WEBINAR

Forecasting Petroleum Product Demand

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Ministry of Energy and Resources

March 21
12 P.M EDT

Moderator

Customer Engagement & Enablement Manager
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Thalia Anagnostou holds a Master's degree in Operational Research from the University of Edinburgh. After learning about the challenges and needs of data analysts in various industries and countries, Thalia has made it her mission to support data software users through webinar series, community events, and educational content. As a Customer Engagement and Enablement Manager at Lumivero, her goal is to support customers through webinar series and user group meetings focused on data science, qualitative research methods and scientific writing.

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Presenter

Dr. Kaase Gbakon, completed his PhD in Petroleum Economics, Management, and Policy with a focus on Energy Systems Modeling, and boasts an extensive background as a Senior Economist at the Ministry of Energy and Resources in Saskatchewan, Canada. With a wealth of experience, he held pivotal roles within the Nigerian National Oil Company including leading the Asset Evaluation and Economics group in Corporate Planning & Strategy, acting as the Lead Commercial in the ANOH Gas Processing Company (AGPC), and serving as a Senior Technical Assistant to the Chief Strategy Officer.

Kaase Gbakon Ph.D., Senior Forestry Economist at Ministry of Energy and Resources

AGENGA

1. Introduction
2. Aim and Objectives
3. Methodology
4. Result
5. Conclusion

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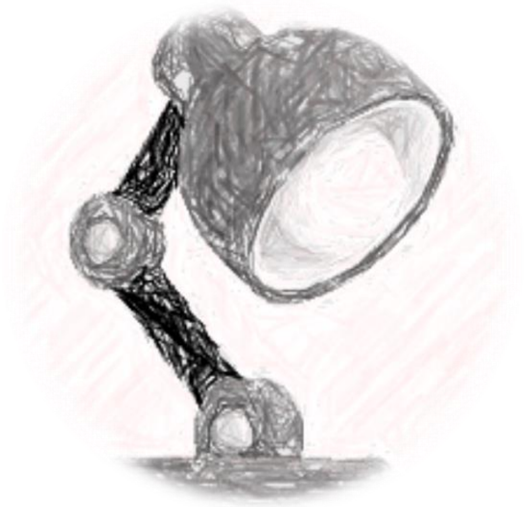
Introduction



- Product demand is a critical requirement for several analytical tasks such as:
  - To optimize integrated oil value chain
  - Refinery project planning
  - Supply planning
  - Budgeting
- Several approaches to model demand:
  - Econometric
  - Engineering end-use accounting
  - Single index methods (growth rates, elasticities..)
- These methods tend to result in "perfect foresight" demand forecasts
- Here, I focus on developing probabilistic time series models of refined product demand forecasts

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Aim & Objectives

AIM

To develop probabilistic time series forecasts of refined petroleum product demand using time series fit function within @RISK

OBJECTIVES

- Analyze historical refined product demand to ascertain the most representative time series model
- Based on the representative time series model, provide probabilistic demand forecasts
- Demonstrate the use of the @RISK Excel add-in software for modelling

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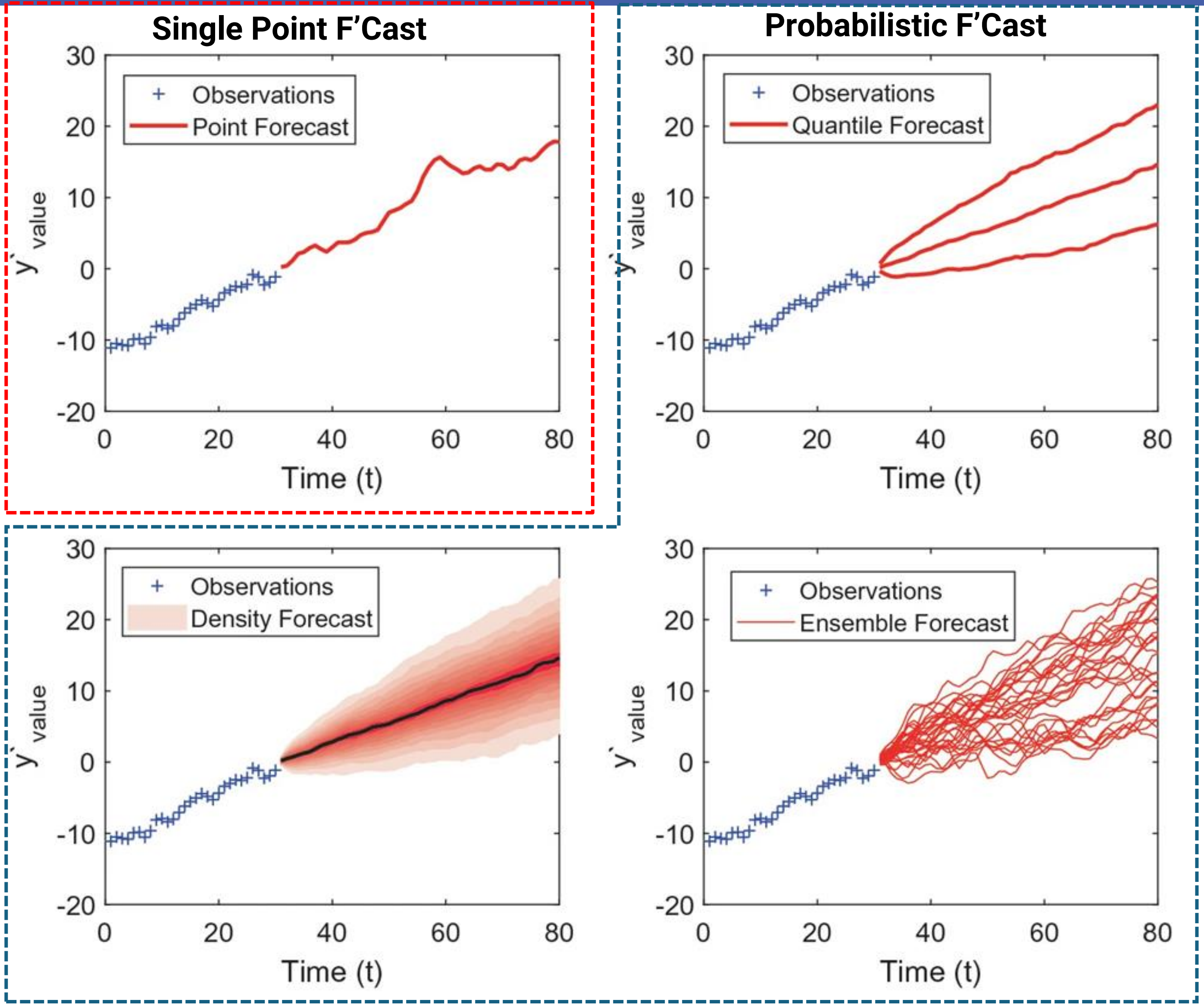
Methods‘ Classification

