	260.388280	262.282414	266.321228	265.108582	256.349466	257.081062	256.078875	260.698958	260.468455	259.295896	...	277.0
259.459119	259.459119	261.346494	265.370897	264.162577	255.434717	256.163703	255.165092	259.768689	259.539008	258.370633	...	276.0
259.108973	259.108973	260.993801	265.012772	263.806083	255.090001	255.818004	254.820740	259.418124	259.188754	258.021956	...	275.6
259.780966	259.780966	261.670682	265.700076	264.490258	255.751571	256.481462	255.481612	260.090919	259.860954	258.691130	...	276.3
259.647799	259.647799	261.536546	265.563875	264.354677	255.620470	256.349986	255.350649	259.957593	259.727746	258.558521	...	276.2

1000 rows × 501 columns

In [7]:

```
mean_values = pd.DataFrame(ONGC.values.mean(axis = 0))
mean_values.head()
```

Out[7]:

	0
0	259.803776
1	261.693658
2	265.723407
3	264.513482
4	255.774028

In [8]:

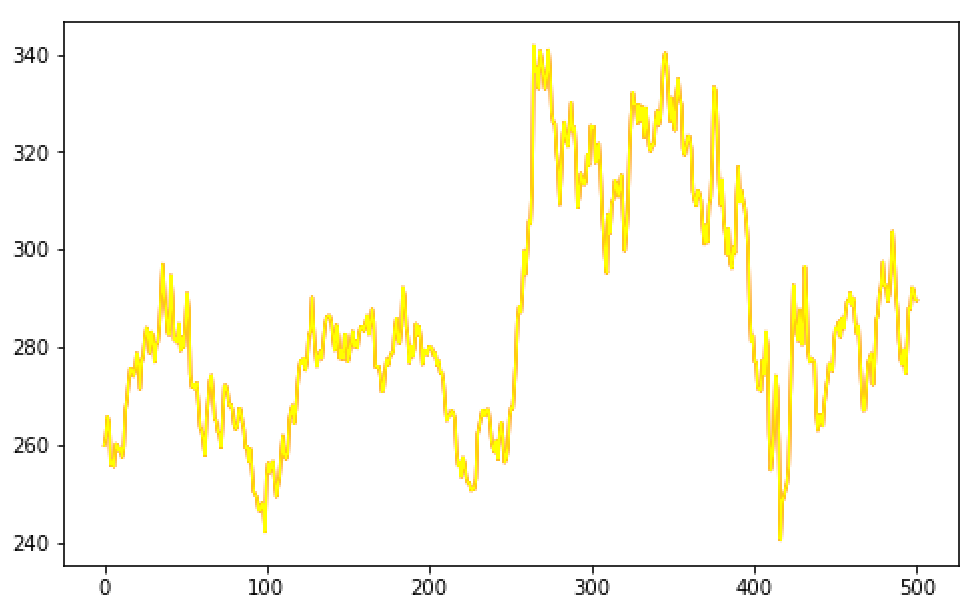
```
# evaluating performance using MSE
y_predicted = mean_values.values
y_true = data['ONGC'].values
percentage_error = ((abs(y_true-y_predicted)/y_true)*100).mean()
percentage_error
```

Out[8]:

```
9.114702437944821
```

In [9]:

