Night's Watch

MATLAB Challenge

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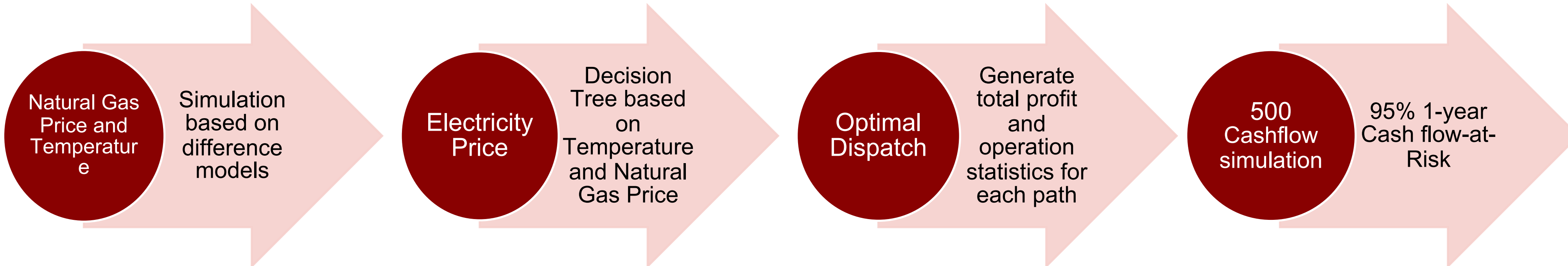
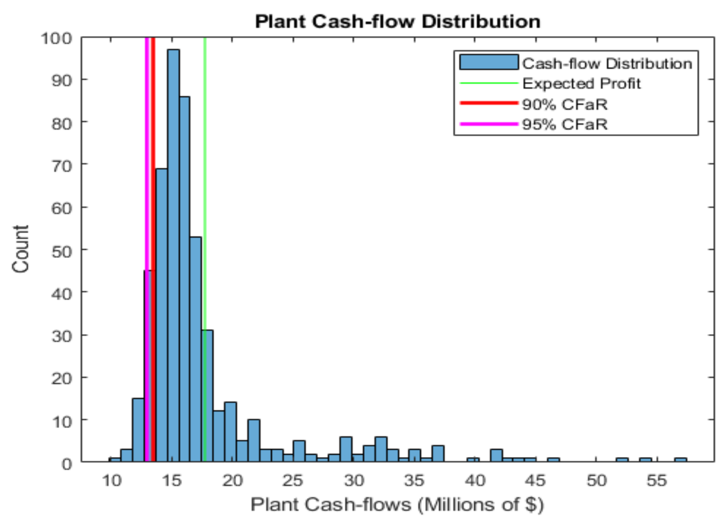
I. Model Overview

Cash flow-at-Risk Model

500 Monte Carlo Scenarios



95% Cash flow-at-Risk 4.7735M



II. Natural Gas Price Model

Natural Gas Price Model

Assumption

Mean Reversion
Constant Volatility
Missing value can be filled by previous data

Model

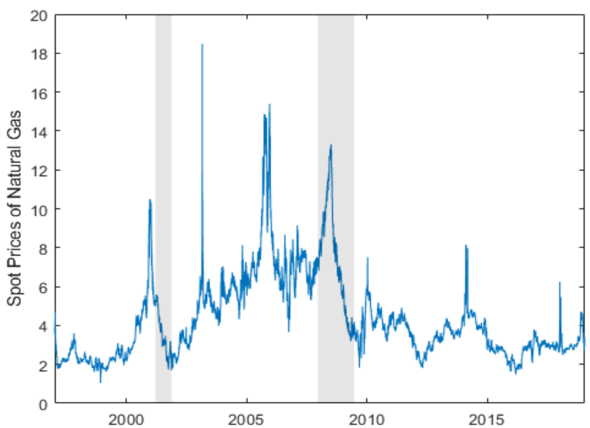
- $dx_t = a(u - x_t)dt + \sigma dz_t$, where $dz_t \sim N(0, \sqrt{dt})$
- $a = Mean\ Reversion\ Rate$
- $u = Mean\ Level$
- $\sigma = Volatility$