1 Statistical Method

2 Machine Learning Method



Statistical Methods
- Exponential smoothing
- Multivariate linear regression
- GARCH
- ARMA

Machine Learning Methods
- Neural networks
- Random forests

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Haben, S., Voss, M., Holderbaum, W., 2023. Time Series Forecasting: Core Concepts and Definitions. Springer, Cham. https://doi.org/10.1007/978-3-031-27852-5_5

Workflow Time Series Fit @RISK

A Historical demand data is extracted and loaded

Test for Stationarity

B Software plots the ACF and PACF to showcase presence or absence of stationarity

Is Series Stationary?

YES → **No Transformation**

NO → **Transform Series**

C Software transforms series to a stationary series by trying different transformation techniques (differencing, logs etc)

Fit Different Models

D Software estimates different time series models such as AR, MA (buffet of 13 models available to try)

Select Best Model based on AIC

E The models are ranked using the AIC criteria (other criteria such as BIC also provided)

F Probabilistic timeseries forecast is produced

Refined products demand analysed

1. LPG (propane)
2. PMS (gasoline)
3. DPK (Kerosene)
4. AGO (diesel)
5. Fuel Oil (FO)

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Steps to Conduct Time Series Forecast in @RISK using Time Series Fit

Refined Products‘ Historical Consumption

Year	LPG	PMS	DPK	AGO	Year	FO
1995	-	30.99	13.61	16.94	**1986**	7.11
1996	-	33.95	15.33	15.51	**1987**	8.83
1997	-	34.02	14.89	17.26	**1988**	12.80
1998	-	32.85	14.45	16.57	**1989**	12.55
1999	-	30.73	13.58	15.48	**1990**	12.87
2000	-	40.77	9.34	17.01	**1991**	13.71
2001	-	50.30	12.52	19.93	**1992**	11.11
2002	-	49.24	15.16	16.95	**1993**	10.54
2003	-	49.87	11.65	15.34	**1994**	10.09
2004	-	53.31	11.97	15.91	**1995**	10.76
2005	0.47	59.97	13.65	14.83	**1996**	5.09
2006	0.29	57.01	13.21	11.17	**1997**	12.18
2007	0.40	51.98	12.92	8.94	**1998**	7.78
2008	0.47	59.50	12.70	9.49	**1999**	11.58
2009	0.29	61.39	9.23	8.80	**2000**	12.22
2010	1.02	69.90	11.17	13.07	**2001**	11.40
2011	1.57	78.58	15.91	15.80	**2002**	9.90
2012	1.24	88.07	17.41	16.46	**2003**	14.50
2013	2.83	99.97	19.45	17.81	**2004**	5.99
2014	3.53	103.59	19.35	18.36	**2005**	8.75
2015	4.29	111.84	16.02	20.44	**2006**	8.12
2016	5.65	109.14	9.13	24.46	**2007**	7.06
2017	6.33	115.34	9.49	29.93	**2008**	5.78
2018	7.18	123.01	8.76	28.84	**2009**	7.24
2019	9.50	-	-	-	**2010**	9.48
2020	11.30	-	-	-		

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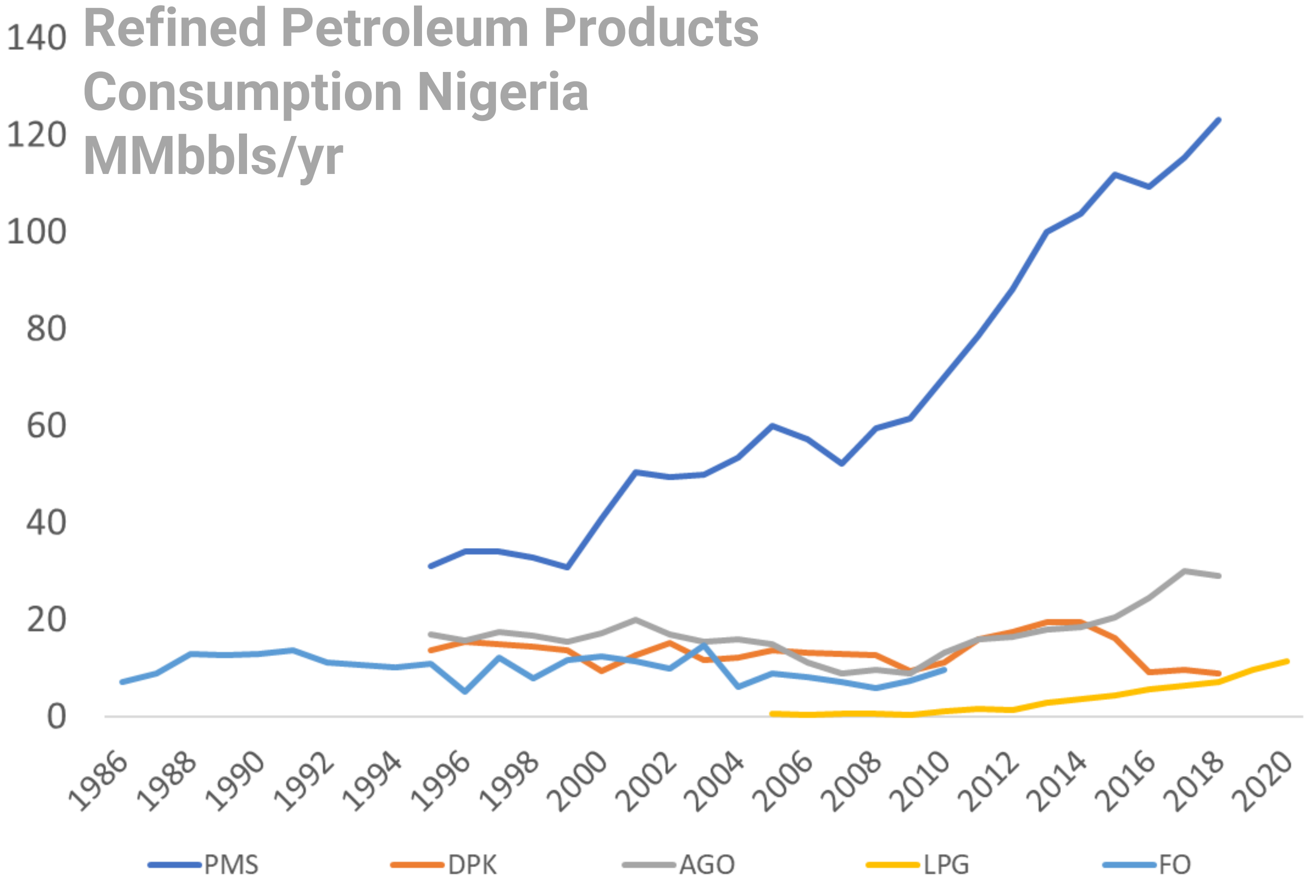