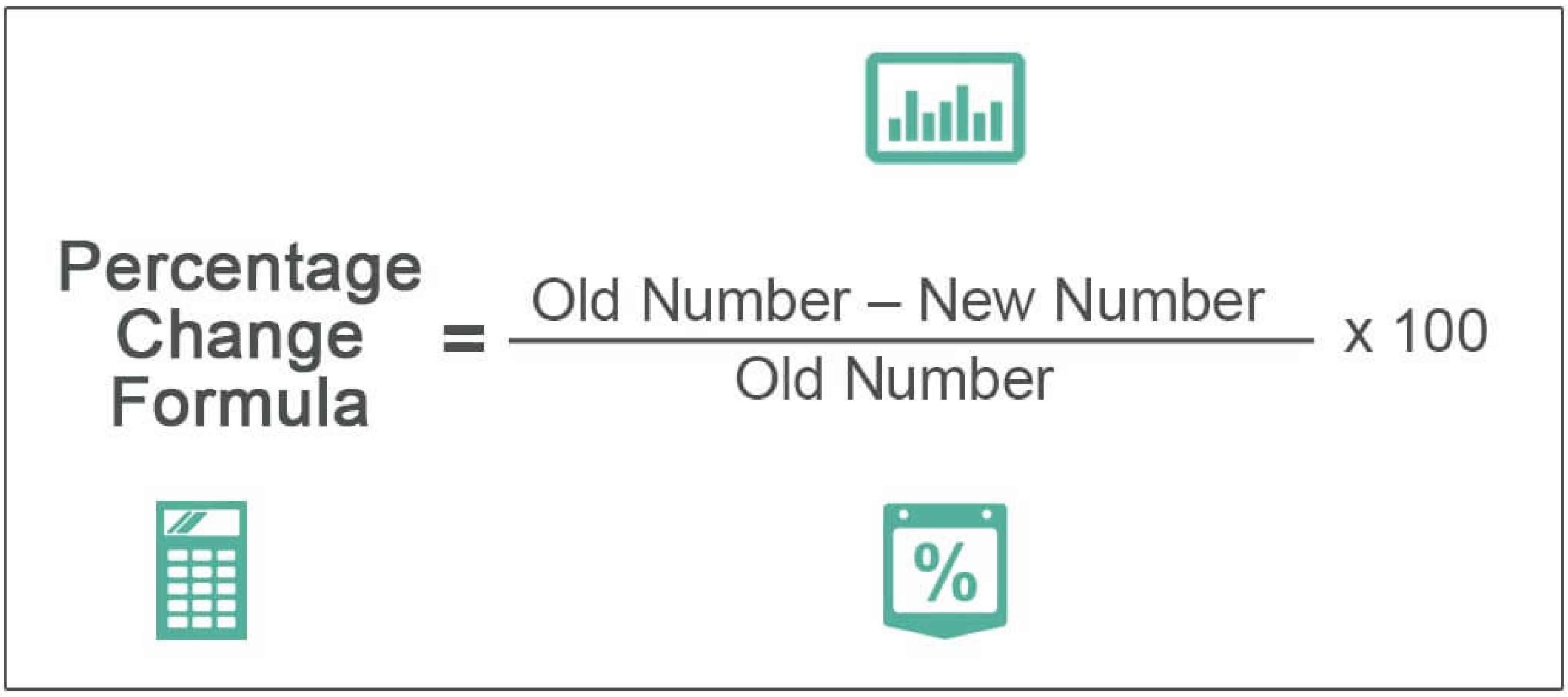
```
plt.figure(figsize= (8,5))
plt.plot(y_predicted, color = 'red')
plt.plot(y_true, color = 'yellow')
plt.figure(figsize=(50,50))
plt.show()
```




```
<Figure size 3600x3600 with 0 Axes>
```

PCT Change

Pandas dataframe.pct_change() function calculates the percentage change between the current and a prior element. This function by default calculates the percentage change from the immediately previous row.



[2]

In [10]:
```python
returns = np.log(1 + pct_change)
returns.head()
```

Out[10]:

	ONGC	NTPC	GAIL
0	NaN	NaN	NaN
1	0.007248	0.012491	0.009190
2	0.015281	-0.003374	0.008472
3	-0.004564	-0.008486	-0.030572
4	-0.033598	-0.011491	-0.005095

Mean:

In mathematics and statistics, the idea of mean is crucial. The most typical or average value among a group of numbers is called the mean. It is a statistical measure of a probability distribution's central tendency along the median and mode. It also goes by the name "expected value."
Different Means:

Mathematical Mean Geometric Mean Harmonic Mean

We used the arithmetic mean in this case: **Arithmetic Mean:**
Arithmetic mean is the result of summing all the values and dividing by the total number of values. To compute, simply sum up all the numbers provided, then divide by the number of numbers given.

