Predicting Crude Oil Price Trends Using Artificial Neural Network Modeling Approach

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Outline

- Introduction
- Methodology
- Data and Sources of Data
- Calculations and Results
- Conclusion

Introduction

- WHAT DICTATES CURRENT TRENDS IN WORLD CRUDE OIL PRICES?
  - 1) TECHNICAL (Exploration & Production Activity)?
    - Plenty of activity worldwide therefore no effect?
  - 2) MARKET FUNDAMENTALS (Supply & Demand)?
    - No shortages foreseen in the near future , so little effect?
  - 3) SEASONAL (Warm & Cold Climates)?
    - Warm weather for the near future but still little effect?
  - 4) PYSCHOLOGICAL (Rumors & False Reports)?
    - Plenty of rumors and false reporting and *very large effect?*
      - *Speculative buying*
      - *Commercial traders raising prices*

Introduction

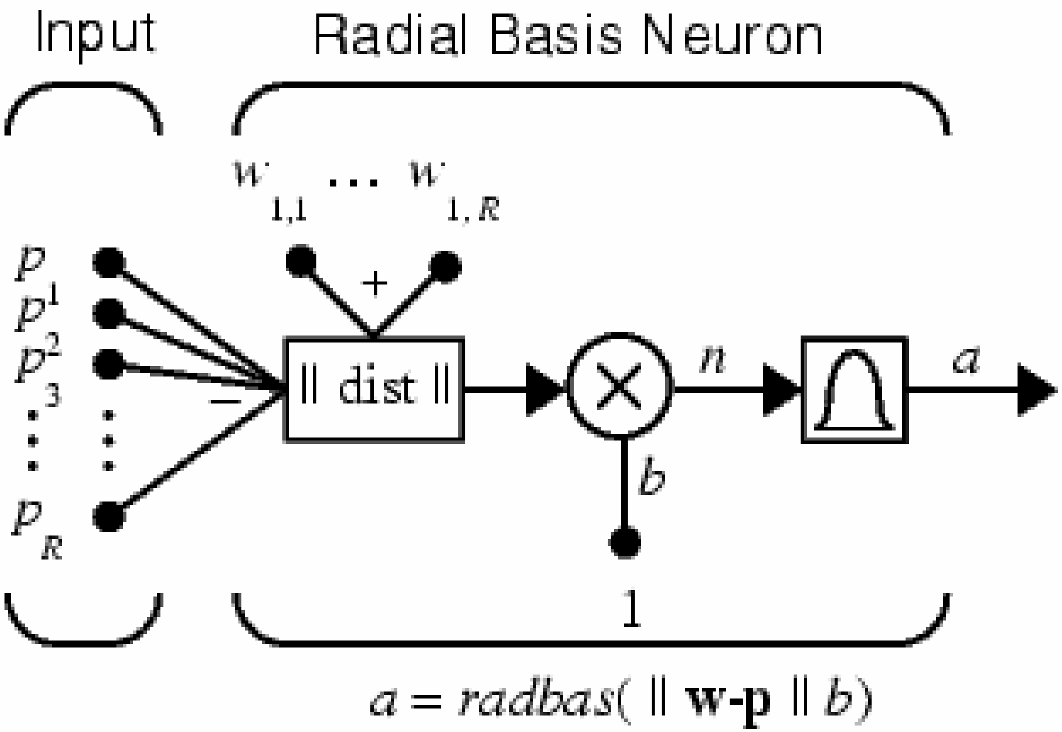
- Accurate estimation of crude oil price trends can optimize production strategies.
- Accurate estimation of crude price trends is likely to lead to some stability in the world oil market.
- Prices are certainly affected by supply and demand in addition to other factors.