Historical LPG consumption between 2005 and 2020 is assembled from different sources.
2005 – 2012 data sourced from Global Data Watch; data for the years 2013, 2016, 2018, 2019, and 2020 sourced from diverse media reports of government press releases.
The missing data for the years 2014, 2015, and 2017 are interpolated
Historical data (1995 to 2018) of PMS (gasoline), DPK (kerosene), and AGO (diesel) from the NNPC ASB.
Historical FO (fuel oil) data (1986 to 2010) is obtained from the IEA.
Note that fuel oil demand data ends in 2010. In the absence of more recent data, this series is used as a basis for forecasting

Result: LPG Represented as Browninan Motion by AIC

Model	AR (1)	AR (2)	ARMA (1,1)	BMMR	BMMRJD
Data Transform	Auto Detect	Auto Detect	Auto Detect	Auto Detect	Auto Detect
Function	None	None	None	None	None
Shift	0	0	0	0	0
Detrend	None	None	None	None	None
Deseasonalize	None	None	None	None	None
Seasonal Period	N/A	N/A	N/A	N/A	N/A
Akaike (AIC) Rank	#4	#2	#3	#5	#1
Akaike (AIC) Fit	40.99	38.99	40.67	40.99	34.16
No. of Parameters	3	4	4	3	6
Parameter #1	μ	μ	μ	μ	μ
Value	3.60	3.62	3.63	3.60	7544.21
Parameter #2	σ	σ	σ	σ	σ
Value	0.76	0.65	0.69	0.77	0.57
Parameter #3	a1	a1	a1	α	α
Value	0.97	1.47	0.95	0.03	0.00
Parameter #4		a2	b1		λ
Value		-0.52	0.41		0.00
Parameter #5					μ Jump
Value					1173.65
Parameter #6					σ Jump
Value					20.69

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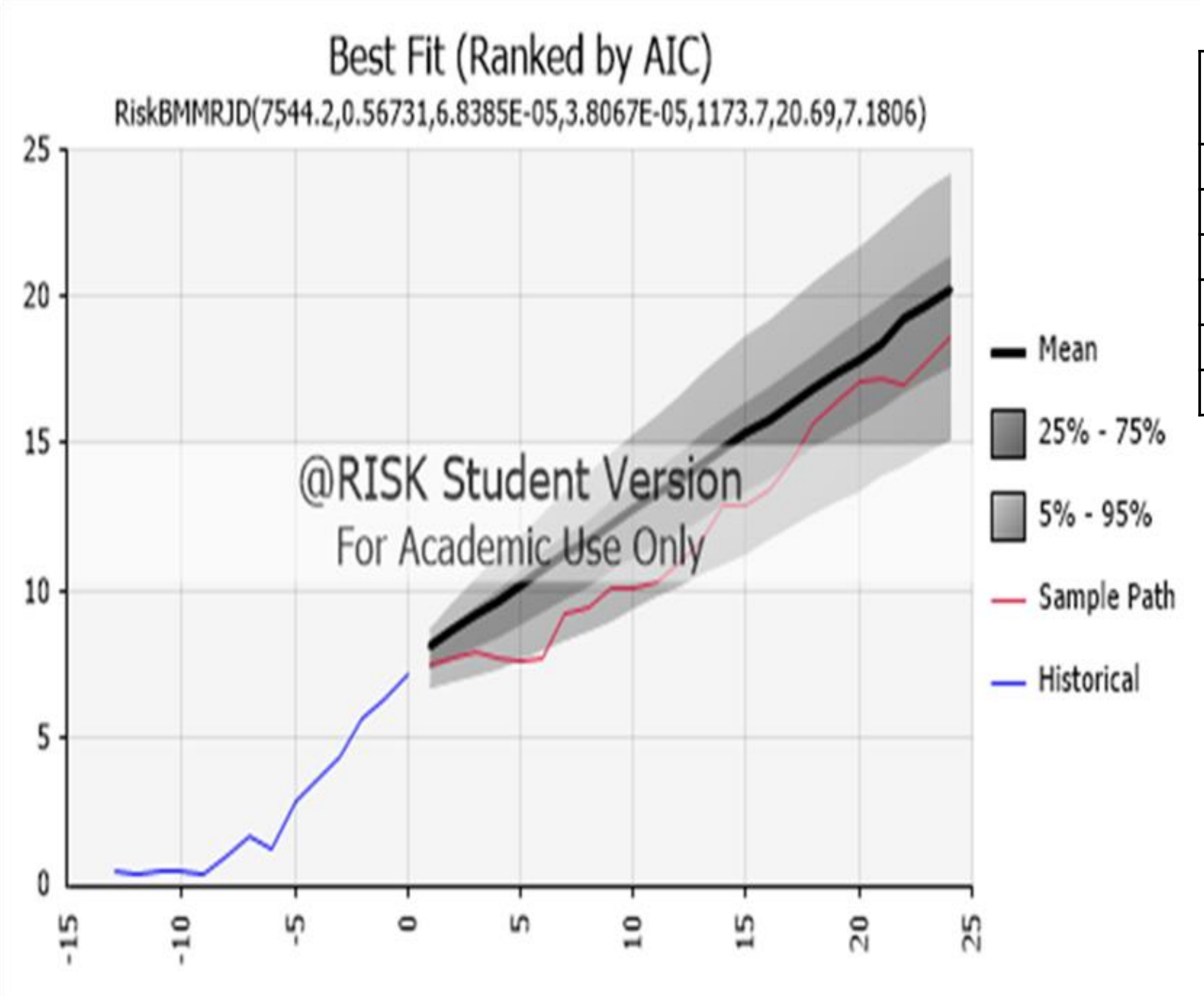
Result: LPG demand forecast to increase to 20MMbbls/yr