Mean of Grouped Data:

$$\bar{x} = \frac{\sum fx}{n}$$

where: $\bar{x}$ = mean
f = frequency of each class
x = mid-interval value of each class
n = total frequency
$\sum fx$ = sum of the producst of mid − interval values and their corresponding frequency

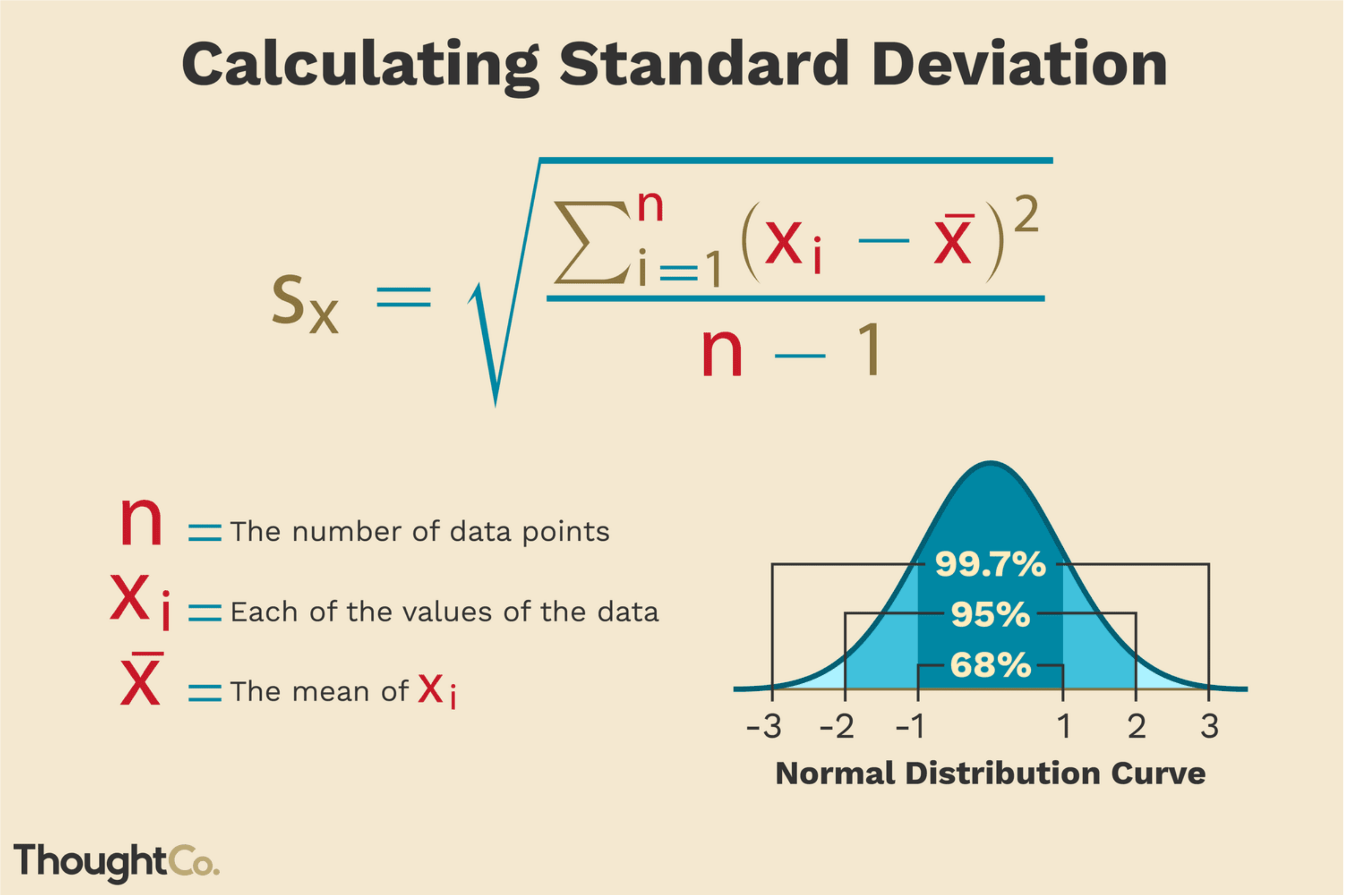
[3]

In [11]:
```python
mean_returns = returns.mean()
mean_returns
```

Out[11]:
```
ONGC    0.000217
NTPC   -0.000294
GAIL   -0.000242
dtype: float64
```

Standard Deviation:

What is Standard Deviation?
The square root of the variance is used to calculate the standard deviation, a statistic that expresses how widely distributed a dataset is in relation to its mean. Calculating each data point's deviation from the mean may determine the standard deviation.