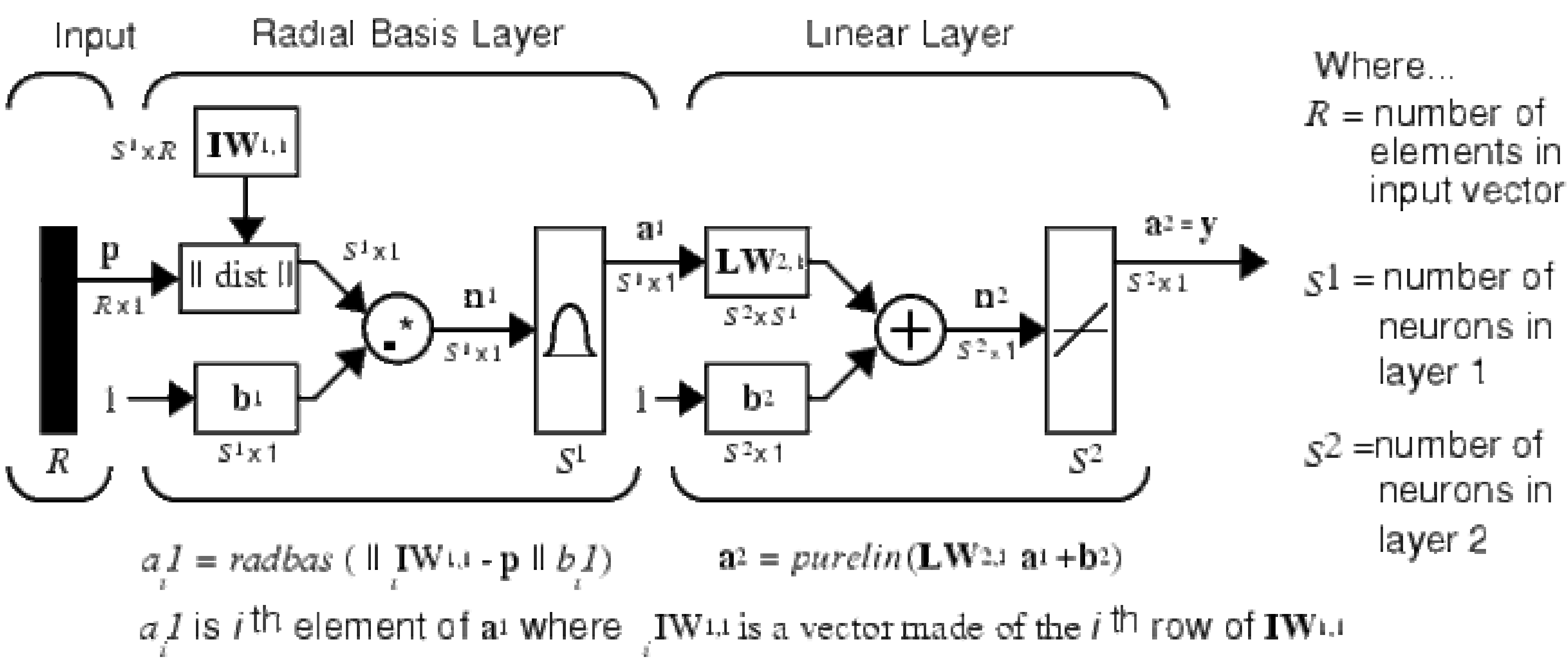
Introduction

- Several authors have used ANN to model complex non-linear system, Moshiri and Fooutan (2004).
- Agbon and Araque (2003) used time series analysis and Chaos-Theory to add some complexity to ANN modeling framework.
- The main objective of this study is to model price trends using ANN with supply and demand levels as input variables.

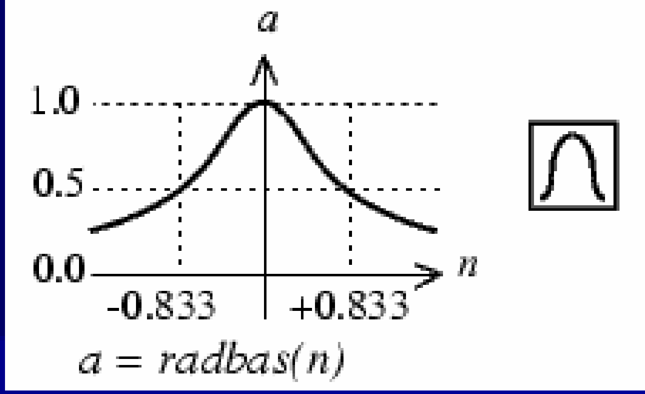
Methodology

- Generalized Regression Neural Network (GRNN) model is used in this study.
- GRNN is a universal approximation for a smooth function.
- GRNN has two layers:
  - Radial basis transfer function.
  - Purelin transfer function


Input
Radial Basis Neuron
$w_{1,1}$ ... $w_{1,R}$
p_1 p_2 p_3 p_R
|| dist ||
n
a
b
1
$a = radbas(\| \mathbf{w}-\mathbf{p} \| b)$

