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Title:	**Forecasting Methods in Oil&Gas Sector. Optimised Theta Model and Application on Annual Oil and Gas Demand Data of European Countries**
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Παράβαση της ανωτέρω ακαδημαϊκής μου ευθύνης αποτελεί ουσιώδη λόγο για την ανάκληση του πτυχίου μου».

Χρήστος Ηλιόπουλος

Ο Δηλών

ABSTRACT

In this thesis, forecasting methods in Oil&Gas industry are studied, relying on historical data. Focus is given on oil and gas yearly demand of European countries and the Theta Model is used, a time series extrapolative forecasting method that topped the M3-Competition 20 years ago, the largest empirical forecasting competition till that date; and performed very good in the recent M4-Competition in 2018. Annual historical data are used, taken from iea and Rystad, from 1990 to 2018 and the Theta method is applied to all time series using a simple excel spreadsheet to construct the model. The fit, as well as the accuracy of the method for the 2019 demand value, are measured with sMAPE and are compared to a benchmark of three simple commonly used methods (Naive, MA3, MA5) and two ready forecasting methods of excel (FRC.LIN, FRC.ETS).

The Theta Model is then optimised for each time series using Solver in Excel in order to define the combination of parameters, number of θ lines, value of each θ and weight in the forecast, that offer the best fit, through sMAPE minimization. This combination is used to forecast the 2019 demand value and forecast error is measured. Finally, we forecast the annual demand until 2024 and compare it with the respective forecasts of Rystad that we have in our possession. The excel spreadsheet that simulates the above and adjusts the respective calculations on data entered by the user, can act as a general free tool for country annual oil&gas demand forecasting, achieving very good point forecasts, without complex calculations or effort need to be done by the user. This tool, in which annual data are simply placed as input and a button is pressed so that Solver automatically extracts the best describing Theta model for the data entered, minimizes error and gives us reliable forecast. Thus, it can be used by users who desire to forecast oil or gas annual demand.

In each case, the model is driven by the amount and differentiation of annual input data and the minimization of total sMAPE of forecasts and results are verified by the optimisation tool Solver.

Keywords

Forecasting, Oil, Gas, Theta Model, sMAPE, optimisation, Solver, extrapolation, θ lines, time series, quantitative method, demand forecast, annual data, energy demand

ΠΕΡΙΛΗΨΗ

Στην παρούσα διπλωματική εργασία μελετώνται μέθοδοι πρόβλεψης στον κλάδο των υδρογονανθράκων, στηριζόμενοι σε παρελθοντικά δεδομένα. Γίνεται επικέντρωση στην ετήσια ζήτηση πετρελαίου και αερίου Ευρωπαϊκών χωρών και χρησιμοποιείται η μέθοδος Theta, μία μέθοδος αποσύνθεσης και προεκβολής χρονοσειρών που κυριάρχησε στον M3-Διαγωνισμό 20 χρόνια πριν, τον μεγαλύτερο εμπειρικό διαγωνισμό προβλέψεων μέχρι τότε και απέδωσε αρκετά καλά στον πρόσφατο M4-Διαγωνισμό το 2018. Χρησιμοποιούνται ετήσια ιστορικά δεδομένα ζήτησης, αντλημένα από την iea και την Rystad, από το 1990 μέχρι το 2018 και εφαρμόζεται η μέθοδος Theta σε όλες τις χρονοσειρές χρησιμοποιώντας απλό υπολογιστικό φύλλο ecxel για την κατασκευή του μοντέλου. Τόσο η προσαρμογή (fit) σε όλη την χρονοσειρά, όσο και η ακρίβεια της μεθόδου για την ζήτηση του 2019, μετρούνται με το σφάλμα sMAPE και συγκρίνονται με τρεις απλές ευρέως χρησιμοποιούμενες μεθόδους (Naive, KMO3, KMO5) και δύο έτοιμες προς χρήση μεθόδους πρόβλεψης του Excel (FRC.LIN, FRC.ETS).

Στην συνέχεια βελτιστοποιείται το μοντέλο Theta για την χρονοσειρά κάθε χώρας, με χρήση του Solver στο Excel, ώστε να καθοριστούν οι παράμετροι, ο αριθμός γραμμών θ, η τιμή του ή των θ και η συνεισφορά (βάρος) κάθε γραμμής στην τελική πρόβλεψη, που δίνουν την καλύτερη προσαρμογή στα δεδομένα, ήτοι ελαχιστοποιούν το sMAPE. Αυτός ο συνδυασμός χρησιμοποιείται για να προβλεφθεί η τιμή ζήτησης του 2019 και μετράται το σφάλμα πρόβλεψης επίσης με το sMAPE. Τέλος, εκτελούνται προβλέψεις με το βελτιστοποιημένο μοντέλο Theta μέχρι το 2024 και συγκρίνονται με τις αντίστοιχες της Rystad σε χώρες για τις οποίες έχουμε δεδομένα στην διάθεσή μας. Το υπολογιστικό φύλλο που προσομοιώνει τα ανωτέρω και προσαρμόζει τους εκάστοτε υπολογισμούς και παραμέτρους στα δεδομένα που εισάγονται από τον χρήστη, μπορεί να λειτουργήσει ως γενικό ελεύθερο εργαλείο για πρόβλεψη εθνικής ετήσιας ζήτησης πετρελαίου και αερίου, επιτυγχάνοντας αξιόπιστες σημειακές προβλέψεις, χωρίς περίπλοκους υπολογισμούς ή καταβολή προσπάθειας από τον χρήστη. Το εργαλείο αυτό, στο οποίο εισάγονται απλά ετήσια δεδομένα και με το πάτημα ενός κουμπιού εξάγεται αυτόματα μέσω του Solver το μοντέλο Theta που προσαρμόζεται βέλτιστα στην εκάστοτε χρονοσειρά, ελαχιστοποιεί το σφάλμα και παρέχει αξιόπιστες

προβλέψεις. Οπότε, μπορεί να χρησιμοποιηθεί από χρήστες που επιθυμούν να προβλέψουν ετήσια ζήτηση πετρελαίου ή αερίου.

Το μοντέλο οδηγείται από τον αριθμό και διαφοροποίηση των ετήσιων δεδομένων εισόδου με στόχο την ελαχιστοποίηση του συνολικού sMAPE των προβλέψεων και τα αποτελέσματα επαληθεύονται από το εργαλείο βελτιστοποίησης Solver.

Λέξεις - Κλειδιά

Τεχνικές Προβλέψεων, Μοντέλο Theta, sMAPE, γραμμές θ, βελτιστοποίηση, Solver, πετρέλαιο, αέριο, πρόβλεψη ζήτησης, ετήσια δεδομένα

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GLOSSARY OF TERMS AND ACRONYMS

AI	Artificial Intelligence
ANN	Artificial Neural Network
ARIMA	Auto Regressive Integrated Moving Average
ARMA	Auto Regressive Moving Average
ARX	Autoregressive with Exogenous Terms
bcm	billion cubic meters
b/d	Barrels per Day
CC	Correlation Coefficient
CO_2	Carbon Dioxide
DEPA	Public Gas Corporation
DNV	Det Norske Veritas
ECD	Economic Cooperation and Development
eia	Energy Information Administration
ES	Exponential Smoothing
EU	European Union
FARX	Fuzzy Autoregressive with Extra Inputs
GA	Genetic Algorithm
GHG	Greenhouse Gas
GM	Grey Model
HEDN	Hellenic Electricity Distribution Network Operator
iea	International Energy Agency
IGB	Gas Interconnector Greece-Bulgaria
kbbld	Killobarel per Day
LNG	Liquified Natural Gas

LR	Linear Regression
LRL	Linear Regression Line
M3-M4	Makridakis' Third Forecasting Competition
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MARNE	Mean Absolute Range Normalized Error
ML	Machine Learning
MLR	Multiple Linear Regression
MSE	Mean Squared Error
NLR	Nonlinear Regression
NN	Neural Network
NRMSE	Normalized Root Mean Squared Error
OPEC	Organization of the Petroleum Exporting Countries
R^2	Squarred Correlation Coefficient
RM	Regression Models
RMSE	Root Mean Square Error
SARIMA	Seasonal Autoregressive Integrated Moving Average
SES	Simple Exponential Smoothing
sMAPE	Symmetric Mean Absolute Percentage Error
SVR	Support Vector Regression
TAP	Trans Adriatic Pipeline
TS	Time Series
UK	United Kingdom
U.S.	United States
WWII	World War Two

CHAPTER 1_INTRODUCTION

1.1 Scope and Objectives

The scope of this dissertation is to offer a solution, concerning the problem of forecasting countries' annual oil and gas demand with better accuracy than the one ready Excel forecasting equations and naive and simple methods offer, without the need for big amount of data or complex equations, models or/and systems. Particularly, we use the well-established and of proven accuracy Theta Model and we optimise it with the help of Solver in excel, offering a ready to use tool, accessible from everyone with the simple press of a button.

Focus is given on the European market and we generalize our results, applying our optimised Theta Model to several European countries' oil and gas demand time series and witnessing the improvement achieved in forecasting error in each case, over other simple ways of forecasting.

It is crucial to mention that our purpose is not to put data, parameters and situations in strict rules and barriers, neither is claimed that the Excel Spreadsheet of Optimised Theta Model beats any other and offers best forecasting accuracy no matter the data or the case.

Our purpose is to reach to a helpful tool, concerning analysis of annual oil and gas demand data and see how the Theta Model adapts in each case and differentiates all the relevant parameters that affect the result, to achieve the best possible forecasting accuracy as far as sMAPE is concerned. This is achieved in a very simple manner, avoiding manual trials and changes of the θ lines and/or their weighted contribution in the final forecast, but either by constructing cleverly the model and applying the free offered Solver of Excel to optimise it.

The differentiation of values according to the time series analyzed each time, is very important and insightful, as we observe the ability and the need of adaptation of the model, like the constant α of SES that is used to project all other θ lines than θ=0. The optimised Theta Forecast can act as a naive method, LRL method, or SES method in certain cases, if this is the best for the data we have as input, or a combination of the above in a different way each time and this shows us how differently our model acts according to the interpretation of the data.

Overall, the problem of expensive, complex or software needed forecasting methods is surpassed and a ready to use Theta Optimised Excel Spreadsheet that simulates all the above and adapts the respective calculations to the data inputted by the user is presented, establishing our effort as a useful tool with a wide range of application and satisfying forecasting accuracy, as it has a dynamic character that adapts to the different data of each country.

1.2 Layout

This thesis consists of two main parts. The first is theoretical and covers the field of forecasting methods used in oil&gas industry, as well as the up-to-date research and applications of the Theta Model. The current and future state of the global and Greek oil&gas market is presented. The field of forecasting methods applied in time series is covered, with focus on statistical ones and then we explore which methods have been used over the years for forecasting in the oil&gas field. Their basic characteristics are analyzed and methods are categorized according to these, with key feature of time (forecasting horizon) as basis. The Theta Model is then introduced and a literature review containing all applications and advances since its proposal 20 years ago, is performed.

The second and main part is the practical application, evaluation and eventually optimisation of the Theta Method, through the careful construction of the simple equations describing it in Excel and the use of the free offered Solver add-in as the optimiser. The error is measured with sMAPE, thus it is the target minimization value and the one that is used for comparison of forecasting accuracy against other commonly used, or ready to use from excel, methods. The oil and gas annual demand time series of two countries are presented as example and the dynamics and results of our model are analyzed extensively. The method is generalized for all European countries there are available data, minimizing the forecasting error and witnessing how the optimised Theta Model adapts to different data to perform as good as possible in terms of forecasting accuracy.

After proving the performance of the Optimised Theta Model for all 37 European countries' time series of which data exist (13 countries for oil demand and 24 countries for gas demand), the Optimised Theta Model is used to forecast demand until 2024 in general and our results are compared in specific with the respective ones from Rystad, for 10 countries in oil demand series for which data exist. For the rest 24 countries for gas demand, forecasts are performed until 2024, generating three different scenarios regarding the response of the market to the COVID-19 effect on demand.

1.3 Background and motivation for the work

Hydrocarbons and particularly oil&gas have always been a crucial energy source, with oil being used more than any other to meet the energy demand for many years; and gas, its "greener brother" being the one that is expected to take over in the near future, according to several short-term predictions (iea, dnv, eia, bp, eni, irena, rystad).

Natural gas, as the least carbon-intensive fossil fuel, will play a key role in the energy transition, eventually overtaking coal as the world's largest energy source by the mid-2020s [21].

Oil's value as an energy source is certainly diminishing, but it will continue to play a vital part in the energy sector for many years to come. Gas will be one of the key sources of energy in the electricity, household, industrial, and transportation sectors at the same time [36].

As I write this in 2021, we are witnessing an unprecedented pandemic and its devastating consequences, together with a massive transition to a lower carbon energy system, with renewables penetrating every year more and more and companies committing to a net-zero and carbon neutral future.

In this context, the forecasting of oil&gas demand, plays and will continue to play a vital role for proper preparation of each country and more realistic anticipation for the next years to come. Thus, in the crucial category of annual oil&gas demand in country level where this thesis falls into (and for which extensive and large number of models have been applied to implement it [75]; [8]), the construction and evaluation of our optimised time series model is more timely and topical than ever.

The Theta model was introduced to me in the Course "Forecasting Techniques" in the 9th semester on School of Electrical and Computer Engineering of NTUA and fascinated me with the combination of simplicity, adaptiveness and forecasting accuracy that displayed. When the forecasting seminar of my present Course "MSc in Oil and Gas Process Systems Engineering" was introduced to us along with Solver in Excel, the idea of testing and if possible optimizing Theta's performance on real Oil&Gas demand data was generated.

After a while, I managed to gain access to European countries' yearly demand data from Rystad and iea, so this idea was put in practice in Excel spreadsheets and in the following chapters it will be presented the context in which this dissertation takes place, our methodology for constructing and evaluating the Optimised Theta Model and the promising results that were witnessed.

CHAPTER 2_GLOBAL ENERGY AND OIL&GAS SECTOR

2.1 Current State

2.1.1 General

In 2020, all oil and gas firms were put to the test. Flights were canceled, vehicles were parked, factories were shut down, and employees were ordered to stay at home. Global demand for oil and gas products and services had collapsed by March. The pricing battle between Russia and Saudi Arabia resulted in an oversupply calamity, with prices dropping and US oil falling into negative territory for the first time in history [106]. The oil and gas value chain was thrown into turmoil as a result of the market meltdown. Demand and prices gradually steadied as the year continued, but remained significantly below the levels seen at the start of the year [23].

In April 2020, global oil demand plunged by 25%, but it has since rallied rapidly, decreasing its losses to just 8%. Looking ahead, oil demand is likely to rebound substantially in 2021, but stay lower than pre-COVID-19 levels, with the base case of Rystad [90] forecasting a 4% drop and the second-wave scenario forecasting a 7% drop [20].

According to the eia, the globe consumed 93.9 million barrels per day of petroleum and liquid fuels in January, down 2.8 million barrels per day from January 2020. Eia estimates that worldwide petroleum and liquid fuel consumption will average 97.7 million b/d in 2021, up 5.4 million b/d from 2020. It also forecasts that petroleum and liquid fuel consumption will rise by 3.5 million barrels per day in 2022, to an average of 101.2 million barrels per day [31].

The recent posted results of oil majors BP, EXXON, SHELL, CHEVRON and TOTAL leave no doubt of how big the hit was in 2020. The combined losses of the 5 above mentioned giants reached the record low of 76 billion dollars.

For instance, Royal Dutch Shell sank to a net loss of $21.7bn (£16bn) last year after the coronavirus pandemic caused demand to slump, which is record loss since 1988.

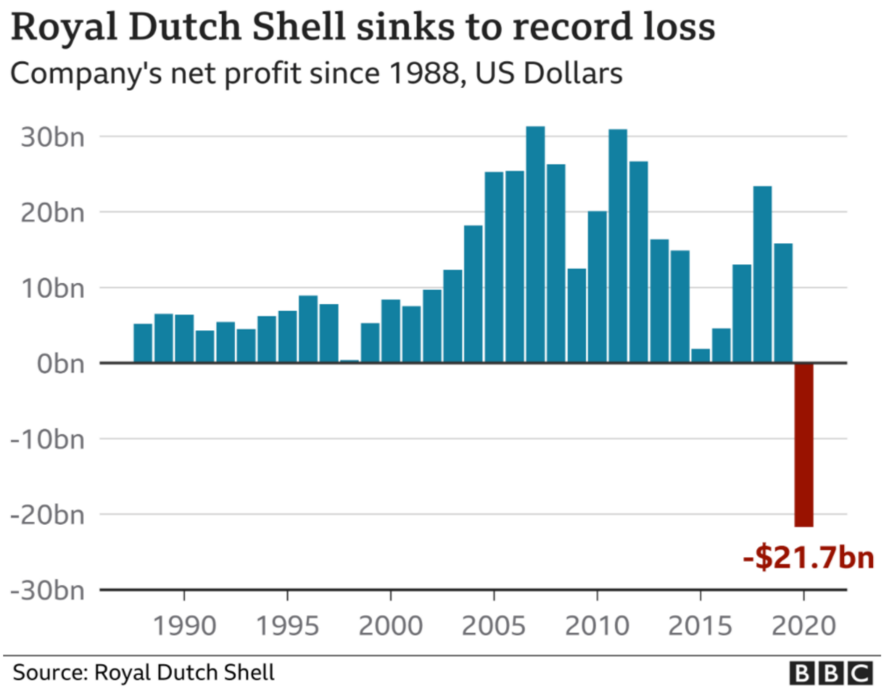


Figure 1 Shell 2020 net loss
Source : https://www.shell.com/

Shell said in September of last year that up to 9,000 jobs might be lost globally as a result of the pandemic's consequences [12]. It also announced that it would reduce 330 workers from its North Sea operations [63]. Even before the virus, the oil industry had to reassess its long-term strategies as part of the shift away from fossil fuels. Because of the Covid impact, firms like Shell are speeding up the transition.

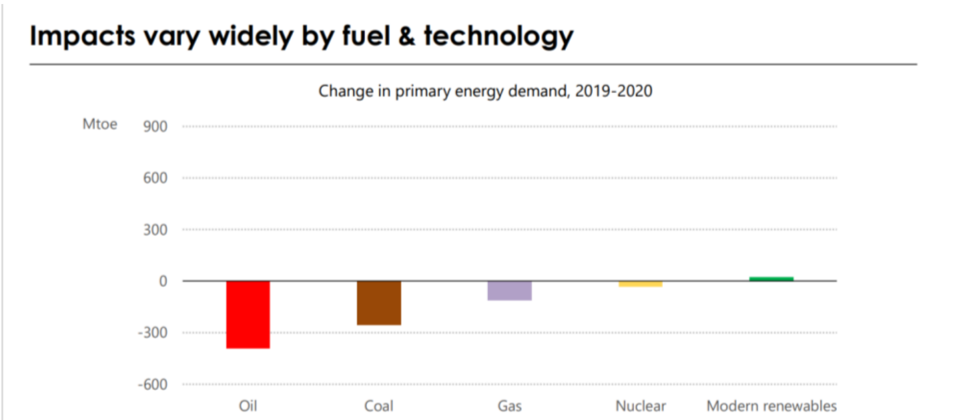


Figure 2 Change in primary energy demand, 2019-2020
Source : IEA WEA 2020 LAUNCH PRESENTATION, PARIS, 13 OCTOBER 2020 [53]

BP sums up 2020 in its newest statistical review with a clear statement: The COVID-19 pandemic had a huge and devastating impact on energy markets, with global primary energy and carbon emissions plummeting at the quickest rates (-4,5% and -6,3%

respectively) since WWII in 1945. Renewable energy, on the other hand, kept rising, with solar power experiencing its highest recorded increase [14].

At the same time, DNV GL sees economic recovery spending in COVID-19 as a missed opportunity, due to the fact that COVID-19 stimulus measures, with the exception of the EU, are mostly focusing on carbon-intensive systems [22].

2.1.2 Oil&Gas

In 2020, primary energy usage declined by 4.5 %, the most since 1945. Oil was the main driver of the drop in energy consumption, accounting for about three-quarters of the net decrease, though natural gas and coal also saw large drops. Despite a decline in overall energy demand, wind, solar, and hydroelectricity all climbed. The United States, India, and Russia were the countries with the greatest reductions in energy consumption. China saw the highest increase (2.1%), making it one of only a few countries where energy demand increased last year [14].

In 2020, the average oil price (Dated Brent) was $41.84/bbl, the lowest recorded since 2004. Oil consumption dropped by 9.1 million barrels per day (b/d), or 9.3%, to its lowest level since 2011. The US (-2.3 million b/d), the EU (-1.5 million b/d), and India (-480,000 b/d) had the biggest decreases in oil demand. China was almost the only country to have a rise in consumption (220,000 b/d). OPEC accounted for two-thirds of the fall in global oil production, which fell dramatically by 6.6 million barrels per day. The highest OPEC losses were in Libya (-920,000 b/d) and Saudi Arabia (-790,000 b/d), while non-OPEC reductions were led by Russia (-1.0 million b/d) and the United States (-600,000 b/d). Refinery utilization dropped to a low of 8% points to 74.1%, by far the lowest level in 35 years [14].

Prices of natural gas have fallen to multi-year lows: in 2020, the US Henry Hub averaged $1.99/mmBtu, the lowest since 1995, while Asian LNG prices (Japan Korea Marker) fell to their lowest level ever ($4.39/mmBtu). Consumption of natural gas has decreased by 81 billion cubic meters (bcm), or 2.3%. Despite this, gas's percentage of primary energy continued to grow, hitting a new high of 24.7%. Russia (-33 bcm) and the United States (-17 bcm) led the declines in gas demand, with China (22 bcm) and Iran (10 bcm) contributing the most rises. Inter-regional gas trade fell by 5.3%, with a 54 billion cubic meters (10.9 %) decline in pipeline trade accounting for the entire drop [22].

2.1.3 The Market in 2019

Things were different of course for 2019 and before the pandemic strike and although total energy demand and oil and gas demand in particular had smaller dynamic, they nevertheless presented growth.

For instance, the highlighted change in the energy sector from BP in 2019, is that the increase in primary energy consumption dropped to 1.3%, less than half of the growth rate in 2018. (2.8%). Renewables and natural gas, which together accounted for three-quarters of the rise in energy consumption, were the driving forces behind it. China was by far the most important energy driver, accounting for more than three quarters of world net increase. The next two largest contributors to growth were India and Indonesia, while the United States and Germany experienced the largest reductions [13].

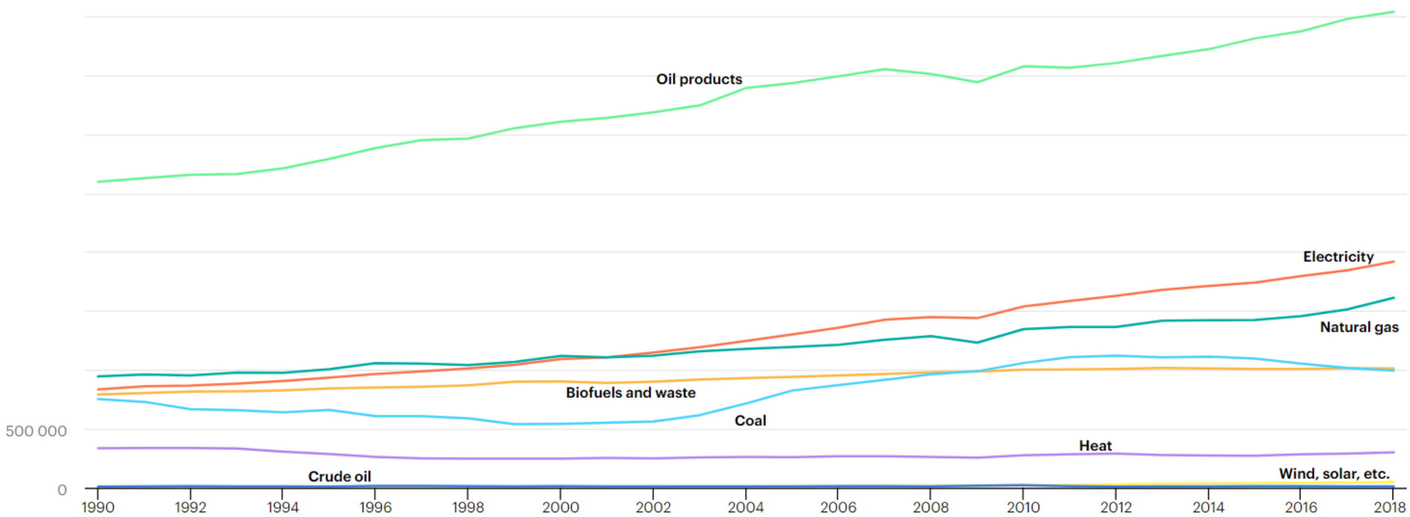


Figure 3 Total final consumption (TFC) by source, World 1990-2018 in ktoe
Source: IEA WEB 2020

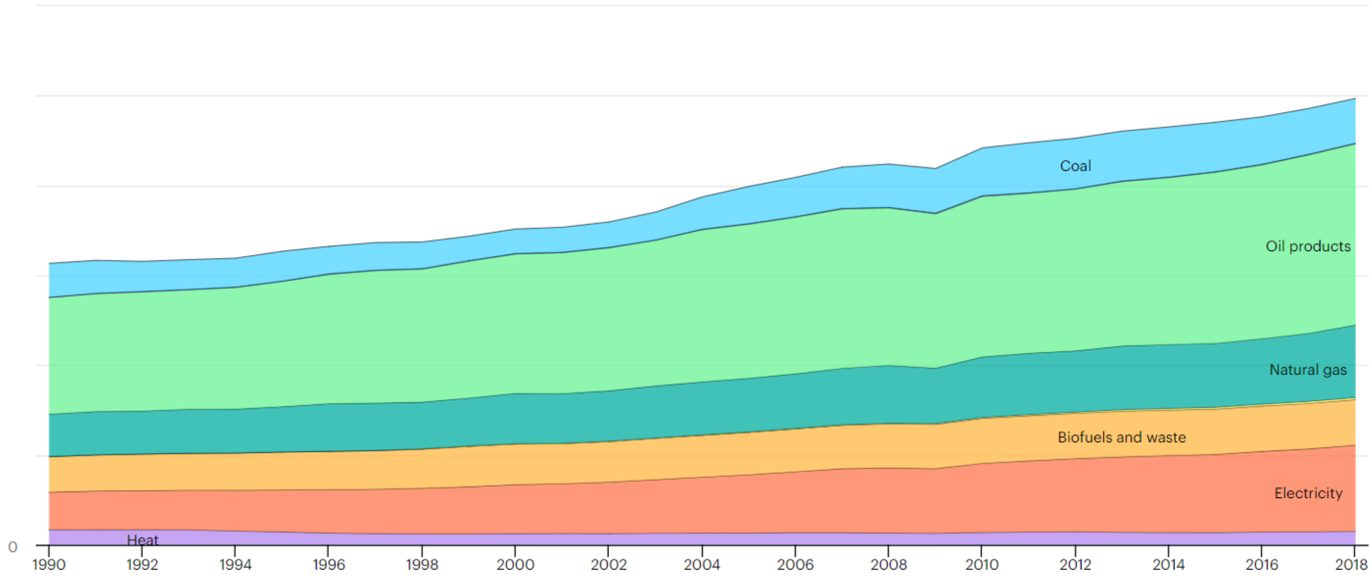


Figure 4 Total final consumption (TFC) by source, World 1990-2018 in ktoe
Source: IEA WEB 2020

Eni also highlighted similar findings for 2019:

In 2019, global il demand continued to grow, but at a slower rate than in the previous ten years (0,8 % vs 1.4 %). The drop in the ECD stifled the long-term growth momentum of non-ECD countries (China and India increased 5.3 % and 2.8 %, respectively). Demand in Europe was in a structural decline, while it was essentially stable in the United States [36].

The 19th World Oil, Gas, and Renewables Review points out emerging decarbonization trends, with the goal of identifying the actions required to address the climate crisis. It also recognizes that LNG has made a significant leap ahead, now accounting for 38% of total traded gas, up 4% in a single year (from 34% in 2018). In 2019, 470 billion cubic meters of LNG were traded, with Asian countries accounting for roughly 70% of the total [35].

2.2 Future Prospects

2.2.1 Summary

Despite the fact that the oil and gas business is used to the highs and lows of economic and pricing cycles, this downturn appears to be unique. In reality, this downturn represents the O&G industry's "great compression." With many companies' viability in jeopardy and long-term declines in petroleum demand, the next decade might be dramatically different for the whole oil and gas value chain. And for many, 2021 will either be a leap year or a test of endurance [20].

The 2020 Energy Transition Outlook of DNV GL forecasts a decarbonizing world in which energy demand plateaus, renewables grow significantly, natural gas becomes the world's largest energy source, and oil demand never again reaches the levels of 2019 [21].

Despite the challenges and high level of unpredictability in the industry, the oil and gas industry has enormous potential in terms of technical competence, management, and financial resources to cut greenhouse gas emissions and ensure inexpensive and dependable energy supply [36].

2.2.2 Possible Outlooks till 2050

In the AEO 2021 of eia, it is concluded that it will take years for US energy consumption to return to 2019 levels, and energy-related carbon dioxide emissions will continue to plummet before leveling off or rising. At the same time, as coal and nuclear power decline in the electrical mix, renewable energy subsidies and dropping technological costs promote robust competition with natural gas [32]. In comparison to the 2008 financial crisis, the COVID-19-related drop in total demand for delivered energy is around 70% bigger. In the Annual Energy Outlook 2021 reference case, eia projects that U.S. energy demand reaches 2029 to return to 2019 levels.

BP (rapid - net zero - business as usual), iea (stated policies - delayed recovery - sustainable development), Enerdata (Base – Blue - Green), eia (high economic growth – reference - low economic growth), all present more or less three different scenarios with projections (forecasts) up to 2050 in their 2020 and 2021 Outlooks but all come down to the same conclusion as far as Oil and Gas is concerned : while remaining needed for decades, it will be increasingly challenged as society shifts away from its reliance on fossil fuels.

According to the DNV GL 2020 and 2021 Energy Transition Outlook, rapid energy electrification and growth in renewables will lower emissions significantly in the coming decades, but fossil fuels will still be required to supply half of the world's energy in 2050. Oil and gas will have a future wherever there is a market for them. The question is what kind of future do we expect that will be [21]; [22].

Uncertainty about the pandemic's lifespan, its social and economic effects, and policy responses give rise to a wide variety of possible energy futures. By considering various assumptions about these critical unknowns, as well as the most recent energy market statistics and a dynamic representation of energy technologies, the iea World Energy Outlook 2020 report along with all previous reports mentioned, project different scenarios, mainly under the following concept [52]:

Optimistic scenario: Covid-19 is progressively brought under control in 2021 (not the case today as I write this thesis), and the global economy returns to pre-crisis levels in the same year. This scenario represents all of today's announced policy intentions and aims, to the extent that they are accompanied by explicit steps to ensure their fulfillment.

Delayed Recovery Scenario: built on the same policy assumptions as the optimistic scenario, but a multi-prolonged pandemic causes long-term economic damage. Only in 2023 will the global economy regain its pre-crisis size, and the pandemic will usher in a decade with the lowest pace of energy demand growth since the 1930s.

Sustainable Development Scenario: a boom in clean energy policies and investment puts the energy system on track to meet all of the Paris Agreement's sustainable energy goals, including energy access and air quality goals.

Net Zero Emissions by 2050 scenario: It contains the first extensive iea modeling of what will be required over the next ten years to bring global CO2 emissions back down to net zero by 2050.