Calibration

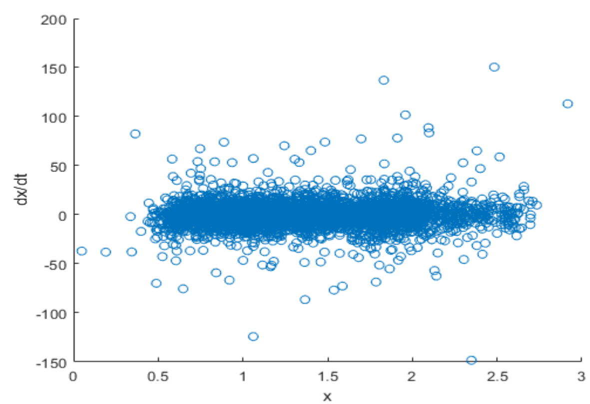
- The reversion rate and mean level can be calibrated from the coefficients of a linear fit between the log prices and their first difference.
- Fitted Model:

$$dx_t = -1.2665(1.3629 - x_t)dt + 0.7281dz_t$$

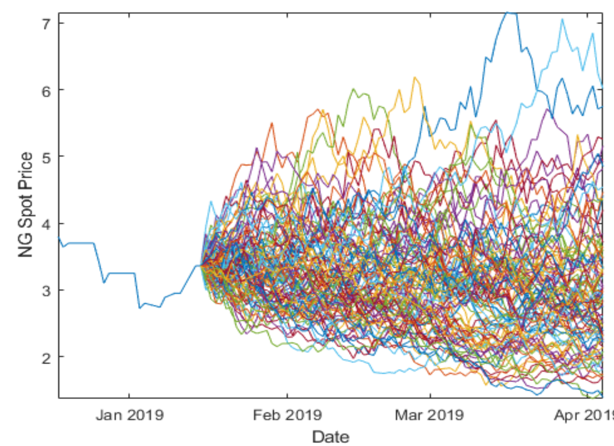
Historical Temperature



Scatter plot of log prices and first difference



Simulation of log Natural Gas Prices



III. Temperature Model

Temperature Model

Assumption

Seasonality Component

Autocorrelation in residuals

Model

- Deterministic Component: Double-Sin

  y = a1∗sin(b1∗x+c1) + a2∗sin(b2∗x+c2)

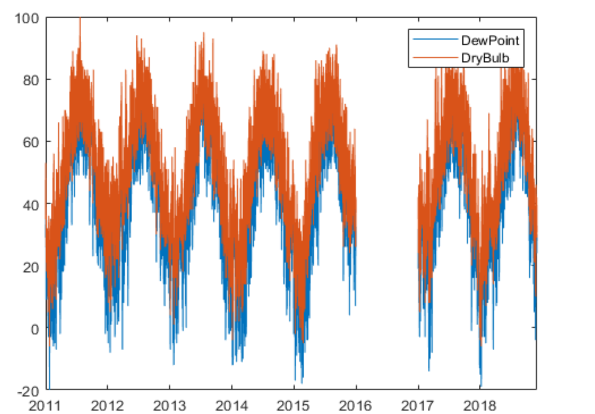
- Stochastic Component: ARIMX with autocorrelation

Calibration

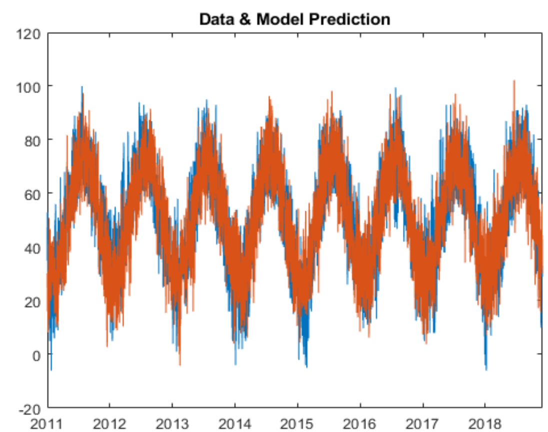
$$y = 22.77 * sin(0.0173 * -1559)\ 0.01598 sin(5.488 * +2.264)$$

$$x_t = 1.317 * x_{t-1} - 0.151 * x_{t-2} - 0.204 * x_{t-3} + 0.01574 * x_{t-4} + 0.1394 * x_{t-23} + 0.00287 * x_{t-24} - 0.148 * x_{t-25} + 0.091 * x_{t-47} + 0.0068 * x_{t-48} - 0.088 * x_{t-49}$$