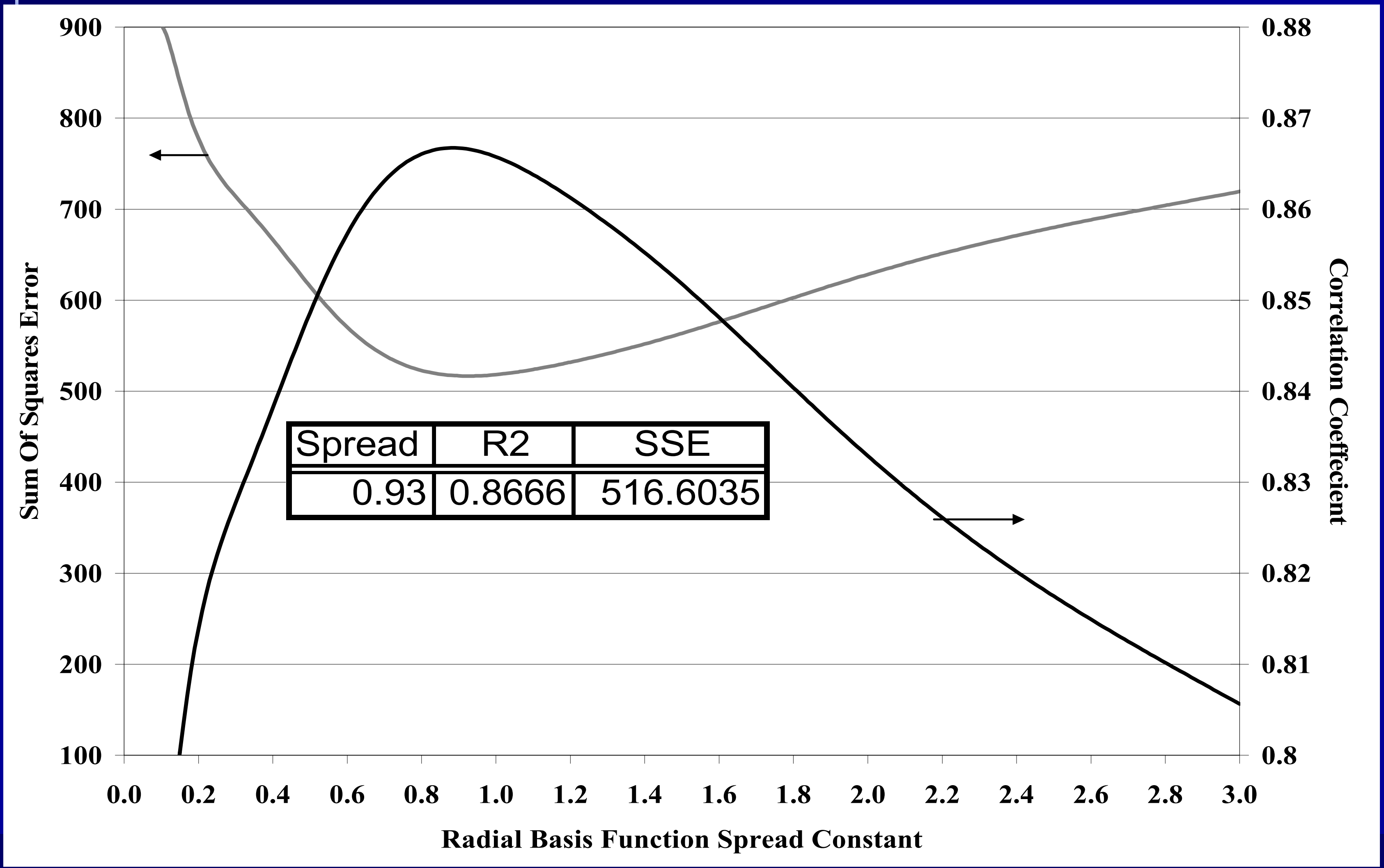

Input
Radial Basis Layer
Linear Layer
$S^1 \times R$
$\mathbf{IW}^{1,1}$
p
$R \times 1$
|| dist ||
$S^1 \times 1$
n^1
$\mathbf{b}^1$
S^1
$\mathbf{a}^1$
$\mathbf{LW}^{2,1}$
$S^2 \times S^1$
n^2
$\mathbf{b}^2$
$S^2 \times 1$
S^2
$\mathbf{a}^2 = \mathbf{y}$
R
Where...
R = number of elements in input vector
$S1$ = number of neurons in layer 1
$S2$ = number of neurons in layer 2
$a_i1 = radbas(\| {}_i\mathbf{IW}^{1,1} - \mathbf{p} \| b_i1)$
$\mathbf{a}^2 = purelin(\mathbf{LW}^{2,1}\ \mathbf{a}^1 + \mathbf{b}^2)$
a_i1 is i th element of $\mathbf{a}^1$ where ${}_i\mathbf{IW}^{1,1}$ is a vector made of the i th row of $\mathbf{IW}^{1,1}$

Methodology



- Radial basis function has a maximum of 1 when its input is 0. As the distance between w and p decreases, the output increases. Thus, a radial basis neuron acts as a detector that produces 1 whenever the input p is identical to its weight vector w.
- The bias b allows the sensitivity of the *radbas* neuron to be adjusted. For example, if a neuron had a bias of 0.1 it would output 0.5 for any input vector p at vector distance of 8.326 (0.8326/b) from its weight vector w.