Iea's World energy Outlook 2020 launch presentation in Paris, on 13th of October 2020 give us a clear insight on all of the above with the following graphs [53]:

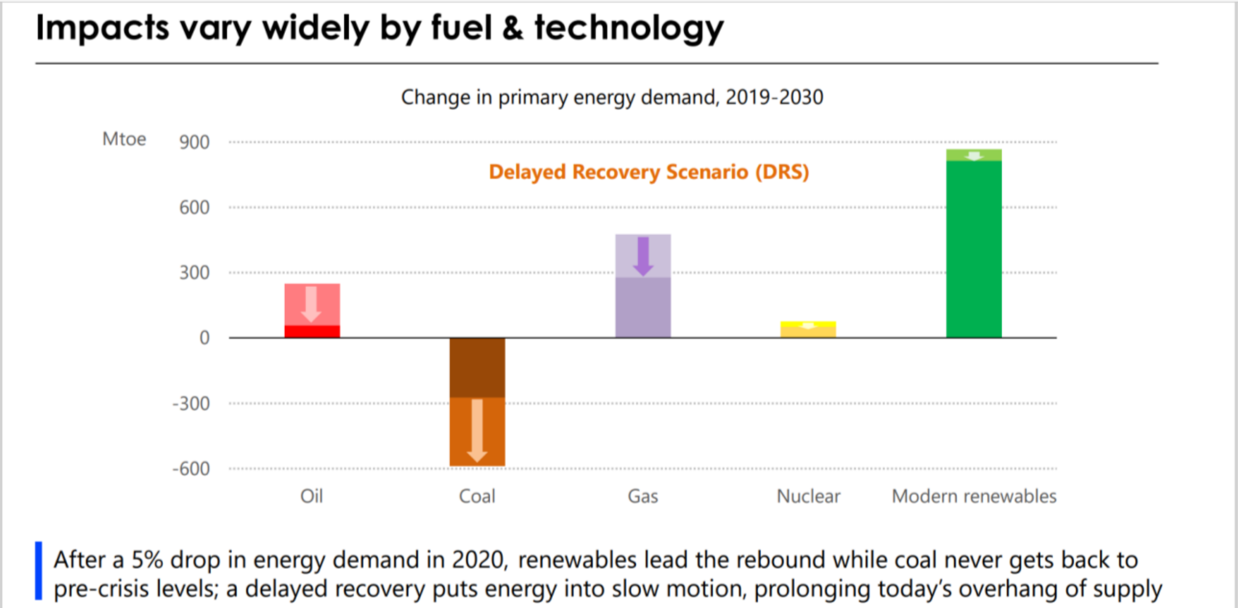


Figure 5 Change in primary energy demand, 2019-2030, Delayed Recovery Scenario

Source : IEA WEA 2020 LAUNCH PRESENTATION, PARIS, 13 OCTOBER 2020 [53]

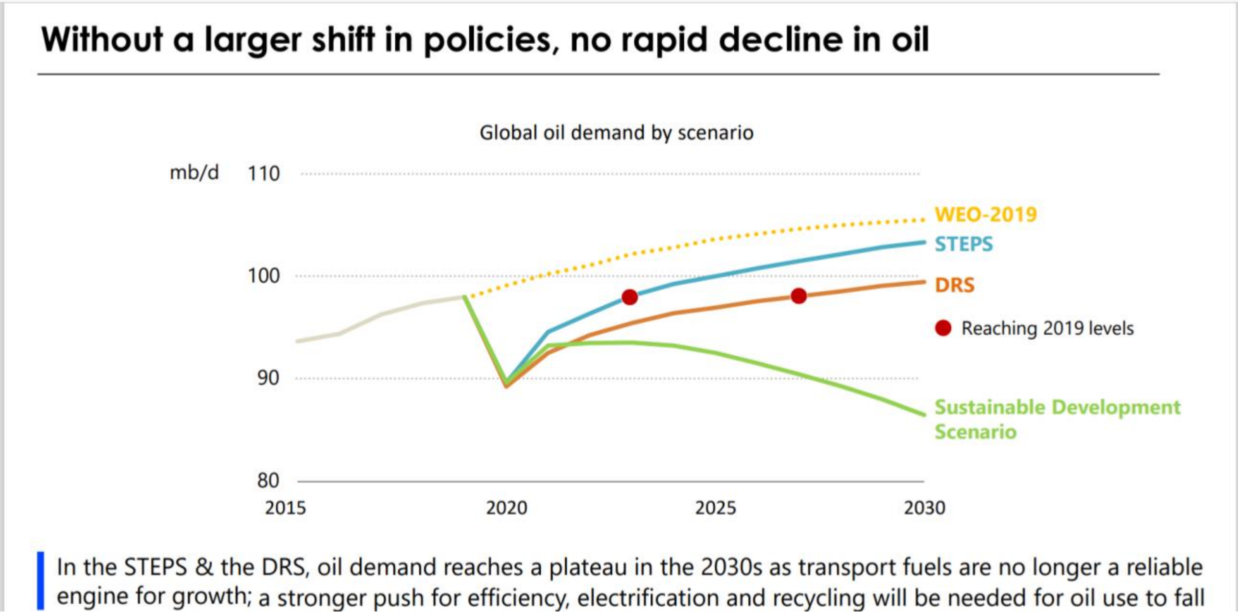


Figure 6 Global oil demand by scenario till 2030

Source : IEA WEA 2020 LAUNCH PRESENTATION, PARIS, 13 OCTOBER 2020 [53]

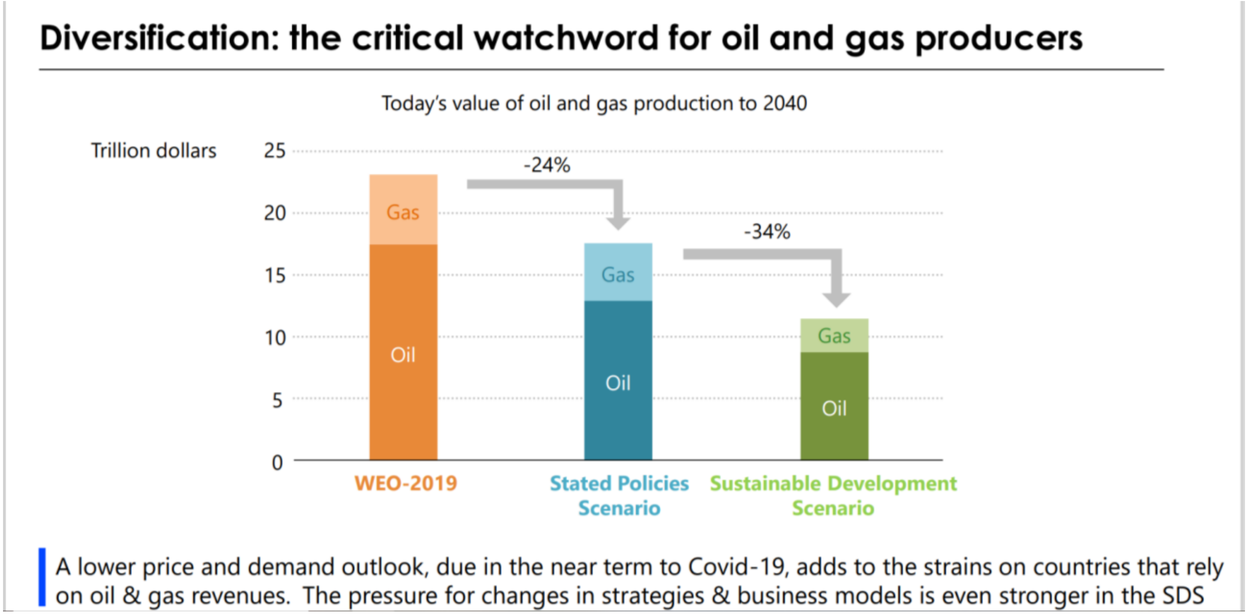


Figure 7 Today's value of oil and gas production to 2040
Source : IEA WEA 2020 LAUNCH PRESENTATION, PARIS, 13 OCTOBER 2020 [53]

An equivalent picture with three different scenarios according to the decarbonization rate and green energy sources penetration, is shown below from Enerdata for projection until 2050 [34]:

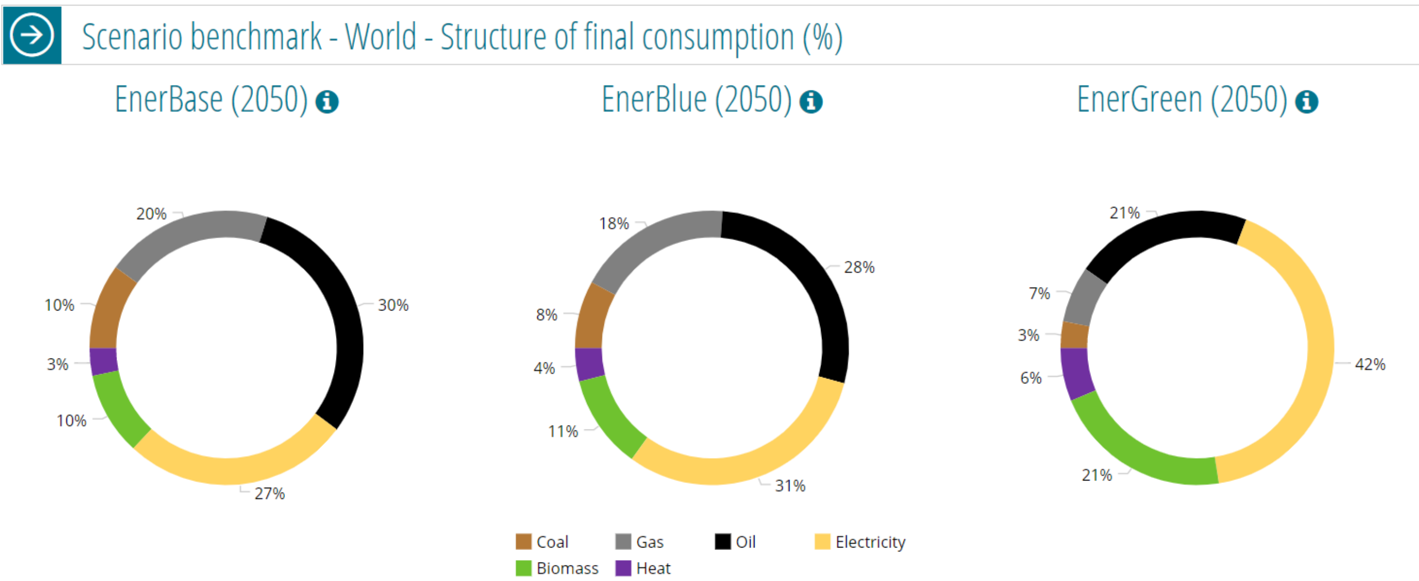


Figure 8 Enedata's final energy consumption scenarios to 2050
Source: https://eneroutlook.enerdata.net/forecast-world-final-energy-consumption.html [34]

DNV GL in its 2020 and 2021 Energy Transition Outlook state that efficiency gains lead to a flattening of energy demand from the 2030s and fossil fuels are gradually losing position but retain a 50% share in 2050 [21]; [22].

Throughout this forecast period, it is expected that the world's final energy demand will remain basically flat until 2050. It is expected to only increase by 3% in the next 15 years, as we approach peak energy consumption in the mid-2030s. By 2050, fossil fuels will account for 54% of primary energy supply, with non-fossil fuels accounting for 46% of the total.

However, the outlook for all fossil fuels is not the same. The supply of coal and oil is on a downward trajectory, and by 2050, they will only account for 9% and 16% of primary energy supply, respectively. Natural gas, on the other hand, will see its proportion of primary energy supply grow from 26% in 2018 to 29% in 2050. The upcoming changes include transitions from fossil fuels to renewables, from coal and oil to natural gas, and from fossil fuels to decarbonized gas.

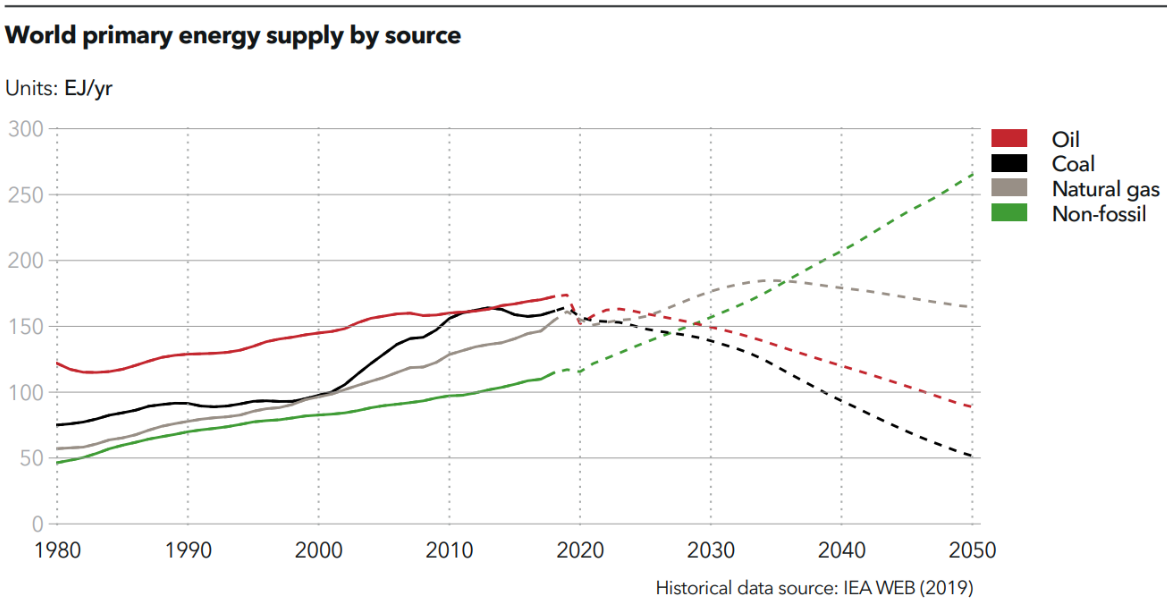


Figure 9 World primary energy supply by source to 2050
Source: DNV GL Energy Transition Outlook 2020 Executive Summary [21]

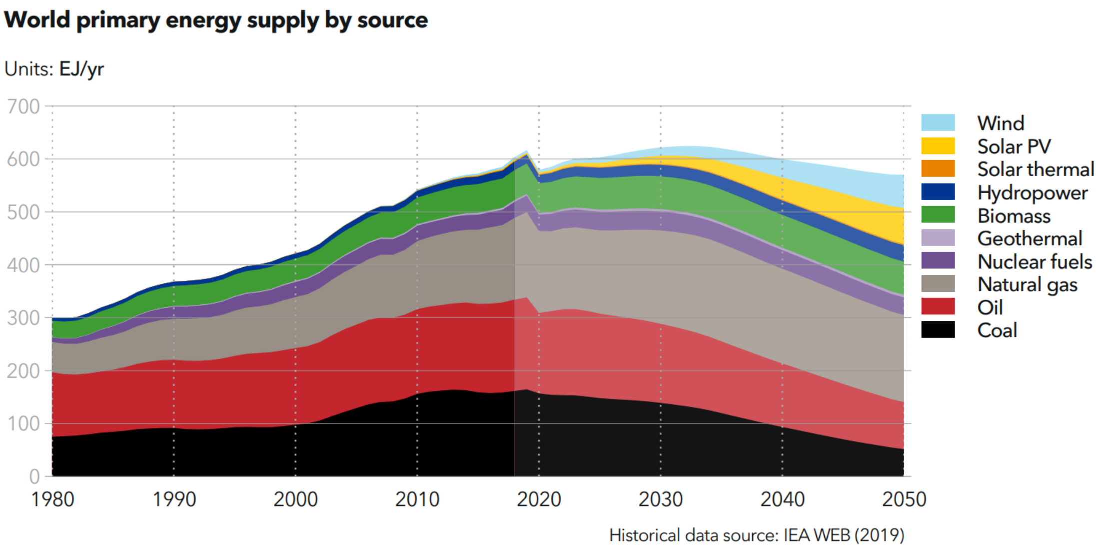


Figure 10 World primary energy supply by source to 2050
Source: DNV GL Energy Transition Outlook 2020 Executive Summary [21]

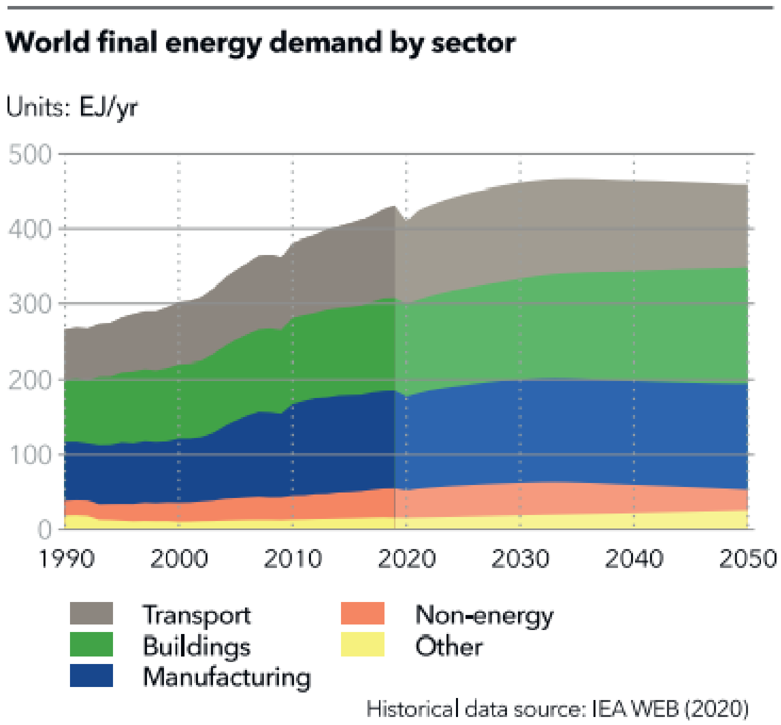


Figure 11 World final energy demand by sector to 2050
Source: DNV GL Energy Transition Outlook 2021 Executive Summary [22]

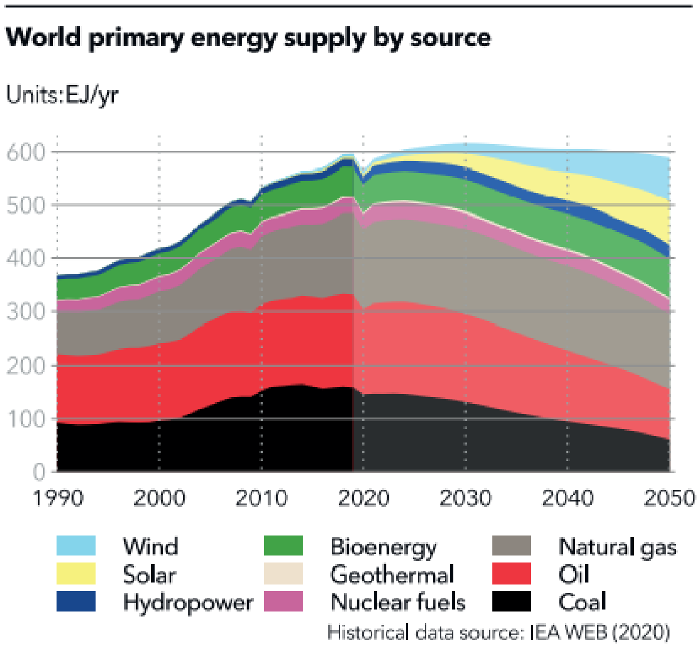


Figure 12 World primary energy supply by source to 2050
Source: DNV GL Energy Transition Outlook 2021 Executive Summary [22]

2.2.3 Anticipated Future for Oil&Gas

Oil demand is expected to never entirely recover from the COVID-19-induced market drop in 2020, and will rebound to some extent until 2023, before steadily decreasing to half of its 2018 level in real terms by 2050.

Natural gas will play a major role in the energy transition as the least carbon-intensive fossil fuel, taking over as the world's largest energy source by the mid-2020s. Global gas demand is expected to peak around a decade from now. By 2050, gas will have surpassed oil as the most important energy source, accounting for 24% of world energy supply. According to DNV's forecast, primary energy demand for natural gas will fall starting in the mid-2030s [21].

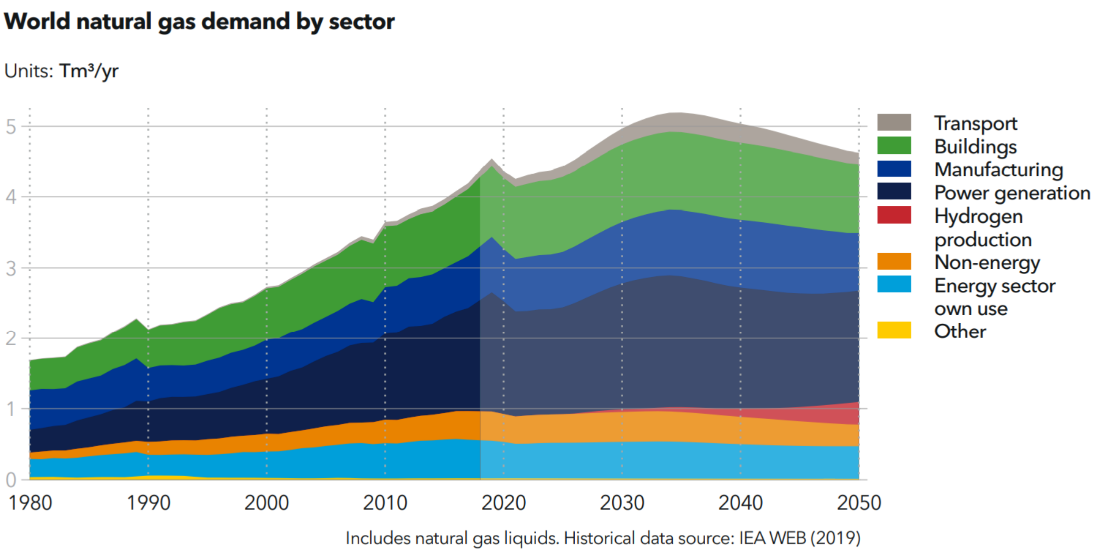


Figure 13 World natural gas demand by sector to 2050
Source: DNV GL Energy Transition Outlook 2020 Executive Summary [21]

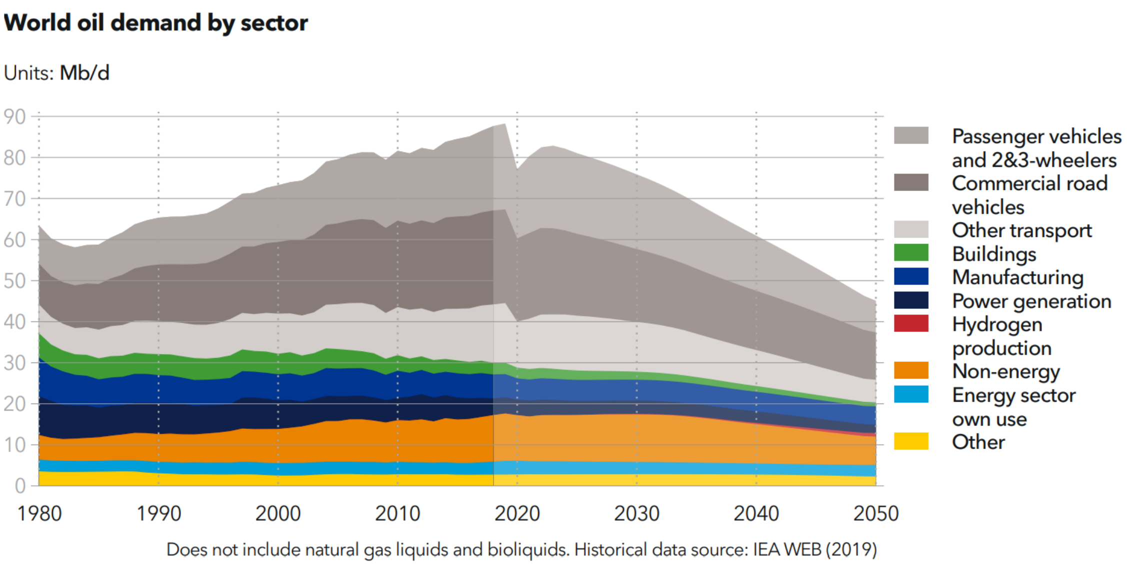


Figure 14 World oil demand by sector to 2050
Source: DNV GL Energy Transition Outlook 2021 Executive Summary [22]

Hydrogen produced from renewable sources, will follow decarbonized gas in replacing some of the final demand for natural gas, mostly in hard-to-abate sectors like cement, steel and aluminum. According to DNV's forecast, 13% of gas will be decarbonized by 2050. The faster the government incentivizes industry to adopt these technologies, the faster technology will advance along the continuum of learning and cost reduction.

2.3 Greek Energy Market

2.3.1 Summary

In brief, Greece is putting in place comprehensive energy industry reforms to foster competitive energy markets, promote investment opportunities, support energy system transmission and provide environmentally and socially sustainable solutions [51].

Greece can be established as an important player in the formulation of the European Union's (EU) energy mix, with major investment opportunities in all energy industries, due to the abundance of renewable energy potential in combination with the ongoing large-scale infrastructural projects. Furthermore, because of its location at the crossroads of East and West, Greece is expected to play a vital role in the South Balkans and the East Mediterranean [47].

2.3.2 Current State and Future Prospects

By promoting and implementing programs that enable sustainable increases in efficiency and by increasing the percentage of natural gas and renewable energy in the energy mix, Greece can handle its economic recovery as a chance to proceed with accelerated longer-term emissions reduction outcomes. The development of a national energy and climate coherent strategy for 2030 and beyond, as well as the integration of climate objectives into integrated energy planning, will be critical parts of this process. The country has witnessed a significant increase in the share of renewables in power generation, even exceeding the solar PV targets set by the government. Improved use of its renewable energy potential could result in a more balanced energy mix and help to increase energy security [51].

The Greek energy system has been characterized in recent years by a decrease in the consumption of conventional fuels, which is based in great part on lignite, which was strategically chosen for electricity production after the 1970s oil crisis. Another important feature of Greece is that the country is heavily reliant on imports, such as crude oil, petroleum products, and natural gas. In this context, we have seen an increasing penetration of Natural Gas in final consumption over the previous decade, while it still represents a modest fraction of total consumption in Greece and is lower than the European average. On the other hand, following the implementation of the carbon tax, natural gas now accounts for a major portion of energy production, with a percentage that is continuously increasing over time [47].

Currently, the COVID-19 pandemic has caused the state's planned privatization of major energy assets, such as the Natural Gas Distributor (DEPA), the Hellenic Electricity Distribution Network Operator (HEDN), and Hellenic Petroleum, to be postponed. National authorities want to liberalize the electricity and natural gas markets even further, separating production and supply from transmission networks. Through mega-infrastructure projects such as the TAP, IGB, EastMed gas pipelines, EuroAsia Interconnector or gas and oil exploration and production, the country aspires to demonstrate its potential to become a European gateway for natural gas, electricity, and natural resources.

2.3.3 The Greek Energy Mix

Greece plans to attain 38% energy efficiency by 2030, with 50% renewables, and no coal in its power mix, as well as a 42% reduction in GHG emissions compared to 1990. As a result of the big financial crisis, total energy consumption has been declining since 2008 [33].

Gross energy consumption in Greece is projected to drop by 11% in 2020 due to COVID-19 impact. Below it can be seen TES and TFC by source, as well as Oil and Natural Gas final consumption, from 1990 to 2019, taken by iea.

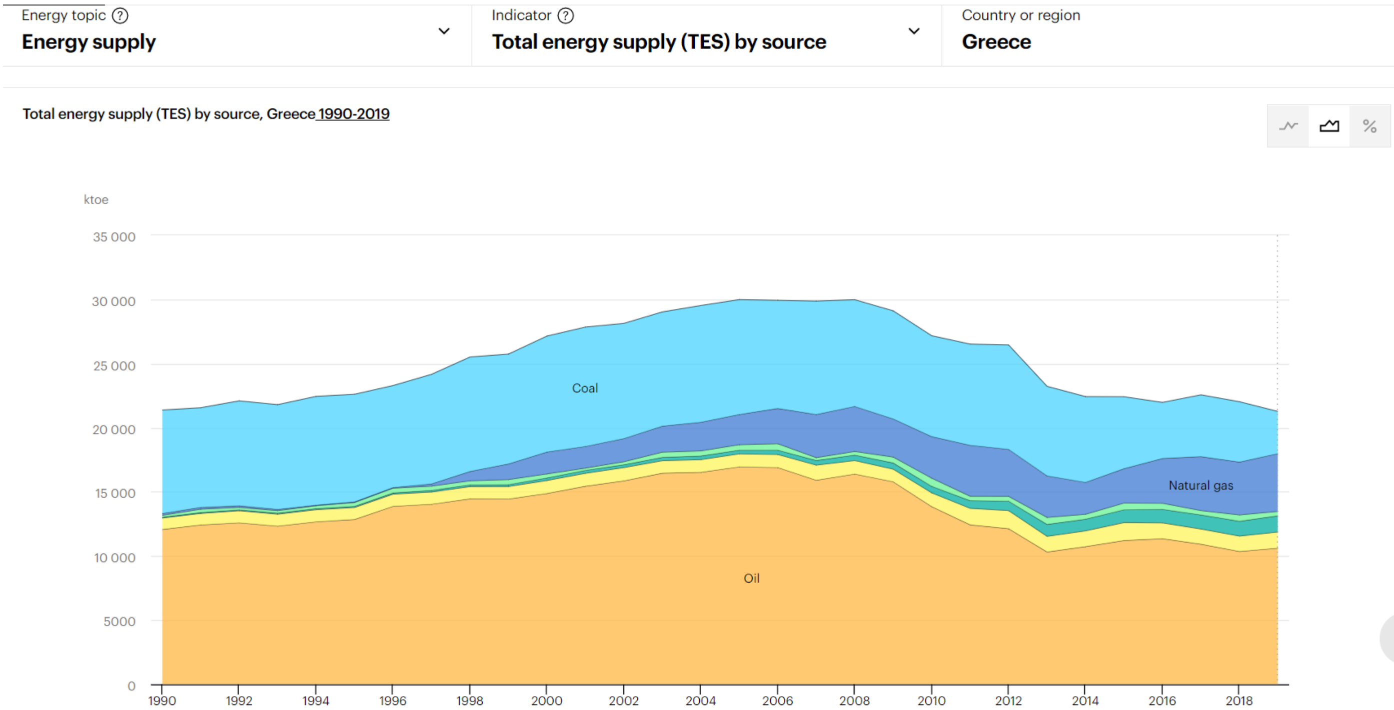


Figure 15 Greece Total energy supply (TES) by source, 1990-2019

Source: [IEA WEB 2020]

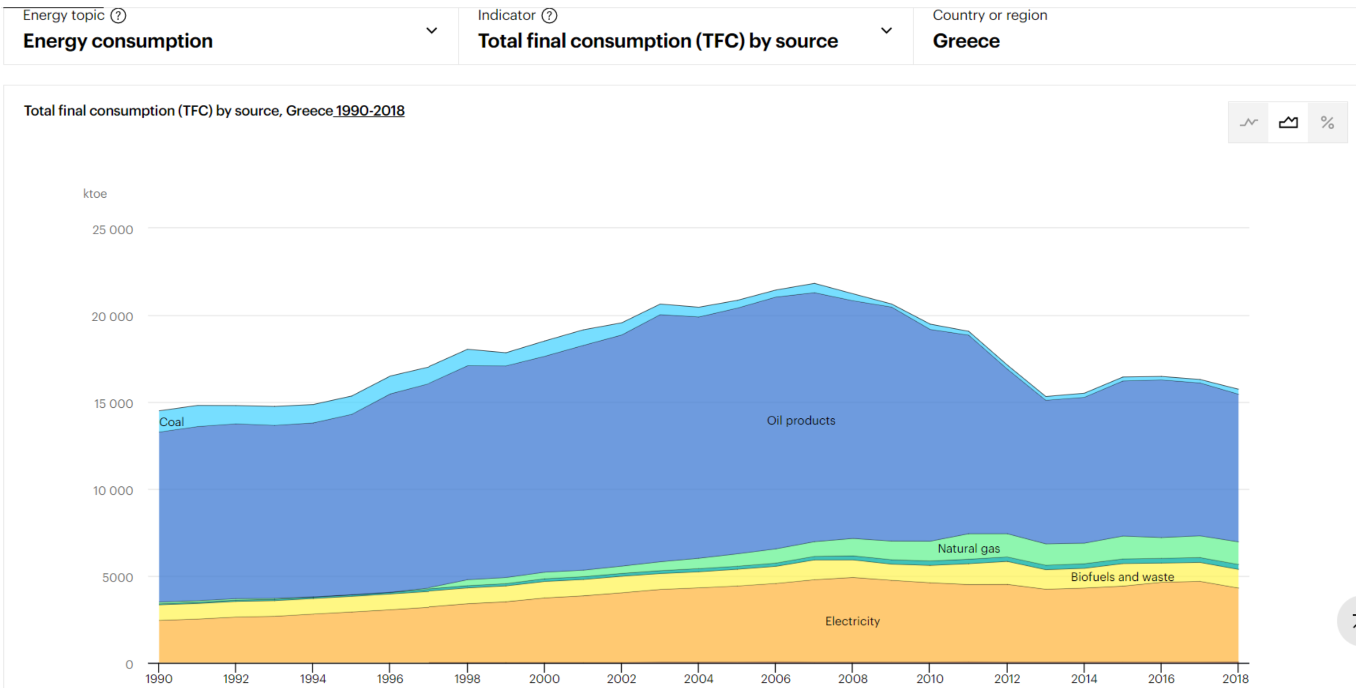


Figure 16 Greece Total final consumption (TFC) by source, 1990-2018

Source: [IEA WEB 2020]

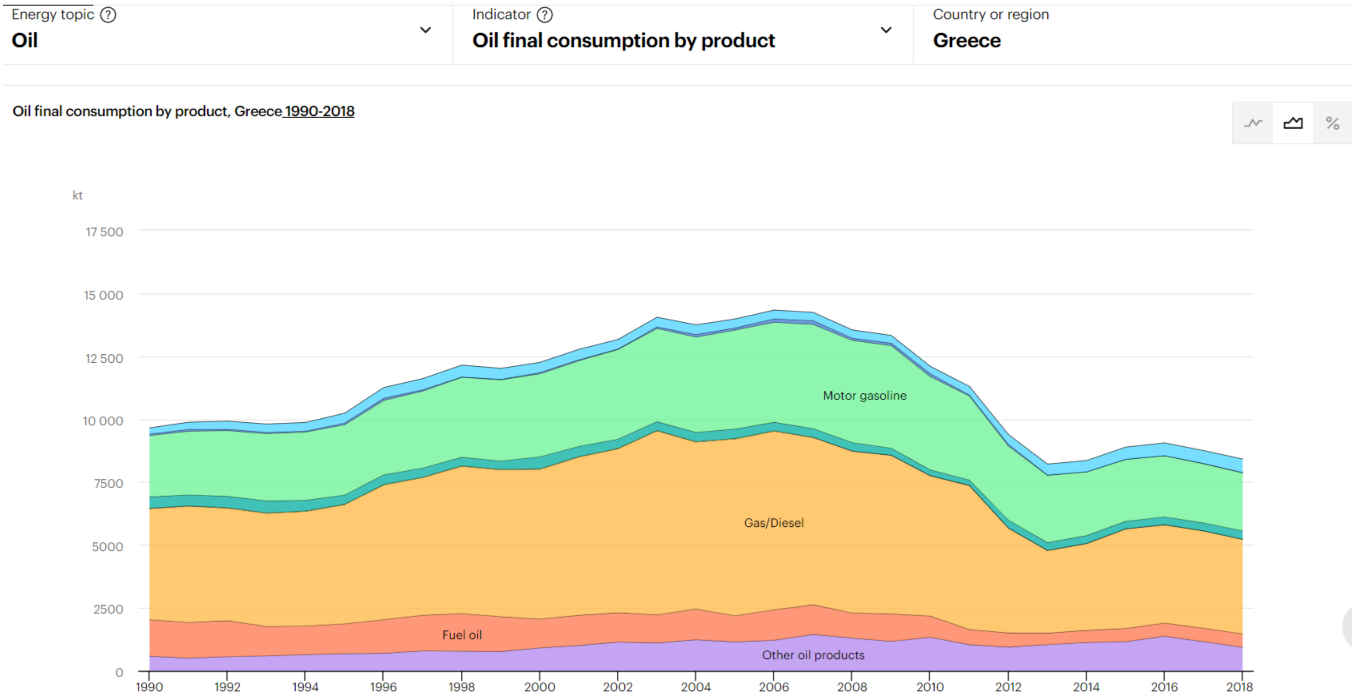


Figure 17 Greece Oil final consumption by product, 1990-2018
Source: [IEA WEB 2020]

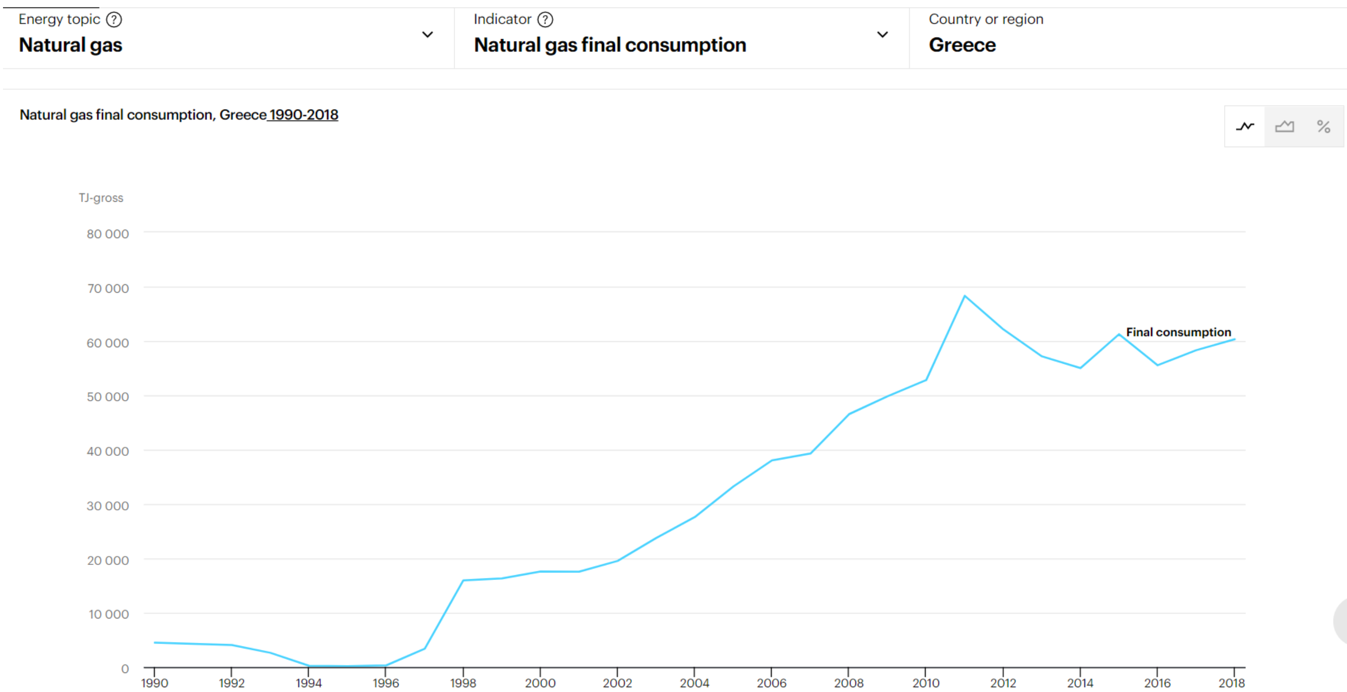


Figure 18 Greece Natural gas final consumption, 1990-2018
Source: [IEA WEB 2020]

The interactive charts presented below from Our World in Data also depict aptly the energy mix of Greece [89].