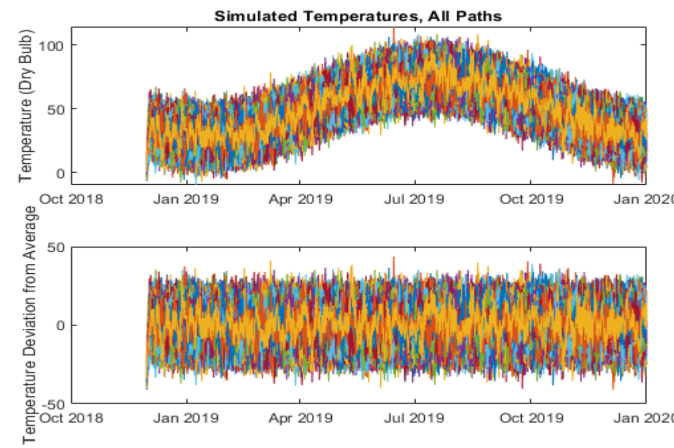
Historical Natural Gas Spot Prices



Fill missing values



Simulation of Temperature



V. Electricity Price Model

Electricity Price Model

Assumption

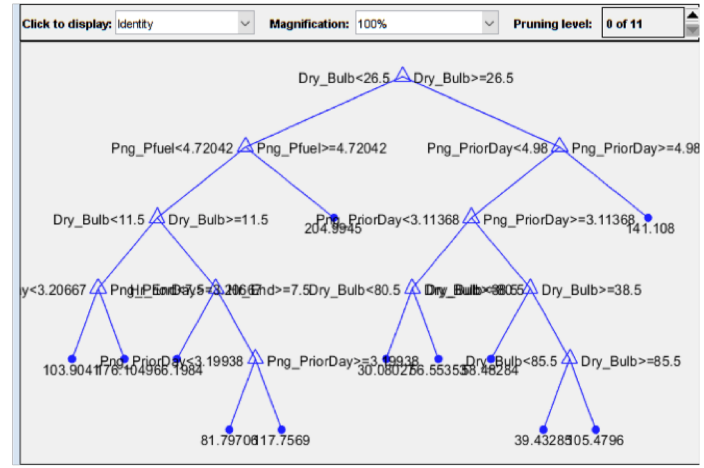
Natural gas price and temperature have impact on electricity price

Autocorrelation in residuals

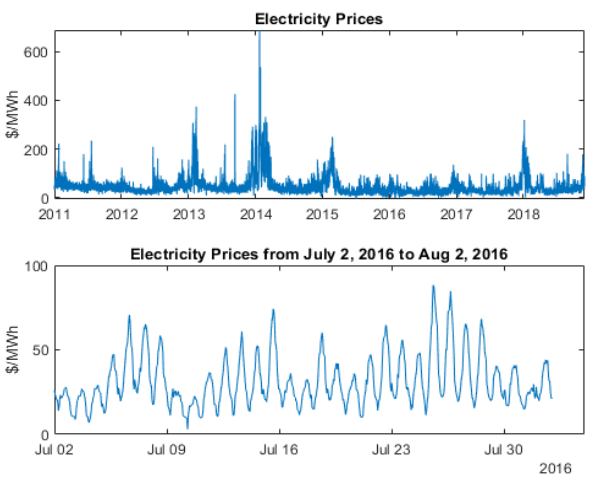
Model

- Deterministic Component: Regression Tree
- Stochastic Component: ARIMX with autocorrelation