Methodology



Methodology

- GRNN predictive power depends on input variables and how these variables can be grouped / normalized.
- Several models were considered in this study.
- The best model was chosen based on the following statistical indicators
  - correlation coefficients (R^2)
  - Sum of Squares Error (SSE)
  - Standard Deviation (St. Dev.)

Data and Sources of Data

- Input Variables
  - OPEC Production
  - World Demand
  - US Domestic Supply
  - OPEC Reserves
  - OECD Demand
  - OECD Consumption
  - OECD Refinery Capacity
  - OECD Refinery Throughput
- Target Predictor: WTI Spot Price ($/bbl)

Data and Sources of Data

- Data were collected from different sources:
  - Energy Information Administration website (EIA).
  - The Annual Statistical Bulletin of OPEC Website.

Data Definitions

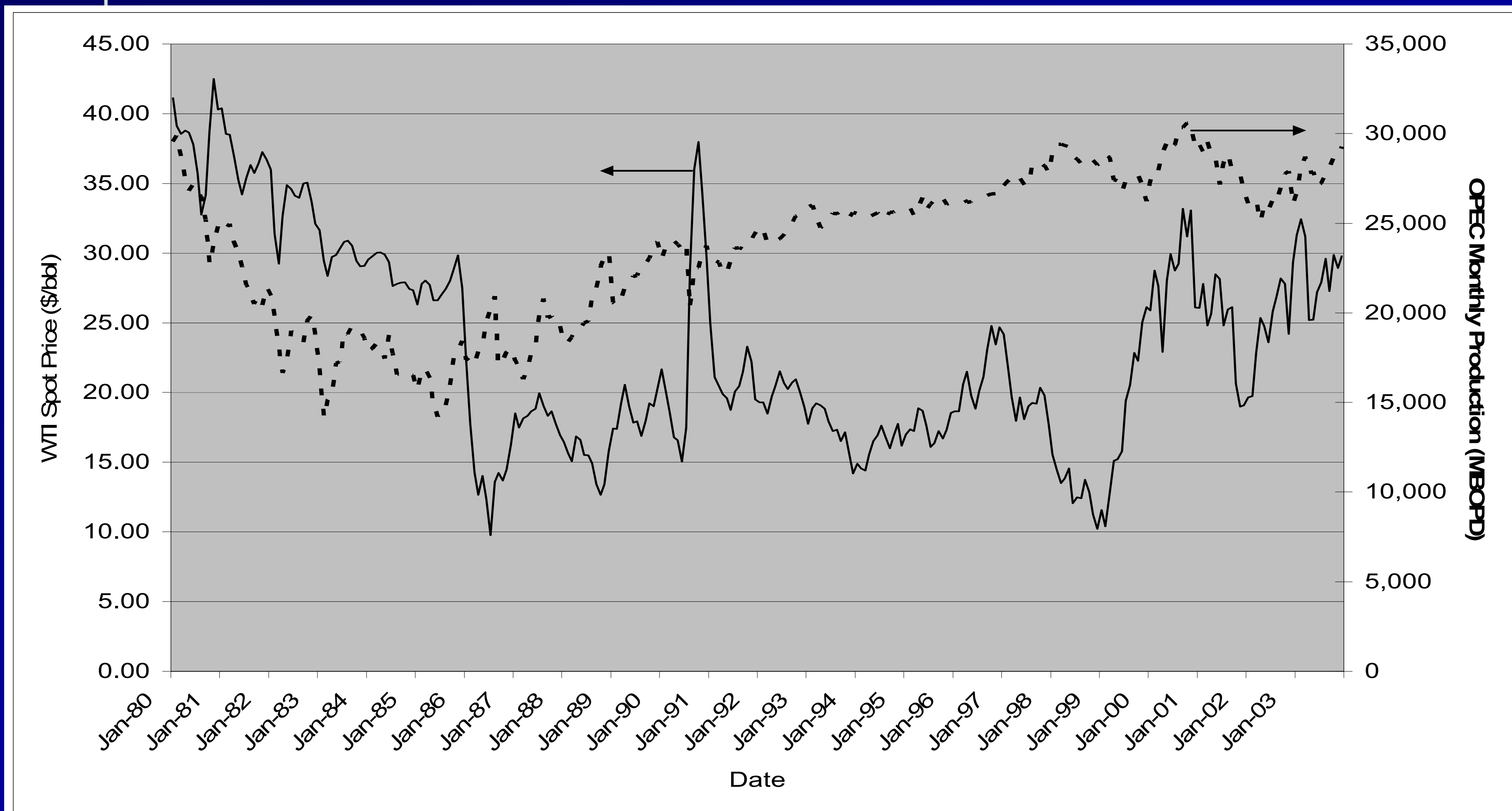
$$\mathrm{Res./Prod} = \frac{\text{OPEC Proved Reserves}}{\text{OPEC Production}}$$

$$\mathrm{OECD\_INDEX} = \frac{\text{Average(Demand, Consumption, Ref. C., Ref. T.)}}{\text{OPEC Production}}$$