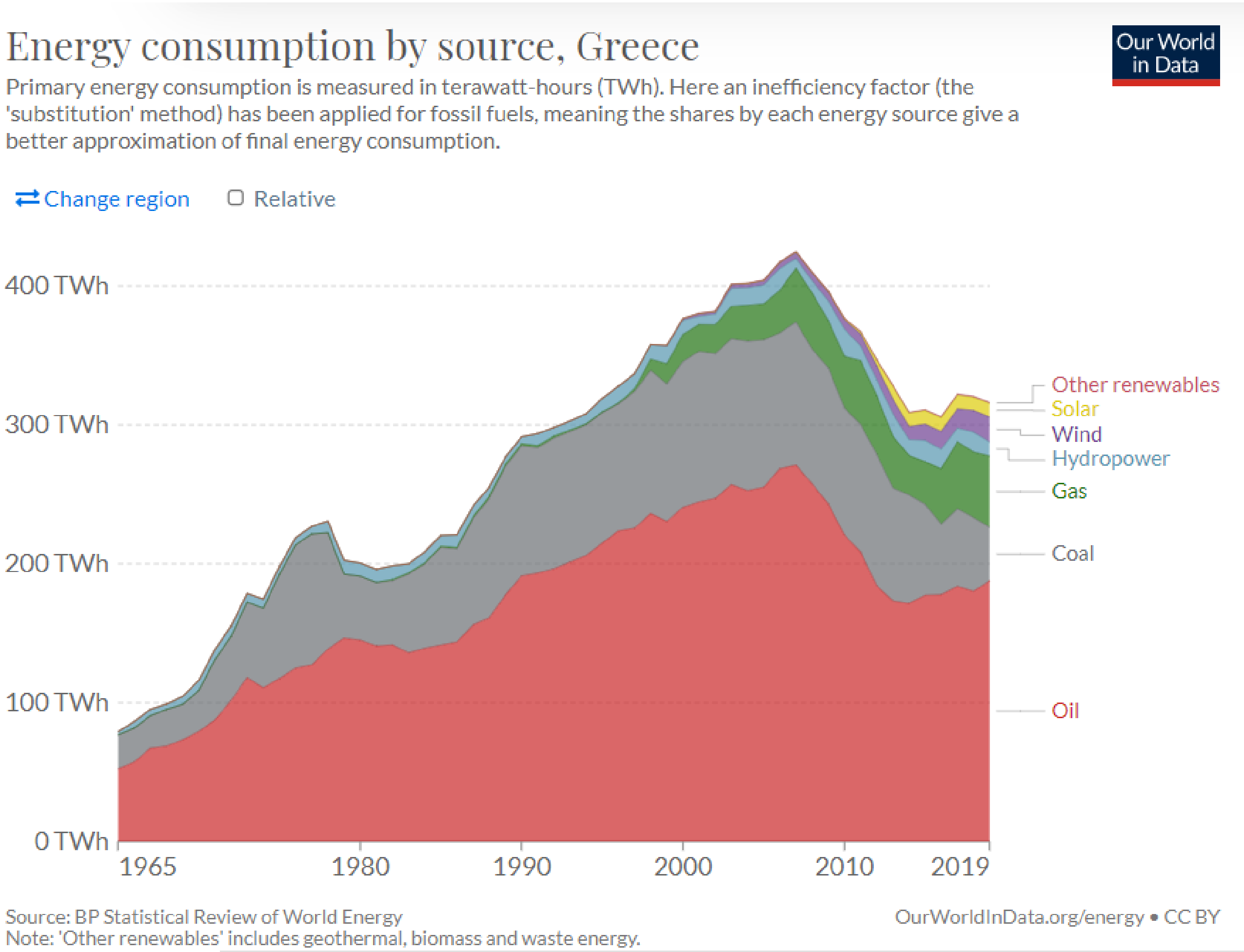


Figure 19 Greece energy consumption by source,1965-2019
Source: [https://ourworldindata.org/energy/country/greece [89]](https://ourworldindata.org/energy/country/greece)

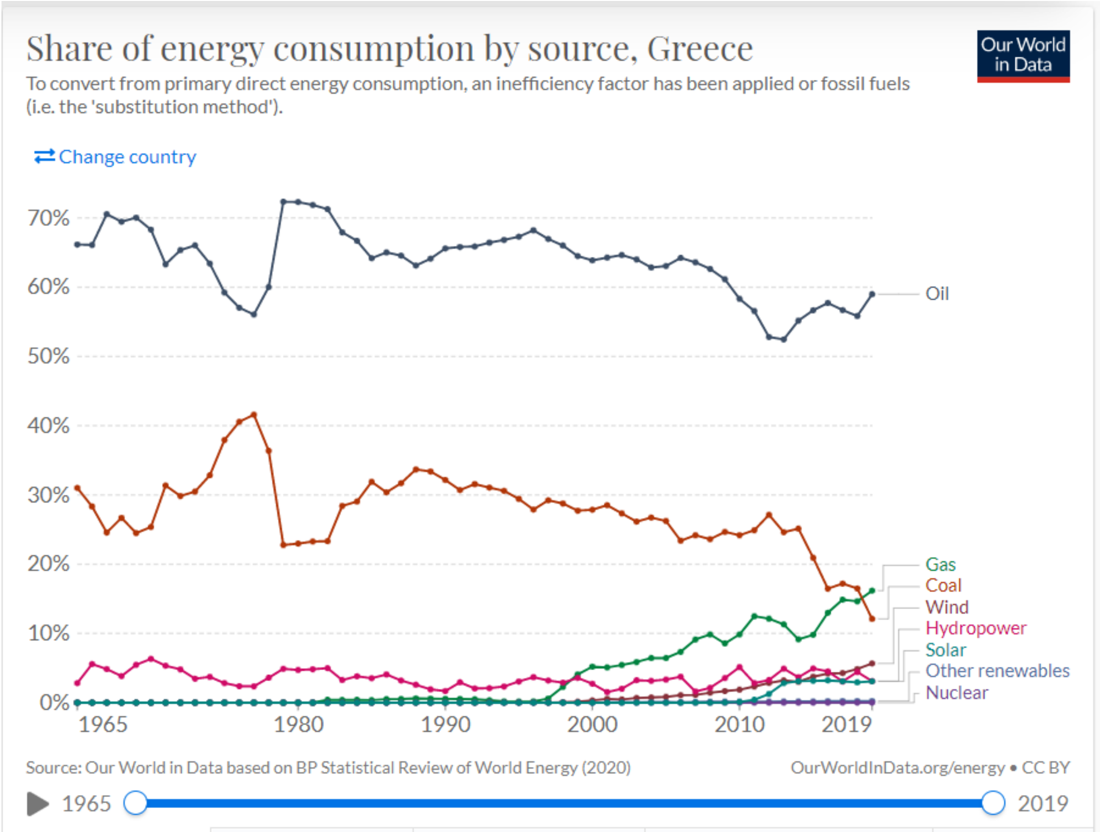


Figure 20 Greece Share of energy consumption by source, 1965-2019
Source: [https://ourworldindata.org/energy/country/greece [89]](https://ourworldindata.org/energy/country/greece)

CHAPTER 3_FORECASTING, THEORETICAL BACKGROUND

3.1 The Art of Forecasting

3.1.1 Definition

Forecasting as a scientific discipline has progressed a lot in the last 45 years, with Nobel prizes being awarded for seminal work in the field, most notably to Engle, Granger and Kahneman [38].

Forecasting is the systematic and methodologically reliable attempt to learn future events and situations before they take place. A forecast is a prediction of some future event or events and is designed to help decision making and planning in the present [97]. It is the process of projecting the values of one or more variables into the future.

3.1.2 Categorization of Methods

Forecasting methods differ greatly in terms of time horizons, factors determining actual outcomes, data patterns, and a variety of other factors.

Techniques for forecasting fall into two main categories: quantitative and qualitative methods. In this thesis, focus is given on a quantitative method, so this category will be further analyzed.

3.2 Quantitative Forecasting Methods

3.2.1 Summary

Quantitative forecasting can only be used if sufficient quantitative information is available. They are essentially time series methods, which anticipate the continuation of historical patterns such as sales growth or national product growth. The use of time series data is at the heart of most forecasting cases. A time series is a chronological sequence of observations in a variable of interest that is time-oriented [42].

Statistical methods are highly beneficial for short- and medium-term forecasting since historical data usually exhibits inertia and does not change substantially very rapidly [112].

Quantitative forecasting makes use of historical data to develop relationships and trends that can be projected in the future. It can be used when three conditions are met [97]:

1. Historical information is available.
2. This knowledge can be quantified using numerical data.
3. It is reasonable to expect that some features of the previous pattern will continue in the future.

This last condition is known as the assumption of continuity [65]; it is a fundamental assumption of all quantitative (and many qualitative) forecasting methods, regardless of how complex they are.

Someone might argue that the presumption is that the forces that created the past will continue to exist in the future. When forecasting short- and medium-term horizons, this is often a true assumption, but falls short when forecasting long term horizons. The longer one tries to forecast into the future, the less confident he becomes of the forecast.

Quantitative forecasting techniques differ significantly, as they were developed by various disciplines for various purposes. Each has its own set of characteristics, precisions, and costs that must be considered while choosing a method, or the most appropriate method for each case. Furthermore, the mathematical models they employ involve a number of constants (smoothing in majority), coefficients and other parameters that the forecaster must determine. The selection of these parameters determines the forecast to a great extent [97].

The most well-known Quantitative methods are [112]: Simple regressions, Multiple regressions, Time trends, Moving averages (Simple, Weighted), Exponential Smoothing

3.2.2 Main Quantitative Methods’ Categorization

Quantitative forecasting techniques are divided into two categories: intuitive or ad hoc methods and fundamental quantitative methods based on statistical concepts. As the initial methods had significant limitations, fundamental methods have become more popular [97].

Extrapolation can be included in most statistical methods (as the method that will be used in this dissertation), but it's performed in a standard way with a systematic approach that tries to reduce forecasting errors.

In time series extrapolation methods, the two best established benchmarks in the field are [28] Damped Trend Exponential smoothing [46] and the Theta method [102].

3.2.3 Time Series Models

Another factor to consider when categorizing quantitative forecasting systems is the underlying model. Time series and explanatory models are the two main types of forecasting models. Explanatory models presume that one or more independent variables have an explanatory relationship with the variable to be projected. Time series forecasting considers the system as if it were a black box, with no effort to detect the factors that influence its behavior. As a result, projections are dependent on previous values of a variable and/or past errors, rather than explanatory variables that may have an impact on the system [97].

Time series models are based on demand data for the item being considered. Because only small amounts of historical data are required, and external variables are redundant, it is not difficult to construct these traditional forecasting models [2]; [84]. The goal of these time series forecasting algorithms is to find patterns in the historical data series and extrapolate these patterns into the future [97].

According to the situation, both time series and explanatory models show advantages. Time series models are most of the cases more easily utilized to forecast. Explanatory models are more effective for policy and decision-making.

The most basic and non-complex time series forecasting models rely solely on data about the variable to be forecasted and make no effort to identify the factors that influence its behavior. As a result, they extrapolate trend and seasonal patterns while ignoring all other data, such as competition activity, economic situation shifts, marketing campaigns etc.

Decomposition methods are helpful for studying the trend and seasonal patterns in a time series. Popular time series models used for forecasting include exponential smoothing models and ARIMA models [83].

3.3 Regression Models

The basic concept of regression models is that the time series of interest y are forecasted by assuming that it has a linear relationship with other time series x.

Linear Regression models use a linear approach to model the relationship between a dependent variable and one or more independent variables [72].

The forecast variable y is sometimes also called the regressand, dependent or explained variable. The predictor variables x are sometimes also called the regressors, independent or explanatory variables [83].

3.3.1 Simple linear regression

The regression model allows for a linear relationship between the forecast variable y and a single predictor variable x in the simplest case: $y_t=\beta_0+\beta_1 x_t+\varepsilon_t$.

The following Figure depicts an example of data from such a model. The coefficients β_0 and β_1 indicate the line's intercept and the slope, respectively. When x=0 the intercept β_0 indicates the predicted value of y. The slope β_1 denotes the average expected change in y as a result from a single unit increase in x [83].

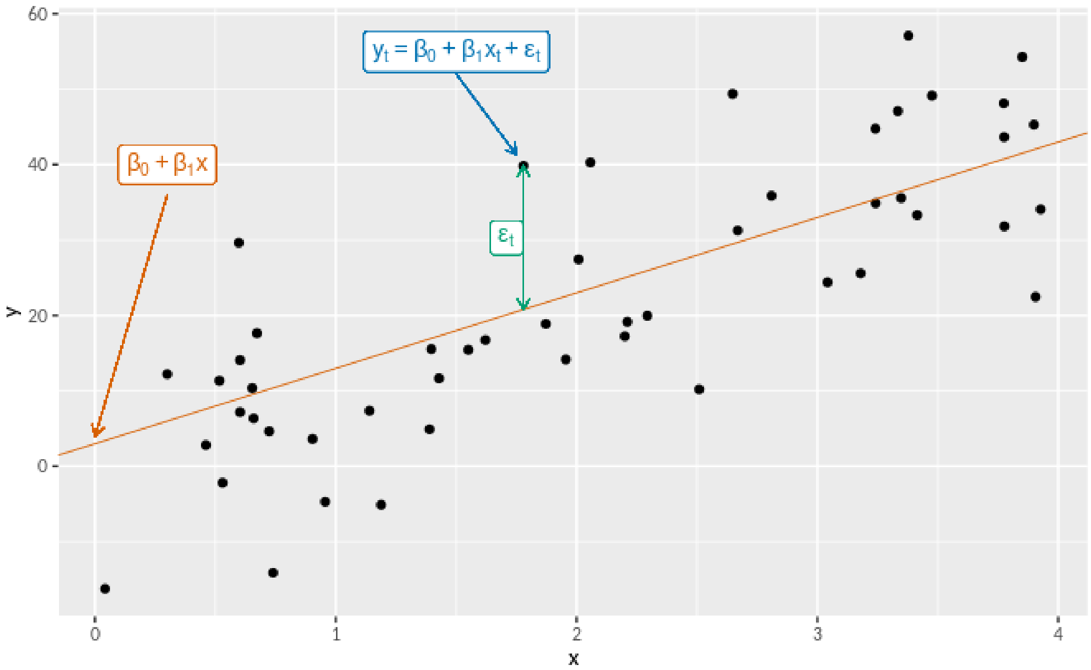


Figure 21 Simple linear regression model example

Source : [Forecasting: Principles and Practice (3rd ed) (otexts.com) [83]]

It's worth noting that the observations aren't in a straight line, but rather are spread around it. Each observation yt can be seen as consisting of the systematic or described part of the model, $\beta_0+\beta_1 x_t$, and the random "error," ε_t. The expression "error" does not refer to a blunder, but rather to a deviation from the underlying straight-line model. It includes anything that may have an impact on y_t other in addition to x_t [83].

3.3.2 Multiple linear regression

When there are two or more predictor variables, the model is called a multiple regression model. The general form of a multiple regression model is $y_t=\beta_0+\beta_1 x_{1,t}+\beta_2 x_{2,t}+\cdots+\beta_k x_{k,t}+\varepsilon_t$ where y is the variable to be forecast and $x_1,\ldots,x_k$ are the k predictor variables. Each of the predictor variables must be numerical. The coefficients $\beta_1,\ldots,\beta_k$ measure the effect of each predictor after taking into account the effects of all the other predictors in the model. Thus, the coefficients measure the marginal effects of the predictor variables [83].

3.4 Exponential Smoothing

Exponential smoothing was introduced in the late 1950s [15]; [48]; [107] and has generated some of the most successful forecasting methods, becoming very popular amongst practitioners. Forecasts based on exponential smoothing methods are weighted averages of previous observations, with the weights decreasing exponentially as the observations age. Thus, the more recent the observation, the larger the associated weight [41].

This framework delivers credible forecasts fast and for a wide range of time series, which is a significant benefit and a major consideration for industrial applications. Their key advantages are their ease of implementation, low computational complexity, and lack of demand for long series, while they are appropriate for short-term forecasting horizons with a large number of elements [38].

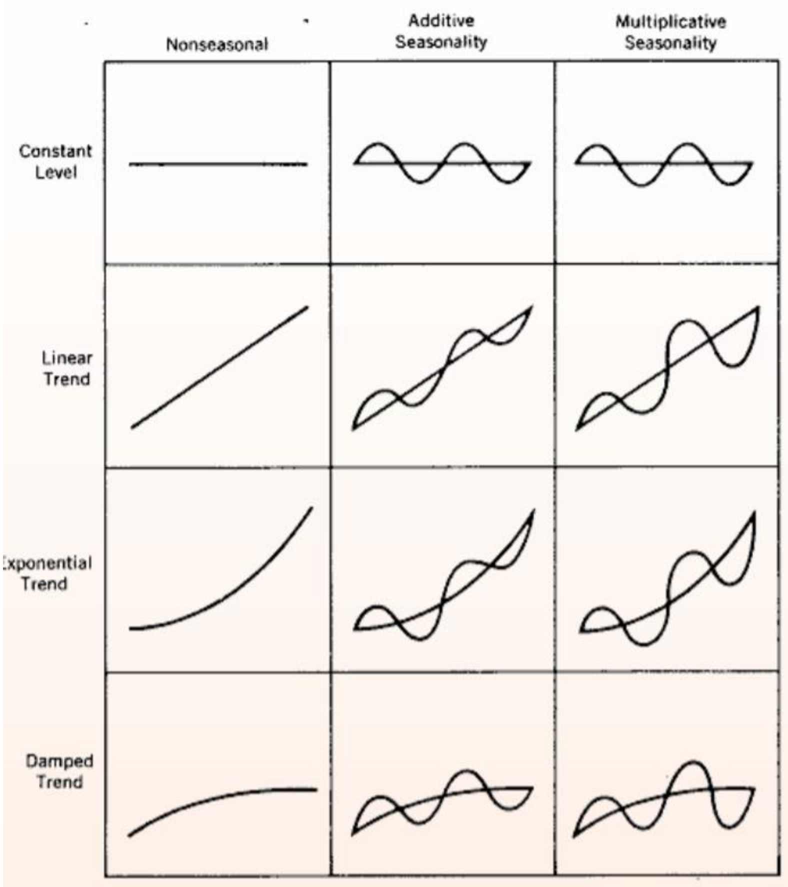


Figure 22 Types of Exponential Models
Source : fsu.gr [38]

3.5 ARIMA Models

ARIMA (Auto Regressive Integrated Moving Average) models (Box & Jenkins, 1971) offer a different perspective on time series forecasting and are an improved form of ARMA [3]. Along with exponential smoothing, they are the two most generally used approaches to time series forecasting and both of which provide practical solutions to the problem. ARIMA models try to characterize the autocorrelations in the data, whereas exponential smoothing models are based on a description of the trend and seasonality in the data.

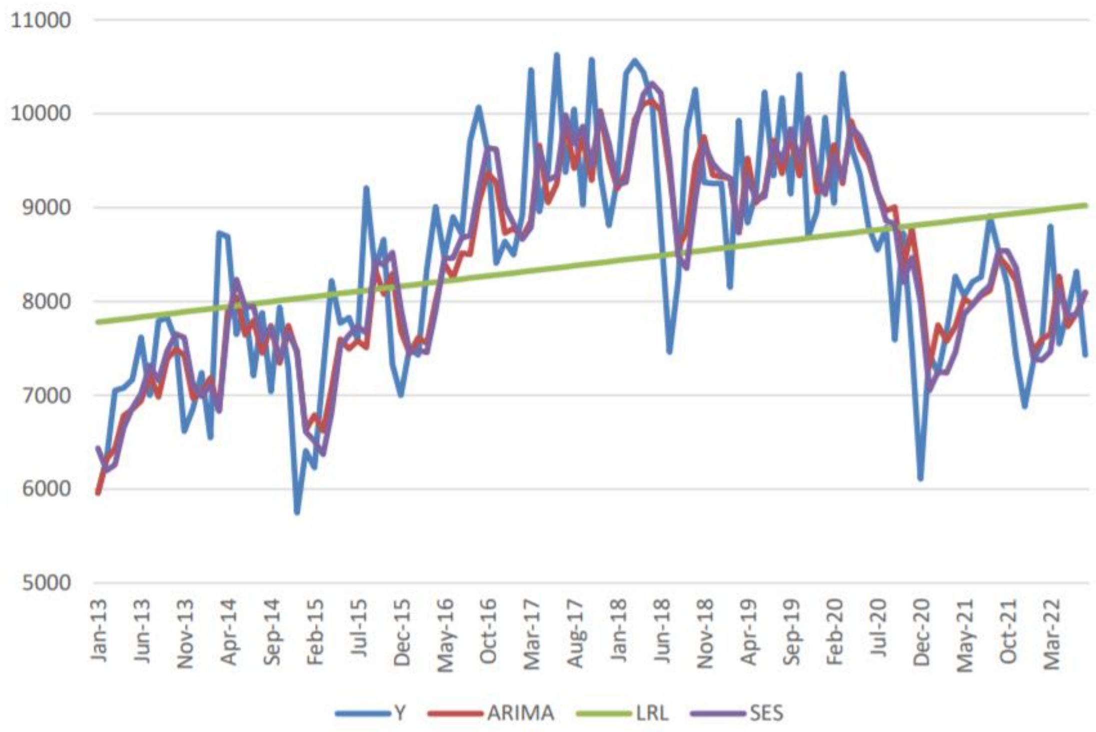


Figure 23 ARIMA vs LRL vs ES
Source : fsu.gr [40]

They approach the logic of classic regression models (e.g., LRL) and exponential smoothing models (e.g., SES) in the sense that they relate future values of time series with its past values and / or errors that were located. Their peculiarity lies in the fact that linear correlation is made without direct use of smoothing or utilization of interpretive variables [40].

To date ARIMA models are still considered the dominant benchmark in empirical forecasting evaluations [44] and find great popularity among researchers in applications spanning from hospitality and production to healthcare and climate forecasting [57]; [43]; [80].

CHAPTER 4_FORECASTING METHODS IN OIL&GAS SECTOR

4.1 Summary

Over the last few decades, traditional models as well as AI-based models have been extensively used to forecast energy consumption. The models have been generally scrutinized in terms of forecasting horizon, application areas, model type, and forecasting accuracy. Time series models, regression models, and gray models are the three main types of traditional models [75]. Artificial neural network-based models and support vector regression machine-based models are the two basic types of AI-based models.

The literature on energy demand forecasting has largely focused on three forecasting aspects [85]: short-term (hour to week) [59]; [94], mid-term (month to five years) [69], and long-term (five to twenty years) [30]. The forecasting horizon can be also divided in a different manner, to three categories in: long-term (yearly) forecasting, medium-term (monthly and quarterly) forecasting, and short-term forecasting (i.e. hourly, daily, weekly) [100]; [17]. In addition, the method used for estimating energy demand is the heart of demand prediction [68].

This thesis falls under mid-term forecasting (annual forecasts) initially and reaches long-term forecasting after the Optimised Model has been established, with projections up to 2024.

4.2 Categorization

Generally, forecasting methods can be categorized into two types [85]: Data-driven approaches, where statistical techniques of the connection involving the demand for energy and its causal variables are thoroughly detected [70]; and model-driven approaches, where this connection has been previously spotted [66].

There is yet another way to classify energy demand forecasting [68]. Using the model, for example, comparing the experimental to the mathematical model, the static to the dynamic model, the univariate to the multivariate model, and so on. But also based on the curve-fitting statistical technique opposed and constructed with artificial intelligence methods [66].

Conventional methods are preferable for yearly energy consumption forecasts at the national level, as our case in this thesis, according to the findings of extensive reviews [75]; [8]; [98]. Nonlinear regression models, for example, can not only explicitly characterize the link between consumption data and influencing factors, but they also have the lowest average MAPE (below 2 %) when it comes to long-term energy consumption predictions [75].

According to Soldo (2012)'s previous research [98], the application area of energy consumption forecasting can be divided into the following main categories: global, national or state level, regional or distributional level (distribution system and city area), separate sectors within distribution levels, and individual customer level.

In general, demand forecasting is done by using mathematical models to estimate historical data/information in order to forecast the trend of future energy demand [68].

4.3 Literature Review

Despite the fact that recent review articles surveyed energy demand forecasting in a specific branch, such as natural gas [64]; [74], and make a category in the specific fields, few pay attention comprehensively to demand forecasting methods of all energy types in the literature. Suganthi and Samuel [66] presented a list of the forecasting methods used for energy demand and described each method in detail. After that, Ghalehklondabi, Ardjmand, Weckman and Young [50] studied the ten most-employed energy demand forecasting methods in the last ten years between 2005 and 2015.

Potocnik et al. [79] presented a recursive ARX model for predicting natural gas consumption in the short term. Chen et al. [108] constructed a FARX for forecasting a day-ahead natural gas consumption. He and Lin [109] used a mixed data sampling method combined with an autoregressive distributed lag to forecast long-term energy consumption of China.

Natural gas consumption forecasting has also been performed using the Autoregressive Moving Average (ARMA) model. Pappas et al. [96], for example, employed an ARMA model to predict the Greek Power system's electrical load. Ervural et al. [10] introduced a forecasting method combining ARMA and genetic algorithm (GA) for Istanbul's gas demand (Turkey).

Melikoglu [74] used a Logistic Regression Model to make accurate forecasts of Turkey's natural gas demand. Shaikh and Ji [39] used the Levenberg-Marquardt algorithm, which is a combination of Gauss-Newton algorithms and gradient descent, to optimise the coefficients of this model.

Chai et al. [54] and Aydin [1] pioneered the use of Simple Linear Regression models in energy demand forecasting. Kovacic and Sarler [71] used a Multiple Linear Regression model optimised by genetic algorithm to forecast the natural gas consumption of a steel factory in Slovenia.

Both of these models are receiving wide acceptance in energy consumption forecasts [6].

Bianco et al. [103] created logarithmic functions to estimate natural gas demand in the residential and nonresidential sectors of Italy. Vondracek et al. [105] developed a nonlinear regression model to estimate natural gas consumption. Ozmen et al. [7] used regression spline models to forecast residential customers' daily natural gas use. Using an exponential model, Assareh et al. [25] and Behrang et al. [67] projected future oil demand. To forecast natural gas consumption, Karadede et al. [110] used a nonlinear regression model optimised by a breeder hybrid algorithm.

Tamba et al. [100] examined at forecasting models in the field of natural gas forecasting from 1949 to 2015. They gave insights into the forecasting horizons, application area, data and methods based on analysis and synthesis of existing research. Furthermore, as AI-based models become more widely used, recent research have conducted extensive assessments of AI-based models for energy consumption predictions [99].

Prior to the rise of AI technology, traditional models such as time series models, regression models, and gray models were used to forecast energy consumption [4]. According to recent study, traditional models can achieve equivalent forecasting accuracy to AI models in energy consumption forecasting if the weight parameters and variables are properly specified [75].

Unlike traditional models, AI-based forecasting models do not rely on an explicit relationship between energy consumption and its influencing elements for prediction, instead learning from a significant amount of historical data [55]. These models, such as the ANN and SVR, excel at dealing with nonlinear problems and are commonly employed in energy consumption forecasting, especially for short-term forecasting. As a result, a number of literature evaluations on AI-based model analysis have been published.

Nia et al. [8] reviewed publications related to energy demand forecasting from 2000 to 2020 with focus on Industry 4.0 solutions and their effects and influences in energy demand forecasting. A total of 267 publications were chosen and about 73 distinctive approaches of energy demand forecasting were discovered. Accordingly, among these approaches, eight methods were found with the most citations, appearing in 56% of the total articles.

Apparently, these are the most often used forecasting methods in the literature, for forecasting energy consumption. Conventional (e.g., Metaheuristic algorithms, Regression model, Grey model, Fuzzy Logic, Time series model, Simulation model) and Intelligent advanced (e.g. Neural Network and Machine Learning) methods are used to classify these methods.

In the following table, the methods that have stand out in the application area of national energy demand for oil as energy source are exhibited, as this is the category our Optimised Theta Model in this thesis falls into.

Year	Author	Title	Model	Source	Category	Citations
2007	Ediger et al. [104]	Forecasting of primary energy demand by fuel in Turkey	ARIMA, SARIMA	Oil	National energy demand	>240
2008	Unler [101]	Energy demand forecast: The case of Turkey with projections to 2025	Particle swarm optimisation (PSO)	Oil	National energy demand	>120
2012	Kiran et al. [73]	Forecasting energy demand of Turkey	A hybrid approach based on Particle Swarm Optimisation and Ant Colony Algorithm	Oil	National energy demand	>110

2013	Ghanbari et al. [5]	Model and simulate fluctuations of energy demand under the influence of related factors	Cooperative Ant Colony Optimisation-Genetic Algorithm (COR-ACO-GA)	all	National energy demand	>40
2018	Wang et al. [81]	Forecasting energy demand in China and India	Single-linear, hybrid-linear, and non-linear time series, grey theory	Oil	National energy demand	>20
2017	Rehman et al. [91]	Forecasting long-term energy demand in Pakistan	Autoregressive Integrated Moving Average (ARIMA), Holt-Winter, the long-range alternative energy planning (LEAP)	all	National energy demand	>15
2012	Assareh et al. [25]	Forecasting energy demand in Iran	Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO) Methods	Oil	National energy demand	>10
2015	Nazari et al. [76]	Develop different models to analyze energy demand of residential and commercial sectors in Iran	The GA and PSO energy demand estimation models (GA-DEM, PSO-GEM)	Oil	Residential	>5

Table 1 Most cited methods for national oil demand
Source: Nia et al., 2021 [8]

Nia et al. [8] came to the following crucial findings in their review: the Energy fuels are the top five research areas from 1979 to 2020. More than half of the researches (59%) examined demand projections for electricity, as resulting from examining the energy types of each article from 2000 to 2020. Coal and oil are in second and third place, with 17% and 10%, respectively. Because fossil fuels cannot be replaced once they are depleted, decision-makers are increasingly looking to renewable energy sources. Renewable energy is an intriguing topic, yet just 3% of publications addressed it. This percentage is predicted to rise over the next ten years. About a third of all publications (34%) looked into national energy demand (as in this dissertation). Finally, according to the types of methodologies employed in publications from 2000 to 2020, the top three methodologies are neural networks, metaheuristic algorithms, and grey modeling, followed by Time Series Modeling (as our Theta Model).

Below are presented some insightful figures of Nia et al. [8] research, that sum up the application areas, energy types, most used methods and most researched categories in the energy and oil&gas sector.

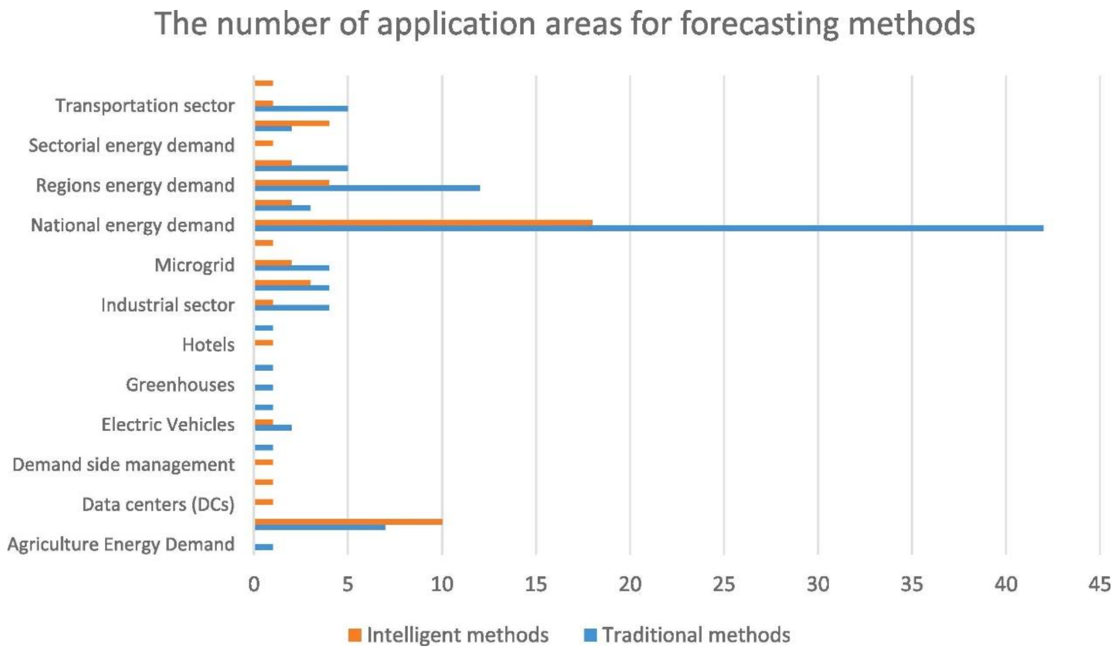


Figure 24 Distribution of forecasting methods across application areas
Source: [Nia et al., 2021 [8]]

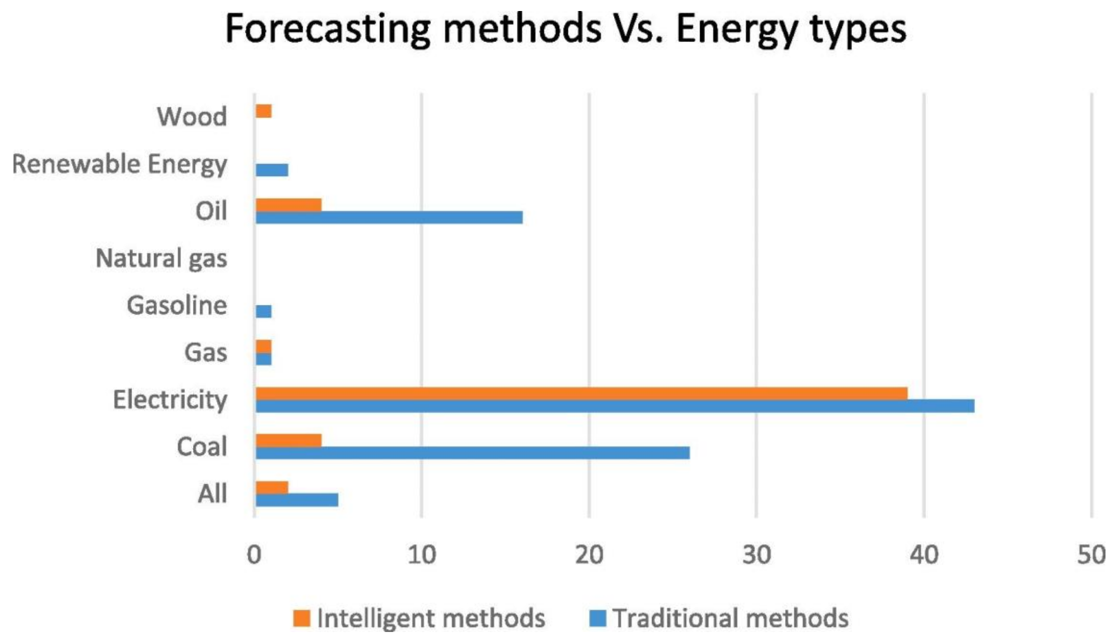


Figure 25 Distribution of forecasting methods across energy types
Source: [Nia et al., 2021 [8]]

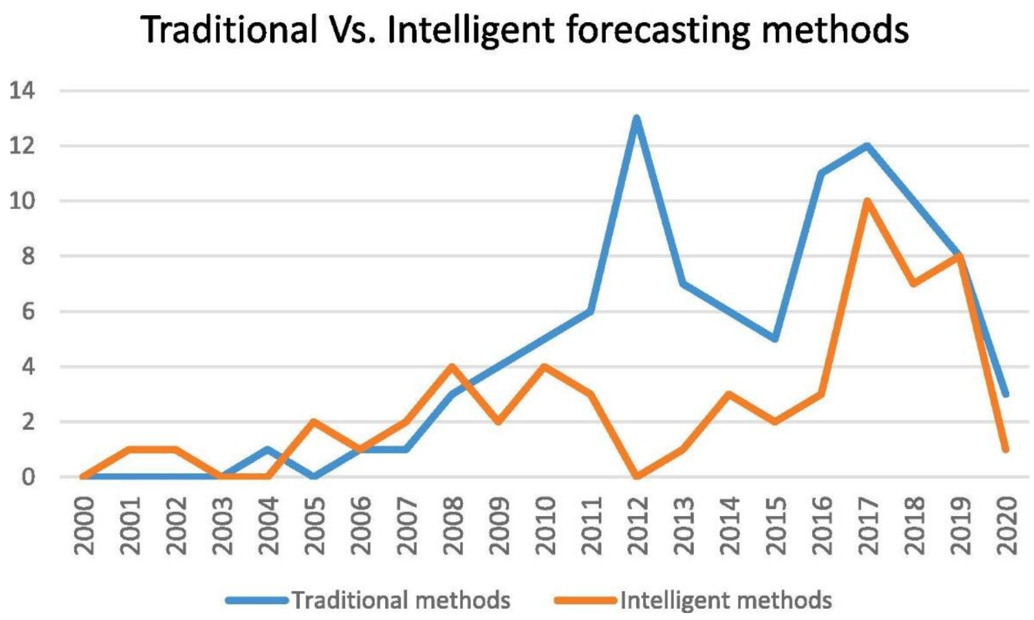


Figure 26 Traditional vs Intelligent forecasting Methods on energy sector
Source: [Nia et al., 2021 [8]]

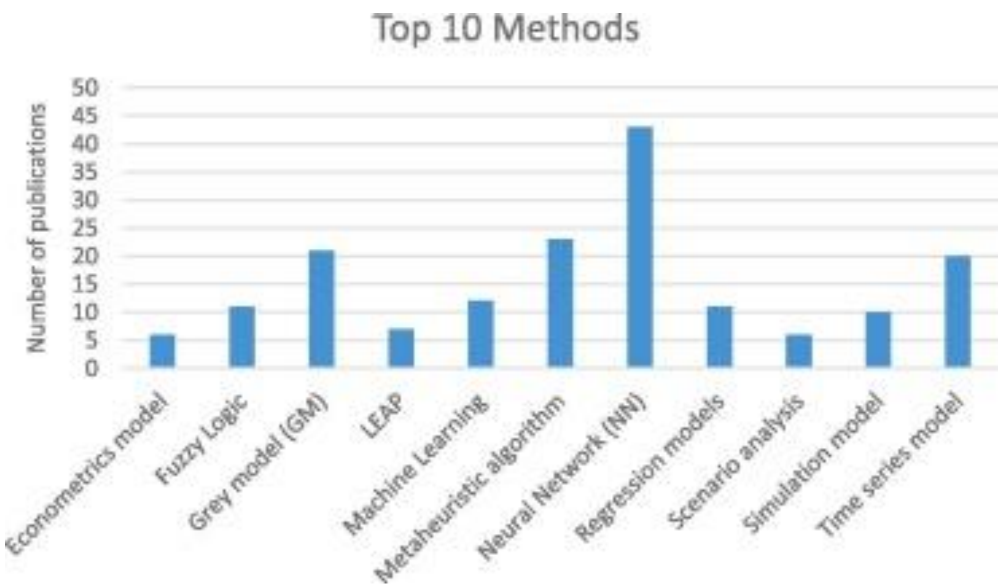


Figure 27 Most used methods on energy sector
Source: [Nia et al., 2021 [8]]

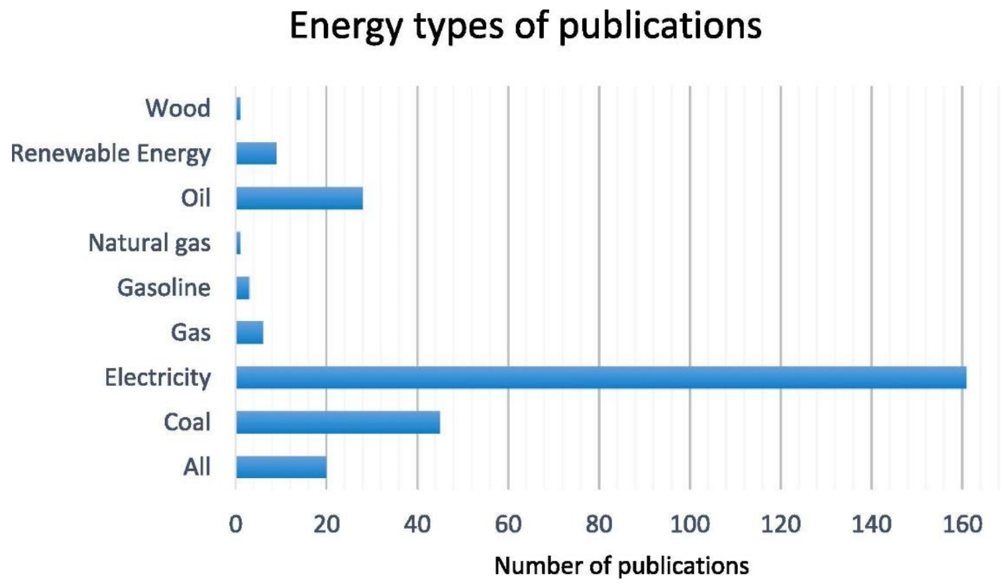


Figure 28 Distribution of forecasting publications across energy sources
Source: Nia et al., 2021 [8]

Wei et al. [75] also provided insightful findings as far as forecasting energy demand is concerned, with focus on conventional models in our case:

In 116 papers reviewed in their study, 128 models were proposed or used as major forecasting models.