Period	Minimum	Maximum	Mean	Std. Deviation	1%	99%
1	5.8217	9.72	7.69	0.57	6.3482	9.0316
5	5.1704	1,185.21	10.00	16.67	6.7624	12.7529
9	5.9593	1,184.74	12.32	23.27	7.8059	15.8961
14	6.948	1,187.17	14.87	23.32	9.264	19.392
19	8.254	1,190.35	17.45	23.37	10.981	22.823
24	9.103	1,192.68	20.06	23.38	12.985	25.928

LPG mean demand is forecast to increase to 20 MMbbls by the 24th period after the historical data ends

Demand ranges from ~ 15 MMbbls to 24 MMbbls by 24^{th} period (i.e. 5^{th} and 95^{th} percentile respectively)

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Result: PMS best represented as ARCH (1) Model by AIC

Model	**AR (1)**	**MA (1)**	**BMMR**	**ARCH (1)**	**GARCH (1,1)**
Data Transform	Auto Detect	Auto Detect	Auto Detect	Auto Detect	Auto Detect
Function	None	None	None	None	None
Shift	0	0	0	0	0
Detrend	First Order	First Order	First Order	First Order	First Order
Deseasonalize	None	None	None	None	None
Seasonal Period	N/A	N/A	N/A	N/A	N/A
Akaike (AIC) Rank	#4	#3	#5	#1	#2
Akaike (AIC) Fit	143.92	143.84	143.92	139.20	141.20
No. of Parameters	3	3	3	3	4
Parameter #1	μ	μ	μ	μ	μ
Value	4.02	4.02	4.02	3.91	3.91
Parameter #2	σ	σ	σ	ω	ω
Value	4.85	4.84	9.46	18.48	18.48
Parameter #3	a1	b1	α	a1	a1
Value	0.16	0.17	1.86	0.29	0.29
Parameter #4					b1
Value					3.44E-15
Parameter #5					
Value					
Parameter #6					
Value					

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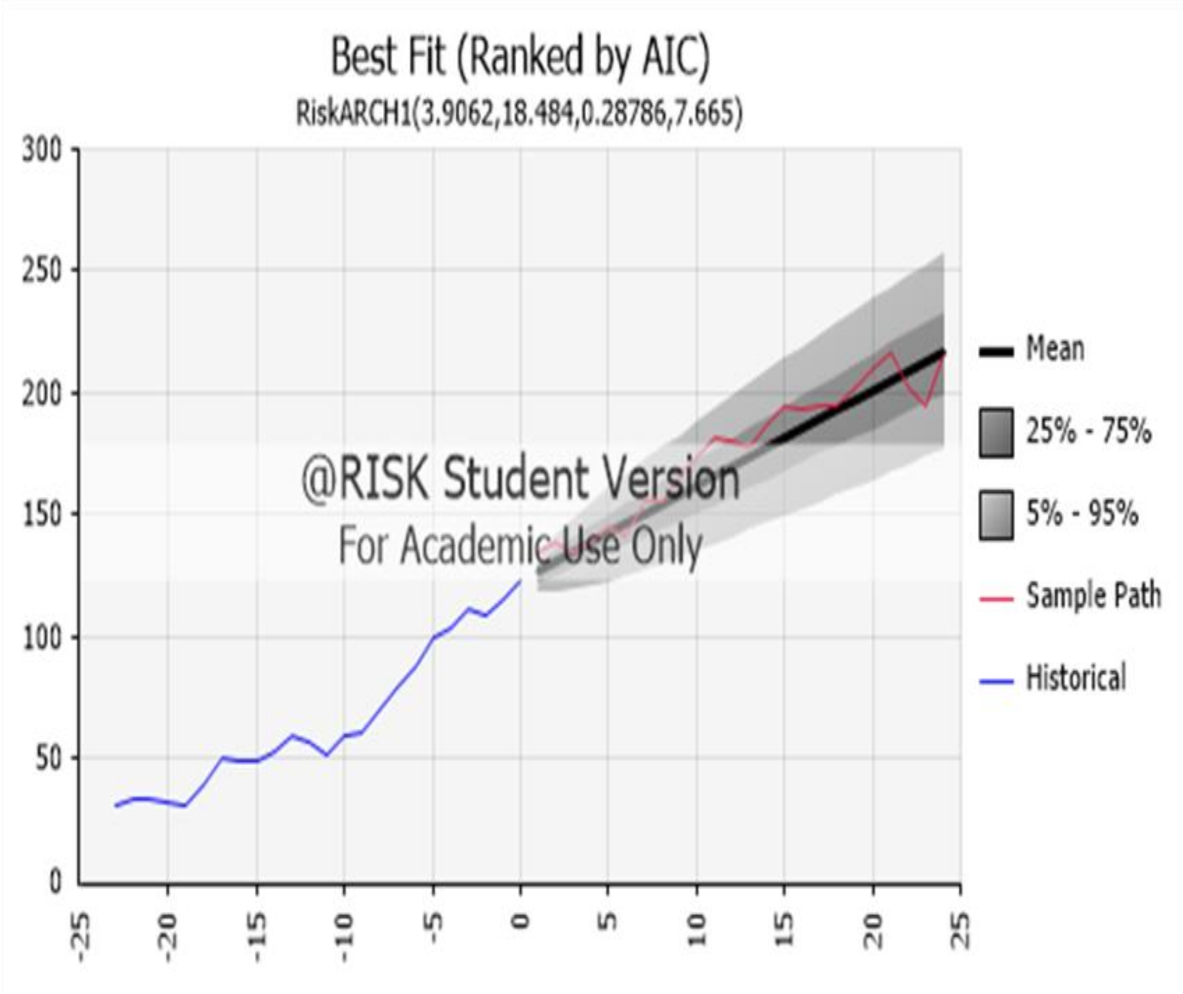
Result: Gasoline demand increases to 220 MMbbls/yr



Period	Minimum	Maximum	Mean	Std. Deviation	1%	99%
1	108.534	142.729	126.849	4.778	115.589	137.723
5	87.634	238.769	142.461	11.473	115.237	171.149
9	97.572	253.899	158.193	15.296	121.933	195.623
14	87.834	265.760	177.746	19.134	131.606	223.985
19	105.68	302.27	197.09	22.22	144.55	252.03
24	121.72	312.29	216.79	24.94	156.38	278.45

Gasoline mean forecast demand is expected to increase from 127 MMbbls to ~ 220 MMbbls over 24 periods (or years)