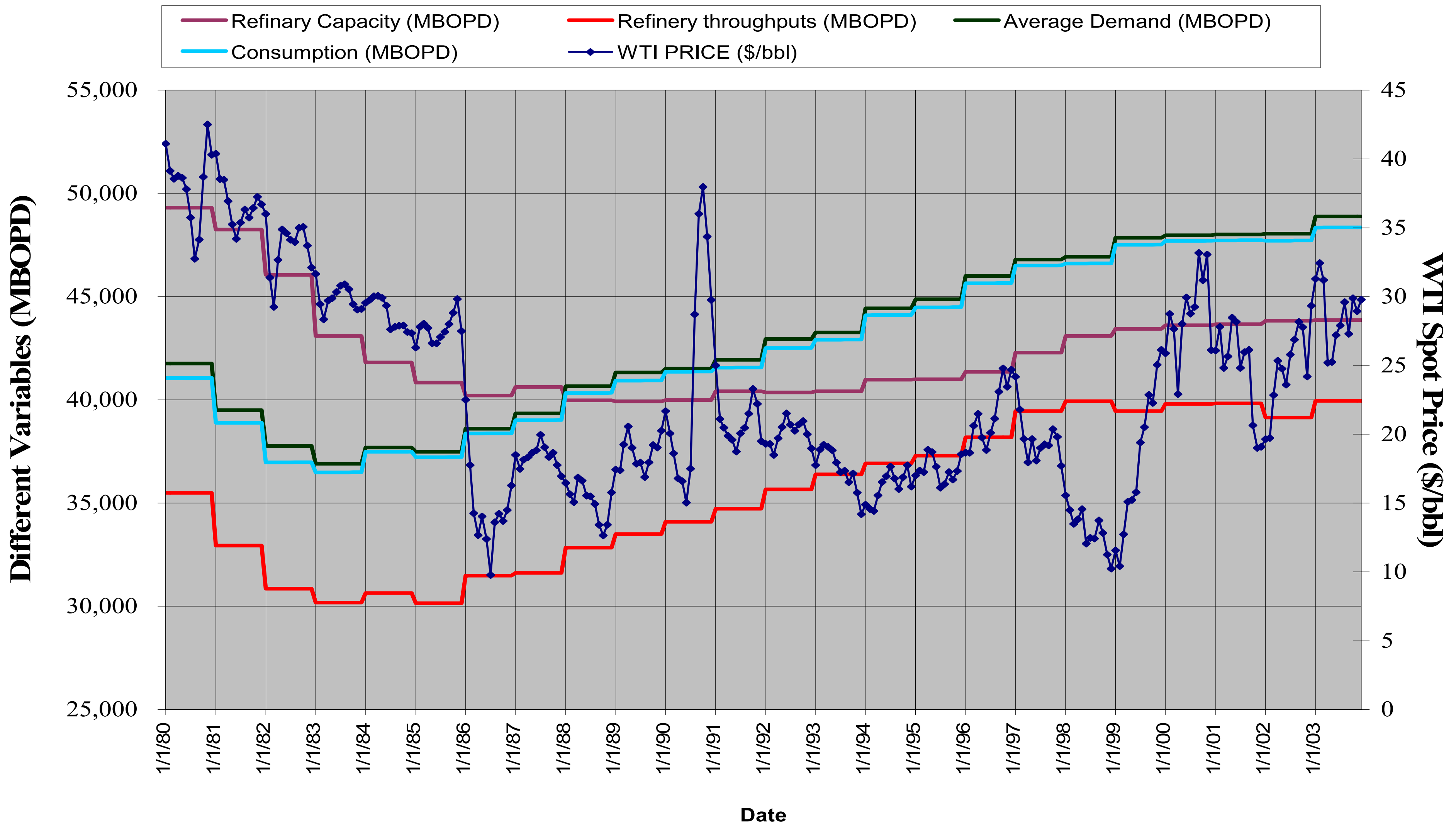
$$\mathrm{WORLD\_INDEX} = \frac{\text{Total World Demand}}{\text{OPEC Production}}$$

$$\mathrm{US\_INDEX} = \frac{\text{US Total Demestic Supply}}{\text{OPEC Production}}$$