For annual energy consumption forecasts at a national level, traditional models are preferred. This sort of conventional model has a lot of expertise in this industry; 68% of traditional models are used to forecast annual energy consumption, and 64% of them are employed at a national level. NLR models, for example, can not only explicitly characterize the link between consumption data and affecting factors, but they also have the lowest average MAPE (1.79%) for long-term energy consumption forecasting in their study.

Altogether, AI-based and conventional models accounted for 48% and 43% of all models, respectively. Both of these models are popular in energy consumption, it may be concluded. Despite the fact that AI-based methods hold the top spot, conventional methods continue to demonstrate their competitive prowess. Recent research suggests that, under certain situations, conventional models, such as MLR and ARIMA, can outperform advanced AI models [75].

Besides, in the recent M4 competition, that has been one of the most important events in the forecasting community since 1982 [95], it was used a large data set of 100.000 time series and the outcome was the following: out of the 17 most accurate methods, 12 were ”combinations” of mostly statistical approaches. The six pure Machine Learning Methods performed poorly, with none of them being more accurate than the combination benchmark and only one being more accurate than Naive2 [92]. The results confirmed that: pure machine learning (ML) and neural network (NN) methods performed worse than standard algorithms like ARIMA or Exponential Smoothing (ES), and still worse against various combinations of these base statistical methods [95].

The majority of methods concentrate on long-term energy consumption forecasting, which is followed by short-term forecasting and medium-term forecasting. The percentages of the models for monthly, daily, hourly and yearly forecasting are 17 %, 23 %, 23 % and 43 %, respectively. Only four models are used in the application field to forecast the world's energy consumption. 67 methods, accounting for 45 % of the total, are utilized to forecast energy use at the national level.

Based on all of the above findings, it can be stated that energy consumption forecasting plays an essential role in the advancement of a country and piques the academics' interest.

The national energy consumption data for most countries can be found on their government website or in easily accessible reports. Energy consumption data at the regional level, on the other hand, is filed by local government departments or businesses, while data at the distribution and consumer levels is monitored by regulating body or customers themselves. These confidential data are difficult to obtain without authentication, especially when the volume of data is large.

The following figure shows a pie chart depicting Wei’s et al. [75] review results, in forecasting horizon and application status for conventional models and artificial intelligence-based models.

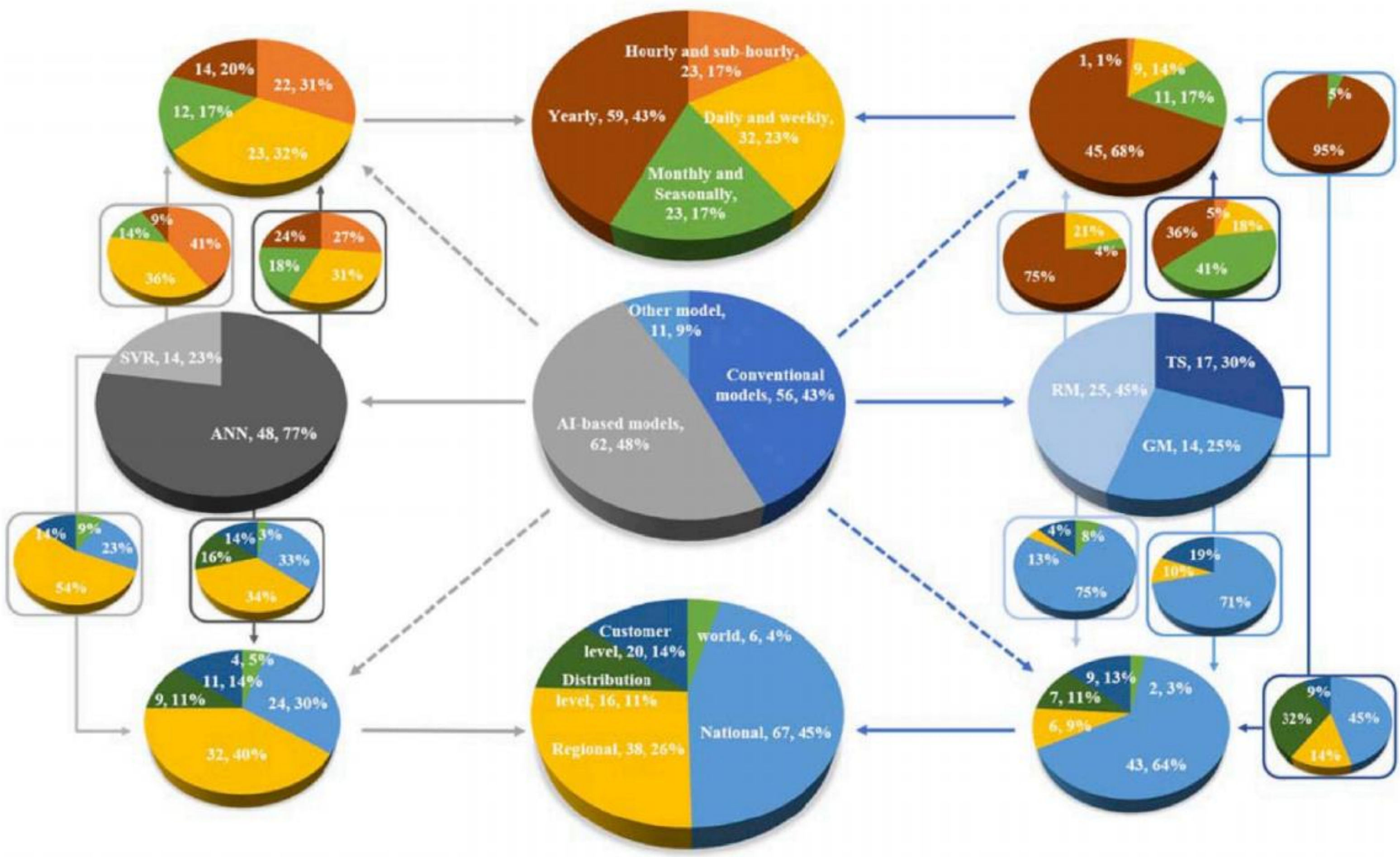


Figure 29 Forecasting horizon and application status for conventional and artificial intelligence-based models
Source: Wei et al., 2019 [75]

According to Figure 29, RM, TS, and GM account for 45 %, 30 %, and 25 % of total conventional models, respectively. Long-term and medium-term energy consumption forecasting do not require as much historical data as short-term energy consumption forecasting and do not require the intricate nonlinear relationship between consumption data and influencing factors [58]. As a result, for yearly and monthly consumption predictions, 85 % of traditional models are used. In fact, 100% and 79% of GM and RM, respectively, focus on yearly and monthly consumption projections. TS models are also active in these domains in 77 % of cases, with 41% of TS models contributing to monthly consumption predictions and 36% of TS models contributing to yearly consumption predictions.

At national level forecasting, 64 % of conventional models are used; 75 %, 71 %, and 45 % for RM, GM, and TS models, respectively. Annual energy consumption forecasting has a greater impact on the development of energy planning and national strategic planning for each country. As a result, these yearly consumption forecasting models are commonly employed at a national level.

To summarize, time series models, regression models, and gray models are all utilized in energy consumption forecasting and represent the conventional models. Many experts have worked to improve the structure of the models or combine them with other advanced methods in order to improve forecasting accuracy. Many improved conventional models and hybrid conventional models were created, according to the findings.

CHAPTER 5_THE THETA MODEL

5.1 Introduction

Assimakopoulos et Nikolopoulos [102] introduced the Theta Model, a method that topped the M3-Competition, the largest empirical forecasting competition until 2017 (S. Makridakis, 2000); and performed fairly well in the recent M4-Competition, taking the 11th place by achieving 4% improvement of forecasting accuracy over the benchmark [93]. The full theoretical underpinnings of the Theta model were presented by Thomakos et Nikolopoulos [18].

The Theta model is a time series forecasting model based on the premise that "an extrapolative method is essentially incapable of capturing all the accessible information hidden in a time series efficiently" [62]. As a result, this approach seeks to support models in capturing the data easier. This is accomplished by splitting the data into more simple series, each of which captures a portion of the information included in the original series. As a result, a decomposition approach is implemented.

5.2 Definition

The Theta Model is a univariate forecasting method which decomposes the original data into two or more lines, called Theta lines, extrapolates them separately using forecasting models of our choice, and then combines their predictions to obtain the final forecasts [29]. The forecasts are combined either equally weighted or through a weight optimisation procedure [62].

The method is based on modifying the time series' local curvature using a Theta (θ) coefficient applied to the second differences in the data. The transformation leads to the creation of new lines that keep the original data's mean and slope but not their curvature [28].

5.3 Key Features

The degree of curve deflation increases as the Theta coefficient decreases, and vice versa. Thus, oscillating lines with $0<\theta<1$ can be used to detect long-term trends (Assimakopoulos, 1995), whereas heavily curved lines with a value of $\theta>1$ can be used to emphasize the series' short-term properties, such as the running level. In practice, θ can be thought of as a transformation that adjusts the curvatures of a series based on the distance between its points and the ones of a simple linear regression in time, derived from θ= 0. In this context, two or more Theta lines can be constructed, extrapolated and combined to mimic the series' short- and long-term behavior [28].

The Theta model, in its original form, consists of two Theta lines with values of θ equal to 0 and 2, calculated on the seasonally adjusted data. This exact model was applied to the monthly M3-Competition's data. Theta line (0) is basically a simple linear regression line, with zero curvature. Theta line (2), on the other hand, depicts a line with double the curvature of the original series. The first line is projected by extrapolating the linear regression line in time, whereas the second is projected using Simple Exponential Smoothing (SES) [46]. The forecasts are then combined with equal weights and finally they are reseasonalized.

The deseasonalization is performed using the classical multiplicative decomposition by moving averages [97], provided that a significant seasonal pattern has been identified at the $(1-\alpha)$ % confidence level [56].

This complete form of Theta competed in the M3-Competition [93] and became well-known for outperforming all of its competitors, especially for monthly series and microeconomic data. It is noteworthy to mention that, despite its simplicity, the model outperformed by far the more complex, sophisticated, advanced methods and expert systems, such as ForecastPro and ForecastX. Till today, it stands out as a difficult benchmark to beat [28].

5.4 Advantages

The Theta transformation proves to be useful in time series forecasting, as a coefficient between 0 and 1 will produce a Theta line with observations that are closer to those of Theta Line (0), with the ability to identify the long-term characteristics of the data like trend (Assimakopoulos, 1995), while a coefficient of θ greater than 1 will give a Theta line with observations that are farther from the ones of Theta Line (0), allowing us to point out the short-term characteristics of the data, like level [29]. As a consequence, Theta can successfully detect and differentiate complex patterns in data, use suitable forecasting methods to project each one separately and combine their extrapolations to achieve better forecasting performance. [45].

Theta's benefit stems from the "divide and conquer" property: there is not any forecasting model capable of effectively capturing all possible time series patterns. Still, improvements in forecasting accuracy (even for traditional models) are possible, if the series is decomposed into numerous lines of a decreased amount of information [29].

At present, original Theta Model is sometimes called as “SES with drift”, since the level of the series obtained by extrapolating Theta Line (2) is drifted by half of the slope of Theta Line (0) [87]. Although this simplification is only valid under certain assumptions [62], it is useful in comprehending how the method works.

There is no limitation on the number and the type of the lines that may be considered for applying the Theta method. For example, a double-lined model of coefficients 0 and $\theta \neq 2$ can be used to adjust the slope of the forecasts [16], while a triple-lined model can be exploited to extract more information from the original data. However, given its simplicity, efficiency, and ease of parameterization, the double-lined model has become the most popular over the years [29].

5.5 Limitations

Even if the optimal value of θ is successfully specified, Theta method will still produce unreasonable forecasts for time series of non-linear trends, like exponential ones [28]. This takes place because Theta drifts Simple Exponential Smoothing forecasts at each point by a constant value. This restriction can result to poor forecasting accuracy, particularly for long-term forecasts where trend ends up being dominant [29].

A second limitation of the Theta method is that the components of level and trend, expressed through Theta Line (θ) and Theta Line (0) respectively, are connected in an additive way. However, the components of time series are not additively connected in all cases. For example, both multiplicative and additive models are available in Exponential Triple Smoothing, giving the algorithm the ability to effectively capture a variety of patterns [86].

5.6 Past Work on Theta Model - Literature Review

In the original form of the Theta Model, when expressed appropriately, θ is the only unknown parameter that has to be determined in order to improve forecasting accuracy across various, different series. Thus, research has mainly focused on its optimal identification, given a predefined error measure [16]; [18]; [56].

Since the Theta Model made its first appearance and taking into account its outstanding performance in the M-3 Competition, a lot of work has gone into both the direction of integrating it in Forecasting Support Systems and verifying its accuracy on various data sets. Nikolopoulos et Assimakopoulos [61] created a system that integrates Theta Model's predictions, succeeding at supporting decisions by judgmental and automated rule-based adjustments. Later, this Theta Model was considered as one of the forecasting techniques of a web-based Forecasting Support System. Moving on, Pagourtzi et al. [27] assessed the Theta model for forecasting the total average dwelling prices in the United Kingdon and quarterly housing prices.

Furthermore, the model was evaluated on a big dataset of non-demand forecasting series by forecasting the S&P500 index's evolution [60] and pointing to potential improvements in supply chain planning and management [62]. In more recent research, Thomakos et Nikolopoulos [19] suggested the expansion of the univariate Theta model for recasting multivariate time series and evaluated its performance in real-world financial and macroeconomic data.

The results of all the above-mentioned studies were highly promising as the performance of the Theta method was on the same level, or above the benchmarks set, outperforming them.

Theta model research has progressed in the direction of fine-tuning its parameters and broadening its application. Constantinidou et al. [16] established a neural network approach for calculating the optimal weights with which each one of the two Theta lines contributes to the final forecast. Petropoulos et Nikolopoulos [37] used multiple Theta lines to bring out more information from the available data and further enhance the accuracy of the model. Thomakos et Nikolopoulos [18] presented a method for determining the optimal value of θ, when using a single Theta line apart from the straight line derived from θ=0 and constructed a formula for optimizing the combination weights of the two Theta lines. Again, with the first line constructed for θ= 0, Fioruci et al. [56] suggested a method which bases on validation scheme the optimal selection of the second Theta line.

More recently, due to the fact that research is more or less focused on combining a straight line (θ=0), useful for identifying the long trend, with the "best" curved one (second Theta Line), useful for identifying the short-term characteristics of the series, Spiliotis, Assimakopoulos et Nikolopoulos [28], addressed the problem if the trend of the model is not linear and expanded the Theta Model to nonlinear trends, particularly for mid or long term forecasts. They suggested the replacement of the original Theta Line (0) with simple nonlinear lines and the construction of a second one, so that the original time series is reconstructed from their combination. This second Theta Line is curved only at the points which diverge from the trend pattern, making it much more stable and effective in modeling level variations.

Finally, in the most recent research to date, Spiliotis, Assimakopoulos et Makridakis [29], generalized the Theta method for automatic time series prediction, so that both linear and non-linear trends are considered, the slope of such trends is adjusted and a multiplicative expression of the Theta model is introduced.

CHAPTER 6_OPTIMISED THETA MODEL

6.1 Construction of the Theta Model in Excel

6.1.1 Introduction

In competitive energy markets, accurate monthly, quarterly, and yearly energy demand forecasting can provide businesses an edge in negotiations and contract execution for medium-term generation, transmission, and distribution [78]. In addition, an accurate long-term energy demand estimate is required to assess the energy demand and provide valuable assistance for strategic decision-making. As a result, the first responsibility for accurate energy demand forecasting is to choose appropriate modeling methodologies that are consistent with the characteristics of predicted areas [82].

The Theta Model has mainly been applied to seasonally adjusted data and the forecasts are combined using equal weights and then reseasonalized. It has become very popular, particularly for monthly series and microeconomic data [28].

In our case, mid-term forecasts (annual data) will be performed, for macroeconomic data, specifically oil and gas demand. This means randomness is present and much stronger than the previous mentioned case and benefit cannot be gained from the deseasonalization process that boosts the performance and accuracy of the Theta Method. Besides, in the subset of Yearly-M3 Competition's 645 series, Theta presented its worst performance.

This will be confirmed as it will be witnessed that the naive method (taking the latest data available, meaning that of the previous year, as our forecast for next year), despite being the simplest method available, so much that even a kid can apply, performs much better than the other benchmarks.

At the same time, it will be also confirmed that our optimised Theta Model through Excel Solver, outperforms the naive method and all other benchmark methods along with any randomness, change and outliner that come up, both in forecast fit (mean/total sMAPE across all data in each time series from 1990 to 2018) as well as and more importantly in point forecast accuracy sMAPE of the 2019 demand value.

6.1.2 Implementation of Original Theta Model

As mentioned before, in its original form, the Theta Model consists of two Theta lines with θ values of 0 and 2. Theta line (0) has zero curvature and equals to a simple linear regression line. On the other hand, Theta line (2) represents a line with double curvature of the original series. The first line is forecasted by extrapolating the regression line, while the second one using Simple Exponential Smoothing (SES) [46]. The forecasts are combined using equal weights.

In practice, the model can be easily implemented in a Microsoft Excel Worksheet via the following steps [62]:

• Step 1: Apply Simple Linear Regression to non-seasonal data and prepare

the LRL line and forecasts

• Step 2: Prepare the values for L(Θ=2) with formula, that is subtracting

the LRL values from the actual data multiplied by two.

• Step 3: Extrapolate L(Θ=2) with either SES or with a simpler method, such as a Moving average or even a Naive forecast [4,5]

• Combine with equal weights the forecasts from SES and LRL.

6.1.3 Implementation of our Optimised Theta Model

In our case, the Theta line (0) is kept, a simple linear regression that represents the trend of our data and defines the long-term characteristics and the second θ coefficient is let to be able to take any value. This second line is forecasted using SES as in the original form of the Theta Model. The above-described model has four decision variables that define it and can be used for optimizing it:

- The value of θ for the second line of our model
- The value of α, for the application of SES in the second Theta line
- The initial/first value for the application of SES in the second Theta line
- The value of w, between 0 and 1, that defines the weight of each Theta line in the final Theta Forecast (w for the Theta line (θ) and 1-w for the Theta line (0))

Going one step further, although it will come up in our case that offers little to no improvement, another θ line can be added, giving our model the flexibility to use two, not only one, more θ lines that are combined with the Theta line (0). This has been investigated before [62] for example with manual trials, keeping each parameter steady each time and changing only one to see in the M3 competition data how further improvement in forecasting accuracy can be achieved.

This is the extensive form of our model that automatically calculates the number and weights of each θ line to the final combined Theta Forecast, along with the best suited for the data parameters a of SES for the two θ lines. The variables of our final Three Theta Line Model that are calculated to optimise it for each time series with the simple press of the button “Solve” in Excel are:

- The value of θ_2 for the second line of our model

- The value of θ_3 for the third line of our model
- The value of α_2, for the application of SES in the second Theta line
- The value of α_3, for the application of SES in the third Theta line
- The initial/first value for the application of SES in the second Theta line
- The initial/first value for the application of SES in the third Theta line
- The value of w_1, between 0 and 1, that defines the weight of Theta line (0) in the final Theta Forecast
- The value of w_2, between 0 and 1, that defines the weight of the second Theta line in the final Theta Forecast
- The value of w_3, between 0 and 1, that defines the weight of the third Theta line in the final Theta Forecast

6.1.4 Construction of Optimised Theta Model in Excel

For our optimisation model, the following steps are performed to bring it to Excel, with respective changes:

• Step 1: Apply Simple Linear Regression directly to annual data and prepare

the LRL line and forecasts

• Step 2: Prepare the values for L(θ) with formula {[(θ*Data)] + [(1-θ)*LRL values]}

• Step 3: Extrapolate L(θ) with SES, letting α take values from α=0 to α=1 (Naive to Theta line (θ)) and letting initial value of SES take any value

• Combine with optimised weights the forecasts from SES and LRL, letting w take values from 0 to 1 with formula {[w*Theta line (θ)] + [(1-w)*Theta line (0)]} so that mean sMAPE from 1990 to 2018 is minimized

Accordingly, for our final optimisation model with two θ lines as described above:

• Step 1: Apply Simple Linear Regression directly to annual data and prepare

the LRL line and forecasts

• Step 2: Prepare the values for L(θ_2) and L(θ_3) with formula

{[(θ_x*Data)] + [(1-θ_x)*LRL values]} and let θ_2 and θ_3 be able to take negative values

• Step 3: Extrapolate $L(\theta_2)$ and $L(\theta_3)$ with SES, letting α_2 and α_3 take values from $\alpha=0$ to $\alpha=1$ (Naïve to Theta line (θ_x)) and letting initial value of each SES take any value

• Combine with optimised weights the forecasts from SES and LRL, letting w take values from 0 to 1 and $w_1+w_2+w_3=1$ with formula

{[w_1*Theta line (0)] + [w_2*Theta line (θ_2)] + [w_3*Theta line (θ_3)]} so that mean sMAPE from 1990 to 2018 is minimized

6.1.5 Evaluation of Forecasting Accuracy

To quantify the performance of models, several indicators have been introduced including CC, squarred correlation coefficient (R^2), mean squared error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), symmetric mean absolute percentage error (sMAPE), root mean square error (RMSE), normalized root mean squared error (NRMSE), and mean absolute range normalized error (MARNE) [77]. For various testing datasets however, the magnitudes of the indicators, such as MAE, MSE, and RMSE, are proven to be always different. Furthermore, very few studies have used CC, R^2, NRMSE, and MARNE [79]; [11]. As a result, the evaluation of the forecasting accuracy of our model, will be done by calculating the sMAPE (as introduced by Chen and Yang [111]).

To compare the accuracy of the methods with unified criteria, sMAPE is presented as the main criterion in this thesis, as it overcomes the asymmetry of MAPE (Makridakis, 1993), strengthened by the fact that this is also the indicator that has been used in M3 (2000) and M4 (2018) Forecasting Competitions.

In his blog, Rob. J. Hyndman said about M4: "The "M" competitions organized by Spyros Makridakis have had an enormous influence on the field of forecasting. They focused attention on what models produced good forecasts, rather than on the mathematical properties of those models. For that, Spyros deserves congratulations for changing the landscape of forecasting research through this series of competitions" [49].

More specifically, there are data from 1990 to 2019 for each oil or gas time series of each country. The mean sMAPE of all forecasts our model produces for each year is calculated, in comparison with the real data from 1990 to 2018 (forecast fit). Moreover, all past 30 values are used to forecast the 2019 value and sMAPE is calculated for this value alone (forecast error). Thus, the overall fit is extracted, a metric of how our model adapts to the whole time series across the 30 annual demand values; and also point single forecast accuracy is calculated, to see how it performs if one would actually use it to forecast next year's oil or gas demand.

Our results are compared to the ones of the naive method (the simplest to use and proven to perform very well with small errors for annual data), the MA3 and MA5 (MA= Moving Average) methods (simple to calculate and used by several companies) and the FRC.LIN (Linear) and FRC.ETS (Exponential Triple Smoothing) methods which are offered for free as ready to use methods in Excel.

With this process, the improvement achieved in forecasting accuracy is evaluated, by implementing the optimised Theta model and the use of the Excel Tool is suggested versus ready to use forecasting equations in Excel or taking the most recent data available as the next forecast.

Two countries will be presented (Germany and Greece) as examples step by step for oil demand and two countries (Austria and Slovakia) for gas demand.

6.1.6 Model Presentation in Excel

The basic Theta model when implemented as described above in a Microsoft Excel Worksheet, has the following image:

	X	Y			Numerator			Denominator				ThetaLine(0)		ThetaLine(2)		SES on ThetaLine(2)	S		Theta		APE(%)
	Period	Data		x-mean(x)=A	y-mean(y)=B	A*B		(x-mean(x))^2	b=slope	-23,265		LRL				with a=0.5	2667,240		Forecast		
1990	1	2817,011		-14	175,94	-2463,14		196	a=const	2990,047		2966,78		2667,24		2667,240	2667,240		2817,011		0,00
1991	2	2829,058		-13	187,98	-2443,8		169				2943,52		2714,60		2667,240	2690,919		2805,379		0,84
1992	3	2841,415		-12	200,34	-2404,11		144	a= average(Y) -			2920,25		2762,58		2690,919	2726,749		2805,586		1,27
1993	4	2908,449		-11	267,38	-2941,14		121	b*average(X)			2896,99		2919,91		2726,749	2823,330		2811,868		3,38
1994	5	2883,356		-10	242,28	-2422,84		100				2873,72		2892,99		2823,330	2858,160		2848,526		1,22
1995	6	2875,633		-9	234,56	-2111,04		81	b= sum(A*B) /			2850,46		2900,81		2858,160	2879,484		2854,309		0,74
1996	7	2922,352		-8	281,28	-2250,24		64	sum(denominator)			2827,19		3017,51		2879,484	2948,498		2853,338		2,39
1997	8	2917,255		-7	276,18	-1933,28		49				2803,93		3030,58		2948,498	2989,540		2876,213		1,42
1998	9	2922,83		-6	281,76	-1690,55		36				2780,66		3065,00		2989,540	3027,269		2885,101		1,30
1999	10	2835,786		-5	194,71	-973,569		25				2757,40		2914,18		3027,269	2970,722		2892,333		1,97
2000	11	2766,751		-4	125,68	-502,715		16				2734,13		2799,37		2970,722	2885,046		2852,427		3,05
2001	12	2807,46		-3	166,39	-499,163		9				2710,87		2904,05		2885,046	2894,550		2797,957		0,34
2002	13	2710,4		-2	69,33	-138,655		4				2687,60		2733,20		2894,550	2813,874		2791,076		2,93
2003	14	2679,222		-1	38,15	-38,1493		1				2664,34		2694,11		2813,874	2753,990		2739,106		2,21
2004	15	2648,038		0	6,97	0		0				2641,07		2655,00		2753,990	2704,497		2697,531		1,85
2005	16	2624,068		1	-17,00	-17,0041		1				2617,81		2630,33		2704,497	2667,413		2661,152		1,40
2006	17	2635,775		2	-5,30	-10,5945		4				2594,54		2677,01		2667,413	2672,211		2630,978		0,18
2007	18	2406,69		3	-234,38	-703,147		9				2571,28		2242,10		2672,211	2457,157		2621,744		8,55
2008	19	2533,462		4	-107,61	-430,443		16				2548,01		2518,91		2457,157	2488,034		2502,585		1,23
2009	20	2434,496		5	-206,58	-1032,88		25				2524,75		2344,24		2488,034	2416,139		2506,391		2,91
2010	21	2466,929		6	-174,14	-1044,86		36				2501,48		2432,37		2416,139	2424,257		2458,811		0,33
2011	22	2392,236		7	-248,84	-1741,86		49				2478,22		2306,25		2424,257	2365,255		2451,237		2,44
2012	23	2389,178		8	-251,90	-2015,16		64				2454,95		2323,40		2365,255	2344,329		2410,104		0,87
2013	24	2435,112		9	-205,96	-1853,64		81				2431,69		2438,54		2344,329	2391,433		2388,008		1,95
2014	25	2373,879		10	-267,19	-2671,93		100				2408,42		2339,34		2391,433	2365,384		2399,928		1,09
2015	26	2367,707		11	-273,37	-3007,02		121				2385,16		2350,26		2365,384	2357,820		2375,271		0,32
2016	27	2383,393		12	-257,68	-3092,15		144				2361,89		2404,89		2357,820	2381,357		2359,857		0,99
2017	28	2450,085		13	-190,99	-2482,84		169				2338,63		2561,54		2381,357	2471,449		2359,993		3,75
2018	29	2333,077		14	-308,00	-4311,94		196				2315,36		2350,79		2471,449	2411,120		2393,406		2,55
2019		2362,299										2292,10				2411,120			2351,609	MAP1	0,4535
2020		2148,325																			
																				MAP3	2,4304
	Average	Average				Sum		Sum									a	w		MAPE	1,8441
	15	2641,073				-47227,9		2030				ΓΡΑΦΗΜΑ↓					0,5	0,5		MAP5	1,7403

Figure 30 Basic Theta Model constructed in Excel

Our optimised Theta model with one more optimum Theta Line to be defined apart from the steady Theta line (0) simple linear regression line, can be seen below:

	INITIAL DATA								PARAMETERS		PARAMETERS					ERROR		
	X	Y		Numerator		Denominator			ThetaLine(0)	ThetaLine(2)	SES on ThetaLine(2)	S		Theta		APE(%)		
	Period	Data	x-mean(x)=A	y-mean(y)=B	A*B	(x-mean(x))^2	b=slope	-23,265	LRL		with a=0.5	2453,699		Forecast				
1990	1	2817,011	-14	175,94	-2463,14	196	a=const	2990,047	2966,78	2693,51	2453,699	2616,271		2817,011		0,00		
1991	2	2829,058	-13	187,98	-2443,8	169			2943,52	2734,68	2616,271	2696,539		2847,993		0,67		
1992	3	2841,415	-12	200,34	-2404,11	144	a= average(Y) -		2920,25	2776,41	2696,539	2750,683		2854,949		0,48		
1993	4	2908,449	-11	267,38	-2941,14	121	b*average(X)		2896,99	2917,90	2750,683	2864,042		2854,280		1,88		
1994	5	2883,356	-10	242,28	-2422,84	100			2873,72	2891,30	2864,042	2882,521		2870,897		0,43		
1995	6	2875,633	-9	234,56	-2111,04	81	b= sum(A*B) /		2850,46	2896,39	2882,521	2891,925		2859,817		0,55		
1996	7	2922,352	-8	281,28	-2250,24	64	sum(denominator)		2827,19	3000,82	2891,925	2965,747		2846,088		2,64		
1997	8	2917,255	-7	276,18	-1933,28	49			2803,93	3010,70	2965,747	2996,223		2851,163		2,29		
1998	9	2922,83	-6	281,76	-1690,55	36			2780,66	3040,06	2996,223	3025,941		2843,585		2,75		
1999	10	2835,786	-5	194,71	-973,569	25			2757,40	2900,42	3025,941	2940,852		2835,786		0,00		
2000	11	2766,751	-4	125,68	-502,715	16			2734,13	2793,65	2940,852	2841,061		2794,475		1,00		
2001	12	2807,46	-3	166,39	-499,163	9			2710,87	2887,11	2841,061	2872,278		2748,871		2,11		
2002	13	2710,4	-2	69,33	-138,655	4			2687,60	2729,20	2872,278	2775,282		2741,510		1,14		
2003	14	2679,222	-1	38,15	-38,1493	1			2664,34	2691,50	2775,282	2718,482		2696,723		0,65		
2004	15	2648,038	0	6,97	0	0			2641,07	2653,78	2718,482	2674,621		2663,669		0,59		
2005	16	2624,068	1	-17,00	-17,0041	1			2617,81	2629,23	2674,621	2643,851		2634,392		0,39		
2006	17	2635,775	2	-5,30	-10,5945	4			2594,54	2669,78	2643,851	2661,425		2608,936		1,02		
2007	18	2406,69	3	-234,38	-703,147	9			2571,28	2270,97	2661,425	2396,733		2597,592		7,63		
2008	19	2533,462	4	-107,61	-430,443	16			2548,01	2521,46	2396,733	2481,289		2503,854		1,18		
2009	20	2434,496	5	-206,58	-1032,88	25			2524,75	2360,08	2481,289	2399,117		2512,062		3,14		
2010	21	2466,929	6	-174,14	-1044,86	36			2501,48	2438,44	2399,117	2425,772		2471,602		0,19		
2011	22	2392,236	7	-248,84	-1741,86	49			2478,22	2321,34	2425,772	2354,973		2462,909		2,91		
2012	23	2389,178	8	-251,90	-2015,16	64			2454,95	2334,94	2354,973	2341,392		2425,768		1,52		
2013	24	2435,112	9	-205,96	-1853,64	81			2431,69	2437,94	2341,392	2406,841		2405,330		1,23		
2014	25	2373,879	10	-267,19	-2671,93	100			2408,42	2345,40	2406,841	2365,186		2407,961		1,43		
2015	26	2367,707	11	-273,37	-3007,02	121			2385,16	2353,32	2365,186	2357,140		2379,328		0,49		
2016	27	2383,393	12	-257,68	-3092,15	144			2361,89	2401,12	2357,140	2386,956		2360,506		0,96		
2017	28	2450,085	13	-190,99	-2482,84	169			2338,63	2541,99	2386,956	2492,056		2352,735		4,05		
2018	29	2333,077	14	-308,00	-4311,94	196			2315,36	2347,68	2492,056	2394,184		2366,941		1,44		
2019		2362,299							2292,10		2394,184			2321,897	MAP1	1,7250		
2020		2148,325																
											VARIABLES				MAP3	2,1533	%	
	Average	Average			Sum	Sum					θ	a	w	init.value	MAPE	1,5435	%	OBJECTIVE FUNCTION
	15	2641,073			-47227,9	2030			ΓΡΑΦΗΜΑ↓		1,824587732	0,677914	0,29	2453,699	MAP5	1,6750	%	

Figure 31 Optimised Theta Model using Solver

Our four variables (value of θ for the second Theta line, value of α for the application of SES in the second Theta line, initial/first value for the application of SES in the second Theta line, value of w between 0 and 1 that defines the weight of each Theta line in the final Theta Forecast (w for the Theta line (θ) and 1-w for the Theta line (0)) are calculated by Solver so that the mean sMAPE of all 29 forecasts from 1990 to 2018 becomes minimum.

The mean (average) sMAPE of all past data is the objective function (MAPE cell) for our linear programming problem. It could be used as target for minimization the average sMAPE of the last three (2016, 2017, 2018) forecasts (MAP3 cell) or the average sMAPE of the last five (2014, 2015, 2016, 2017, 2018) forecasts (MAP5 cell) that in some cases could give us smaller sMAPE for the 2019 demand value forecast (MAP1 cell) but the target is the model to adapt (fit) as good as possible across the whole time series and use all 29 past values to extract information for the future.