Demand ranges from ~ 175 MMbbls to ~250 MMbbls by 24th period (i.e. 5th and 95th percentile respectively)

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Result: DPK (Kerosene) best represented as MA (1) by AIC

Model	AR (1)	AR (2)	MA (1)	MA (2)	ARMA (1,1)
Data Transform	Auto Detect	Auto Detect	Auto Detect	Auto Detect	Auto Detect
Function	None	None	None	None	None
Shift	0	0	0	0	0
Detrend	None	None	None	None	None
Deseasonalize	None	None	None	None	None
Seasonal Period	N/A	N/A	N/A	N/A	N/A
Akaike (AIC) Rank	#5	#2	#1	#4	#3
Akaike (AIC) Fit	115.81	113.41	112.53	113.99	113.80
No. of Parameters	3	4	3	4	4
Parameter #1	μ	μ	μ	μ	μ
Value	13.12	13.29	13.20	13.18	13.14
Parameter #2	σ	σ	σ	σ	σ
Value	2.36	2.14	2.14	2.16	2.15
Parameter #3	a1	a1	b1	b1	a1
Value	0.61	0.85	0.92	0.91	0.29
Parameter #4		a2		b2	b1
Value		-0.42		0.21	0.66
Parameter #5					
Value					
Parameter #6					
Value					

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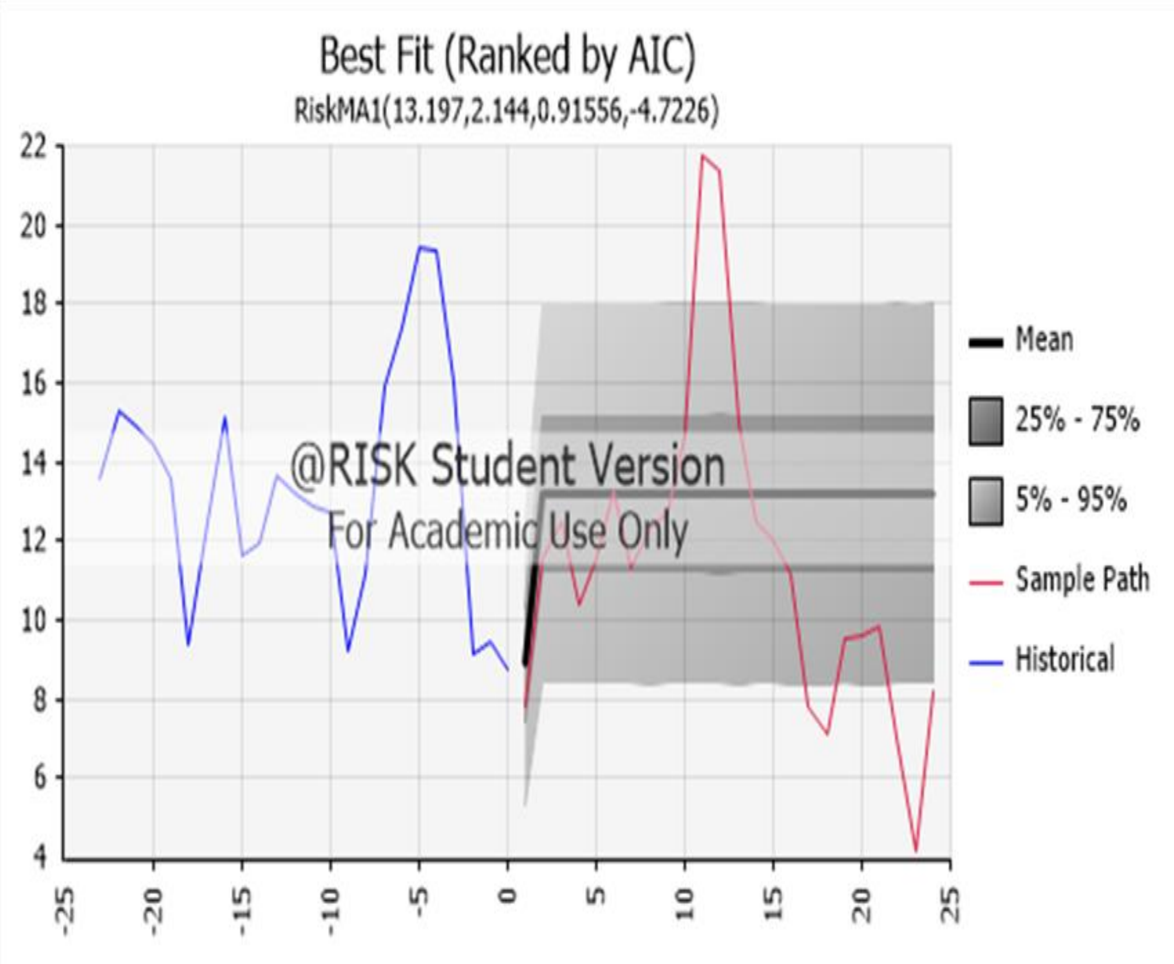
Result: Kerosene demand reaches 13 MMbbls/yr



Period	Minimum	Maximum	Mean	Std. Deviation	1%	99%
1	0.6963	16.4171	8.8620	2.1078	3.9071	13.5238
5	4.237	23.017	13.130	2.907	6.544	20.044
9	3.700	24.852	13.186	2.899	6.624	20.168
14	1.517	23.791	13.237	2.901	6.199	19.939
19	3.417	23.643	13.185	2.923	6.435	20.080
24	3.103	24.366	13.134	2.923	6.159	19.874

Kerosene mean forecast demand is expected to increase from ~9 MMbbls to ~ 13 MMbbls over 24 periods (or years)

Kerosene demand forecast lies between ~ 8 MMbbls and 18 MMbbls by 24th period (i.e. 5th and 95th percentile respectively)

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Result: AGO (diesel) best represented by ARCH (1)

Model	AR (1)	MA (1)	BMMR	ARCH (1)	GARCH (1,1)
Data Transform	Auto Detect	Auto Detect	Auto Detect	Auto Detect	Auto Detect
Function	None	None	None	None	None
Shift	0	0	0	0	0
Detrend	First Order	First Order	First Order	First Order	First Order
Deseasonalize	None	None	None	None	None
Seasonal Period	N/A	N/A	N/A	N/A	N/A
Akaike (AIC) Rank	#5	#3	#4	#1	#2
Akaike (AIC) Fit	108.00	107.26	108.00	104.97	106.97
No. of Parameters	3	3	3	3	4
Parameter #1	μ	μ	μ	μ	μ
Value	0.46	0.41	0.46	0.61	0.61
Parameter #2	σ	σ	σ	ω	ω
Value	2.22	2.18	3.66	3.69	3.69
Parameter #3	a1	b1	α	a1	a1
Value	0.29	0.42	1.25	0.35	0.35
Parameter #4					b1
Value					1.02E-15
Parameter #5					
Value					
Parameter #6					
Value					