Data Trends

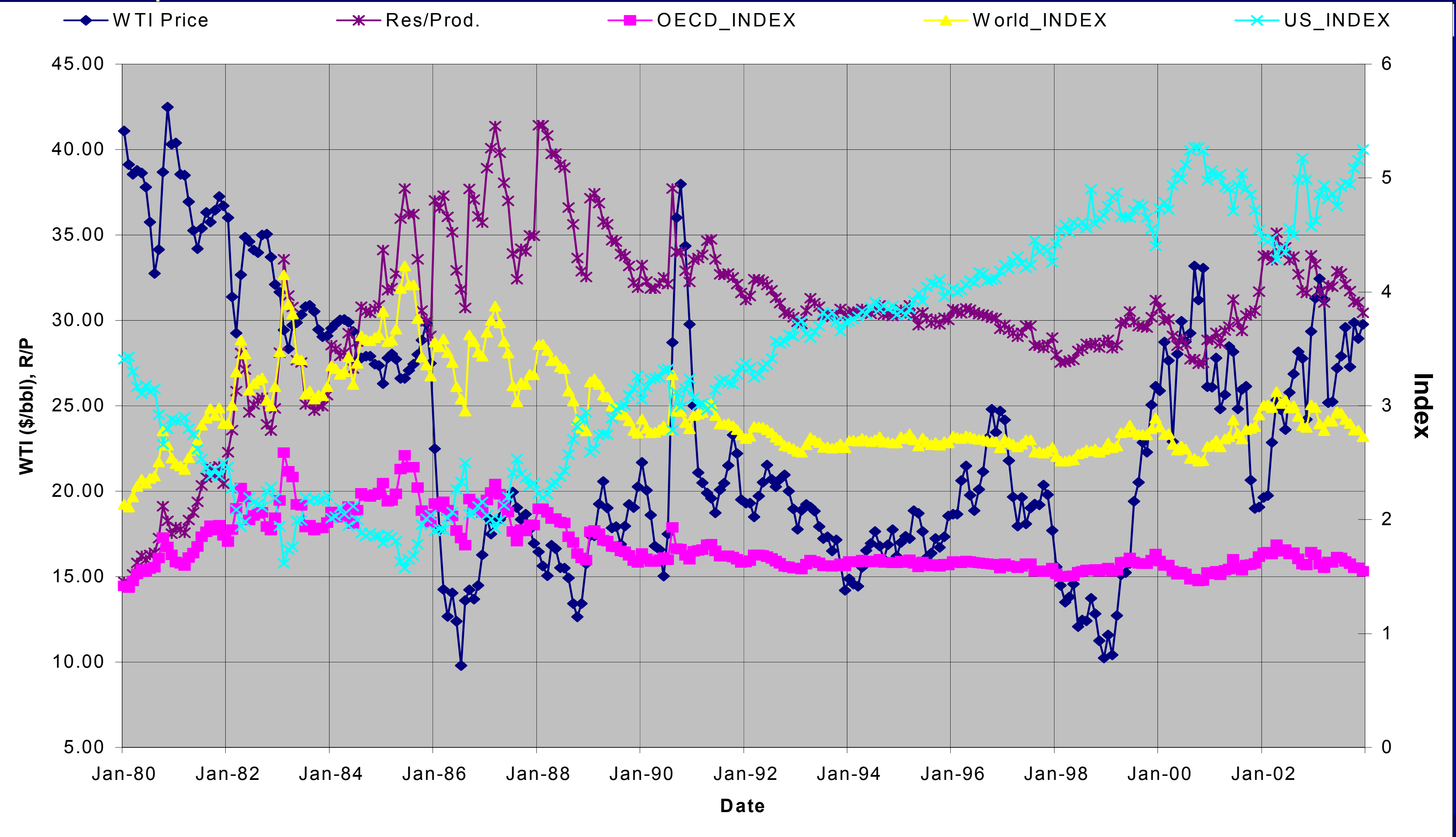

45.00
40.00
35.00
30.00
25.00
20.00
15.00
10.00
5.00
0.00
WTI Spot Price ($/bbl)
35,000
30,000
25,000
20,000
15,000
10,000
5,000
0
OPEC Monthly Production (MBOPD)
Jan-80
Jan-81
Jan-82
Jan-83
Jan-84
Jan-85
Jan-86
Jan-87
Jan-88
Jan-89
Jan-90
Jan-91
Jan-92
Jan-93
Jan-94
Jan-95
Jan-96
Jan-97
Jan-98
Jan-99
Jan-00
Jan-01
Jan-02
Jan-03
Date

Data Trends



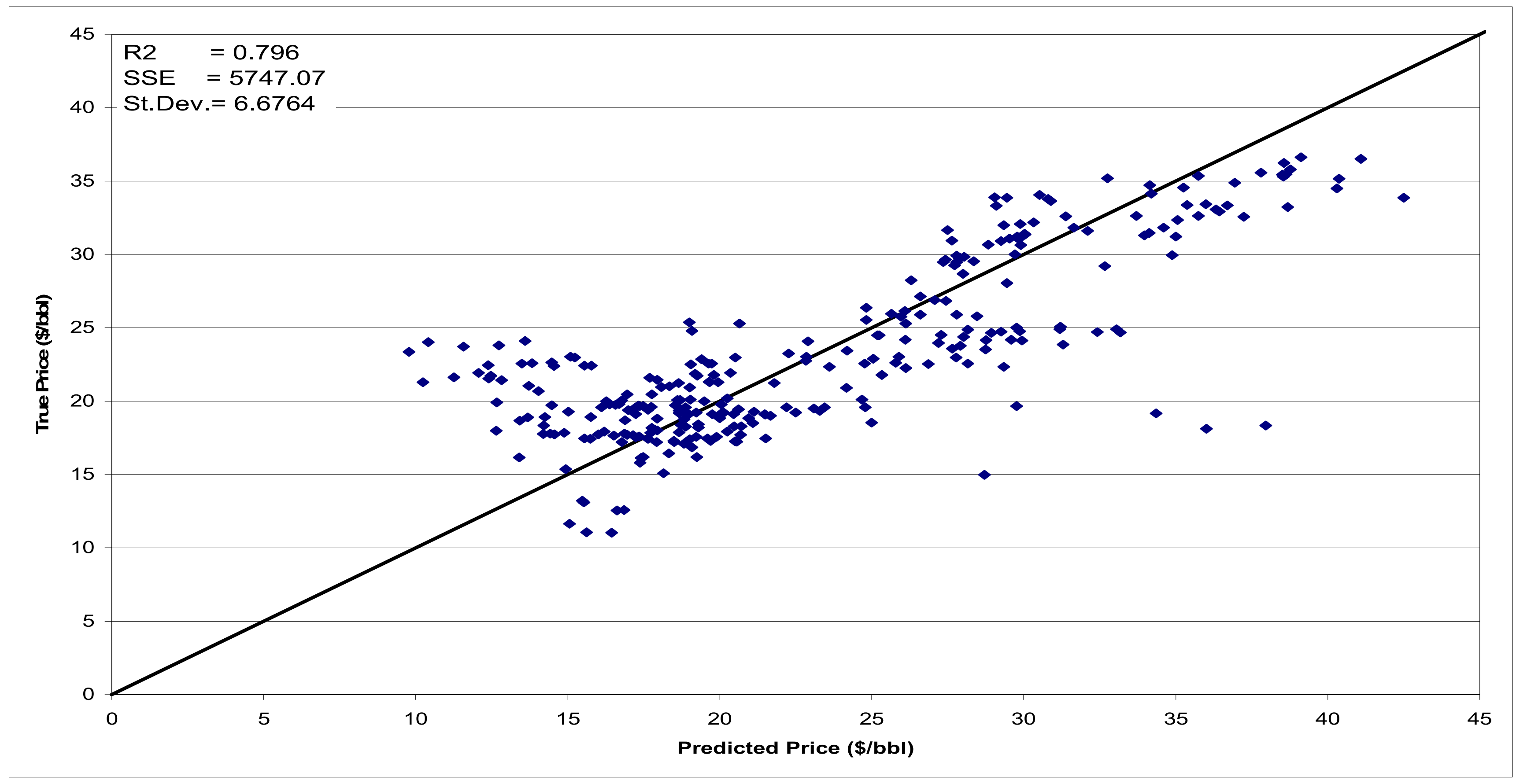
Refinary Capacity (MBOPD)
Refinery throughputs (MBOPD)
Average Demand (MBOPD)
Consumption (MBOPD)
WTI PRICE ($/bbl)
Different Variables (MBOPD)
WTI Spot Price ($/bbl)
55,000
50,000
45,000
40,000
35,000
30,000
25,000
45
40
35
30
25
20
15
10
5
0
1/1/80
1/1/81
1/1/82
1/1/83
1/1/84
1/1/85
1/1/86
1/1/87
1/1/88
1/1/89
1/1/90
1/1/91
1/1/92
1/1/93
1/1/94
1/1/95
1/1/96
1/1/97
1/1/98
1/1/99
1/1/00
1/1/01
1/1/02
1/1/03
Date