Accordingly, when using the final form of the model, being able to use two more Theta Lines to describe it and optimise it, the following picture comes up:

ThetaLine(0)		ThetaLine(2)	Theta(3)	SES on ThetaLine(3)	S3	SES on ThetaLine(2)	S2		Theta		APE(%)
LRL				with a=0.5	2.674,05	with a=0.5	2620,441		Forecast		
2966,78		2620,44	2674,05	2.674,05	2.674,05	2620,441	2620,441		2878,856		2,17
2943,52		2678,83	2719,80	2.674,05	2.708,38	2620,441	2658,592		2861,607		1,14
2920,25		2737,94	2766,16	2.708,38	2.751,74	2658,592	2710,437		2854,106		0,45
2896,99		2923,49	2919,39	2.751,74	2.877,54	2710,437	2849,637		2850,004		2,03
2873,72		2896,00	2892,55	2.877,54	2.888,80	2849,637	2879,929		2868,341		0,52
2850,46		2908,68	2899,66	2.888,80	2.896,95	2879,929	2898,710		2858,347		0,60
2827,19		3047,25	3013,18	2.896,95	2.984,17	2898,710	2995,757		2845,631		2,66
2803,93		3065,99	3025,43	2.984,17	3.015,13	2995,757	3041,646		2853,177		2,22
2780,66		3109,42	3058,53	3.015,13	3.047,70	3041,646	3085,927		2847,340		2,62
2757,40		2938,67	2910,61	3.047,70	2.944,83	3085,927	2989,716		2841,184		0,19
2734,13		2809,56	2797,89	2.944,83	2.834,57	2989,716	2872,013		2798,856		1,15
2710,87		2934,24	2899,66	2.834,57	2.883,41	2872,013	2912,666		2751,398		2,02
2687,60		2740,32	2732,16	2.883,41	2.769,92	2912,666	2800,064		2744,909		1,27
2664,34		2698,76	2693,43	2.769,92	2.712,52	2800,064	2733,875		2698,517		0,72
2641,07		2657,18	2654,69	2.712,52	2.669,12	2733,875	2683,767		2664,421		0,62
2617,81		2632,29	2630,04	2.669,12	2.639,80	2683,767	2650,132		2634,418		0,39
2594,54		2689,89	2675,13	2.639,80	2.666,31	2650,132	2676,109		2608,603		1,04
2571,28		2190,67	2249,59	2.666,31	2.353,62	2676,109	2358,951		2598,086		7,65
2548,01		2514,36	2519,57	2.353,62	2.478,14	2358,951	2460,490		2498,966		1,37
2524,75		2316,04	2348,35	2.478,14	2.380,75	2460,490	2366,116		2508,668		3,00
2501,48		2421,58	2433,95	2.380,75	2.420,67	2366,116	2402,352		2466,925		0,00
2478,22		2279,39	2310,16	2.420,67	2.337,75	2402,352	2322,013		2459,157		2,76
2454,95		2302,85	2326,39	2.337,75	2.329,23	2322,013	2309,492		2421,056		1,33
2431,69		2439,61	2438,38	2.329,23	2.411,13	2309,492	2394,503		2400,691		1,42
2408,42		2328,54	2340,91	2.411,13	2.358,44	2394,503	2351,407		2405,328		1,32
2385,16		2344,80	2351,05	2.358,44	2.352,89	2351,407	2347,092		2376,645		0,38
2361,89		2411,61	2403,92	2.352,89	2.391,18	2347,092	2389,246		2358,242		1,06
2338,63		2596,37	2556,47	2.391,18	2.515,21	2389,246	2524,569		2351,775		4,09
2315,36		2356,33	2349,98	2.515,21	2.391,23	2524,569	2414,647		2369,173		1,54
2292,10				2.391,23		2414,647			2323,075	MAP1	1,6743
										MAP3	2,2303
			θ3	θ2	a3	w3	a2	w1	w2	MAPE	1,6454
ΓΡΑΦΗΜΑ↓			1,95452	2,312467142	0,750369	0,030341195	0,65335	0,74	0,228226	MAP5	1,6767

Figure 32 Optimised Theta Model with two Theta Lines using Solver

6.2 Application of the Model

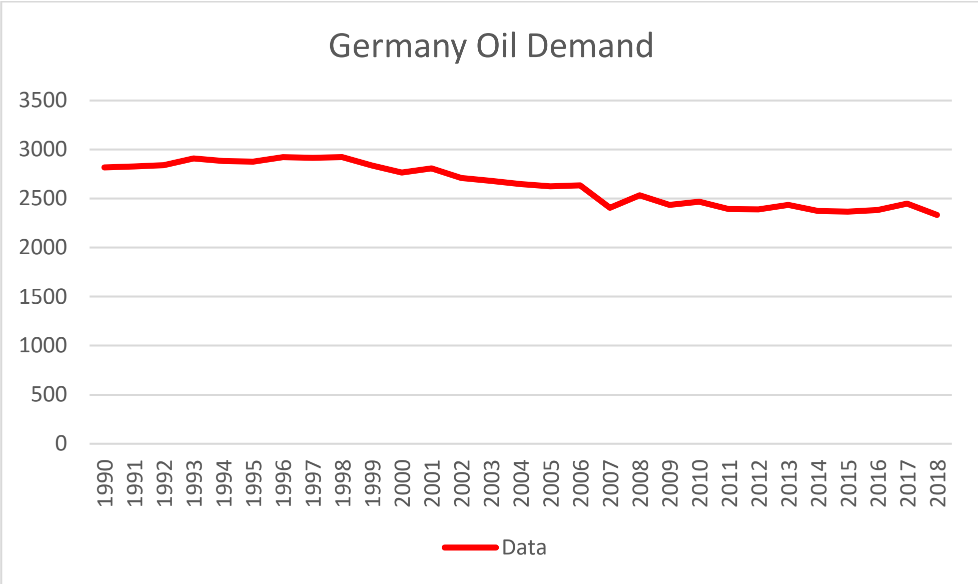
6.2.1 Germany Yearly Oil Demand

Now it will be seen and analyzed the case of Germany Oil demand. The data has been taken by eia and refers to the sum of total liquids of oil demand in kbbld, meaning sum of jet fuel, motor gasoline, kerosene, distillates, residual fuel oil, lpg and other refined.

The data obtained are the following:

	Period	Data
1990	1	2817,011
1991	2	2829,058
1992	3	2841,415
1993	4	2908,449
1994	5	2883,356
1995	6	2875,633
1996	7	2922,352
1997	8	2917,255
1998	9	2922,83
1999	10	2835,786
2000	11	2766,751
2001	12	2807,46
2002	13	2710,4
2003	14	2679,222
2004	15	2648,038
2005	16	2624,068
2006	17	2635,775
2007	18	2406,69
2008	19	2533,462
2009	20	2434,496
2010	21	2466,929
2011	22	2392,236
2012	23	2389,178
2013	24	2435,112
2014	25	2373,879
2015	26	2367,707
2016	27	2383,393
2017	28	2450,085
2018	29	2333,077
2019		2362,299
2020		2148,325

Table 2 Germany Annual Oil Demand Data 1990-2018



Plot 1 Germany Annual Oil Demand plot 1990-2018

Due to the almost linear form of the time series and the small, but clear dampened trend, it can be seen below that all methods perform very well (all have mean SMAPE and 2019 sMAPE below 3%).

ThetaLine(0)	ThetaLine(2)	SES on ThetaLine(2)	S		Theta		APE(%)	NAÏVE	APE(%)	KMO 3	APE(%)	KMO 5	APE(%)	FRC.LIN	APE(%)	FRC.ETS	APE(%)	
LRL		with a=0.5	2667,240		Forecast													
2966,78	2667,24	2667,240	2667,240		2817,011		0,00	2817,011	0		0		0	2966,782	5,17899	2995,05	6,126548	
2943,52	2714,60	2667,240	2690,919		2805,379		0,84	2817,011	0,426723		0		0	2943,517	3,965632	2972,025	4,928978	
2920,25	2762,58	2690,919	2726,749		2805,586		1,27	2829,058	0,435864		0		0	2920,252	2,736597	2948,999	3,715916	
2896,99	2919,91	2726,749	2823,330		2811,868		3,38	2841,415	2,331673	2829,161	2,7638		0	2896,987	0,394877	2925,973	0,600698	
2873,72	2892,99	2823,330	2858,160		2848,526		1,22	2908,449	0,866505	2859,641	0,825891		0	2873,722	0,334682	2902,947	0,67715	
2850,46	2900,81	2858,160	2879,484		2854,309		0,74	2883,356	0,268217	2877,74	0,073257	2855,858	0,690048	2850,457	0,879331	2879,921	0,14902	
2827,19	3017,51	2879,484	2948,498		2853,338		2,39	2875,633	1,61158	2889,146	1,142781	2867,582	1,891912	2827,192	3,310181	2856,896	2,26524	
2803,93	3030,58	2948,498	2989,540		2876,213		1,42	2922,352	0,174589	2893,781	0,807921	2886,241	1,068789	2803,927	3,96168	2833,87	2,899783	
2780,66	3065,00	2989,540	3027,269		2885,101		1,30	2917,255	0,190934	2905,08	0,609141	2901,409	0,735582	2780,662	4,985289	2810,844	3,906263	
2757,40	2914,18	3027,269	2970,722		2892,333		1,97	2922,83	3,023082	2920,812	2,954042	2904,285	2,386694	2757,397	2,803016	2787,818	1,705958	
2734,13	2799,37	2970,722	2885,046		2852,427		3,05	2835,786	2,464417	2891,957	4,42524	2894,771	4,522456	2734,132	1,185952	2764,792	0,070831	
2710,87	2904,05	2885,046	2894,550		2797,957		0,34	2766,751	1,460616	2841,789	1,215347	2872,995	2,307376	2710,867	3,5008	2741,767	2,367672	
2687,60	2733,20	2894,550	2813,874		2791,076		2,93	2807,46	3,51804	2803,333	3,370952	2850,017	5,021803	2687,603	0,844664	2718,741	0,307258	
2664,34	2694,11	2813,874	2753,990		2739,106		2,21	2710,4	1,156967	2761,537	3,025875	2808,646	4,716721	2664,338	0,557095	2695,715	0,6137	
2641,07	2655,00	2753,990	2704,497		2697,531		1,85	2679,222	1,170721	2732,361	3,134432	2759,924	4,137814	2641,073	0,263396	2672,689	0,926598	
2617,81	2630,33	2704,497	2667,413		2661,152		1,40	2648,038	0,909305	2679,22	2,079901	2722,374	3,677431	2617,808	0,238878	2649,663	0,970653	
2594,54	2677,01	2667,413	2672,211		2630,978		0,18	2624,068	0,445141	2650,443	0,554935	2693,838	2,178861	2594,543	1,576679	2626,638	0,347287	
2571,28	2242,10	2672,211	2457,157		2621,744		8,55	2635,775	9,086227	2635,961	9,093244	2659,501	9,980294	2571,278	6,61263	2603,612	7,860656	
2548,01	2518,91	2457,157	2488,034		2502,585		1,23	2406,69	5,132285	2555,511	0,866566	2598,759	2,544596	2548,013	0,572708	2580,586	1,84293	
2524,75	2344,24	2488,034	2416,139		2506,391		2,91	2533,462	3,984167	2525,309	3,66197	2569,607	5,400007	2524,748	3,639745	2557,56	4,930402	
2501,48	2432,37	2416,139	2424,257		2458,811		0,33	2434,496	1,323406	2458,216	0,353807	2526,898	2,40175	2501,483	1,39095	2534,534	2,70343	
2478,22	2306,25	2424,257	2365,255		2451,237		2,44	2466,929	3,074321	2478,295	3,5339	2495,47	4,224265	2478,218	3,53077	2511,508	4,864564	
2454,95	2323,40	2365,255	2344,329		2410,104		0,87	2392,236	0,127913	2431,22	1,744358	2446,762	2,381539	2454,953	2,715671	2488,483	4,071833	
2431,69	2438,54	2344,329	2391,433		2388,008		1,95	2389,178	1,904311	2416,114	0,783239	2443,26	0,334029	2431,688	0,140724	2465,457	1,23841	
2408,42	2339,34	2391,433	2365,384		2399,928		1,09	2435,112	2,546599	2405,509	1,323561	2423,59	2,072367	2408,423	1,444641	2442,431	2,846645	
2385,16	2350,26	2365,384	2357,820		2375,271		0,32	2373,879	0,26036	2399,39	1,329234	2411,467	1,831275	2385,158	0,734344	2419,405	2,159901	
2361,89	2404,89	2357,820	2381,357		2359,857		0,99	2367,707	0,660335	2392,233	0,370189	2391,622	0,344666	2361,893	0,906178	2396,379	0,543375	
2338,63	2561,54	2381,357	2471,449		2359,993		3,75	2383,393	2,759565	2374,993	3,112558	2389,854	2,488916	2338,628	4,65498	2373,354	3,1816	
2315,36	2350,79	2471,449	2411,120		2393,406		2,55	2450,085	4,892505	2400,395	2,844355	2402,035	2,912653	2315,363	0,762129	2350,328	0,736693	
2292,10		2411,120			2351,609	MAP1	0,4535	2333,077	1,244711	2388,852	1,117753	2381,628	0,814922	2292,098	3,016522	2327,302	1,492518	
						MAP3	2,4304	%	2,7708	%	2,1090	%	1,9154	%	2,1078	%	1,4872	%
			a	w		MAPE	1,8441	%	2,0074	%	2,1539	%	2,9272	%	2,2008	%	2,3986	%
ΓΡΑΦΗΜΑ↓			0,5	0,5		MAP5	1,7403	%	2,2239	%	1,7960	%	1,9300	%	1,7005	%	1,8936	%

Figure 33 Germany Oil demand basic Theta Model vs benchmark methods

The conventional Theta Model has already both the best fit and the smallest error in this case, achieving the best sMAPE across all time series with 1,84% along with the best sMAPE for the 2019 forecast value with 0,45%. If Solver is used to determine the best combination of a and w that gives the smallest possible error, the following picture is taken:

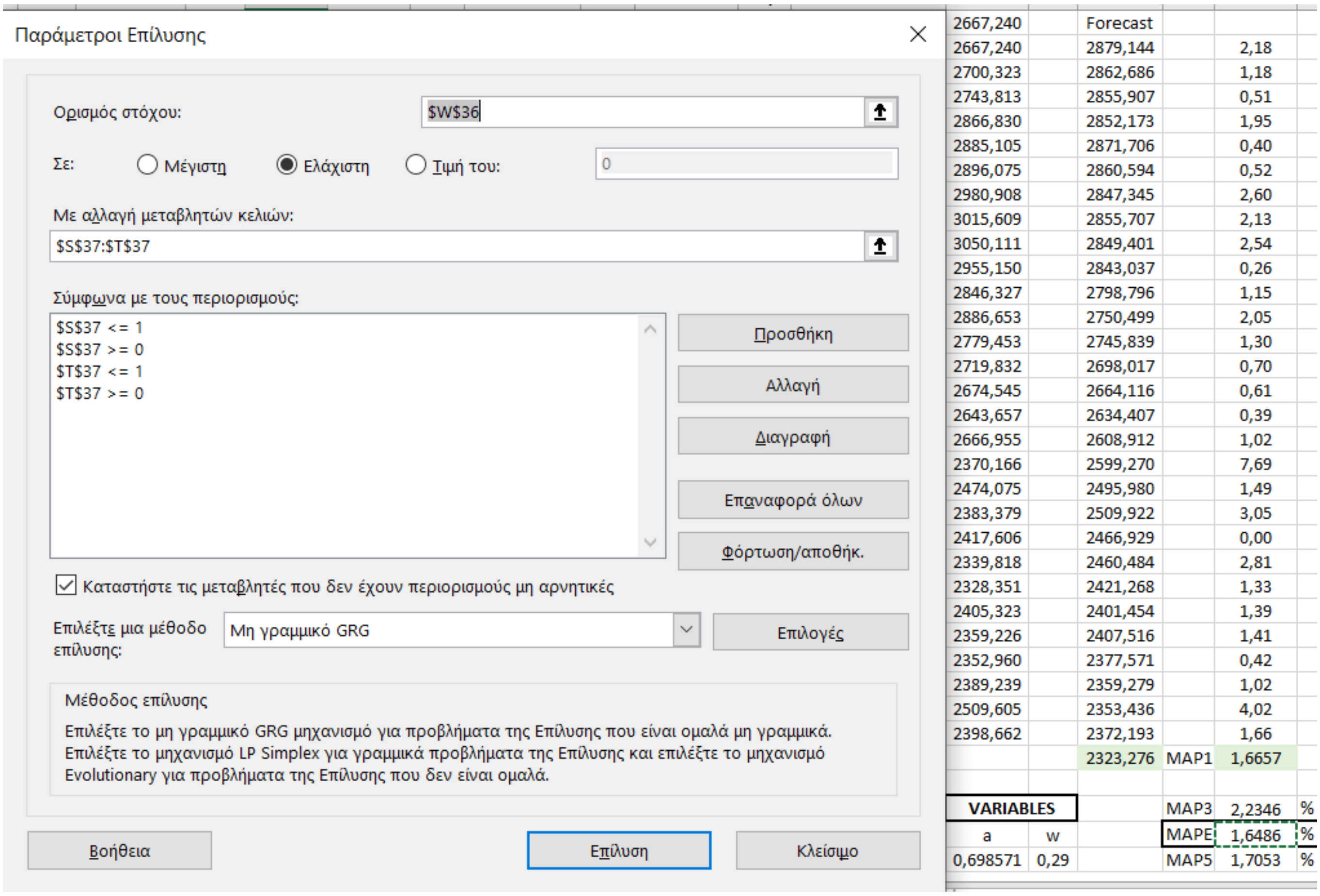


Figure 34 Germany Oil demand Solver Execution

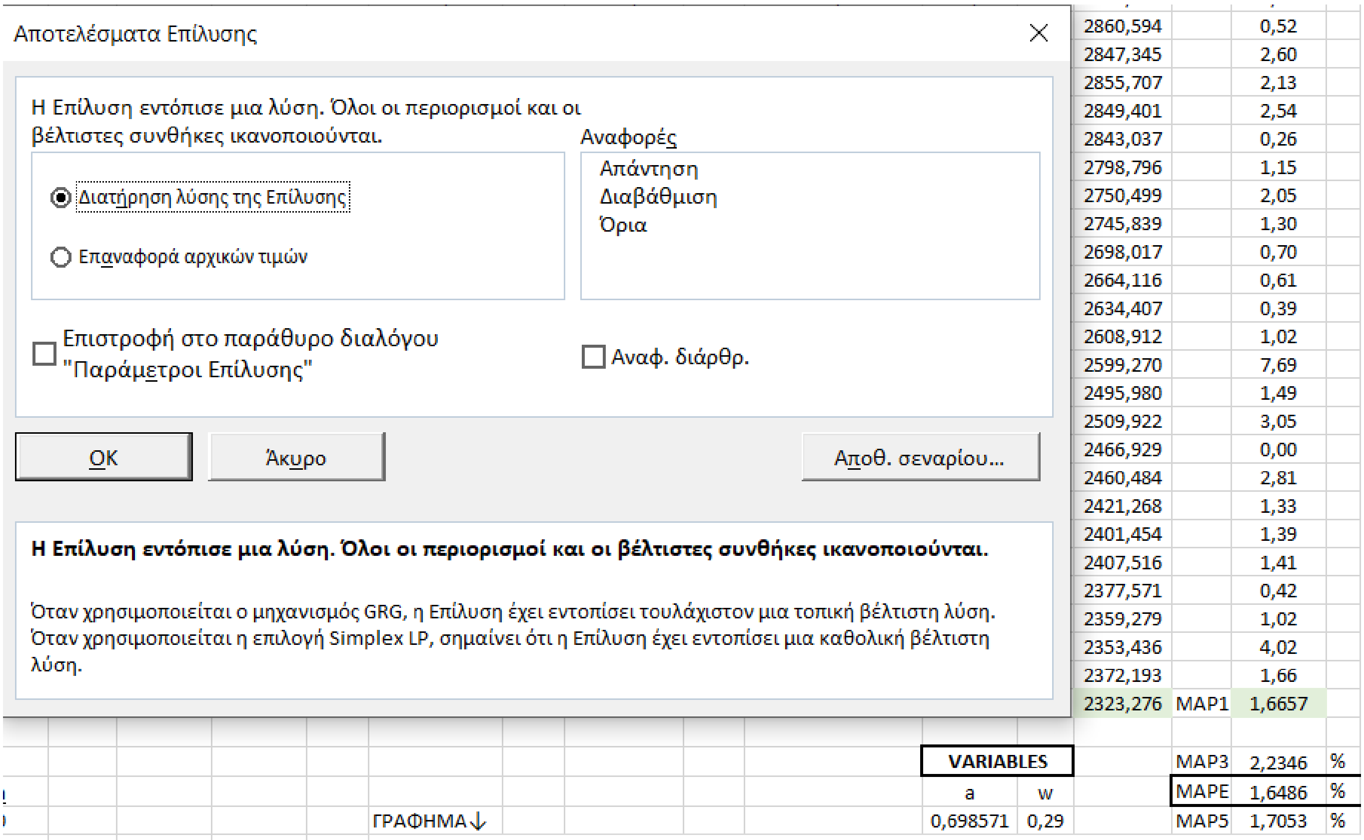
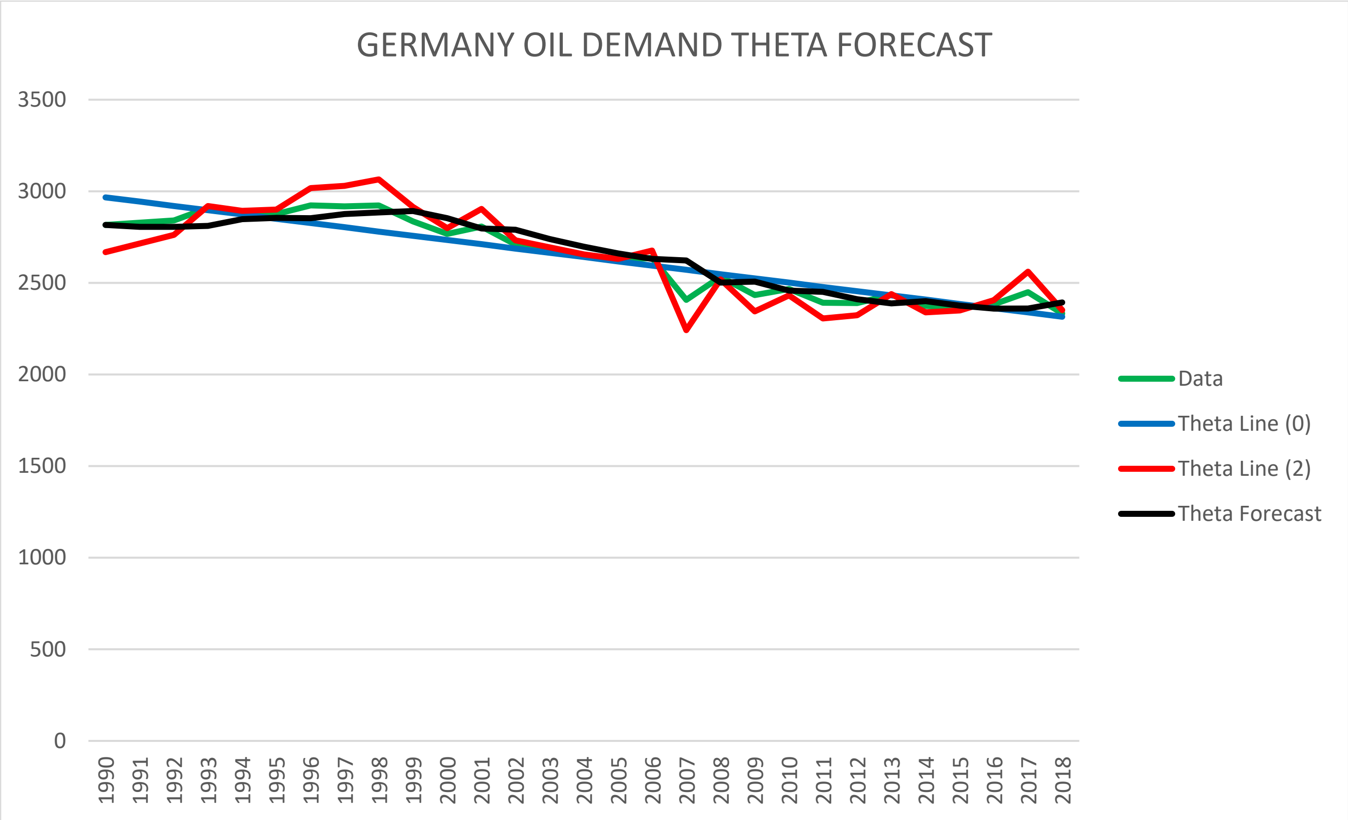


Figure 35 Germany Oil demand Solver Solution

Mean sMAPE is reduced further to 1,6486% with an α of approximately 0,7 and w of approximately 0,3, meaning this combination offers the best fit to the data. For the value of weight w, this result is very logical, due to the linear form of this time series and it means that that Theta Line (0), the LRL, contributes with more than 70% in the final Theta Forecast. The value of a, the closer it is to 1, the less smoothening takes place in Theta Line (2). In fact, when a=1, this means that SES in Theta Line (2) becomes naive, keeping the Theta Line (2) as it is in order to then contribute in the Theta Forecast. The value a = 0,7 is higher than the initial 0,5, but still offers a certain degree of smoothing, together with taking into account the initial value of SES. This initial value, along with θ, a and w will be determined in the next step, in our Optimised Theta Model with two Theta Lines.

It is observed that sMAPE of 2019 forecast raised from 0,45% to 1,65%. This does not mean that optimisation failed, or is not needed here, as the evaluation will be done in the end, calculating the average sMAPE of all 2019 forecasts of all oil time series from European Countries available. In addition, the goal is our optimised model to be used for future annual oil demand forecasts (e.g. until 2024), so the best way to construct it in order to use it as a tool for any time series that might appear, considering that some aspects of the past pattern will continue into the future (assumption of continuity, underlying premise of all quantitative forecasting methods), is by minimizing the average sMAPE of all past 29 values, defining the best possible fit to all series' data.

In the next graph, it is seen how Theta Method Works in our case and how the two Theta Lines combine in order to extract the Forecast that best adapts to our current data:



Plot 2 Germany Oil demand Plot, Theta Method forecasting with Theta Lines combination

The form and application of our Optimised Theta Model is now reached with two Theta Lines, where the second Theta Line can take any value θ and is not prior given the value of 2. Solver is used with the constraints seen below and the following result is got:

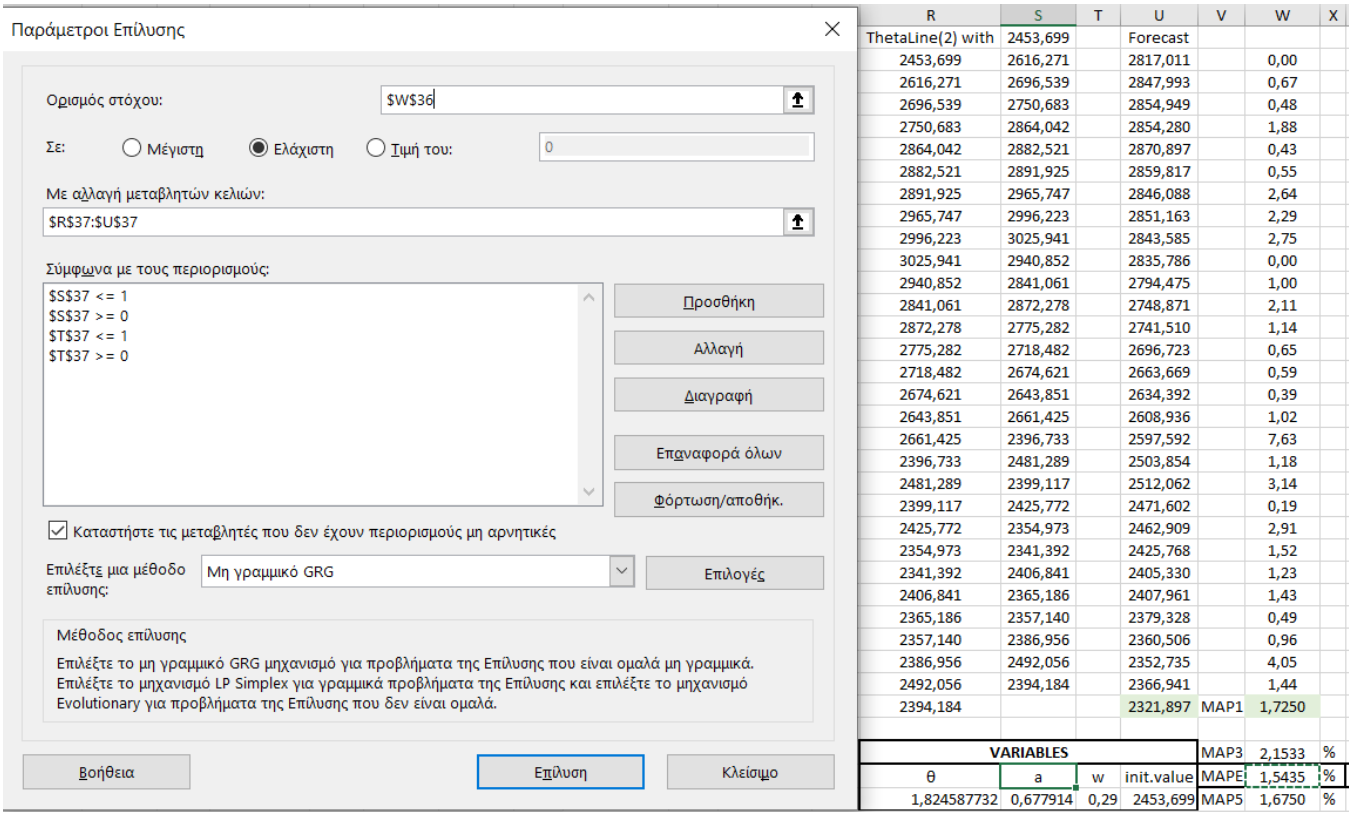


Figure 36 Germany Oil demand Optimised Theta Model Solver Execution with constraints

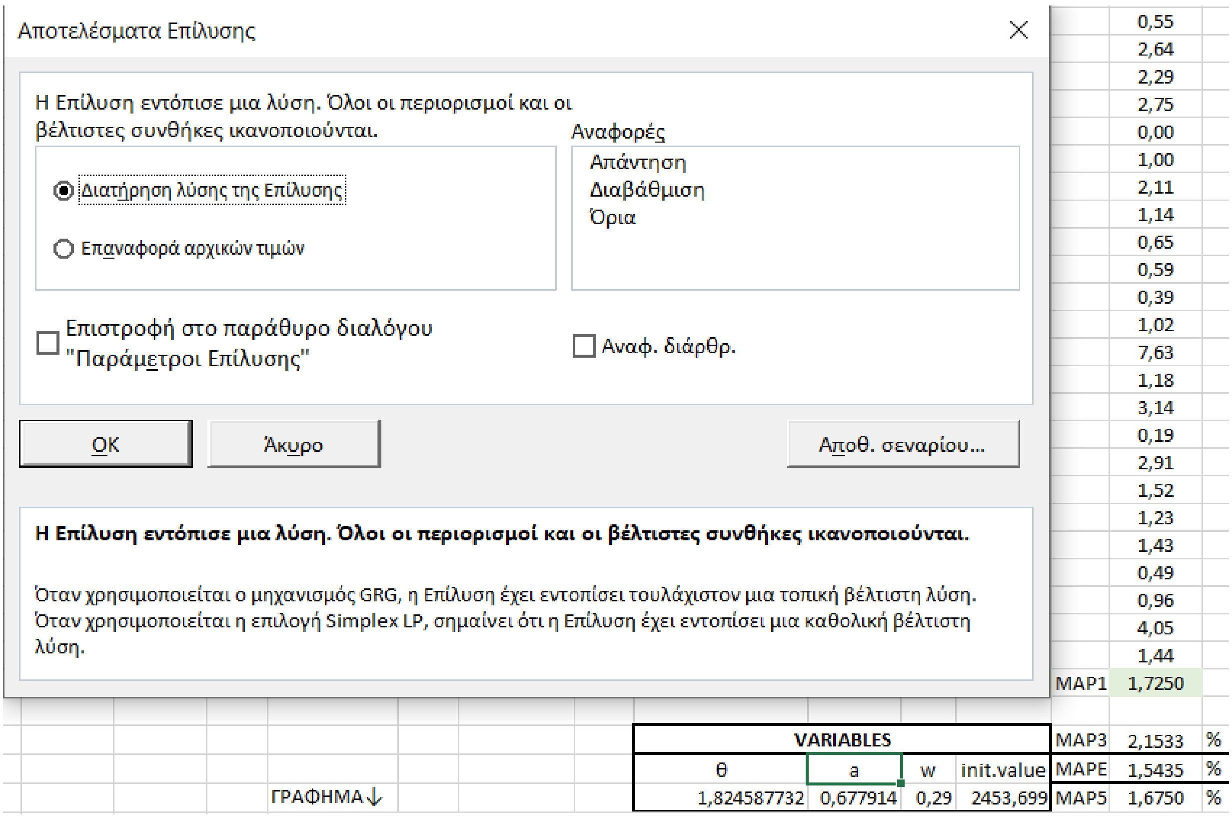


Figure 37 Germany Oil demand Optimised Theta Model Solver Solution

The mean sMAPE came down to 1,5435%, with Solver assigning the value of 1,82 to θ and 2.453,69 to the initial value of SES on Theta Line (1,82), with α and w remaining almost identical with the previous optimisation of the conventional Theta Method.

Adding another Theta Line in our Model in order to possibly achieve even better results, the form of our final Optimised Three Theta Line Model is constructed and executing Solver with the constraints mentioned in the previous chapter, the following results are given:

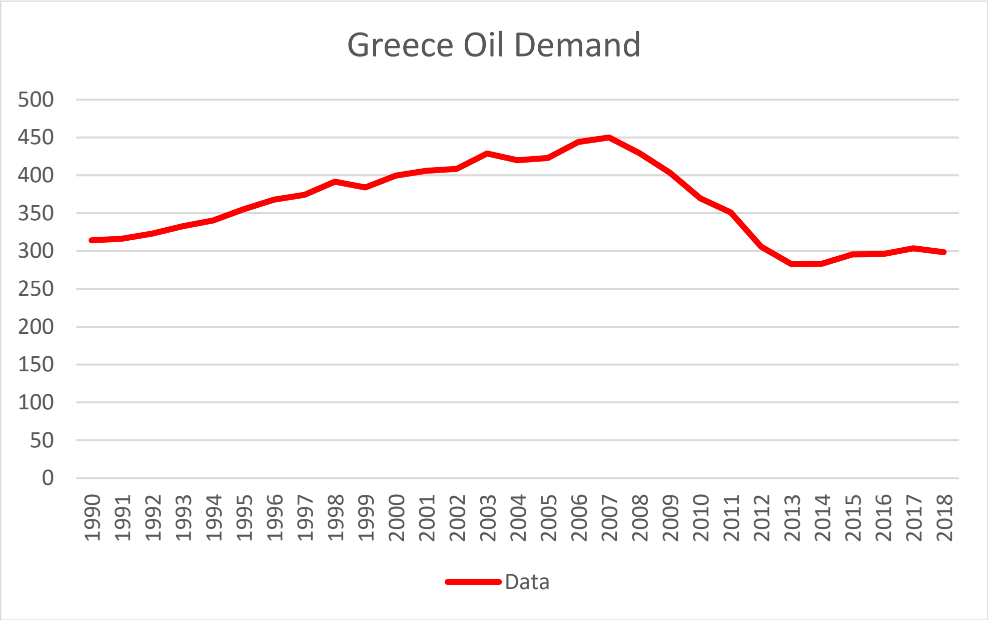
LRL				ThetaLine(3) with	2.641,44	ThetaLine(2) with	2353,794		Forecast			
2966,78		2620,44	2674,05	2.641,44	2.665,91	2353,794	2528,008		2817,011		0,00	
2943,52		2678,83	2719,80	2.665,91	2.706,35	2528,008	2626,550		2840,264		0,40	
2920,25		2737,94	2766,16	2.706,35	2.751,23	2626,550	2699,330		2846,731		0,19	
2896,99		2923,49	2919,39	2.751,23	2.877,41	2699,330	2845,787		2847,454		2,12	
2873,72		2896,00	2892,55	2.877,41	2.888,77	2845,787	2878,594		2867,459		0,55	
2850,46		2908,68	2899,66	2.888,77	2.896,94	2878,594	2898,247		2858,041		0,61	
2827,19		3047,25	3013,18	2.896,94	2.984,17	2898,247	2995,596		2845,525		2,66	
2803,93		3065,99	3025,43	2.984,17	3.015,13	2995,596	3041,590		2853,140		2,22	
2780,66		3109,42	3058,53	3.015,13	3.047,70	3041,590	3085,907		2847,327		2,62	
2757,40		2938,67	2910,61	3.047,70	2.944,83	3085,907	2989,709		2841,180		0,19	
2734,13		2809,56	2797,89	2.944,83	2.834,57	2989,709	2872,010		2798,855		1,15	
2710,87		2934,24	2899,66	2.834,57	2.883,41	2872,010	2912,665		2751,398		2,02	
2687,60		2740,32	2732,16	2.883,41	2.769,92	2912,665	2800,064		2744,909		1,27	
2664,34		2698,76	2693,43	2.769,92	2.712,52	2800,064	2733,875		2698,517		0,72	
2641,07		2657,18	2654,69	2.712,52	2.669,12	2733,875	2683,767		2664,420		0,62	
2617,81		2632,29	2630,04	2.669,12	2.639,80	2683,767	2650,132		2634,418		0,39	
2594,54		2689,89	2675,13	2.639,80	2.666,31	2650,132	2676,109		2608,603		1,04	
2571,28		2190,67	2249,59	2.666,31	2.353,62	2676,109	2358,951		2598,086		7,65	
2548,01		2514,36	2519,57	2.353,62	2.478,14	2358,951	2460,490		2498,966		1,37	
2524,75		2316,04	2348,35	2.478,14	2.380,75	2460,490	2366,116		2508,668		3,00	
2501,48		2421,58	2433,95	2.380,75	2.420,67	2366,116	2402,352		2466,925		0,00	
2478,22		2279,39	2310,16	2.420,67	2.337,75	2402,352	2322,013		2459,157		2,76	
2454,95		2302,85	2326,39	2.337,75	2.329,23	2322,013	2309,492		2421,056		1,33	
2431,69		2439,61	2438,38	2.329,23	2.411,13	2309,492	2394,503		2400,691		1,42	
2408,42		2328,54	2340,91	2.411,13	2.358,44	2394,503	2351,407		2405,328		1,32	
2385,16		2344,80	2351,05	2.358,44	2.352,89	2351,407	2347,092		2376,645		0,38	
2361,89		2411,61	2403,92	2.352,89	2.391,18	2347,092	2389,246		2358,242		1,06	
2338,63		2596,37	2556,47	2.391,18	2.515,21	2389,246	2524,569		2351,775		4,09	
2315,36		2356,33	2349,98	2.515,21	2.391,23	2524,569	2414,647		2369,173		1,54	
2292,10				2.391,23		2414,647			2323,075	MAP1	1,6743	
										MAP3	2,2303	%
			θ3	θ2	a3	w3	a2	w1	w2	MAPE	1,5405	%
ΡΑΦΗΜΑ↓			1,954519	2,312467142	0,750369	0,030341195	0,6533499	0,74	0,228226	MAP5	1,6767	%

Figure 38 Germany Oil demand Optimised Theta Model with two Theta Lines result

The use of a third Theta Line reduces slightly further the mean sMAPE from 1,5435% to 1,5405% , along with 2019 forecast sMAPE of 1,6743% . The value of w3=0,03 means that the third line is almost not used at all to describe our system in this case and offers the minimum contribution in the final forecast.