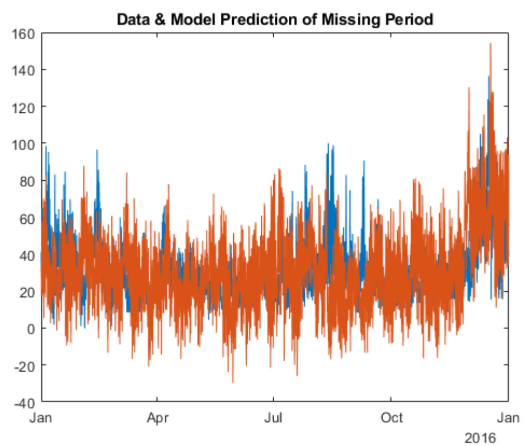
Calibration



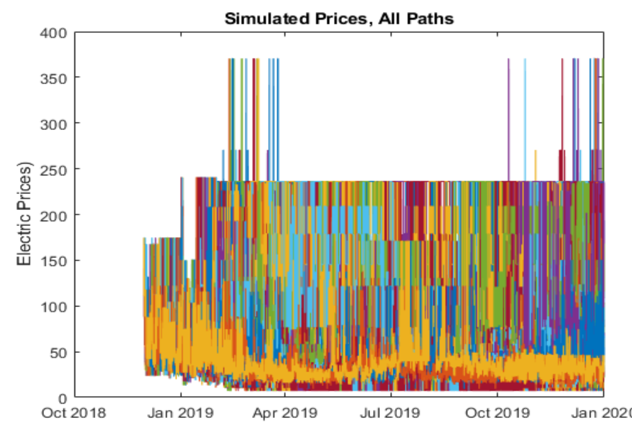
Historical Electricity Price



Simulation with filled Temperature data



Simulation of Temperature



IV. Hybrid Electricity Model & Economic Dispatch

Hybrid Electricity Model & Economic Dispatch

Dispatch function

- Generate profits and earning based on optimal dispatch
- Optimal Dispatch is calculated based on capacity, heat rate, costs per minutes, minutes of running, Electricity Prices, Natural Gas

Cash flow in each simulated scenario

- Apply Dispatch function in each simulation path and forcast cash flow in each scenario

V. Strengths and Weaknesses

Strengths and Weaknesses

Model	Strengths	Weaknesses
Natural Gas	• Energy Commodity prices are more complex to simulate due to its physical constraints. This model reflects the mean reversion in Natural Gas Prices.	• The Brownian motion model assumes constant volatility, which is not able to capture the volatility changes subject to shocks
Temper ature	• The model takes into account the seasonality, autocorrelation, and random features of temperature and gives a reasonable filling of the missing data	• The model fails to take time trend in temperature
Electrici ty Price	• Regression Tree catches the discrete feature of electricity price, which gives an efficient estimating of “jumping” feature	• Residual of regression does not display a homoscedastic pattern, so there might be other components that are not incorporated by the model.
Cash flow-at-Risk	• Incorporating natural gas price and temperature into the model simulates the optimal dispatch from both demand and supply aspect	• Lack of stress testing, missing extreme conditions

Appendix

Appendix

Natural Gas price regression summary

```
mdl = fitlm(x, dxdt,'linear','VarNames',{'x','dxdt'})
```

```
mdl =
Linear regression model:
    dxdt ~ 1 + x

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    _______    __________

    (Intercept)    -1.7261     0.49313    -3.5003    0.00046839
    x               1.2665     0.34403     3.6814    0.00023413


Number of observations: 5564, Error degrees of freedom: 5562
Root Mean Squared Error: 11.8
R-squared: 0.00243,  Adjusted R-Squared 0.00225
F-statistic vs. constant model: 13.6, p-value = 0.000234
```

```
revRate   = -mdl.Coefficients.Estimate(2)
```

```
revRate = -1.2665
```

```
meanLevel = mdl.Coefficients.Estimate(1)/revRate
```

```
meanLevel = 1.3629
```

```
res = dxdt - predict(mdl,x);
vol = std(res) * sqrt(dt)
```

```
vol = 0.7281
```