Data Trends



WTI Price
Res/Prod.
OECD_INDEX
World_INDEX
US_INDEX
45.00
40.00
35.00
30.00
25.00
20.00
15.00
10.00
5.00
WTI ($/bbl), R/P
6
5
4
3
2
1
0
Index
Jan-80
Jan-82
Jan-84
Jan-86
Jan-88
Jan-90
Jan-92
Jan-94
Jan-96
Jan-98
Jan-00
Jan-02
Date

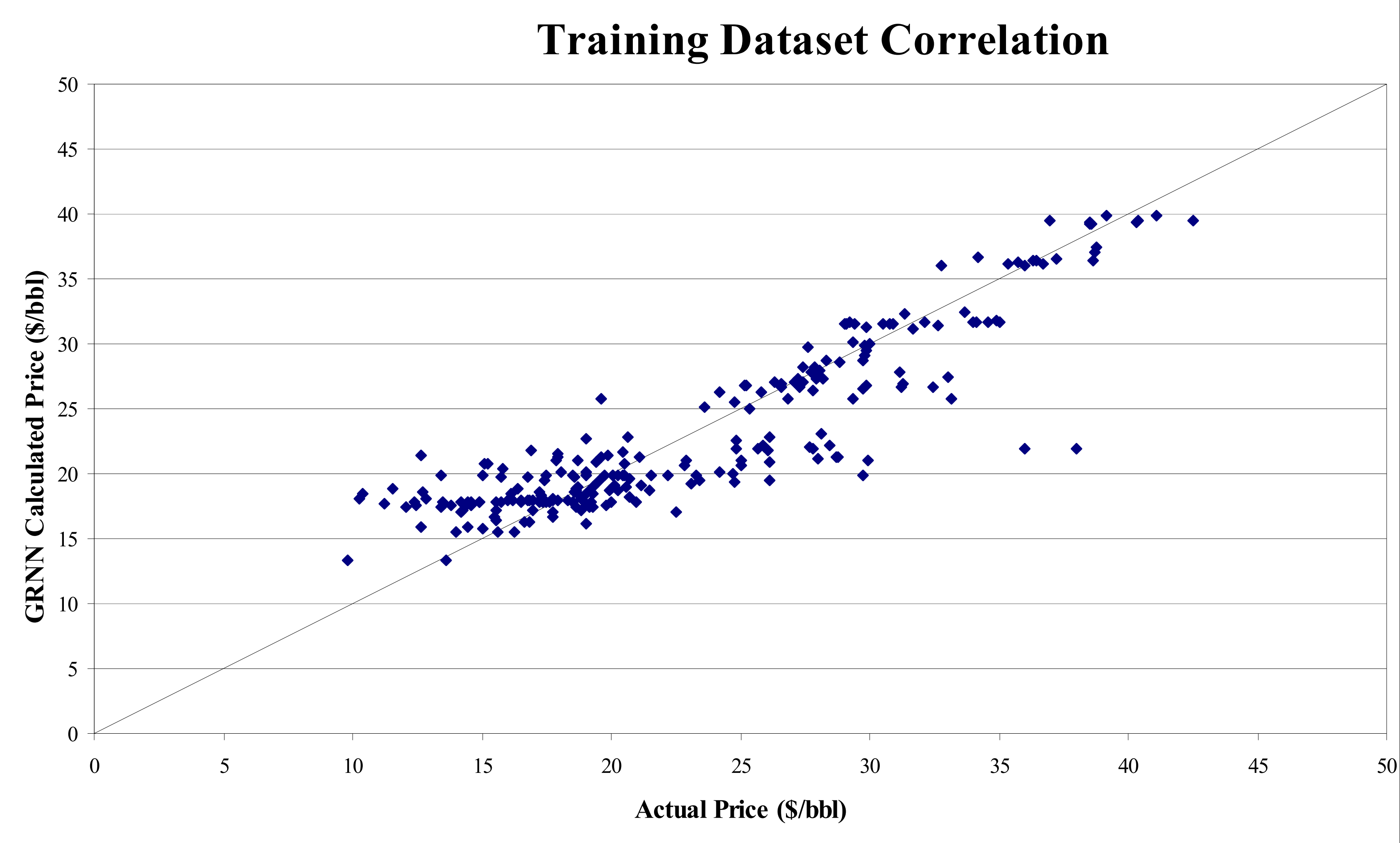
OLS Estimation and Results



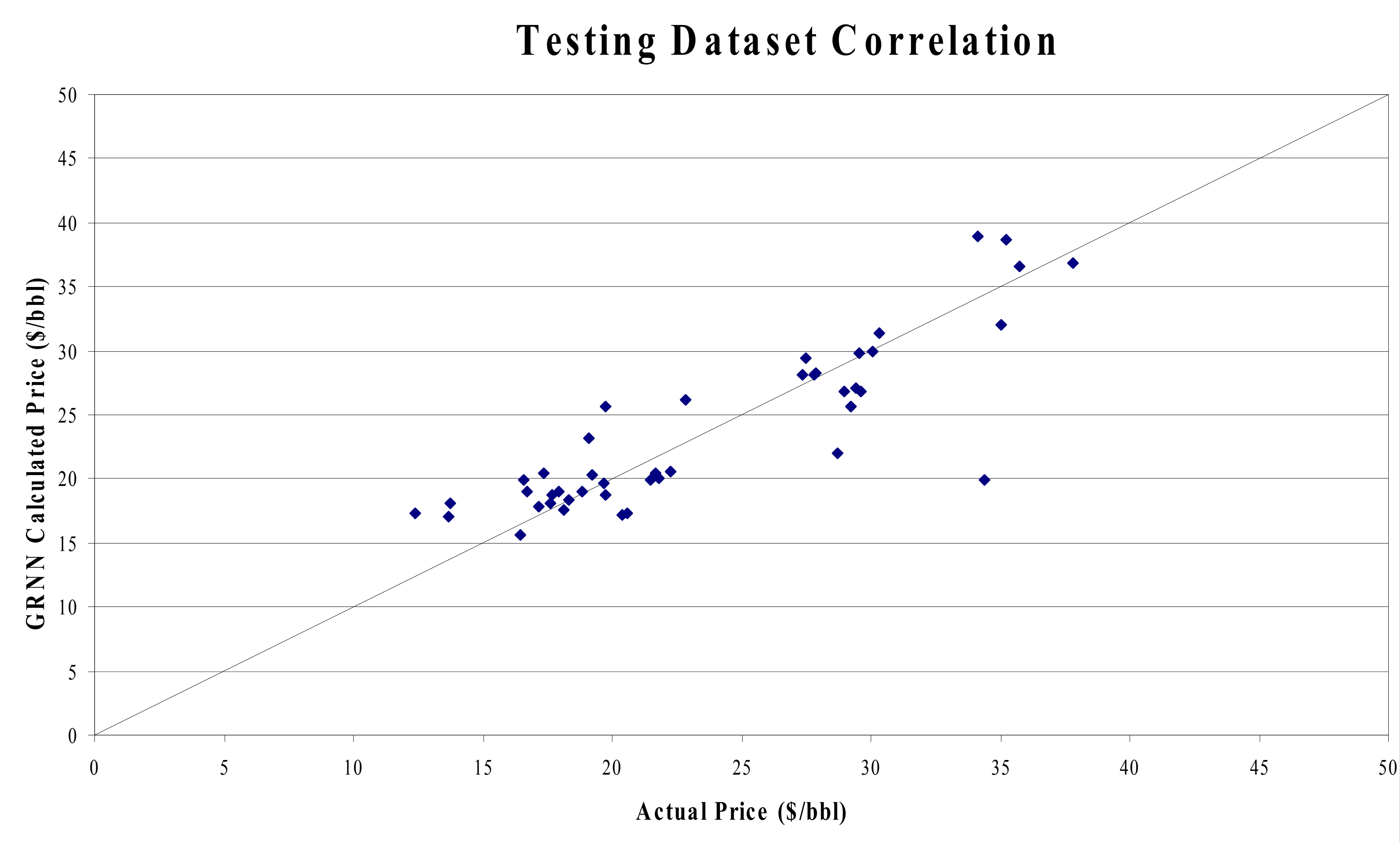
Model Estimation and Results

- OLS predictor target can be better enhanced using GRNN.