6.2.2 Greece Yearly Oil Demand

The second country it will be analyzed for the oil demand is Greece, which has a very different time series, with change in trend and steep dampening (years where economic crisis hit) as presented below:



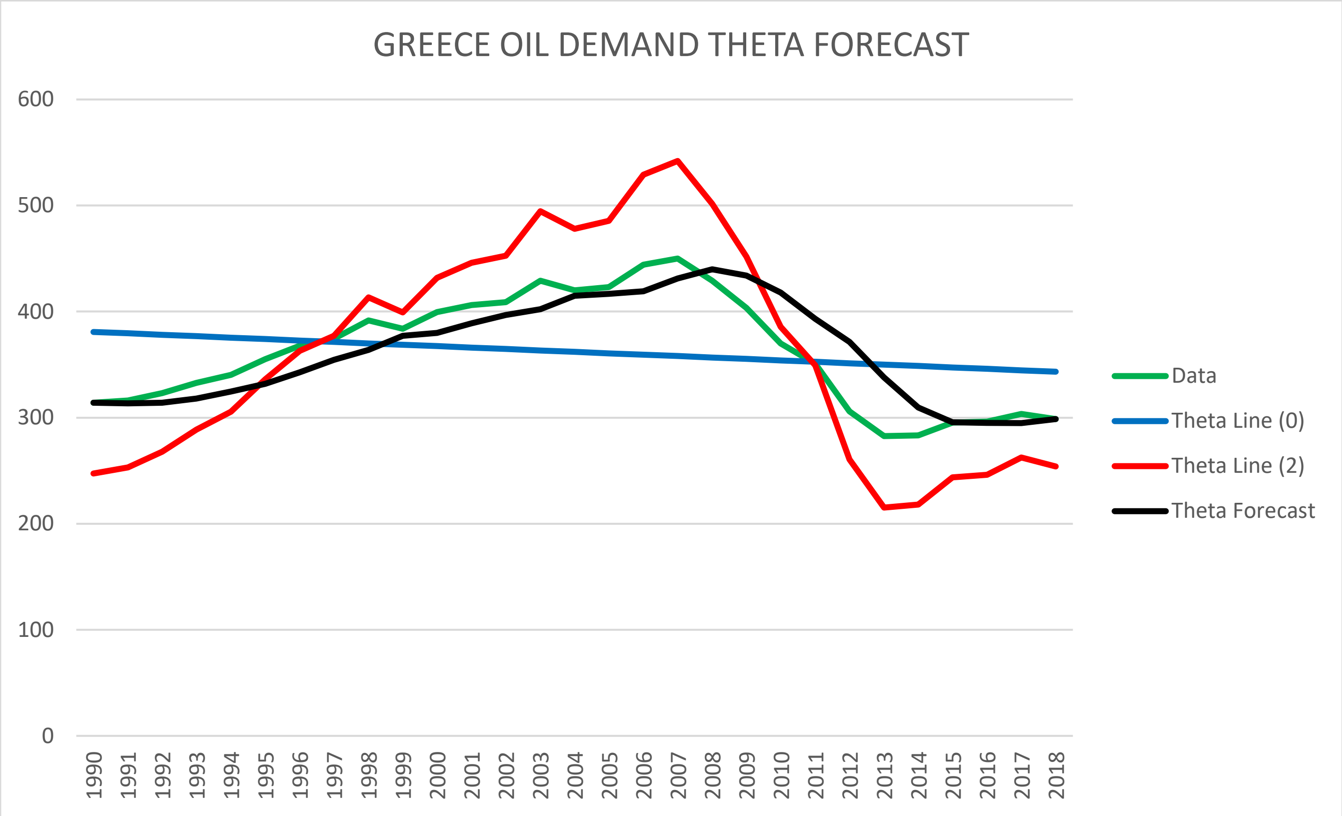
Plot 3 Greece Annual Oil Demand plot 1990-2018

All forecasting methods are applied and the following results are extracted:

ThetaLine(0)		ThetaLine(2)		SES on ThetaLine(2)	S		Theta		APE(%)	NAÏVE	APE(%)	KMO 3	APE(%)	KMO 5	APE(%)	FRC.LIN	APE(%)	FRC.ETS	APE(%)
LRL				with a=0.5	247,368		Forecast												
380,80		247,37		247,368	247,368		314,085		0,00	314,0849	0		0		0	380,8024	19,20237	336,1114	6,775322
379,46		253,22		247,368	250,294		313,416		0,93	314,0849	0,716191		0		0	379,4646	18,14358	334,7736	5,66141
378,13		268,01		250,294	259,152		314,210		2,78	316,3425	2,103762		0		0	378,1269	15,70421	333,4359	3,158426
376,79		288,69		259,152	273,923		317,970		4,54	323,0683	2,950065	317,8319	4,583591		0	376,7891	12,41593	332,0982	0,193594
375,45		305,52		273,923	289,721		324,687		4,75	332,7417	2,300329	324,0508	4,94604		0	375,4514	9,768042	330,7604	2,897449
374,11		336,11		289,721	312,913		331,917		6,75	340,4849	4,204904	332,0983	6,697	325,3445	8,748572	374,1137	5,212179	329,4227	7,504912
372,78		362,97		312,913	337,940		342,844		7,04	355,1095	3,530518	342,7787	7,062052	333,5494	9,786582	372,7759	1,32424	328,085	11,43375
371,44		377,27		337,940	357,607		354,689		5,40	367,872	1,747031	354,4888	5,451549	343,8553	8,493374	371,4382	0,782316	326,7472	13,58095
370,10		413,41		357,607	385,510		363,854		7,39	374,3554	4,542806	365,779	6,858547	354,1127	10,09405	370,1005	5,685176	325,4095	18,50266
368,76		399,16		385,510	392,337		377,136		1,79	391,7569	2,00931	377,9948	1,56671	365,9157	4,81354	368,7627	4,038887	324,0718	16,91776
367,43		431,86		392,337	412,096		379,881		5,07	383,9636	4,001123	383,3587	4,158737	374,6115	6,46524	367,425	8,399573	322,734	21,29259
366,09		446,09		412,096	429,091		389,092		4,27	399,6401	1,600116	391,7869	3,584402	383,5176	5,716477	366,0873	10,36013	321,3963	23,28305
364,75		452,79		429,091	440,938		396,920		2,94	406,0864	0,658006	396,5634	3,030781	391,1605	4,402091	364,7495	11,3812	320,0586	24,34291
363,41		494,58		440,938	467,759		402,175		6,45	408,7673	4,829153	404,8312	5,796034	398,0429	7,485222	363,4118	16,55307	318,7208	29,49644
362,07		477,92		467,759	472,837		414,916		1,22	428,9957	2,120311	414,6164	1,288894	405,4906	3,514164	362,0741	14,81225	317,3831	27,83158
360,74		485,62		472,837	479,229		416,787		1,52	419,9951	0,755044	419,2527	0,93196	412,6969	2,507871	360,7363	15,9308	316,0454	28,98525
359,40		529,07		479,229	504,149		419,314		5,77	423,1782	4,854889	424,0563	4,647721	417,4045	6,22759	359,3986	21,11303	314,7076	34,13347
358,06		542,03		504,149	523,091		431,105		4,30	444,2342	1,299877	429,1358	4,756837	425,0341	5,716588	358,0609	22,76569	313,3699	35,80657
356,72		501,70		523,091	512,393		439,907		2,46	450,0465	4,73974	439,153	2,290223	433,2899	0,946246	356,7231	18,4459	312,0321	31,61645
355,39		451,84		512,393	482,119		433,889		7,23	429,2093	6,146451	441,1633	8,889581	433,3326	7,10151	355,3854	12,70864	310,6944	26,01683
354,05		385,63		482,119	433,877		418,083		12,25	403,6147	8,733169	427,6235	14,49152	430,0566	15,05579	354,0477	4,363501	309,3567	17,81055
352,71		349,27		433,877	391,572		393,293		11,37	369,8411	5,230651	400,8883	13,27326	419,3891	17,75754	352,7099	0,489094	308,0189	13,04084
351,37		260,53		391,572	326,051		371,472		19,34	350,989	13,71152	374,8149	20,23137	400,7401	26,82624	351,3722	13,8201	306,6812	0,238442
350,03		215,22		326,051	270,636		338,043		17,86	305,9508	7,925343	342,2603	19,08596	371,921	27,28403	350,0344	21,30903	305,3435	7,726938
348,70		217,94		270,636	244,287		309,666		8,89	282,6274	0,243985	313,1891	10,0154	342,6046	18,94382	348,6967	20,68905	304,0057	7,044814
347,36		243,59		244,287	243,938		295,823		0,12	283,3178	4,200531	290,632	1,652248	318,5452	7,514834	347,359	16,14261	302,668	2,405458
346,02		246,27		243,938	245,106		294,980		0,40	295,474	0,227703	287,1397	3,088638	303,6718	2,508844	346,0212	15,53289	301,3303	1,734867
344,68		262,51		245,106	253,809		294,895		2,91	296,1475	2,484597	291,6464	4,015739	292,7035	3,654079	344,6835	12,67515	299,9925	1,194732
343,35		253,96		253,809	253,887		298,578		0,03	303,5982	1,641629	298,4066	0,083151	292,233	2,173616	343,3458	13,92241	298,6548	0
342,01				253,887			297,947	MAP1	4,7972	298,6548	4,560185	299,4668	4,288787	295,4385	5,64226	342,008	8,987554	297,3171	5,008854
								MAP3	1,1098	%	1,4513	%	2,3958	%	2,7788	%	14,0435	%	0,9765
					a	w		MAPE	5,3709	%	3,5539	%	6,2492	%	8,9057	%	12,5411	%	14,5044
ΓΡΑΦΗΜΑ↓					0,5	0,5		MAP5	2,4668	%	1,7597	%	3,7710	%	6,9590	%	15,7924	%	2,4760

Figure 39 Greece Oil demand basic Theta Model vs benchmark methods

As expected, due to greater randomness in comparison with the German Oil Demand, the methods perform much worse (both in total and point sMAPE) and only the naive method has error below 5%, the benchmark for a forecasting method to be considered reliable. The Theta Method's mean sMAPE is slightly higher than 5% and second best in this case. The graphical visualization of the Theta Forecast can be seen below:



Plot 4 Greece Oil demand Plot, Theta Method forecasting with Theta Lines combination

All data are put to our Optimised Theta Model with two Theta Lines and the Solve button is hit and the results are the following:

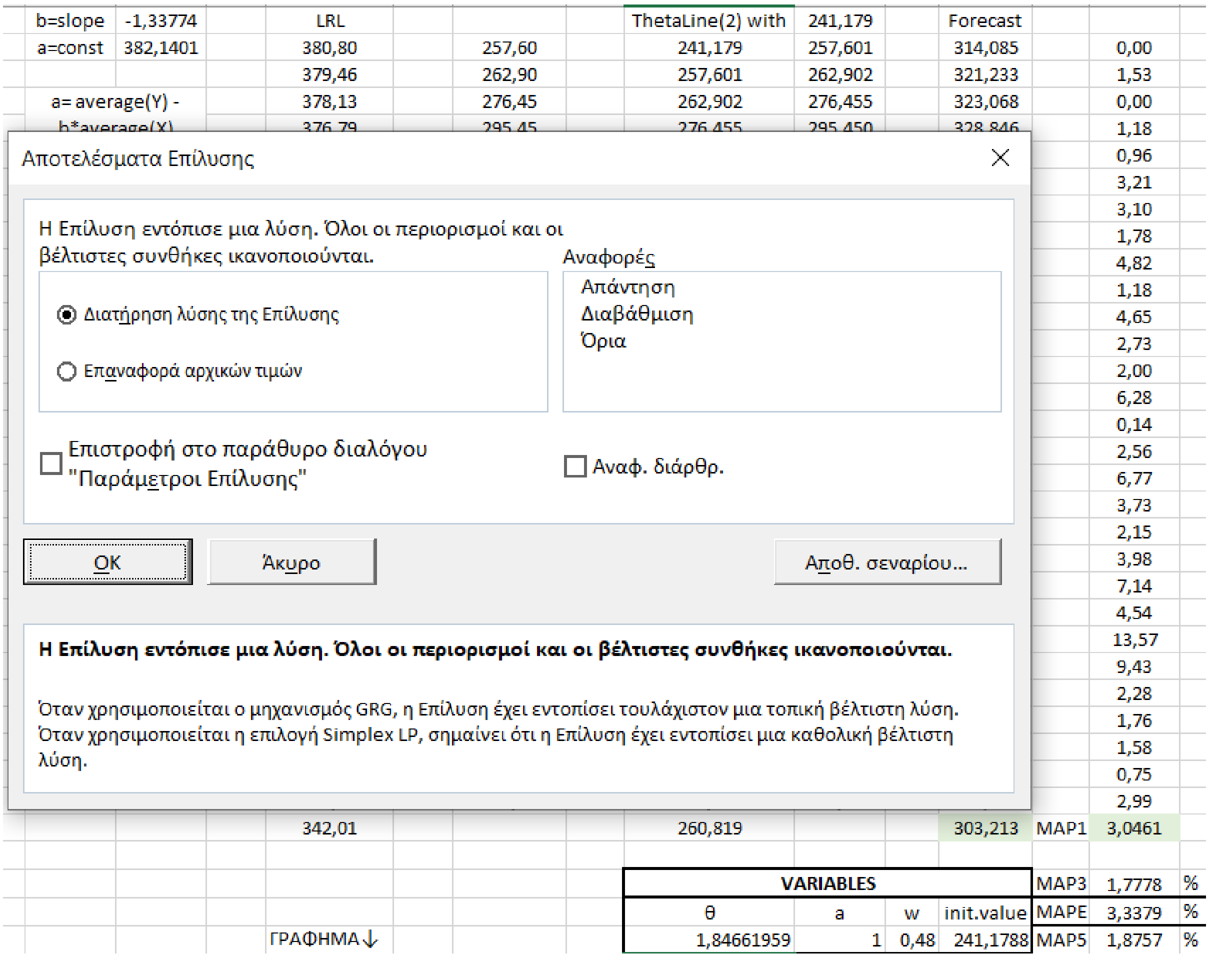


Figure 40 Greece Oil demand Optimised Theta Model Solver Solution

A big reduction in average sMAPE is witnessed as well as 2019 point forecast error, bringing our Theta Model in the first place (smallest error) for both of the above. The average sMAPE is 3,3379%, lower than the initially best performing 3,5539% of the naive method (Theta Model fits better now on the data) and the 2019 sMAPE is 3,0461%, much lower from the initially best performing 4,2887% of the MA3 method.

The above optimised sMAPEs are achieved for θ=1,8466, a=1 and w=0,48. This means, that L (θ=1,84) is extrapolated with naive forecast and combined almost evenly (slightly more weight is given to the Theta Line (0) as w=0,48) with the LRL line for the generation of the final Theta Forecast.

Here there is a great example of the flexibility of our model and how it adapts to the data, outperforming all other benchmark methods, although in its conventional form (Theta Method with θ=2, a=0,5 and w=0,5) it had almost 2% difference in average sMAPE from the best performing method.

To see if the performance of the method can be further improved, Optimised Three Theta Line Model is Solved and the results are the following:

ThetaLine(0)		ThetaLine(2)	Theta(3)	SES on ThetaLine(3)	S3	SES on ThetaLine(2)	S2		Theta		APE(%)
LRL				with a=0.5	243,22	with a=0.5	221,176		Forecast		
380,80		225,89	250,73	243,22	250,73	221,176	225,886		314,085		0,00
379,46		232,90	256,41	250,73	256,41	225,886	232,896		316,342		0,00
378,13		250,28	270,79	256,41	270,79	232,896	250,282		318,439		1,44
376,79		274,51	290,92	270,79	290,92	250,282	274,512		324,805		2,41
375,45		294,26	307,28	290,92	307,28	274,512	294,260		333,986		1,93
374,11		329,99	337,06	307,28	337,06	294,260	329,986		341,323		3,96
372,78		361,39	363,22	337,06	363,22	329,986	361,389		355,234		3,50
371,44		378,21	377,13	363,22	377,13	361,389	378,212		367,367		1,88
370,10		420,39	412,32	377,13	412,32	378,212	420,386		373,501		4,77
368,76		404,06	398,40	412,32	398,40	420,386	404,059		390,065		1,58
367,43		442,23	430,23	398,40	430,23	404,059	442,228		382,560		4,37
366,09		458,96	444,07	430,23	444,07	442,228	458,964		397,476		2,14
364,75		466,96	450,56	444,07	450,56	458,964	466,958		403,574		1,28
363,41		515,70	491,27	450,56	491,27	466,958	515,696		406,075		5,49
362,07		496,57	474,99	491,27	474,99	515,696	496,566		425,340		1,26
360,74		505,73	482,47	474,99	482,47	496,566	505,725		416,682		1,55
359,40		556,39	524,79	482,47	524,79	505,725	556,385		419,663		5,69
358,06		571,65	537,39	524,79	537,39	556,385	571,650		439,718		2,32
356,72		525,03	498,04	537,39	498,04	571,650	525,035		445,211		3,66
355,39		467,37	449,41	498,04	449,41	525,035	467,373		425,245		5,22
354,05		390,72	384,84	449,41	384,84	467,373	390,720		400,735		8,02
352,71		348,71	349,35	384,84	349,35	390,720	348,714		368,411		4,84
351,37		245,90	262,82	349,35	262,82	348,714	245,905		350,341		13,53
350,03		193,52	218,62	262,82	218,62	245,905	193,517		307,257		8,35
348,70		196,89	221,24	218,62	221,24	193,517	196,888		284,916		0,56
347,36		226,88	246,21	221,24	246,21	196,888	226,883		285,516		3,43
346,02		230,22	248,79	246,21	248,79	226,883	230,215		297,069		0,31
344,68		249,28	264,59	248,79	264,59	230,215	249,284		297,652		1,98
343,35		239,57	256,22	264,59	256,22	249,284	239,574		304,710		2,01
342,01				256,22		239,574			299,928	MAP1	4,1350
										MAP3	1,4318
			θ3	θ2	a3	w3	a2	w1	w2	MAPE	3,3612
ΓΡΑΦΗΜΑ↓			1,94954	2,321980959	1	0,293166258	1	0,54	0,165274	MAP5	1,6572

Figure 41 Greece Oil demand Optimised Theta Model with two Theta Lines result

The use of another Theta Line does not offer any improvement. In fact, although both measured errors remain lower in comparison with all other methods, they are higher than the equivalents achieved with the Optimised Two Theta Line Model.

The above procedure is performed for all 13 countries’ oil demand time series and the combined results are presented in the following table:

6.2.3 Results of All 13 European countries’ Oil Demand Time Series

OIL		GERMANY	GREECE	ITALY	SPAIN	NETHERLANDS	AUSTRIA	UN. KING	BELGIUM	BULGARIA	FRANCE	SWITZERL	HUNGARY	CYPRUS	AVERAGE
BEST sMAPE OF REST		2,0074	3,5539	2,2925	3,5158	1,9616	2,8372	1,6298	3,4009	7,0250	1,7598	2,4549	4,2558	4,6611	3,1812
THETA MAPE	2	1,8441	5,3709	2,9154	5,0860	2,9002	3,3535	2,2127	3,5004	8,4048	2,0581	2,3854	5,5764	5,8059	3,9549
NAÏVE	1	2,0074	3,5539	2,2925	3,5158	1,9616	2,8372	1,6298	3,4009	7,0250	1,7598	2,4549	4,2558	4,6611	3,1812
KMO3	3	2,1539	6,2492	3,8406	5,7831	3,5899	3,7483	2,6323	3,9796	8,1787	2,1534	2,5446	6,4322	7,0651	4,4885
KMO5	4	2,9272	8,9057	5,8818	8,4260	5,0808	4,9140	3,3711	5,0090	9,4554	2,9718	3,0165	8,1206	8,7735	5,9118
FRC.LIN	5	2,2008	12,5411	5,7541	11,1192	5,7577	5,8247	2,6564	5,7785	9,5017	3,9763	3,3683	6,6122	9,3667	6,4967
FRC.ETS	6	2,3986	14,5044	51,4658	11,8655	9,8246	6,0498	3,2807	5,7182	13,7924	5,8665	9,6030	17,2039	9,7597	12,4102
OPTIMIZED THETA-SOLVER		1,5405	3,3379	1,8938	3,1068	1,7305	2,6518	1,4059	2,8823	6,1995	1,6157	2,2403	3,9709	4,3165	2,8379
BEST 2019 OF REST		0,8149	4,2888	3,7528	0,3067	3,5154	1,6130	0,7935	1,9649	0,1399	0,1006	0,6480	0,4361	1,0119	1,4913
THETA 2019	1	0,4535	4,7972	2,5227	0,9538	4,7026	2,8269	1,5184	0,4330	0,1174	0,7765	2,0244	6,1591	1,3131	2,1999
NAÏVE 2019	2	1,2447	4,5602	5,4306	0,3067	3,5154	2,1308	2,5192	2,7754	2,1779	0,1006	2,5848	0,4361	1,0119	2,2149
KMO3 2019	4	1,1178	4,2888	3,7528	1,6928	4,2208	3,5739	2,6091	2,1178	3,0742	1,2058	1,2917	7,2250	1,5931	2,9049
KMO5 2019	5	0,8149	5,6423	4,3572	4,2147	3,7375	4,6791	0,8294	4,3682	2,3840	2,0230	0,6480	11,3373	6,1330	3,9360
FRC.LIN 2019	6	3,0165	8,9876	4,8915	9,4838	13,2418	3,0683	0,7935	1,9649	13,5695	4,9045	2,4630	18,4957	7,7200	7,1231
FRC.ETS 2019	3	1,4925	5,0089	7,0363	0,9129	4,2239	1,6130	1,8420	3,4729	0,1399	1,4564	6,0693	1,2739	6,2651	3,1390
OPT THETA 2019		1,6657	3,0461	4,2890	1,4447	3,5627	1,0478	1,5146	2,1489	2,0673	0,1290	2,1221	3,3815	0,1375	2,0428
															AVRG
IMPROVEMENT		-23,26%	-6,08%	-17,39%	-11,63%	-11,78%	-6,53%	-13,74%	-15,25%	-11,75%	-8,19%	-8,74%	-6,69%	-7,39%	-11,75%

Table 3 Results of all 13 European Countries' Oil Demand Time series

Key findings: The naive method has the smallest sMAPE in 11 out of 13 countries, with the Theta Method being first in the other two (Germany and Switzerland). The naive method has also the smallest average sMAPE across all time series (3,1812%), followed by the Theta Method (3,9549%).

Our Optimised Theta Model outperforms the naive method and the conventional Theta Model in every single country, achieving at the same time the smallest average sMAPE (2,8379%), offering an average 11,75% reduction and being lower even from the average best sMAPE combined from each country. The following graph offers a visualization of the above, gathering the average sMAPE across all time series:

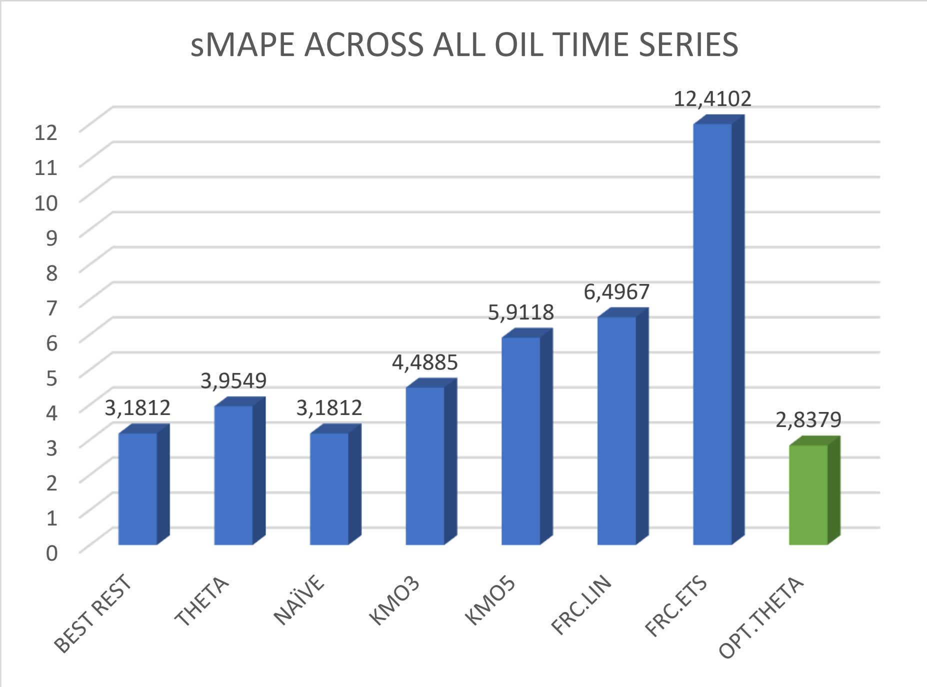


Chart 1 Model "fit" (mean sMAPE) across all Oil Demand time series

The results for the 2019 oil demand forecast, which is our performance evaluation criteria, are similar but slightly different, as the Theta Method has already the smallest average sMAPE (2,1999%), before optimisation, followed closely by the naive method (2,2149%) and both achieve smallest error in 4 countries evenly. Our Optimised Theta Model again further improves the accuracy of the Theta Method, bringing the average sMAPE to 2,0428% and having the smallest error in Greece, Austria and Cyprus. Below the relevant graph:

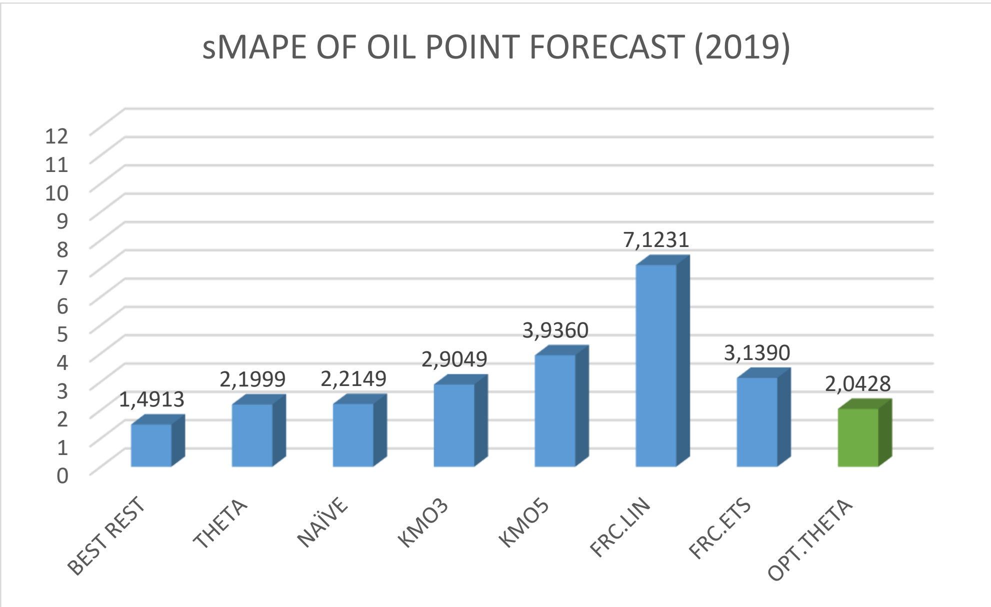


Chart 2 Model point forecast accuracy (sMAPE 2019 value) across all Oil demand time series

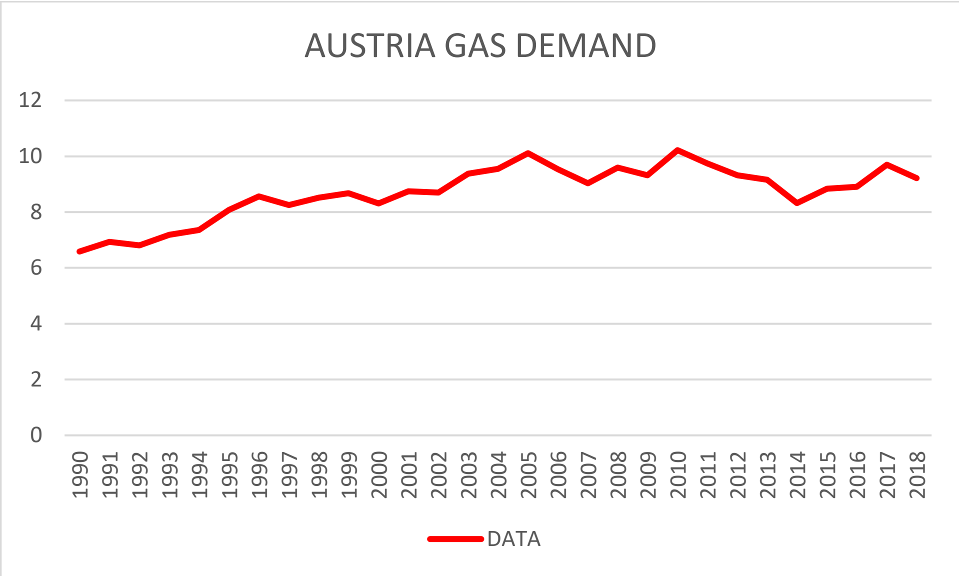
6.2.4 Austria Yearly Gas Demand

Moving on with gas demand time series, the case of Austria Gas demand will be analyzed as the first reference example. The data has been acquired by Rystad, along with 23 more countries' annual demand as already mentioned and refers to the sum of total gas demand in billion cubic meters.

The data obtained for Austria are the following:

	Period	Data
1990	1	6,586201
1991	2	6,932813
1992	3	6,808081
1993	4	7,187202
1994	5	7,361495
1995	6	8,075951
1996	7	8,557295
1997	8	8,249347
1998	9	8,519197
1999	10	8,679799
2000	11	8,303983
2001	12	8,749638
2002	13	8,702259
2003	14	9,377945
2004	15	9,548086
2005	16	10,10636
2006	17	9,530238
2007	18	9,031216
2008	19	9,589306
2009	20	9,323382
2010	21	10,21821
2011	22	9,74493
2012	23	9,321
2013	24	9,159642
2014	25	8,324188
2015	26	8,841934
2016	27	8,909365
2017	28	9,695125
2018	29	9,219796
2019		9,569374
2020		8,878861

Table 4 Austria Annual Gas Demand Data 1990-2018



Plot 5 Austria Annual Gas Demand plot 1990-2018

The results of the conventional Theta Method and all other benchmark methods can be seen in the below spreadsheet:

ThetaLine(0)		ThetaLine(2)		SES on ThetaLine(2)	S		Theta		APE(%)	NAÏVE	APE(%)	KMO 3	APE(%)	KMO 5	APE(%)	FRC.LIN	APE(%)	FRC.ETS	APE(%)	
LRL				with a=0.5	5,660		Forecast													
7,51		5,66		5,660	5,660		6,586		0,00	6,586201	0		0		0	7,512626	13,14188	6,820636	3,497244	
7,60		6,27		5,660	5,964		6,629		4,48	6,586201	5,12777		0		0	7,598311	9,159616	6,90632	0,382868	
7,68		5,93		5,964	5,948		6,824		0,23	6,932813	1,815486		0		0	7,683995	12,08818	6,992004	2,665541	
7,77		6,60		5,948	6,276		6,859		4,68	6,808081	5,41784	6,775698	5,894243		0	7,769679	7,788752	7,077689	1,535423	
7,86		6,87		6,276	6,572		7,066		4,10	7,187202	2,395995	6,976032	5,37698		0	7,855363	6,49107	7,163373	2,728038	
7,94		8,21		6,572	7,391		7,257		10,69	7,361495	9,256142	7,118926	12,59668	6,975158	14,62739	7,941048	1,684501	7,249057	10,79143	
8,03		9,09		7,391	8,240		7,709		10,43	8,075951	5,787734	7,541549	12,61886	7,273108	16,22431	8,026732	6,398482	7,334742	15,38574	
8,11		8,39		8,240	8,313		8,176		0,89	8,557295	3,664599	7,998247	3,090919	7,598005	8,220202	8,112416	1,673789	7,420426	10,57987	
8,20		8,84		8,313	8,577		8,256		3,14	8,249347	3,218526	8,294198	2,67643	7,886258	7,716202	8,198101	3,841487	7,50611	12,64359	
8,28		9,08		8,577	8,826		8,430		2,92	8,519197	1,867574	8,441946	2,778369	8,152657	6,2634	8,283785	4,668991	7,591794	13,37305	
8,37		8,24		8,826	8,532		8,598		3,48	8,679799	4,425587	8,482781	2,130226	8,416318	1,343694	8,369469	0,785514	7,677479	7,840387	
8,46		9,04		8,532	8,788		8,494		2,97	8,303983	5,226515	8,500993	2,882735	8,461924	3,343262	8,455153	3,423285	7,763163	11,948	
8,54		8,86		8,788	8,826		8,665		0,43	8,749638	0,542967	8,577807	1,440415	8,500393	2,34692	8,540838	1,8723	7,848847	10,31244	
8,63		10,13		8,826	9,478		8,726		7,20	8,702259	7,474318	8,585293	8,825265	8,590975	8,759233	8,626522	8,347072	7,934532	16,67483	
8,71		10,38		9,478	9,931		9,095		4,86	9,377945	1,797958	8,943281	6,541489	8,762725	8,578115	8,712206	9,155162	8,020216	17,39349	
8,80		11,41		9,931	10,673		9,364		7,62	9,548086	5,680893	9,20943	9,287013	8,936382	12,28791	8,797891	13,84312	8,1059	21,96828	
8,88		10,18		10,673	10,425		9,778		2,57	10,10636	5,867839	9,677464	1,532986	9,296858	2,479197	8,883575	7,023674	8,191585	15,1074	
8,97		9,09		10,425	9,759		9,697		7,11	9,530238	5,376971	9,728228	7,431052	9,452978	4,563484	8,969259	0,688391	8,277269	8,71188	
9,05		10,12		9,759	9,941		9,407		1,92	9,031216	5,994354	9,555938	0,348577	9,518769	0,738295	9,054944	5,732196	8,362953	13,66238	
9,14		9,51		9,941	9,724		9,541		2,31	9,589306	2,812123	9,383587	0,64366	9,561041	2,516987	9,140628	1,979572	8,448637	9,844065	
9,23		11,21		9,724	10,467		9,475		7,55	9,323382	9,158189	9,314635	9,251856	9,5161	7,115623	9,226312	10,20234	8,534322	17,95905	
9,31		10,18		10,467	10,322		9,889		1,47	10,21821	4,741539	9,710299	0,356004	9,53847	2,141319	9,311996	4,543583	8,620006	12,25078	
9,40		9,24		10,322	9,783		9,860		5,62	9,74493	4,44699	9,762174	4,623696	9,581409	2,755298	9,397681	0,819296	8,70569	6,826652	
9,48		8,84		9,783	9,310		9,633		5,04	9,321	1,746238	9,76138	6,360523	9,639366	5,103712	9,483365	3,472862	8,791375	4,103026	
9,57		7,08		9,310	8,194		9,439		12,56	9,159642	9,556876	9,408524	12,22978	9,553433	13,75177	9,569049	13,91432	8,877059	6,428265	
9,65		8,03		8,194	8,112		8,925		0,93	8,324188	6,032184	8,934943	1,046408	9,353594	5,624019	9,654734	8,788605	8,962743	1,357049	
9,74		8,08		8,112	8,095		8,926		0,19	8,841934	0,75973	8,775255	1,516689	9,078339	1,87877	9,740418	8,912198	9,048427	1,54877	
9,83		9,56		8,095	8,830		8,961		7,87	8,909365	8,446993	8,691829	10,91313	8,911226	8,426147	9,826102	1,341894	9,134112	5,958959	
9,91		8,53		8,830	8,679		9,371		1,62	9,695125	5,025969	9,148808	0,772928	8,986051	2,567804	9,911786	7,234011	9,219796	0	
10,00				8,679			9,338	MAP1	2,4465	9,219796	3,721058	9,274762	3,126829	8,998082	6,153696	9,997471	4,375736	9,30548	2,796246	
								MAP3	3,2286	%	4,7442	%	4,4009	%	4,2909	%	5,8294	%	2,5026	%
					a	w		MAPE	4,3062	%	4,7738	%	5,1218	%	6,2239	%	6,1730	%	9,0855	%
ΓΡΑΦΗΜΑ↓					0,5	0,5		MAP5	4,6344	%	5,9644	%	5,2958	%	6,4497	%	8,0382	%	3,0586	%

Figure 42 Austria Gas demand basic Theta Model vs benchmark methods

The Theta Method outperforms all other methods both in total average sMAPE (4,3062%) and 2019 forecast sMAPE (2,4465%), followed by the naive method and FRC.ETS method respectively in these errors.