[1]

What Does Standard Deviation Tell You?
Standard deviation describes how dispersed a set of data is. It compares each data point to the mean of all data points, and standard deviation returns a calculated value that describes whether the data points are in close proximity or whether they are spread out. In a normal distribution, standard deviation tells you how far values are from the mean.

Why Is Standard Deviation Important?
Standard deviation is important because it can help users assess risk. Consider an investment option with an average annual return of 10% per year. However, this average was derived from the past three year returns of 50%, -15%, and -5%. By calculating the standard deviation and understanding your low likelihood of actually averaging 10% in any single given year, you're better armed to make informed decisions and recognizing underlying risk.

In [12]:
```
std_returns = returns.std()
std_returns
```

Out[12]:
```
ONGC    0.016547
NTPC    0.014004
GAIL    0.014273
dtype: float64
```

Normal Distribution:

The normal distribution, also known as the Gaussian distribution, is the most important probability distribution in statistics for independent, random variables. Most people recognize its familiar bell-shaped curve in statistical reports.

The normal distribution is a continuous probability distribution that is symmetrical around its mean, most of the observations cluster around the central peak, and the probabilities for values further away from the mean taper off equally in both directions. Extreme values in both tails of the distribution are similarly unlikely. While the normal distribution is symmetrical, not all symmetrical distributions are normal. For example, the Student’s t, Cauchy, and logistic distributions are symmetric.

As with any probability distribution, the normal distribution describes how the values of a variable are distributed. It is the most important probability distribution in statistics because it accurately describes the distribution of values for many natural phenomena. Characteristics that are the sum of many independent processes frequently follow normal distributions. For example, heights, blood pressure, measurement error, and IQ scores follow the normal distribution.

Normal Distribution Formula

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

$\mu =$ mean of x

$\sigma =$ standard deviation of x

$\pi \approx 3.14159 \ldots$

$e \approx 2.71828 \ldots$

[4]

In [13]:
```
# random normal returns with mean = mean_returns and std = std_returns for all three companies.
simulated_returns = 1 + np.random.normal(mean_returns, std_returns, size = (total_days,3))
simulated_returns = pd.DataFrame(simulated_returns, columns=["ONGC", "NTPC", "GAIL"])
simulated_returns
```

Out[13]:

	ONGC	NTPC	GAIL
0	0.975121	1.013541	0.998233
1	1.014930	0.993999	1.006819
2	1.005757	1.013035	0.964018
3	0.982012	0.968338	0.995079
4	0.995088	0.996696	0.999265
...	...	...	...
496	0.970651	0.995377	1.015618
497	0.985159	0.988401	0.986407
498	0.993289	0.997295	0.998142
499	1.000280	0.997175	1.022594
500	1.007786	0.985402	0.981642

501 rows × 3 columns

In [14]:
```
ONGC_returns = simulated_returns.iloc[:, 0]
NTPC_returns = simulated_returns.iloc[:, 1]
GAIL_returns = simulated_returns.iloc[:, 2]

# chosing last day price from dataset as initial value for prediction.
ONGC_initial_value = data["ONGC"].iloc[-1]
NTPC_initial_value = data["NTPC"].iloc[-1]
GAIL_initial_value = data["GAIL"].iloc[-1]
```

In [15]:
```
prediction_ONGC = pd.DataFrame(ONGC_initial_value * ONGC_returns.cumprod(), columns=['ONGC'])
prediction_NTPC = pd.DataFrame(NTPC_initial_value * NTPC_returns.cumprod(), columns=['NTPC'])
prediction_GAIL = pd.DataFrame(GAIL_initial_value * GAIL_returns.cumprod(), columns=['GAIL'])
```