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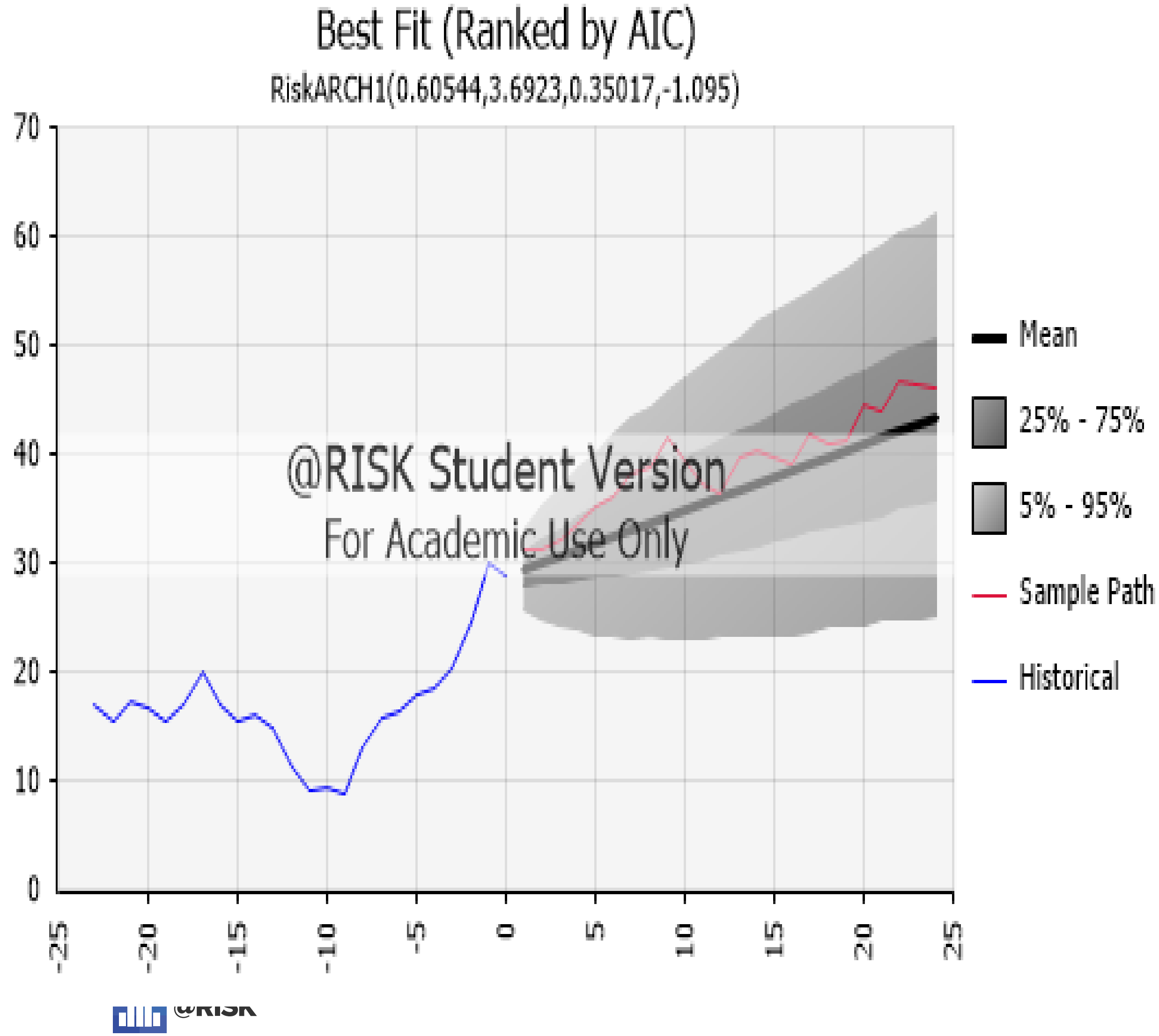
Result: AGO (diesel) best represented by ARCH (1)



Period	Minimum	Maximum	Mean	Std. Deviation	1%	99%
1	19.438	39.561	29.444	2.204	24.336	34.634
5	5.949	53.543	31.910	5.206	18.799	44.598
9	-12.519	69.148	34.363	7.076	17.220	51.631
14	-10.374	73.656	37.193	8.989	15.914	58.714
19	-10.849	81.053	40.329	10.378	15.679	64.989
24	-10.061	87.814	43.406	11.698	16.228	70.359

diesel mean forecast demand is expected to increase from ~30 MMbbls to ~ 43 MMbbls over 24 periods (or years)

After 24 periods (years), the mean diesel demand forecast ranges from 25 MMbbls to 60 MMbbls i.e. 5th to 95th percentile

Result: FO (fuel oil) best represented by ARCH (1)

Model	**AR (1)**	**AR (2)**	**MA (2)**	**ARCH (1)**	**GARCH (1,1)**
Data Transform	Auto Detect	Auto Detect	Auto Detect	Auto Detect	Auto Detect
Function	None	None	None	None	None
Shift	0	0	0	0	0
Detrend	None	None	None	None	None
Deseasonalize	None	None	None	None	None
Seasonal Period	N/A	N/A	N/A	N/A	N/A
Akaike (AIC) Rank	#5	#4	#3	#1	#2
Akaike (AIC) Fit	123.35	122.75	121.70	119.45	121.40
No. of Parameters	3	4	4	3	4
Parameter #1	μ	μ	μ	μ	μ
Value	9.86	9.72	9.77	10.01	10.02
Parameter #2	σ	σ	σ	ω	ω
Value	2.53	2.39	2.32	6.52	6.24
Parameter #3	a1	a1	b1	a1	a1
Value	0.20	0.14	-0.09	0.01	1.26E-15
Parameter #4		a2	b2		b1
Value		0.32	0.57		0.11
Parameter #5					
Value					
Parameter #6					
Value					