Solver is applied and the above errors are further improved, reducing them to 3,8627% and 0,2215% respectively, with a=0,7595 and w=0,34 as it can be seen in the following figure:

ThetaLine(0)		ThetaLine(2)		SES on ThetaLine(2)	S		Theta		APE(%)	
LRL				with a=0.5	5,660		Forecast			
7,51		5,66		5,660	5,660		6,877		4,31	
7,60		6,27		5,660	6,121		6,933		0,00	
7,68		5,93		6,121	5,978		7,147		4,86	
7,77		6,60		5,978	6,454		7,154		0,46	
7,86		6,87		6,454	6,768		7,374		0,17	
7,94		8,21		6,768	7,864		7,538		6,89	
8,03		9,09		7,864	8,793		7,971		7,10	
8,11		8,39		8,793	8,484		8,346		1,17	
8,20		8,84		8,484	8,755		8,296		2,65	
8,28		9,08		8,755	8,999		8,445		2,74	
8,37		8,24		8,999	8,421		8,585		3,33	
8,46		9,04		8,421	8,894		8,444		3,56	
8,54		8,86		8,894	8,871		8,662		0,46	
8,63		10,13		8,871	9,827		8,710		7,38	
8,71		10,38		9,827	10,250		9,095		4,86	
8,80		11,41		10,250	11,135		9,296		8,35	
8,88		10,18		11,135	10,407		9,656		1,31	
8,97		9,09		10,407	9,409		9,463		4,67	
9,05		10,12		9,409	9,952		9,177		4,40	
9,14		9,51		9,952	9,613		9,419		1,02	
9,23		11,21		9,613	10,826		9,359		8,78	
9,31		10,18		10,826	10,334		9,832		0,89	
9,40		9,24		10,334	9,506		9,719		4,18	
9,48		8,84		9,506	8,997		9,491		3,56	
9,57		7,08		8,997	7,541		9,373		11,85	
9,65		8,03		7,541	7,912		8,929		0,98	
9,74		8,08		7,912	8,038		9,113		2,26	
9,83		9,56		8,038	9,197		9,212		5,11	
9,91		8,53		9,197	8,689		9,666		4,73	
10,00				8,689			9,548	MAP1	0,2215	
					VARIABLES			MAP3	4,0308	%
					a	w		MAPE	3,8627	%
ΓΡΑΦΗΜΑ↓					0,759504	0,34		MAP5	4,9843	%

Figure 43 Austria Gas demand Solver Solution

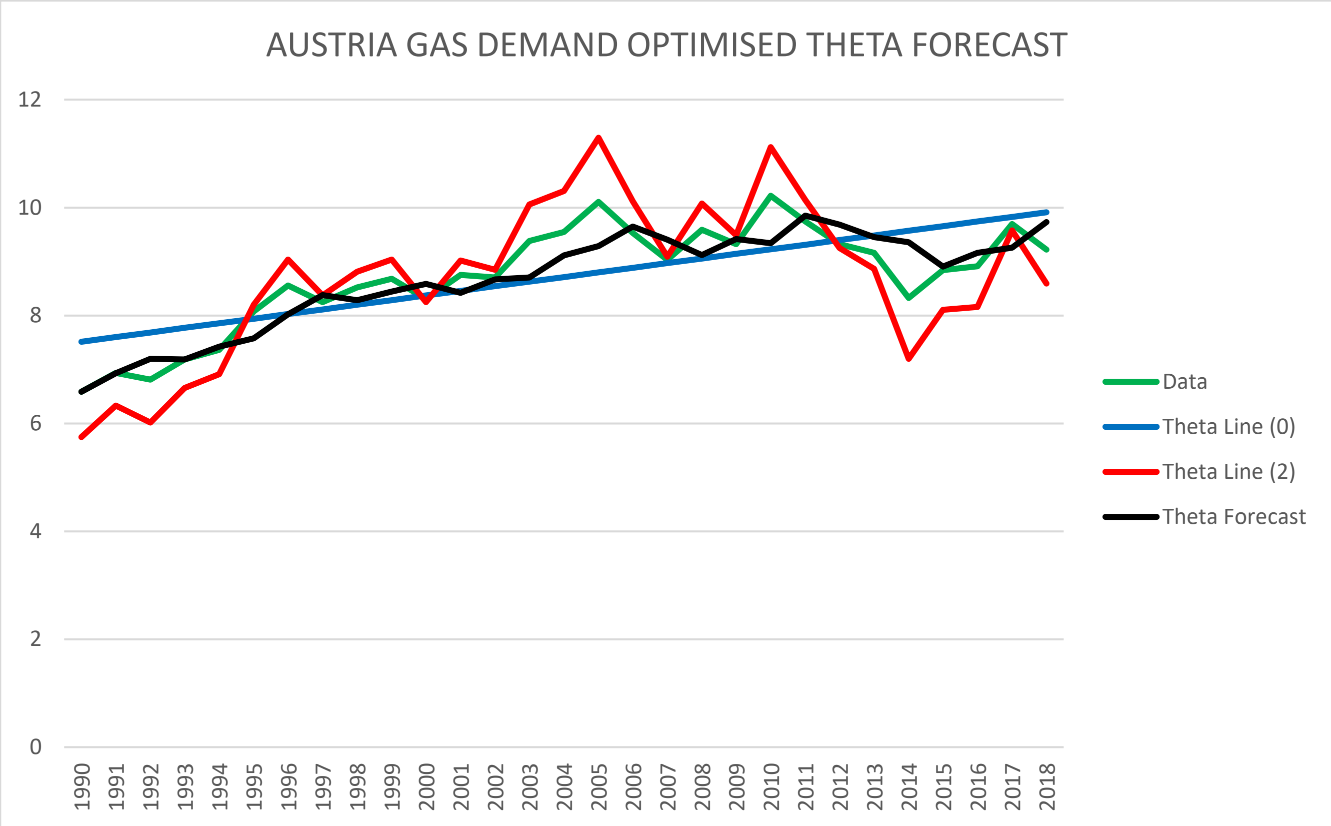
Next step is the application of our Optimised Theta Model in order to further improve the performance of our forecasts. The results obtained from Solver can be seen in the following figure:

ThetaLine(0)		ThetaLine(2)		SES on ThetaLine(2)	S		Theta		APE(%)	
LRL				with a=0.5	4,767		Forecast			
7,51		5,75		4,767	5,614		6,586		0,00	
7,60		6,33		5,614	6,233		6,929		0,06	
7,68		6,01		6,233	6,043		7,195		5,52	
7,77		6,66		6,043	6,576		7,187		0,00	
7,86		6,91		6,576	6,868		7,424		0,84	
7,94		8,20		6,868	8,020		7,579		6,35	
8,03		9,04		8,020	8,902		8,024		6,43	
8,11		8,37		8,902	8,444		8,379		1,56	
8,20		8,81		8,444	8,761		8,281		2,83	
8,28		9,04		8,761	9,002		8,445		2,74	
8,37		8,24		9,002	8,346		8,583		3,30	
8,46		9,02		8,346	8,927		8,418		3,86	
8,54		8,85		8,927	8,859		8,671		0,36	
8,63		10,06		8,859	9,898		8,705		7,44	
8,71		10,31		9,898	10,251		9,112		4,67	
8,80		11,29		10,251	11,153		9,288		8,44	
8,88		10,12		11,153	10,256		9,649		1,24	
8,97		9,09		10,256	9,244		9,403		4,04	
9,05		10,07		9,244	9,963		9,119		5,03	
9,14		9,49		9,963	9,553		9,418		1,01	
9,23		11,12		9,553	10,908		9,336		9,02	
9,31		10,14		10,908	10,241		9,850		1,08	
9,40		9,25		10,241	9,384		9,682		3,80	
9,48		8,87		9,384	8,936		9,450		3,12	
9,57		7,20		8,936	7,429		9,355		11,67	
9,65		8,10		7,429	8,014		8,904		0,70	
9,74		8,16		8,014	8,137		9,158		2,75	
9,83		9,58		8,137	9,383		9,256		4,63	
9,91		8,59		9,383	8,698		9,733		5,42	
10,00				8,698			9,559	MAP1	0,1063	
				VARIABLES				MAP3	4,2681	%
				θ	a	w	init.value	MAPE	3,7205	%
ΓΡΑΦΗΜΑ↓				1,907029015	0,86565	0,34	4,766512	MAP5	5,0334	%

Figure 44 Austria Gas demand Optimised Theta Model Solver Solution

The optimum parameters that give us average sMAPE=3,7205% (improved forecast fit) and 2019 sMAPE=0,1063% (extremely low forecasting error), with both values lower that before, are θ=1,9070, a=0,8656 and w=0,3374. The θ value for our second Theta Line (θ) is very close to the initially used θ=2 but slightly lower, emphasizing with similar way to the short-term characteristics of the data. The α value of SES is closer to 1, giving greater importance to the most recent data and applying little smoothing. The w value gives more weight to the linear and long-term characteristics, as Theta Line (0) contributes with 76% to the final Theta Forecast.

In the following graph it can be seen see for Austria how the Optimised Theta Model splits the initial data in two Theta Lines and then combines them for the generation of the forecasts:



Plot 6 Austria Gas demand Plot, Optimised Theta Method forecasting with Theta Lines combination

If another Theta Line is added to the Optimised Theta Model, it can be seen that no further improvement can be achieved and Solver even gives w3=0, meaning there is no need for another Theta Line and the optimisation is performed again with two Theta Lines. So, in the case of Austria Gas Demand, the Optimised Theta Model with two Theta Lines is kept that was presented before. The results of the Optimised Three Theta Line Model can be found below:

ThetaLine(0)		ThetaLine(2)	Theta(3)	SES on ThetaLine(3)	S3	SES on ThetaLine(2)	S2		Theta		APE(%)	
LRL				with a=0.5	5,69	with a=0.5	4,349		Forecast			
7,51		5,33	5,69	5,69	5,69	4,349	5,091		6,586		0,00	
7,60		6,03	6,29	5,69	6,16	5,091	5,802		6,864		1,00	
7,68		5,62	5,96	6,16	6,01	5,802	5,661		7,133		4,66	
7,77		6,39	6,63	6,01	6,49	5,661	6,218		7,152		0,49	
7,86		6,69	6,89	6,49	6,80	6,218	6,576		7,376		0,20	
7,94		8,26	8,21	6,80	7,90	6,576	7,855		7,541		6,85	
8,03		9,28	9,07	7,90	8,81	7,855	8,937		7,976		7,03	
8,11		8,44	8,38	8,81	8,48	8,937	8,556		8,354		1,26	
8,20		8,96	8,83	8,48	8,75	8,556	8,860		8,303		2,57	
8,28		9,22	9,06	8,75	8,99	8,860	9,133		8,453		2,65	
8,37		8,21	8,24	8,99	8,40	9,133	8,435		8,593		3,42	
8,46		9,15	9,03	8,40	8,90	8,435	8,979		8,449		3,49	
8,54		8,92	8,86	8,90	8,87	8,979	8,936		8,669		0,38	
8,63		10,40	10,10	8,87	9,83	8,936	10,049		8,717		7,31	
8,71		10,69	10,35	9,83	10,24	10,049	10,533		9,104		4,77	
8,80		11,89	11,37	10,24	11,12	10,533	11,562		9,306		8,25	
8,88		10,41	10,15	11,12	10,36	11,562	10,687		9,668		1,43	
8,97		9,12	9,09	10,36	9,37	10,687	9,493		9,472		4,77	
9,05		10,32	10,10	9,37	9,94	9,493	10,119		9,183		4,33	
9,14		9,57	9,50	9,94	9,60	10,119	9,703		9,427		1,11	
9,23		11,57	11,17	9,60	10,83	9,703	11,120		9,366		8,70	
9,31		10,33	10,16	10,83	10,31	11,120	10,523		9,841		0,99	
9,40		9,22	9,25	10,31	9,48	10,523	9,530		9,727		4,26	
9,48		8,72	8,85	9,48	8,99	9,530	8,914		9,497		3,62	
9,57		6,63	7,13	8,99	7,53	8,914	7,179		9,377		11,90	
9,65		7,74	8,06	7,53	7,94	7,179	7,602		8,930		0,99	
9,74		7,78	8,11	7,94	8,07	7,602	7,736		9,114		2,27	
9,83		9,52	9,57	8,07	9,24	7,736	9,089		9,214		5,09	
9,91		8,28	8,55	9,24	8,70	9,089	8,473		9,671		4,78	
10,00				8,70		8,473			9,551	MAP1	0,1915	
										MAP3	4,0457	%
			θ3	θ2	a3	w3	a2	w1	w2	MAPE	3,7427	%
ΓΡΑΦΗΜΑ↓			1,96266	2,360825262	0,782347	0	0,759773	0,71	0,29281	MAP5	5,0047	%

Figure 45 Austria Gas demand Optimised Theta Model with two Theta Lines result

6.2.5 Slovakia Yearly Gas Demand

etaLine(0)	ThetaLine(2)	SES on	S		Theta		APE(%)	NAÏVE	APE(%)	KMO 3	APE(%)	KMO 5	APE(%)	FRC.LIN	APE(%)	FRC.ETS	APE(%)	
LRL		ThetaLine(2) with	5,412		Forecast													
6,73	5,41	5,412	5,412		6,069		0,00	6,068526	0		0		0	6,725511	10,27017	6,37043	4,854169	
6,67	4,12	5,412	4,767		6,042		11,26	6,068526	11,70641		0		0	6,671667	21,11621	6,316586	15,69379	
6,62	5,26	4,767	5,012		5,693		4,20	5,397402	9,517958		0		0	6,617823	10,84907	6,262742	5,343621	
6,56	5,19	5,012	5,103		5,788		1,57	5,936794	0,975563	5,800907	1,339901		0	6,56398	11,00722	6,208899	5,455645	
6,51	4,72	5,103	4,910		5,807		3,39	5,879158	4,627417	5,737785	2,194119		0	6,510136	14,79584	6,155055	9,207743	
6,46	5,99	4,910	5,449		5,683		9,07	5,613257	10,29762	5,809736	6,863628	5,779027	7,392933	6,456292	3,685259	6,101211	1,971048	
6,40	6,71	5,449	6,082		5,926		10,13	6,222666	5,248297	5,905027	10,47934	5,809855	12,09899	6,402448	2,401181	6,047367	8,102603	
6,35	6,96	6,082	6,521		6,215		6,84	6,558051	1,465775	6,131325	8,189483	6,041985	9,654375	6,348605	4,71077	5,993524	10,45765	
6,29	7,23	6,521	6,875		6,408		5,38	6,654887	1,599455	6,478535	4,284545	6,185604	8,906279	6,294761	7,159805	5,93968	12,95096	
6,24	7,45	6,875	7,161		6,558		4,27	6,762187	1,202965	6,658375	2,749896	6,36221	7,296802	6,240917	9,218363	5,885836	15,0542	
6,19	7,59	7,161	7,377		6,674		3,18	6,844026	0,664614	6,7537	1,993115	6,608363	4,168025	6,187073	10,74565	5,831992	16,62789	
6,13	8,58	7,377	7,979		6,755		8,53	6,889664	6,562511	6,831959	7,402571	6,741763	8,729404	6,13323	18,14492	5,778149	24,04195	
6,08	7,92	7,979	7,948		7,029		0,44	7,357138	5,00196	7,030276	0,458499	6,90158	1,389032	6,079386	14,05054	5,724305	20,02466	
6,03	7,50	7,948	7,722		6,987		3,28	6,998116	3,44391	7,081639	4,629869	6,970226	3,044686	6,025542	11,50638	5,670461	17,54756	
5,97	7,14	7,722	7,433		6,847		4,31	6,761187	3,049899	7,038814	7,071304	6,970026	6,090303	5,971698	9,359731	5,616617	15,46581	
5,92	8,16	7,433	7,798		6,676		5,32	6,558075	7,092647	6,772459	3,878419	6,912836	1,827286	5,917855	17,32441	5,562774	23,44733	
5,86	6,96	7,798	7,381		6,831		6,29	7,040318	9,305343	6,786527	5,639164	6,942967	7,915513	5,864011	8,963875	5,50893	15,18694	
5,81	6,33	7,381	6,856		6,596		8,30	6,414318	5,513259	6,670904	9,429924	6,754403	10,6707	5,810167	4,376977	5,455086	10,67362	
5,76	6,57	6,856	6,712		6,306		2,31	6,070167	1,501192	6,508268	5,466138	6,568813	6,391306	5,756323	6,807302	5,401242	13,1579	
5,70	4,85	6,712	5,782		6,207		16,20	6,161981	15,47306	6,215489	16,33219	6,448972	19,98931	5,70248	7,750435	5,347399	1,325209	
5,65	6,29	5,782	6,038		5,715		4,38	5,277001	12,34457	5,836383	2,284856	6,192757	3,641555	5,648636	5,553243	5,293555	12,03253	
5,59	5,47	6,038	5,752		5,816		5,03	5,971277	7,660458	5,80342	4,811932	5,978949	7,788663	5,594792	1,151735	5,239711	5,403918	
5,54	4,87	5,752	5,312		5,647		8,11	5,530724	6,036911	5,593001	7,15541	5,80223	10,82053	5,540948	6,221434	5,185867	0,399414	
5,49	5,39	5,312	5,349		5,400		0,68	5,206622	4,319288	5,569541	2,418059	5,629521	3,488995	5,487105	0,926981	5,132024	5,761485	
5,43	3,57	5,349	4,457		5,391		18,03	5,436475	18,8636	5,391274	18,03579	5,48442	19,73347	5,433261	18,80499	5,07818	12,08729	
5,38	3,87	4,457	4,166		4,918		6,10	4,499348	2,799729	5,047482	8,690307	5,328889	14,0977	5,379417	15,03642	5,024336	8,231521	
5,33	3,97	4,166	4,066		4,746		2,12	4,627106	0,408642	4,85431	4,384184	5,060055	8,530752	5,325573	13,62908	4,970492	6,747527	
5,27	4,60	4,066	4,331		4,669		5,52	4,646053	6,009908	4,590836	7,204197	4,883121	1,035061	5,27173	6,619912	4,916649	0,350807	
5,22	4,51	4,331	4,419		4,775		1,83	4,933927	1,451954	4,735695	2,648532	4,828582	0,70626	5,217886	7,044775	4,862805	0	
5,16		4,419			4,792	MAP1	1,6952	4,862805	0,223284	4,814262	1,226543	4,713848	3,334067	5,164042	5,785524	4,808961	1,336697	
						MAP3	3,1578	%	2,6235	%	4,7456	%	3,4240	%	9,0979	%	2,3661	%
			a	θ		MAPE	5,7263	%	5,8623	%	6,0014	%	7,7253	%	9,6287	%	10,2622	%
ΑΦΗΜΑ↓			0,5	0,5		MAP5	6,7217	%	5,9068	%	8,1926	%	8,8206	%	12,2270	%	5,4834	%

Figure 46 Slovakia Gas demand basic Theta Model vs benchmark methods

ThetaLine(0)	ThetaLine(2)	SES on	S		Theta		APE(%)	
LRL		ThetaLine(2) with	5,412		Forecast			
6,73	5,41	5,412	5,412		6,179		1,80	
6,67	4,12	5,412	4,483		6,147		12,99	
6,62	5,26	4,483	5,040		5,729		3,56	
6,56	5,19	5,040	5,151		5,930		0,86	
6,51	4,72	5,151	4,838		5,945		5,73	
6,46	5,99	4,838	5,668		5,783		7,33	
6,40	6,71	5,668	6,422		6,097		7,29	
6,35	6,96	6,422	6,811		6,379		4,23	
6,29	7,23	6,811	7,113		6,510		3,81	
6,24	7,45	7,113	7,354		6,604		3,57	
6,19	7,59	7,354	7,526		6,673		3,20	
6,13	8,58	7,526	8,287		6,713		9,16	
6,08	7,92	8,287	8,020		6,998		0,00	
6,03	7,50	8,020	7,643		6,856		1,39	
5,97	7,14	7,643	7,283		6,667		1,65	
5,92	8,16	7,283	7,917		6,486		8,19	
5,86	6,96	7,917	7,230		6,719		4,64	
5,81	6,33	7,230	6,581		6,401		5,31	
5,76	6,57	6,581	6,571		6,100		1,02	
5,70	4,85	6,571	5,331		6,064		13,88	
5,65	6,29	5,331	6,025		5,517		7,92	
5,59	5,47	6,025	5,623		5,774		4,30	
5,54	4,87	5,623	5,082		5,575		6,83	
5,49	5,39	5,082	5,301		5,318		2,20	
5,43	3,57	5,301	4,050		5,378		17,79	
5,38	3,87	4,050	3,924		4,826		4,21	
5,33	3,97	3,924	3,955		4,742		2,04	
5,27	4,60	3,955	4,417		4,723		4,36	
5,22	4,51	4,417	4,482		4,885		0,45	
5,16		4,482			4,880	MAP1	0,1366	
						MAP3	2,2832	%
			a	θ		MAPE	5,1622	%
ΓΡΑΦΗΜΑ↓			0,720993	0,42		MAP5	5,7701	%

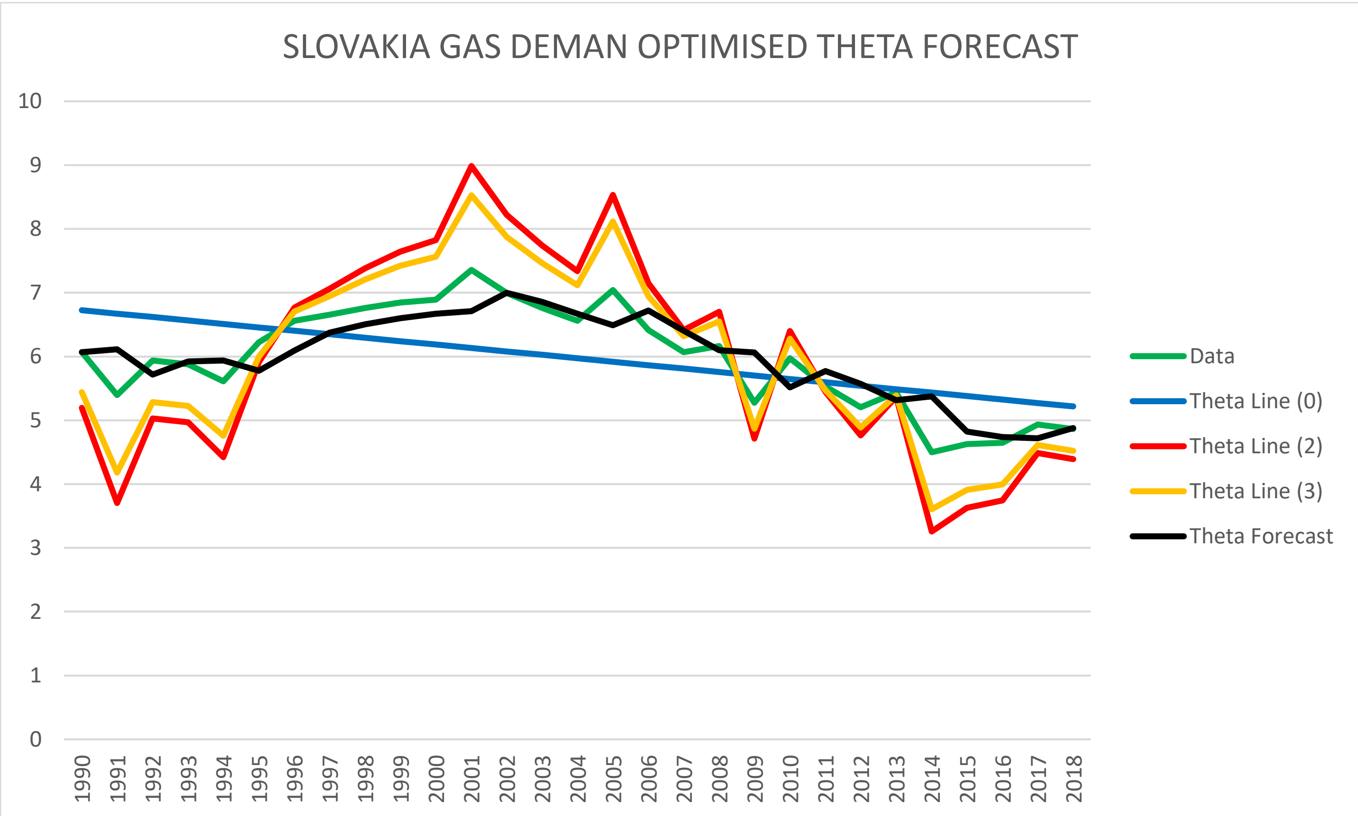
Figure 47 Slovakia Gas demand Solver Solution

ThetaLine(0)	ThetaLine(2)	SES on	S		Theta		APE(%)	
LRL		ThetaLine(2) with	5,130		Forecast			
6,73	5,42	5,130	5,348		6,069		0,00	
6,67	4,14	5,348	4,437		6,127		12,66	
6,62	5,26	4,437	5,060		5,720		3,72	
6,56	5,20	5,060	5,168		5,945		1,11	
6,51	4,73	5,168	4,836		5,957		5,95	
6,46	5,99	4,836	5,707		5,789		7,22	
6,40	6,71	5,707	6,464		6,116		6,98	
6,35	6,96	6,464	6,836		6,396		3,97	
6,29	7,22	6,836	7,128		6,518		3,68	
6,24	7,44	7,128	7,363		6,606		3,53	
6,19	7,58	7,363	7,529		6,671		3,22	
6,13	8,57	7,529	8,310		6,708		9,23	
6,08	7,91	8,310	8,005		6,998		0,00	
6,03	7,49	8,005	7,615		6,841		1,17	
5,97	7,14	7,615	7,255		6,649		1,37	
5,92	8,15	7,255	7,929		6,469		8,46	
5,86	6,96	7,929	7,197		6,714		4,57	
5,81	6,33	7,197	6,542		6,381		5,00	
5,76	6,56	6,542	6,557		6,080		1,34	
5,70	4,86	6,557	5,276		6,055		13,72	
5,65	6,29	5,276	6,040		5,495		8,30	
5,59	5,47	6,040	5,609		5,778		4,38	
5,54	4,88	5,609	5,057		5,569		6,72	
5,49	5,39	5,057	5,305		5,310		2,35	
5,43	3,58	5,305	4,003		5,381		17,84	
5,38	3,88	4,003	3,913		4,813		3,93	
5,33	3,97	3,913	3,960		4,744		2,09	
5,27	4,60	3,960	4,442		4,731		4,19	
5,22	4,51	4,442	4,495		4,899		0,73	
5,16		4,495			4,888	MAP1	0,3033	
						MAP3	2,3361	%
			a	θ		MAPE	5,0842	%
ΓΡΑΦΗΜΑ↓		1,987659247	0,753424	0,41	5,130183	MAP5	5,7554	%

Figure 48 Slovakia Gas demand Optimised Theta Model Solver Solution

ThetaLine(0)	ThetaLine(2)	Theta(3)	SES on	S3	SES on	S2		Theta		APE(%)	
LRL			ThetaLine(3) with	5,27	ThetaLine(2) with	4,856		Forecast			
6,73	5,19	5,44	5,27	5,39	4,856	5,097		6,069		0,00	
6,67	3,70	4,18	5,39	4,51	5,097	4,103		6,112		12,42	
6,62	5,03	5,29	4,51	5,07	4,103	4,764		5,715		3,80	
6,56	4,97	5,22	5,07	5,18	4,764	4,910		5,921		0,70	
6,51	4,42	4,76	5,18	4,87	4,910	4,561		5,938		5,62	
6,46	5,91	6,00	4,87	5,69	4,561	5,524		5,777		7,43	
6,40	6,77	6,71	5,69	6,43	5,524	6,409		6,091		7,39	
6,35	7,06	6,95	6,43	6,81	6,409	6,875		6,374		4,30	
6,29	7,38	7,21	6,81	7,10	6,875	7,238		6,506		3,86	
6,24	7,65	7,42	7,10	7,33	7,238	7,529		6,602		3,60	
6,19	7,82	7,56	7,33	7,50	7,529	7,740		6,671		3,22	
6,13	8,99	8,53	7,50	8,25	7,740	8,628		6,712		9,17	
6,08	8,22	7,88	8,25	7,98	8,628	8,337		6,998		0,00	
6,03	7,74	7,46	7,98	7,60	8,337	7,911		6,857		1,41	
5,97	7,34	7,12	7,60	7,25	7,911	7,503		6,669		1,67	
5,92	8,53	8,11	7,25	7,88	7,503	8,238		6,487		8,18	
5,86	7,15	6,94	7,88	7,20	8,238	7,460		6,719		4,64	
5,81	6,42	6,32	7,20	6,56	7,460	6,716		6,402		5,33	
5,76	6,70	6,55	6,56	6,55	6,716	6,706		6,100		1,01	
5,70	4,71	4,87	6,55	5,33	6,706	5,283		6,064		13,87	
5,65	6,40	6,28	5,33	6,02	5,283	6,080		5,516		7,93	
5,59	5,45	5,47	6,02	5,62	6,080	5,628		5,771		4,26	
5,54	4,76	4,89	5,62	5,09	5,628	5,010		5,573		6,79	
5,49	5,37	5,39	5,09	5,31	5,010	5,266		5,316		2,24	
5,43	3,26	3,61	5,31	4,07	5,266	3,834		5,375		17,74	
5,38	3,63	3,91	4,07	3,95	3,834	3,686		4,823		4,14	
5,33	3,74	4,00	3,95	3,98	3,686	3,726		4,737		1,94	
5,27	4,48	4,61	3,98	4,44	3,726	4,267		4,718		4,47	
5,22	4,39	4,52	4,44	4,50	4,267	4,355		4,879		0,34	
5,16			4,50		4,355			4,876	MAP1	0,0408	
									MAP3	2,2505	%
				a3	θ3	a2	θ1	θ2	MAPE	5,0856	%
ΓΡΑΦΗΜΑ↓		1,956348	2,330382226	0,728447	0,130312242	0,712976	0,62	0,249591	MAP5	5,7252	%

Figure 49 Slovakis Gas demand Optimised Theta Model with two Theta Lines result



Plot 7 Slovakia Gas demand Plot, Optimised Theta Method forecasting with two Theta Lines combination

6.2.6 Results of All 24 European countries' Gas Demand Time Series

GAS	GERMANY	AUSTRIA	ITALY	SPAIN	NETH/ANDS	POLAND	UN. KING	FRANCE	BELARUS	BELGIUM	BULGARIA	CROATIA	CZECH	DENMARK	HUNGARY	IRELAND	LATVIA	MOLDOVA	ROMANIA	SERVIA	SLOVAKIA	SLOVENIA	SWEDEN	SWITZERL	AVERAGE
BEST sMAPE	3,6518	4,3062	4,9421	8,8044	4,2841	3,0050	5,0692	4,5366	5,7816	4,6404	8,6887	5,0080	4,4343	6,5278	5,7851	5,4662	10,6122	3,6518	5,8774	13,8237	5,7263	5,2758	9,4752	4,6050	5,9991
THETA MAPE	3,6518	4,3062	5,5907	10,7532	4,2841	4,2238	6,9416	4,8593	5,7816	4,9664	9,9368	5,0080	4,7760	9,9951	6,3089	6,3311	12,6333	4,0025	7,4690	16,9713	5,7263	6,1081	9,5239	4,8321	6,8742
NAÏVE	3,6720	4,7738	4,9421	8,8044	4,3065	3,9555	5,0692	4,5366	5,9732	4,6404	8,6887	5,3619	4,4343	6,5278	5,7851	5,4662	10,6122	3,6518	5,8774	16,8655	5,8623	5,2758	9,4752	5,5085	6,2528
KMO3	4,3474	5,1218	7,0300	15,7027	4,8329	5,7814	7,8184	5,3980	6,7122	6,5142	11,6380	5,5761	5,4012	10,5237	7,2355	9,1262	13,5755	4,7905	8,6366	19,2525	6,0014	6,8924	11,8601	5,6037	8,1405
KMO5	5,4115	6,2239	9,7433	23,0363	5,0026	7,5733	10,1879	6,9614	7,4961	8,5111	12,3781	6,6921	6,7444	14,3434	9,9010	12,3979	13,7205	6,0477	11,5889	13,8237	7,7523	8,6821	12,5404	6,7931	9,7314
FRC.LIN	5,6939	6,1730	11,2663	20,9723	5,0510	3,5266	15,2882	8,2021	6,1070	8,1992	11,6410	6,0461	8,8979	22,5378	11,0345	10,1674	17,3459	7,4128	8,7655	17,4063	9,6287	11,8581	9,6610	4,6050	10,3120
FRC.ETS	5,6672	9,0855	15,0103	17,5718	7,9807	3,0050	42,9508	13,6203	6,0909	9,2964	14,0249	6,0721	10,3437	31,5325	12,0362	9,9616	17,1044	7,4555	29,2471	24,7323	10,2622	13,1827	9,8804	16,8440	14,2899
OPTIMIZED THETA-:	2,9816	3,7205	4,3291	6,5561	3,3171	2,6808	4,5276	3,7446	5,0156	3,2963	7,5658	4,4836	3,9640	5,8120	5,1424	4,7119	8,7916	3,1255	5,3865	14,0672	5,0856	4,8514	7,1082	3,3795	5,1519
BEST 2019 OF REST	0,2522	2,7962	1,1180	9,5393	2,3936	1,1246	0,6997	0,5978	3,5013	0,6685	4,4006	2,6448	2,0614	4,7587	0,2428	1,7760	0,3761	0,7755	3,4422	2,0708	0,2233	1,2586	11,2229	0,3584	2,4293
THETA 2019	1,2439	2,4465	1,4336	11,4923	4,4595	3,3171	0,0090	0,0212	8,4120	2,5091	8,7472	3,5254	3,3214	6,9064	1,2870	3,3907	2,2055	3,3788	0,1388	6,0322	1,6952	1,8081	20,6581	3,2488	4,2370
NAÏVE 2019	0,2522	3,7211	2,4118	13,4243	4,6534	2,3638	0,6997	2,3193	7,1991	0,6685	7,7880	4,9170	4,8519	4,7587	0,7619	1,7760	4,8494	2,2408	7,2992	6,7211	0,2233	1,2586	19,3527	1,8362	4,4312
KMO3 2019	1,1819	3,1268	2,0973	15,6176	4,2715	4,8817	0,7394	0,5978	10,8141	4,8498	14,1106	3,5727	2,0614	6,5326	0,2428	5,3457	1,0075	5,6257	4,0093	9,9542	1,2265	1,5168	22,1697	4,7625	5,4298
KMO5 2019	5,8288	6,1537	6,7002	19,0385	5,4600	9,1487	3,6598	3,7712	11,1143	8,5482	15,2669	7,9215	6,0141	5,9325	4,8294	10,7441	0,3761	7,3976	3,4422	2,0708	3,3341	5,0831	27,9865	9,5117	7,8889
FRC.LIN 2019	1,6871	4,3757	10,9590	11,4638	2,3936	4,0293	12,6019	9,9619	3,5013	5,7325	10,0785	2,6448	2,3502	34,1517	7,2515	6,0665	11,8704	3,7386	30,2481	13,8772	5,7855	9,2010	11,2229	1,5788	9,0322
FRC.ETS 2019	0,4145	2,7962	1,1180	9,5393	5,0587	1,1246	4,2083	1,2162	3,5829	0,8303	4,4006	3,2419	4,5398	5,3422	1,0217	4,5663	2,0714	0,7755	6,7520	5,9730	1,3367	1,2814	12,8870	0,3584	3,5182
OPT THETA 2019	0,4555	0,1059	0,0804	10,2235	0,4602	2,9076	1,8875	1,2029	5,9304	1,2272	1,9581	2,2290	3,3418	6,8596	0,9413	0,1032	1,0766	0,7872	1,5811	0,7017	0,0408	0,4546	15,0172	1,3856	2,5400
AVRG																									
-14,69%	-18,35%	-13,60%	-12,40%	-25,54%	-22,57%	-10,79%	-10,68%	-17,46%	-13,25%	-28,97%	-12,92%	-10,47%	-10,61%	-10,97%	-11,11%	-13,80%	-17,16%	-14,41%	-8,35%	1,76%	-11,19%	-8,04%	-24,98%	-26,61%	-14,6863%

Table 5 Results of all 24 European Countries' Oil Demand Time series

The results of all 24 countries' gas demand time series (data obtained by Rystad – European Gas Demand by Country in billion cubic meters-), confirm the previous findings from the application of our Optimised Theta Model for the oil demand. It offers significant improvement of overall forecasting fit, lowering the average sMAPE 14,6863% and achieving at the same time the lower sMAPE in each one of the countries separately, except Servia where the MA5 method performs slightly better (although the 2019 point forecast accuracy of our model, which is the basic metric, is exceptional in this case, at 0,7%).