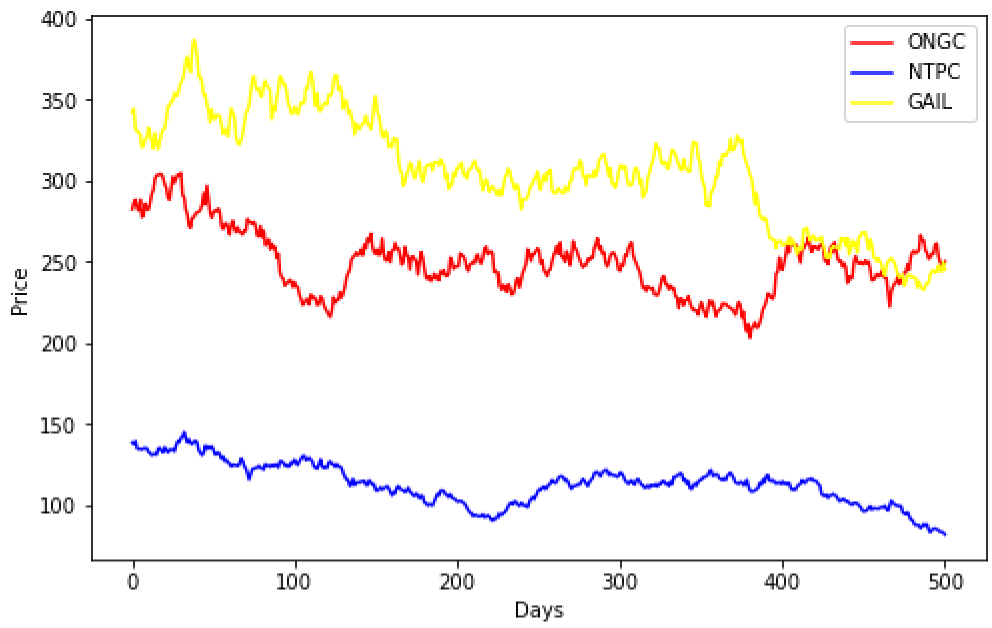
In [16]:
```
predictions = pd.concat([prediction_ONGC, prediction_NTPC, prediction_GAIL], axis = 1, ignore_index=False)
predictions
```

Out[16]:

	ONGC	NTPC	GAIL
0	282.346364	138.551058	342.034490
1	286.561659	137.719588	344.366751
2	288.211454	139.514777	331.975877
3	283.027143	135.097505	330.342103
4	281.636888	134.651123	330.099365
...	...	...	...
496	253.601616	84.638580	247.828967
497	249.837879	83.656856	244.460127
498	248.161293	83.430573	244.005929
499	248.230902	83.194884	249.519104
500	250.163541	81.980410	244.938494

501 rows × 3 columns

In [17]:
```
plt.figure(figsize=(8,5))
plt.plot(predictions['ONGC'], color = 'red')
plt.plot(predictions['NTPC'], color = 'blue')
plt.plot(predictions['GAIL'], color = 'yellow')
plt.xlabel('Days')
plt.ylabel('Price')
plt.legend(['ONGC','NTPC','GAIL'])
plt.show()
```



In [18]:
```
ongc_data = temp_ongc.iloc[:,1:]
ongc_data.head()
```

Out[18]:

	Prev Close	Open	High	Low	Last	Close	VWAP
0	256.60	257.50	262.85	256.45	258.60	258.35	259.82
1	258.35	261.10	264.50	259.65	263.80	263.20	261.71
2	263.20	264.00	267.60	261.10	266.30	266.70	265.74
3	266.70	268.45	269.95	261.00	262.05	261.75	264.53
4	261.75	256.40	258.40	253.65	255.85	255.65	255.79

In [19]:
```
independent_parameters = ongc_data.iloc[:,:6]
dependent_parameter = ongc_data.iloc[:,-1]
```

Correlation Formula

How does correlation work?

A statistical metric known as correlation describes how closely two variables are connected linearly. (meaning they change together at a constant rate). It's a typical technique for expressing straightforward connections without explicitly stating cause and consequence. How is the correlation calculated? The strength of the association is measured by the sample correlation coefficient, or r. The statistical significance of correlations is also examined.

What are some of correlation analysis' drawbacks?