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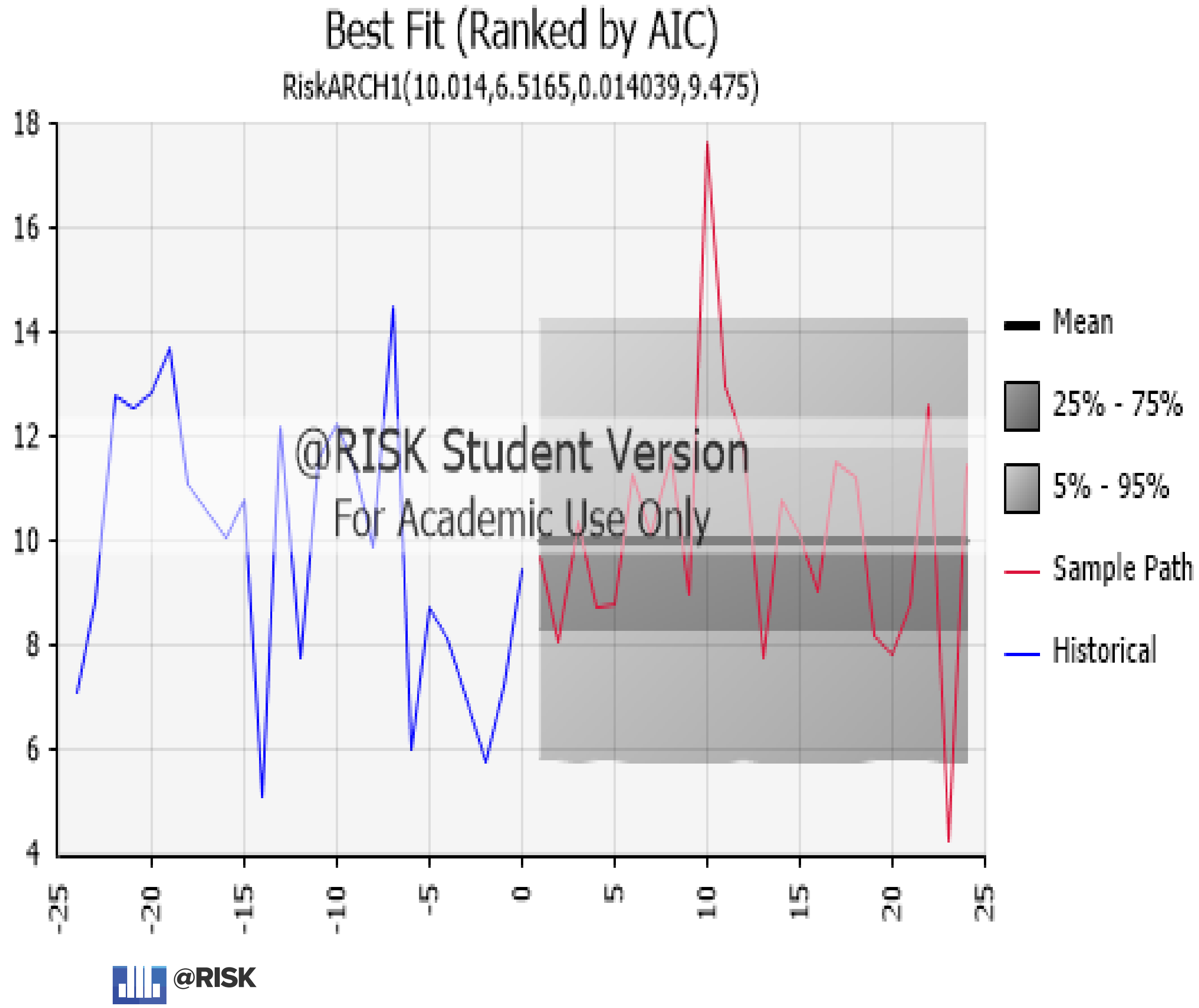
Result: Mean fuel oil demand 10 MMbbls/yr



Period	Minimum	Maximum	Mean	Std. Deviation	1%	99%
1	1.349	19.630	9.998	2.525	4.046	15.767
5	0.794	19.116	9.976	2.567	3.922	16.101
9	-0.101	19.630	10.056	2.576	4.159	16.001
14	0.406	19.766	9.979	2.564	4.011	16.068
19	-0.854	19.258	10.019	2.547	4.232	15.807
24	0.624	19.323	10.047	2.586	4.184	15.999

mean forecast demand is expected to keep stable at ~ 10 MMbbls/yr over 24 periods (or years)

After 24 periods (years), the mean diesel demand forecast ranges from 6 MMbbls to 14 MMbbls (i.e. 5th and 95th percentile respectively)

Result: Summary of Demand Time Series

S/N	Product	Model Process	Specification of Arguments
1	LPG (propane)	Brownian Motion with Mean Reversion Jump Diffusion $\boldsymbol{BMMRJD(\mu, \sigma, \alpha, \lambda, \mu_j, \sigma_j, Y_O)}$	μ = 7544.21 σ = 0.00 α = 0.00 λ = 0.00 μ_j = 1173.65 σ_j = 20.69 Y_O = 11.3
2	PMS (gasoline)	Auto – Regressive Conditional Heteroskedasticity of a first order $\boldsymbol{ARCH1(\mu, \omega, \alpha_1, Y_O)}$	μ =3.91 ω = 18.48 α_1= 0.29 Y_O = 7.665
3	DPK (kerosene)	Moving Average of first order $\boldsymbol{MA(\mu, \sigma, b_1, \varepsilon_O)}$	μ = 13.20 σ = 2.14 b_1 = 0.92 ε_O = -4.7226
4	AGO (diesel)	Auto – Regressive Conditional Heteroskedasticity of a first order $\boldsymbol{ARCH1(\mu, \omega, \alpha_1, Y_O)}$	μ =0.61 ω = 3.69 α_1= 0.35 Y_O = -1.095
5	FO (fuel oil)	Auto – Regressive Conditional Heteroskedasticity of a first order $\boldsymbol{ARCH1(\mu, \omega, \alpha_1, Y_O)}$	μ =10.01 ω = 6.52 α_1= 0.01 Y_O = 9.475

Brownian

$\boldsymbol{\mu}$ is drift, $\boldsymbol{\sigma}$ is volatility, $\boldsymbol{\alpha}$ is the speed of reversion, $\boldsymbol{\lambda}$ is the jump rate, $\boldsymbol{\mu_j}$ is the jump size mean, $\boldsymbol{\sigma_j}$ is the jump size standard deviation, and $\boldsymbol{Y_O}$ is the value of the data feed at time 0.