GNNN Estimation & Results



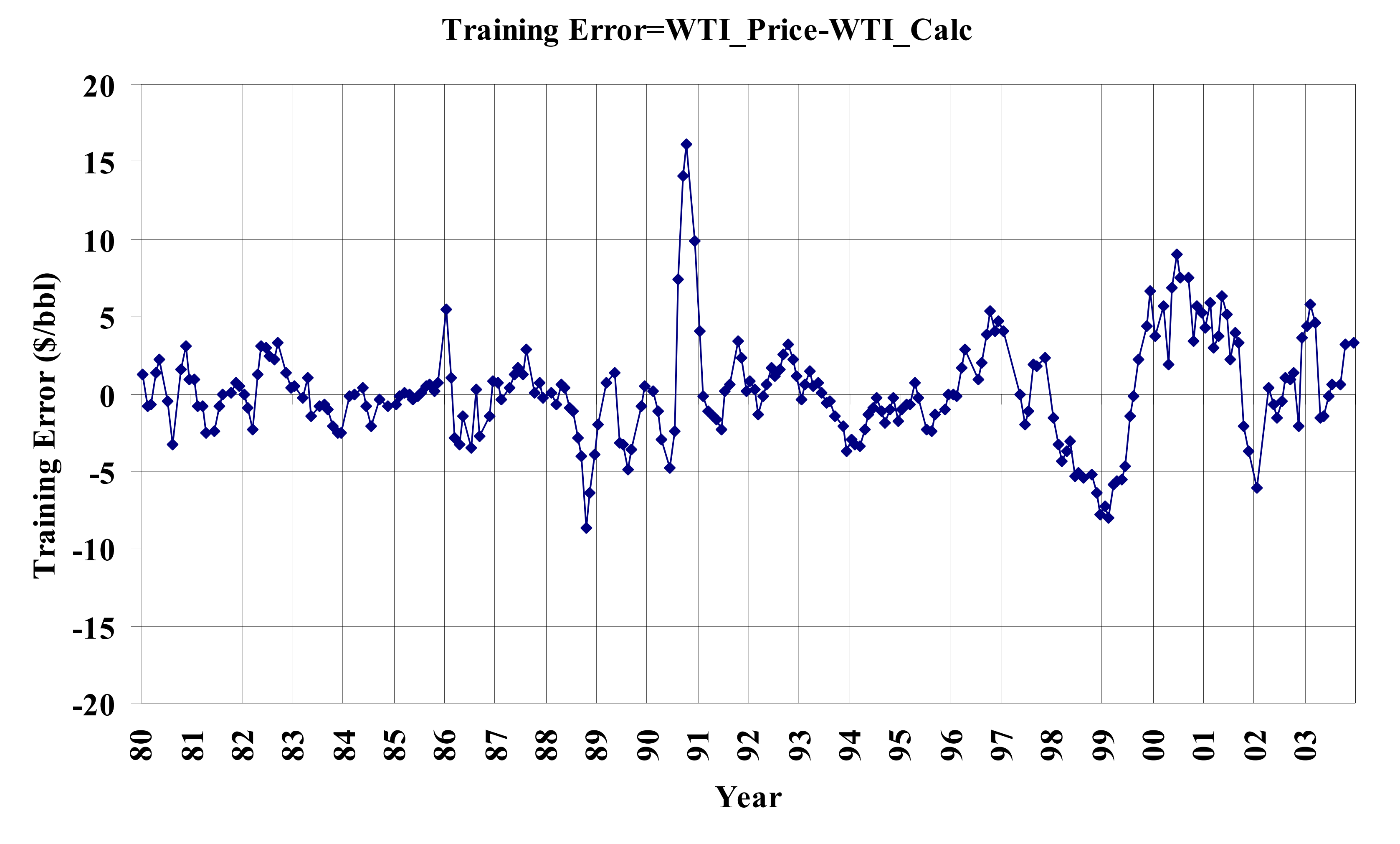
GNNN Estimation & Results



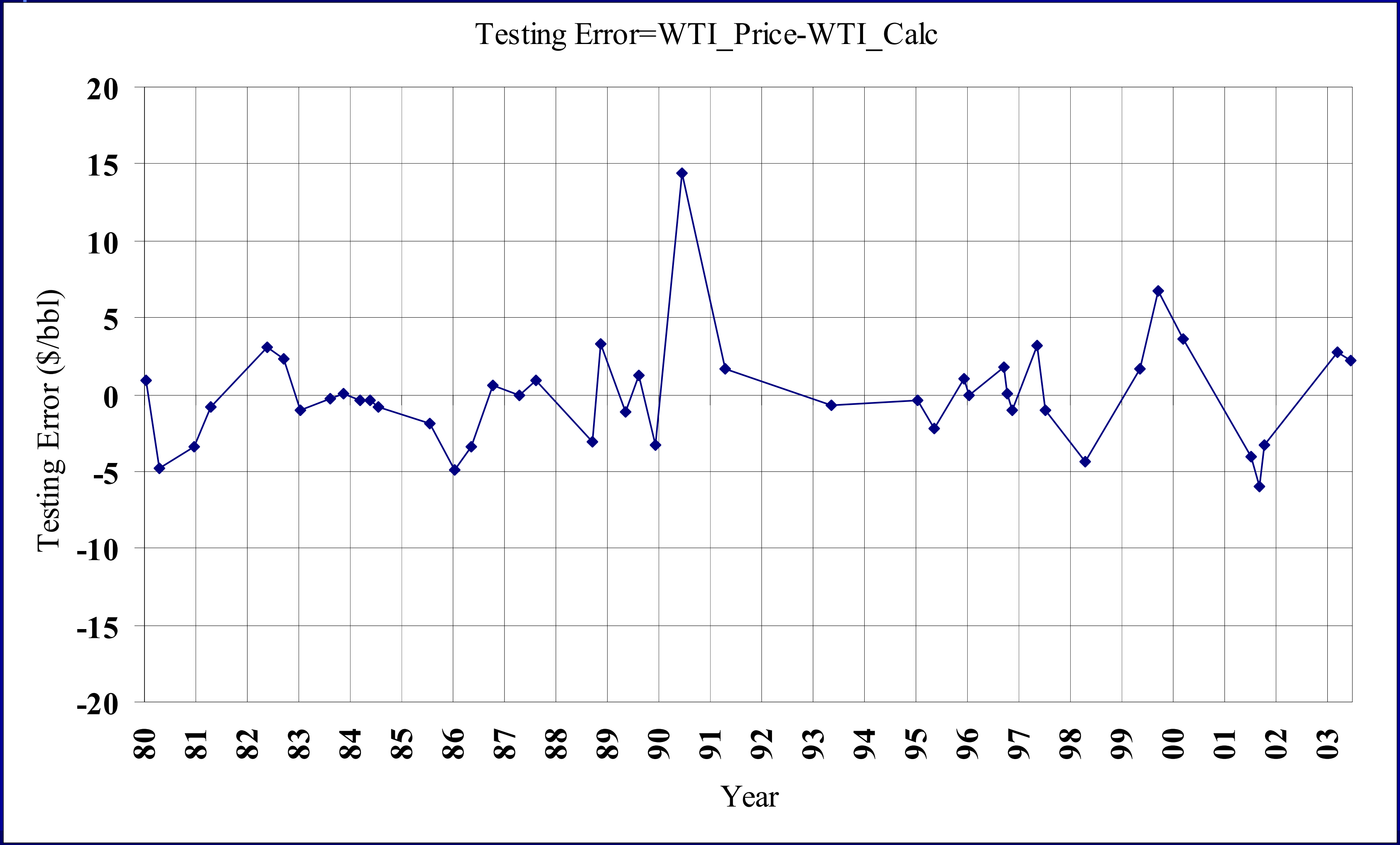
GRNN Estimation & Results

GRNN Performance		
Parameter	Training	Testing
R^2	0.8976	0.8666
SSE	2678.2807	516.6035
St.Dev.	3.3168	3.4659

GNNN Estimation & Results



GNNN Estimation & Results



Conclusion

- GRNN can predict crude oil prices with a reasonable degree of accuracy, taking into account different supply and demand levels in OECD Europe, WORLD and North America.
- The network captured with a better accuracy the correct behavior in comparison to the regular regression analysis. Although the data plots show good correlation between the input parameters and price data.
- Price driven indices were used in this study to show the effect of different factors on the behavior of crude prices