Correlation cannot examine the presence or impact of other factors beyond the two under investigation. It's important to note that correlation cannot explain causation and effect. Curvilinear connections cannot be adequately described by correlation.

$$r_{xy} = \frac{\Sigma(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\Sigma(x_i - \bar{x})^2 \, \Sigma(y_i - \bar{y})^2}}$$

r_{xy} = correlation coefficient between x and y

x_i = the values of x within a sample

y_i = the values of y within a sample

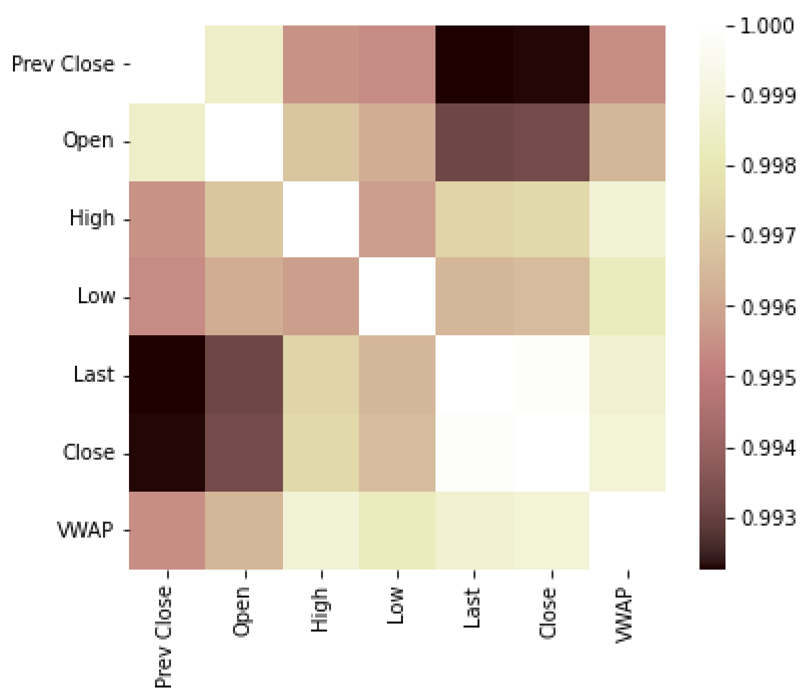
$\bar{x}$ = the average of the values of x within a sample

$\bar{y}$ = the average of the values of y within a sample

[5]

In [20]:
```
plt.figure(figsize=(6,5))
sns.heatmap(ongc_data.corr(), annot=False, cmap='pink')
```

Out[20]: <AxesSubplot:>



Conclusion: VWAP depends nearly on all the independent parameters.

Since all are having correlation value in range (0.993, 0.999)

In [21]:
```
x_train = independent_parameters.iloc[:501,:]
y_train = dependent_parameter.iloc[:501]
```

Linear Regression Model for Predictions:

Linear regression is one of the easiest and most popular Machine Learning algorithms. It is a statistical method that is used for predictive analysis. Linear regression makes predictions for continuous/real or numeric variables such as sales, salary, age, product price, etc.

Linear regression algorithm shows a linear relationship between a dependent (y) and one or more independent (y) variables, hence called as linear regression. Since linear regression shows the linear relationship, which means it finds how the value of the dependent variable is changing according to the value of the independent variable.

Types of Linear Regression:

Linear regression can be further divided into two types of the algorithm:

Simple Linear Regression:
If a single independent variable is used to predict the value of a numerical dependent variable, then such a Linear Regression algorithm is called Simple Linear Regression.

Multiple Linear regression:
If more than one independent variable is used to predict the value of a numerical dependent variable, then such a Linear Regression algorithm is called Multiple Linear Regression.

In this case we have used Multiple Linear Regression.