MA

$\boldsymbol{\mu}$ is the mean, $\boldsymbol{\sigma}$ is the volatility parameter, $\boldsymbol{\alpha_1}$ is the moving average coefficient, and $\boldsymbol{\varepsilon_O}$ is the initial error term

ARCH

$\boldsymbol{\mu}$ is the mean, $\boldsymbol{\omega}$ is the volatility parameter, $\boldsymbol{\alpha_1}$ is the error coefficient, and $\boldsymbol{Y_O}$ is the value of data feed at time 0.

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Technical details on @RISK here: https://tinyurl.com/ybxww66m

Result: Summary of Demand Time Series

Forecasts of Mean Refined Petroleum Product Demand in MMbbls/annum

F'Cast Period	LPG	PMS	DPK	AGO	FO
1	8.12	126.91	8.86	29.44	10.01
5	10.18	142.55	13.20	31.87	10.01
9	12.24	158.19	13.20	34.30	10.01
14	14.81	177.73	13.20	37.33	10.01
19	17.39	197.28	13.20	40.37	10.01
24	20.25	216.82	13.20	43.41	10.01

Background: Use Case for Probabilistic Time Series Forecasting

Challenge

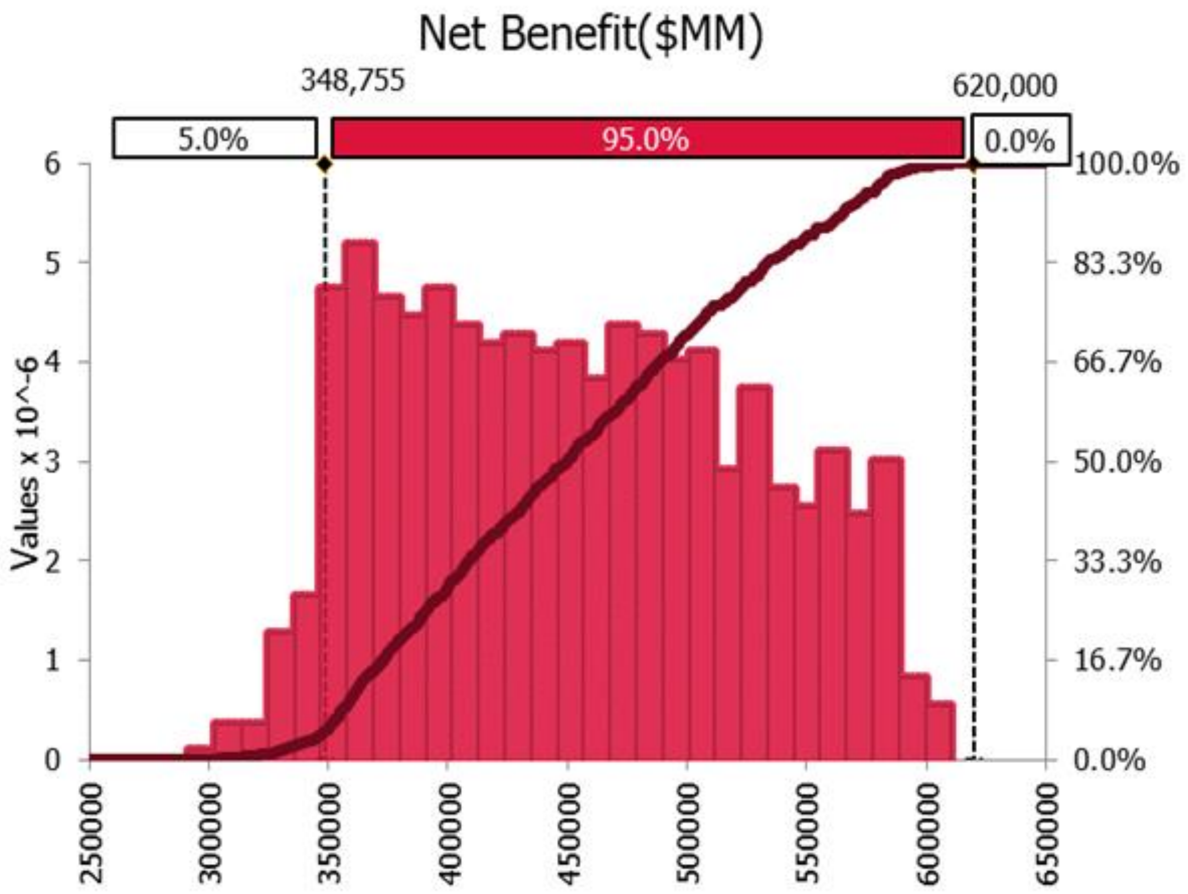
To ascertain the optimal allocation of projected oil production and refined products to meet demand under three scenarios representing possible versions of the future

Deterministic Solution

- The optimization framework for optimal oil and product utilization is developed.
- Three scenarios are defined using deterministic inputs such as:
  - oil production
  - domestic product demand
  - energy prices
  - domestic refining capacity
- This enabled the deterministic solution under each of the three scenarios

…But the BIG question of uncertainty remains, especially as it pertains to the time dependent product (energy) demand

Result: Use Case for Probabilistic Time Series Forecasting



Note: The probabilistic outcome includes other stochastic variables other than the probabilistic demand forecasts

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Gbakon, K., Ajienka J., Iledare O., Gogo, J., 2022, *Optimal Allocation of Future Oil Production under Uncertainty: Lessons from Nigeria for Emerging Oil Producing Countries*, The International Journal of Science & Technoledge ISSN 2321 – 919X. Vol 10 Issue 9 DOI No.:10.24940/theijst/2022/v10/i9/ST2209-001 September, 2022

Scenario	Net Benefit ($ billion)	Likelihood P (X<Net Benefit)
Energy Transition	192	0%
Stated Policy	718	100%
Business as Usual	423	40%

- Under three deterministic scenarios, the net benefits calculated are compared to the likelihood of their occurrence as adjudged from the stochastic simulation
- Each scenario included a “perfect foresight” outlook for refined product demand
- The median net benefit is ~ $450 billion

Demonstration

Key concluding points

- Harnessed the value of probabilistic time series forecasting to capture uncertainty. Developed statistical time series forecasts for five refined products providing a probability range within which predictive values can lie

- Select the best statistical demand model for each refined product based on historical trend, and then project probabilistic future values based on the selected models

- Probabilistic forecast is an important component of optimizing the allocation of future oil production to meet demand for these products

- Probabilistic forecasts to reflect uncertainty and ultimately deliver more robust optimization results.

Questions?

Free Learning Resources

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The Data Landscape

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