Appendix

Temperature model summary

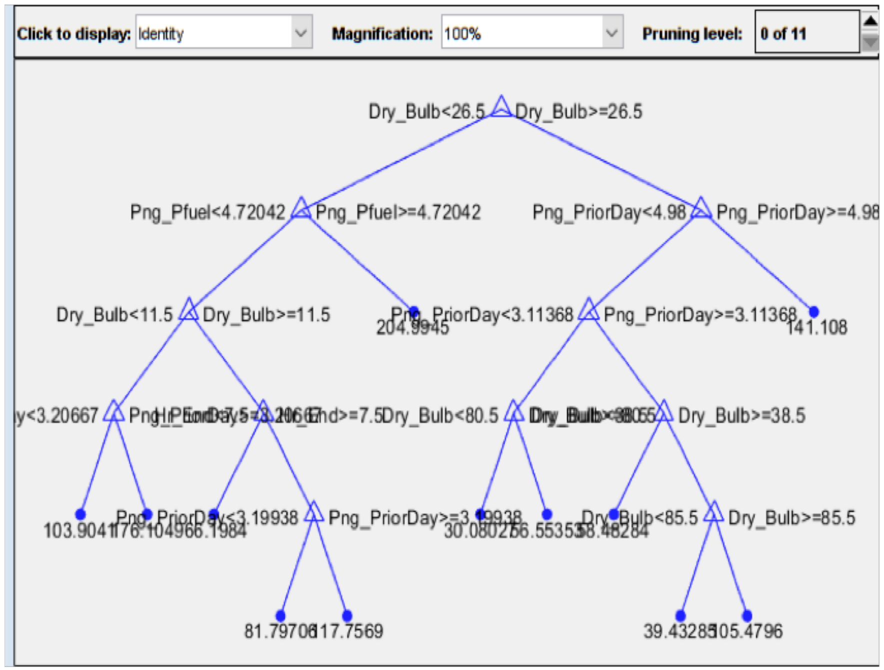
```
model =
     General model Sin2:
     model(x) =  a1*sin(b1*x+c1) + a2*sin(b2*x+c2)
     Coefficients (with 95% confidence bounds):
       a1 =       22.77  (22.66, 22.87)
       b1 =     0.01734  (0.01733, 0.01734)
       c1 =       -1559  (-1563, -1555)
       a2 =     0.01598  (-0.08931, 0.1213)
       b2 =       5.488  (5.48, 5.495)
       c2 =       2.264  (-5621, 5626)
```

```
Effective Sample Size: 60551
Number of Estimated Parameters: 13
LogLikelihood: -85648.4
AIC: 171323
BIC: 171440
```

	Value	StandardError	TStatistic	PValue
Constant	-0.0081649	0.013797	-0.5918	0.55399
AR{1}	1.317	0.003305	398.5	0
AR{2}	-0.15082	0.0056532	-26.679	8.239e-157
AR{3}	-0.20443	0.006037	-33.863	2.334e-251
AR{4}	0.01574	0.0034436	4.571	4.8547e-06
AR{23}	0.1394	0.0035702	39.046	0
AR{24}	0.0028747	0.0062495	0.45999	0.64552
AR{25}	-0.14879	0.0036798	-40.435	0
AR{47}	0.091294	0.0037671	24.235	9.5575e-130
AR{48}	0.006776	0.0065123	1.0405	0.29811
AR{49}	-0.088026	0.003765	-23.38	6.8468e-121
Beta(1)	0.019089	0.00059513	32.075	9.7386e-226
Variance	0.99124	0.004224	234.67	0

Appendix

Electricity Price model summary



Effective Sample Size: 60313
Number of Estimated Parameters: 11
LogLikelihood: -198430
AIC: 396883
BIC: 396982

	Value	StandardError	TStatistic	PValue
Constant	-0.3307	0.04963	-6.6633	2.6776e-11
AR{1}	0.98789	0.0011186	883.13	0
AR{2}	-0.15461	0.0016413	-94.198	0
AR{3}	0.00017018	0.0017575	0.09683	0.92286
AR{4}	0.0030077	0.0012049	2.4962	0.012552
AR{23}	0.12462	0.0011472	108.63	0
AR{24}	0.32529	0.0014227	228.65	0
AR{25}	-0.39366	0.0009921	-396.79	0
AR{48}	0.017337	0.00057432	30.188	3.4224e-200
Beta(1)	0.097154	0.00063915	152	0
Variance	42.188	0.040876	1032.1	0

Appendix

Annual Global Temperature trend