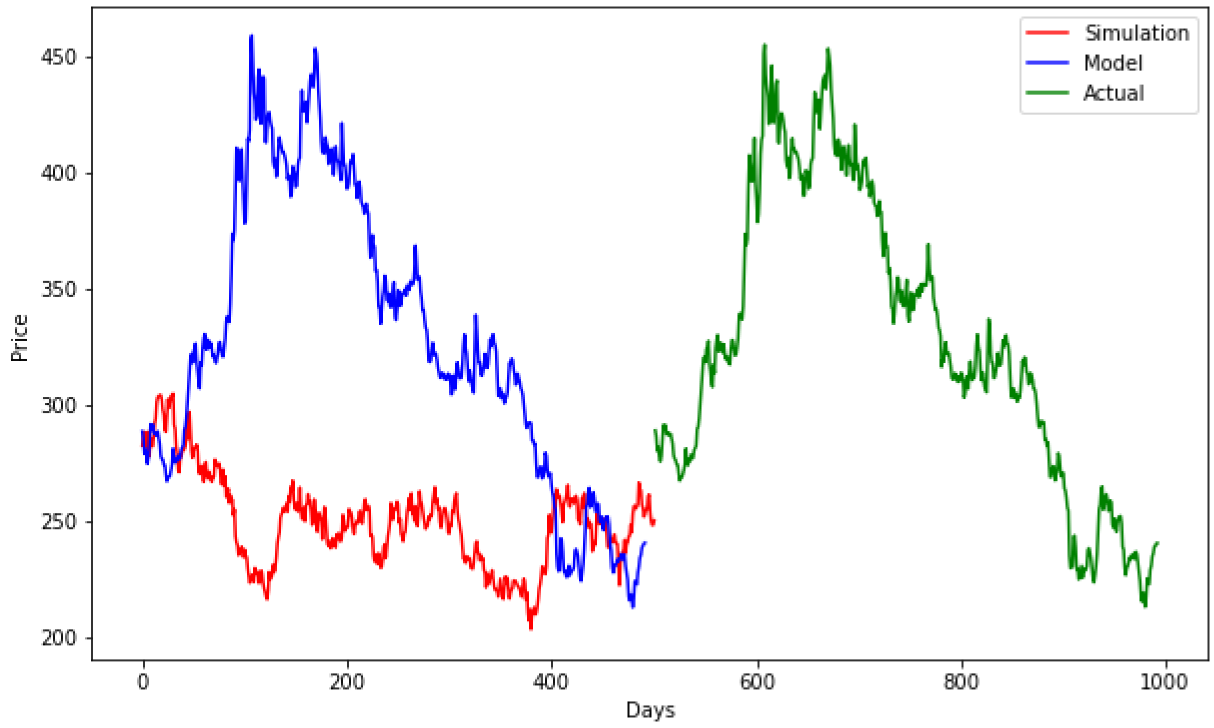
In [22]:
```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(x_train, y_train)
model.coef_
```

Out[22]:
```
array([ 0.02504623,  0.00697272,  0.3604232 ,  0.22975417, -0.09677132,
        0.4761617 ])
```

In [23]:
```
x_test = independent_parameters.iloc[501:993,:]
y_test = dependent_parameter.iloc[501:993]
y_predicted_model = model.predict(x_test)
error = ((y_test - y_predicted_model)**2).mean()
error
```

Out[23]:
```
1.3241865601535558
```

In [24]:
```
plt.figure(figsize=(10,6))
plt.plot(predictions['ONGC'], color = 'red')
plt.plot(y_predicted_model, color = 'blue')
plt.plot(y_test, color = 'green')
plt.legend(['Simulation', "Model", 'Actual'])
plt.xlabel("Days")
plt.ylabel("Price")
plt.show()
```



Conclusions:

There is slight change in the Stock Prices predicted by linear model and Simulations. The prices predicted by linear model are similar to the actual prices, giving Mean Square Error of **1.32**. The reason for difference in this error can be the consideration of independent parameters in linear model and which were not taken into account in performing Monte Carlo Simulations.

Rereferences:

1. https://www.thoughtco.com/thmb/qmSnmY_b1ztjvvdp-QhdT4-DA8c=/1500x0/filters:no_upscale():max_bytes(150000):strip_icc()/calculate-a-sample-standard-deviation-3126345-v4-CS-01-5b76f58f46e0fb0050bb4ab2.png

2. https://cdn.wallstreetmojo.com/wp-content/uploads/2019/11/Percentage-Change-Formula-1.jpg

3. https://qph.cf2.quoracdn.net/main-qimg-cb5a6703bdfd5e2a15cf8865607a1590

4. https://www.onlinemathlearning.com/image-files/normal-distribution-formula.png

5. https://v.fastcdn.co/u/11443291/57605682-0-correlation-formula-.JPG