The initial ranking across methods is also identical, with the naive performing best in forecasting fit with 6,2528%, Theta Method following with 6,8742% and FRC.ETS of Excel comes in the last place with over 14% sMAPE. The Optimised Theta Model lowers the average sMAPE close to 5%, with 5,1519% beating at the same time the average of best performing method from each country combined (5,9991%), apart the Theta Method. The graphical representation that offers us clear visualization can be found below:

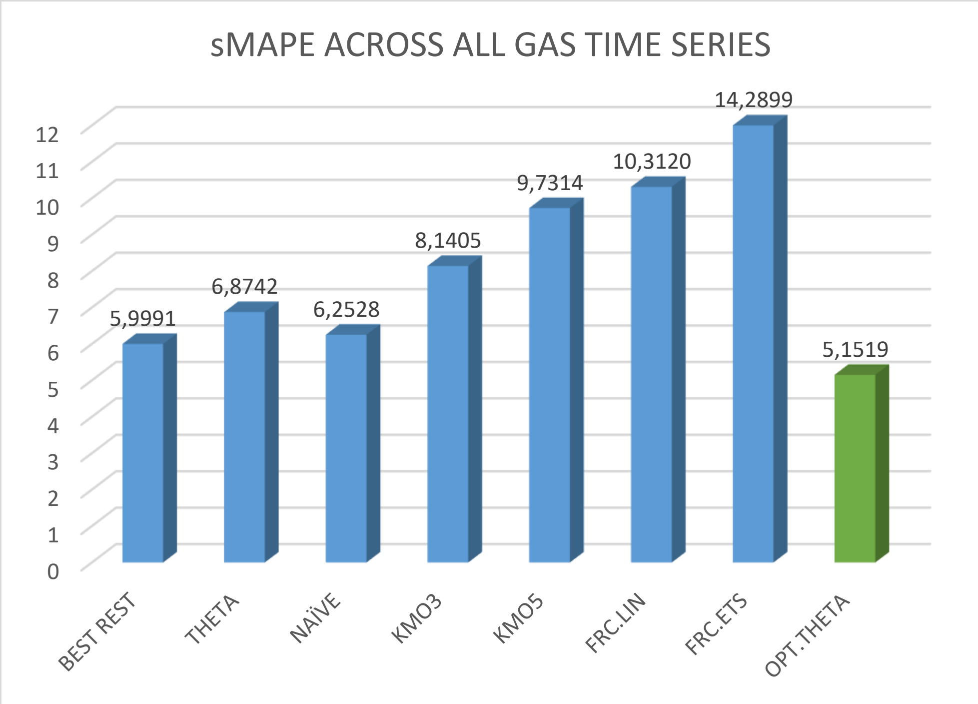


Chart 3 Model "fit" (mean sMAPE) across all Gas Demand time series

As far as the 2019 forecast accuracy is concerned, a surprise is witnessed. The FRC.ETS (Exponential Triple Smoothing) has the best overall forecasting accuracy, with average sMAPE of 3,5182% while in the sMAPE across all time series had the worst performance. This means that although the model does not fit well across all time series, forecasts well the annual demand. Probably the most recent data have no clear pattern or trend, so exponential smoothing manages to interpret them and smooth these data. Besides, most of the times exponential smoothing allows us to forecast efficiently on a more relevant basis of recent data, as history and experience has proven.

The conventional Theta Method follows with 4,2370% and very closely in the third place the naive method is found with 4,4312%. When our optimised model comes in, the results are again impressive, as it lowers the average 2019 forecast sMAPE of all 24 countries to 2,54%, outperforming all other methods in 8 of them accordingly and almost equalizing the average best sMAPE combined from each country (2,4293%). This proves that our model not only fits well, but also forecasts well.

The corresponding diagram is seen below:

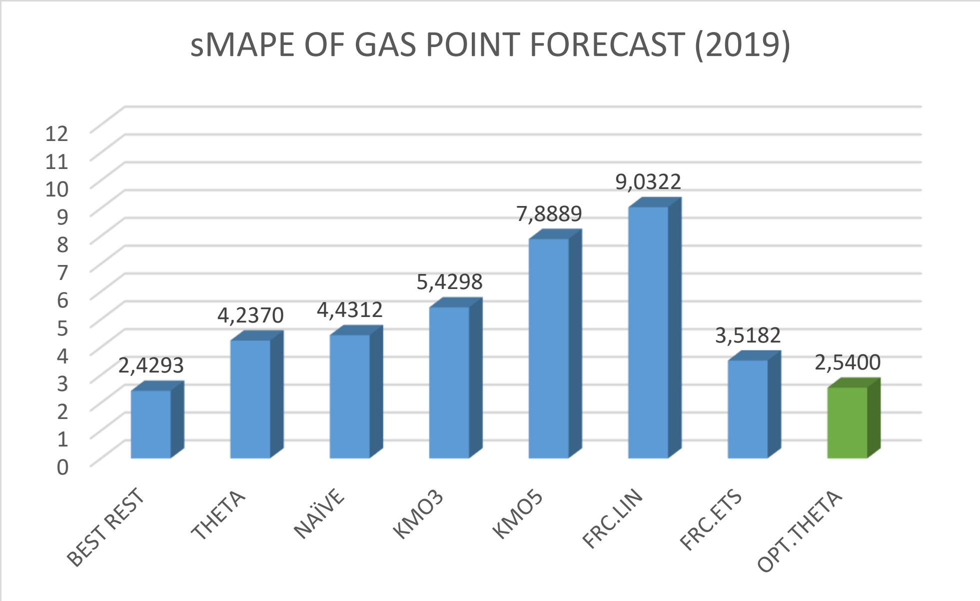


Chart 4 Model point forecast accuracy (sMAPE 2019 value) across all Gas demand time series

6.2.7 Results of All 37 European countries' Oil&Gas Demand Time Series

The combined results for all 37 countries' oil&gas time series from 1990 to 2019 (1.110 data) are presented. The adaptiveness and efficiency of our model has been proven, both for oil and gas different Europe's countries annual demand time series.

If the results are combined and the sMAPE is calculated for all 37 countries as a group of oil&gas annual demand, our Optimised Theta model achieves 4,3388% sMAPE forecasting fit across all data-set from 1990 to 2018 (average of all countries), which is a 16,14% improvement over the second best performing, naive method with 5,1736%.

In terms of point yearly forecast that evaluates the forecasting error (accuracy) of our model, our Optimised Theta model achieves 2,3653% sMAPE in 2019 average of all countries forecast, which is a vast 30,12% improvement over the second best performing, ETS function of excel with 3,3850%.

Below the graphs for total average sMAPE and 2019 forecast average sMAPE are presented:

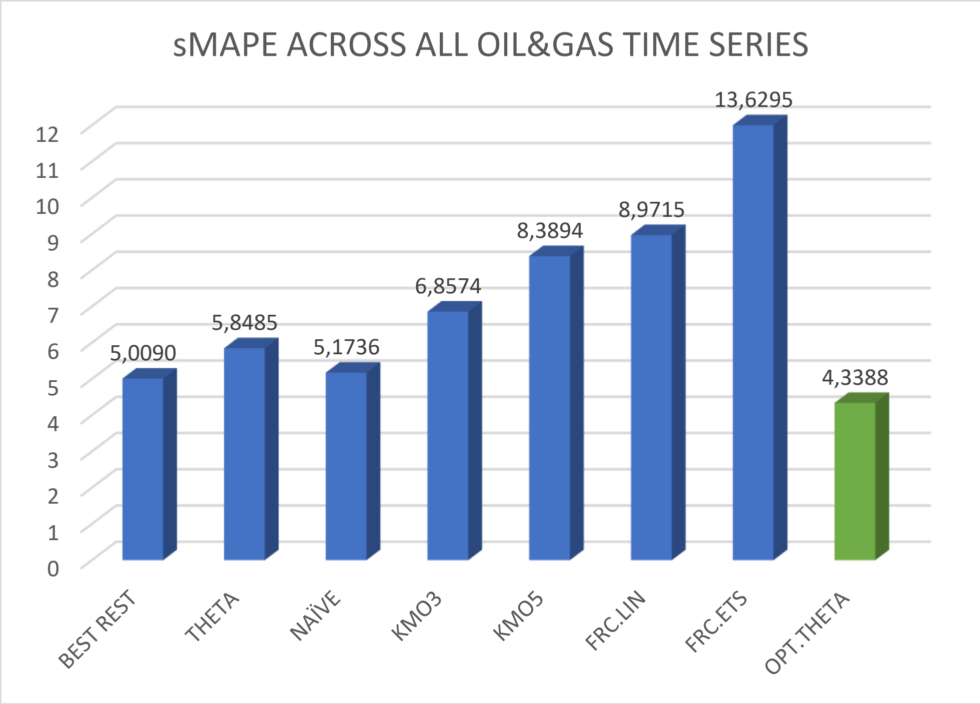


Chart 5 Model "fit" (mean sMAPE) across all Oil&Gas Demand time series

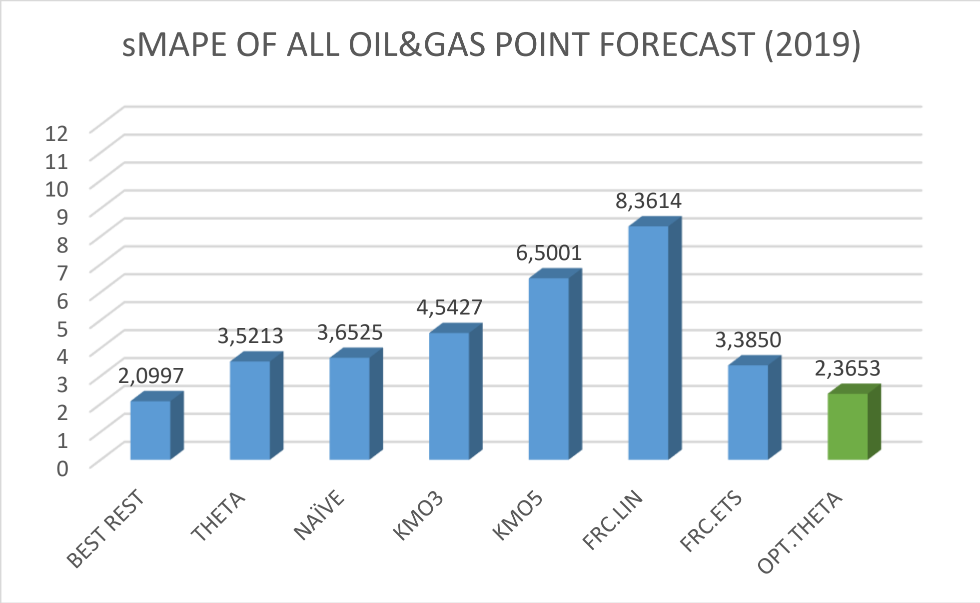


Chart 6 Model point forecast accuracy (sMAPE 2019 value) across all Oil&Gas demand time series

It is clear and evident that our Optimised Theta Model can be trusted for using it instead of other widely used simple methods or ready to use functions in excel (which basically apply other widely used quantitative statistical methods like LR and ES). The optimum combination of LRL and ES that are combined in Theta, rather than their single use, offers very good forecasting accuracy, with a model that can handle different time series of annual oil&gas data. Thus, with the ready to use constructed form in Excel that was presented, anyone can put the annual data he desires and hit “Solve” to get a next year demand forecast.

CHAPTER 7_FORECASTS TO 2024 USING OUR THETA MODEL

7.1 Oil Demand Time Series Forecasting

7.1.1 What the model would give from 2019 to 2024, Covid absence

Now the forecast horizon can be extended and see what the model will give. Taking into account the data from 1990 to 2018 and the defined parameters of our optimised Theta Model with two Theta Lines, we forecast six years ahead from 2019 to 2024. Every year's forecasted demand value is used as data for that particular year, in order to construct the Theta Line (θ) and apply SES for the preparation of next year's forecast. The 2019 forecast demand derived from our Optimised Theta Model is then placed as data for 2019 and again our optimised Theta Model is applied with w, a, θ and initial SES value that have been specified before. The 2020 forecast demand is placed as data for 2020 to proceed and so on until the 2024 annual demand value is acquired.

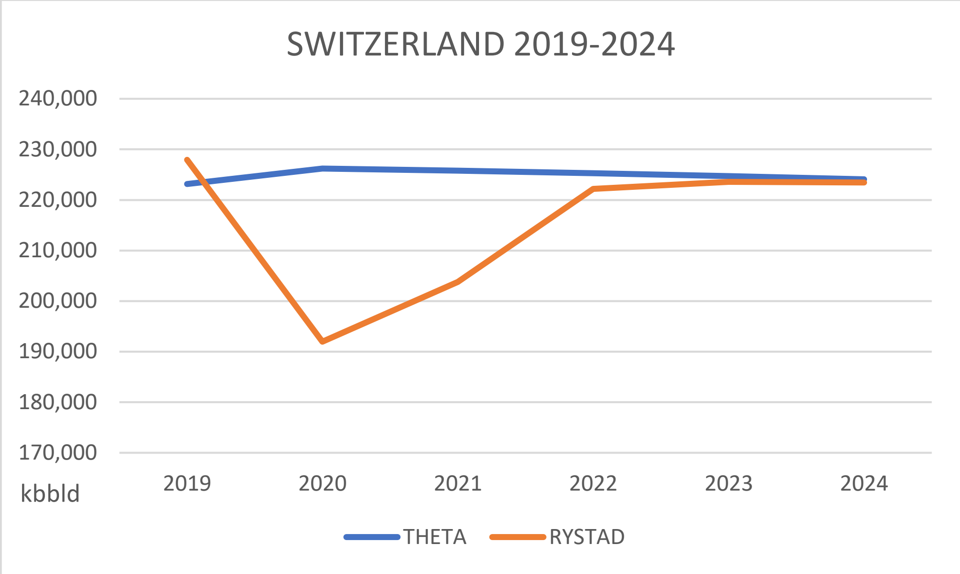
7.1.2 Comparison with Rystad's forecasts, taking into account data until 2020

In the oil demand series, there from Rystad forecasts for 10 out of 13 countries until 2024 and it is very interesting and insightful to compare our forecasts and results from our model with the ones from Rystad. As expected, and as it would be impossible for someone to know it and impossible for our statistical model to capture it, the 2020 forecast will appear very big error and the actual 2020 value will be much lower due to Coronavirus.

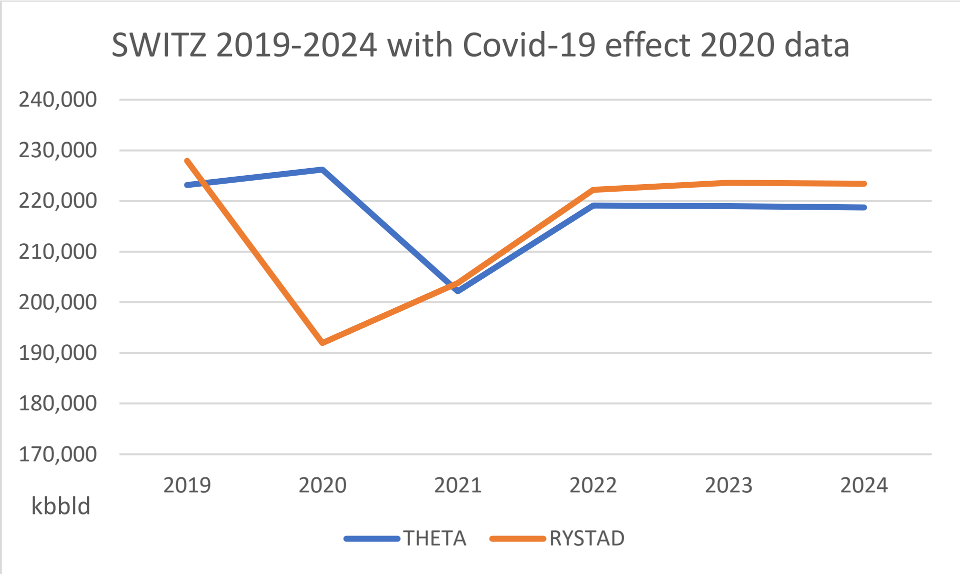
As Rystad's forecasts were generated in the beginning of 2021, so until 2020 there are actual data and the forecast horizon is four years ahead, data will also be used (where available) until 2020 in order to generate a second set of forecasts, where the damping in the 2020 value of our time series is taken into account as a result of Coronavirus. Of course, this will be detected by our model after 2020 that the reduction in demand will appear, so the adjustment through sMAPE and SES application will be visible from the 2021 forecast and on.

The average sMAPE is also calculated between our forecasts and the equivalent ones from Rystad, both for 2019-2024 period (what if, Covid absence) and 2021-2024 period (2020 Covid data included) and the results are at least satisfying, giving credibility to our model, as not only the average sMAPE is very low in almost all countries but in addition the trend and evolution of the forecasted time series in the future is very similar in almost every case. This means that although the reduction in demand for 2020 is different for each country, ranging from 3,1303% to 23,9247% with an average of 14,4120%, our model can be trusted for forecasting the annual oil demand until 2024 and particularly for 2022, 2023 and 2024 which represent the "return to normality" and comeback of the trend that was present before the Coronavirus. Values in kbbld.

7.1.2.1 SWITZERLAND



Plot 8 Switzerland Oil demand Optimised Theta model vs Rystad forecast to 2024

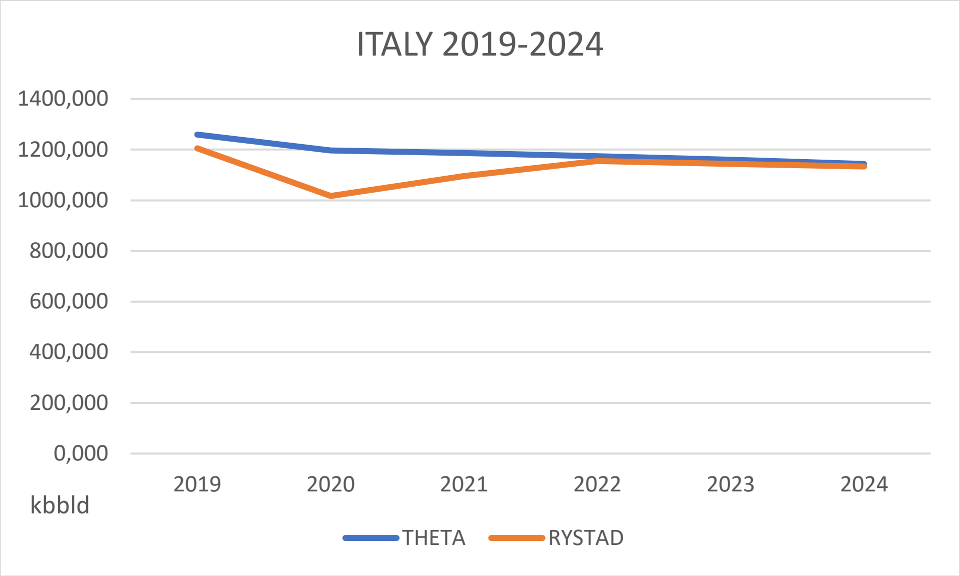


Plot 9 Switzerland Oil demand Optimised Theta model vs Rystad forecast to 2024 with Covid effect 2020 data

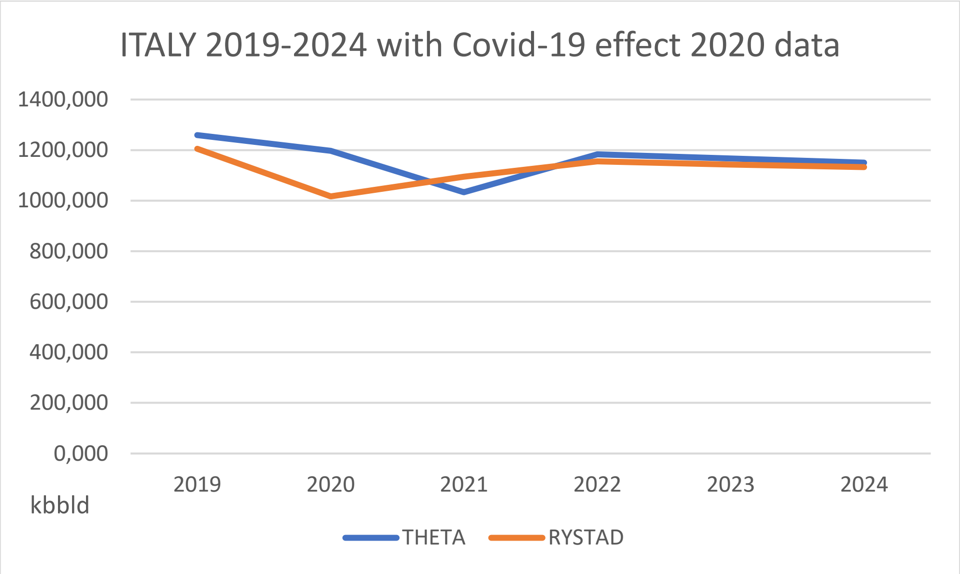
Theta	sMAPE vs Rystad
2019-2024	5,156779
2021-2024	3,111418
2022-2024	0,7337

Theta with Covid 2020	sMAPE vs Rystad
2019-2024	4,145182
2021-2024	1,594022
2022-2024	1,8623

7.1.2.2 ITALY



Plot 10 Italy Oil demand Optimised Theta model vs Rystad forecast to 2024

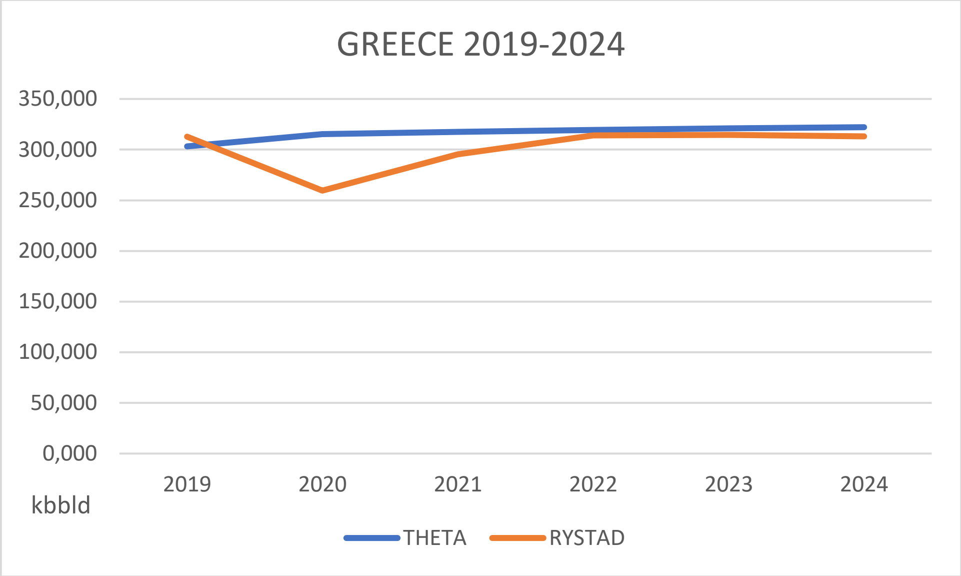


Plot 11 Italy Oil demand Optimised Theta model vs Rystad forecast to 2024 with Covid effect 2020 data

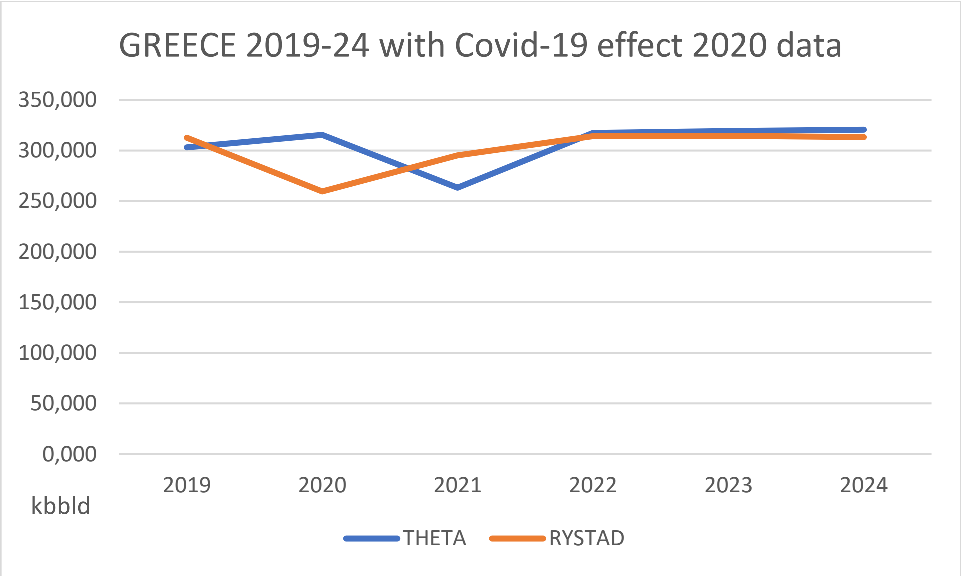
Theta	sMAPE vs Rystad
2019-2024	5,4293
2021-2024	2,9784
2022-2024	1,2977

Theta with Covid 2020	sMAPE vs Rystad
2019-2024	5,4037
2021-2024	2,9400
2022-2024	1,9826

7.1.2.3 GREECE



Plot 12 Greece Oil demand Optimised Theta model vs Rystad forecast to 2024

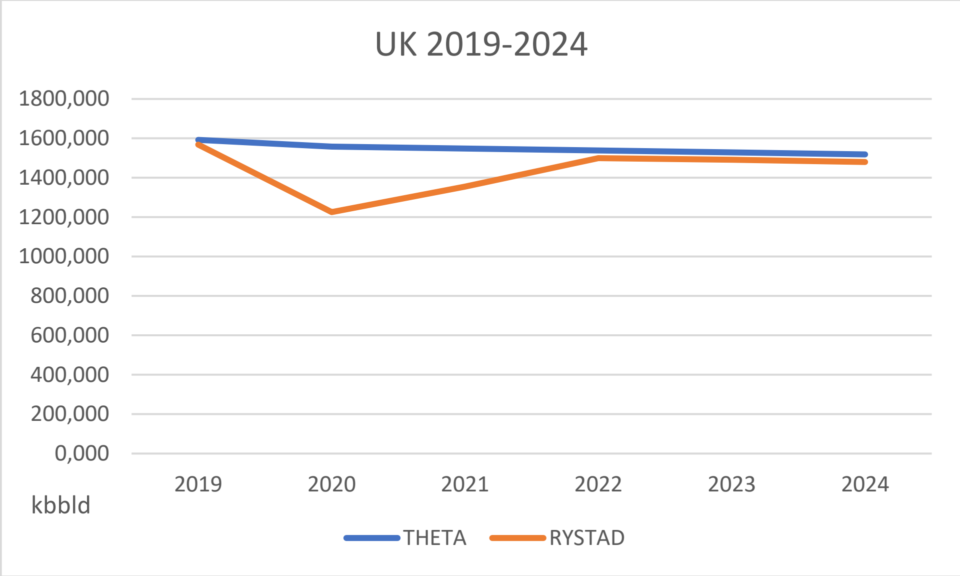


Plot 13 Greece Oil demand Optimised Theta model vs Rystad forecast to 2024 with Covid effect 2020 data

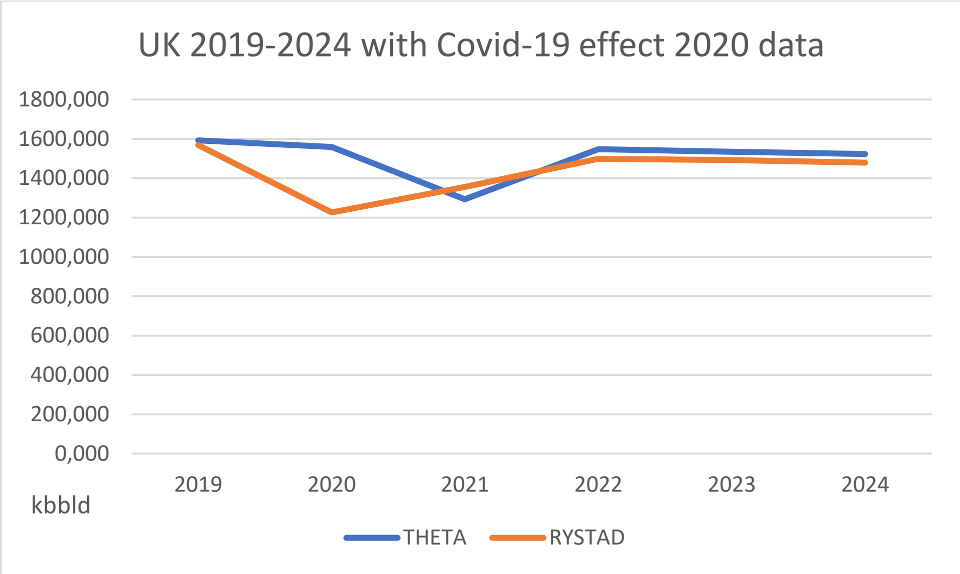
Theta	sMAPE vs Rystad
2019-2024	6,0446
2021-2024	3,4503
2022-2024	2,1742

Theta with Covid 2020	sMAPE vs Rystad
2019-2024	6,4672
2021-2024	4,0841
2022-2024	1,6165

7.1.2.4 UNITED KINGDOM



Plot 14 UK Oil demand Optimised Theta model vs Rystad forecast to 2024

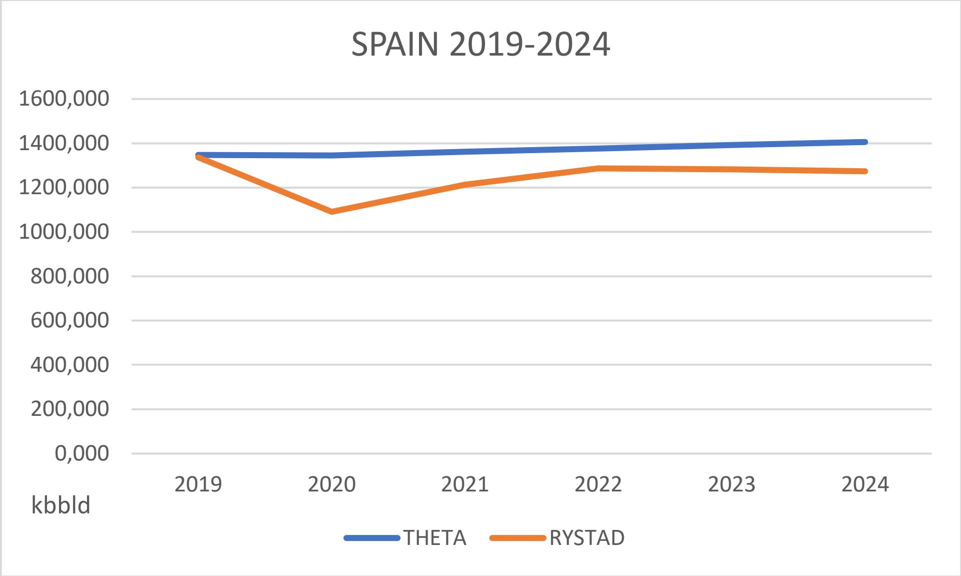


Plot 15 UK Oil demand Optimised Theta model vs Rystad forecast to 2024 with Covid effect 2020 data

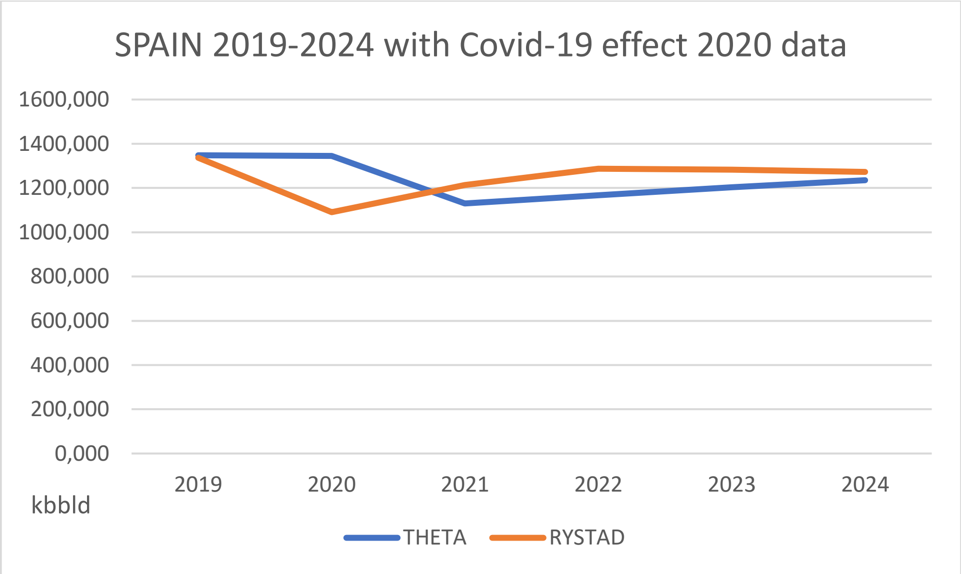
Theta	sMAPE vs Rystad
2019-2024	7,7469
2021-2024	5,2605
2022-2024	2,5552

Theta with Covid 2020	sMAPE vs Rystad
2019-2024	6,4931
2021-2024	3,3797
2022-2024	2,9432

7.1.2.5 SPAIN



Plot 16 Spain Oil demand Optimised Theta model vs Rystad forecast to 2024

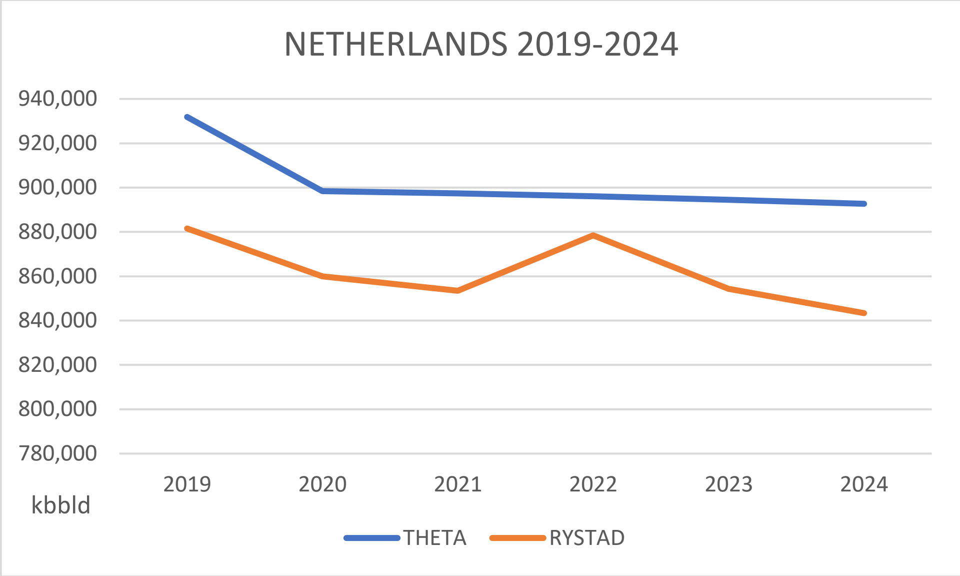


Plot 17 Spain Oil demand Optimised Theta model vs Rystad forecast to 2024 with Covid effect 2020 data

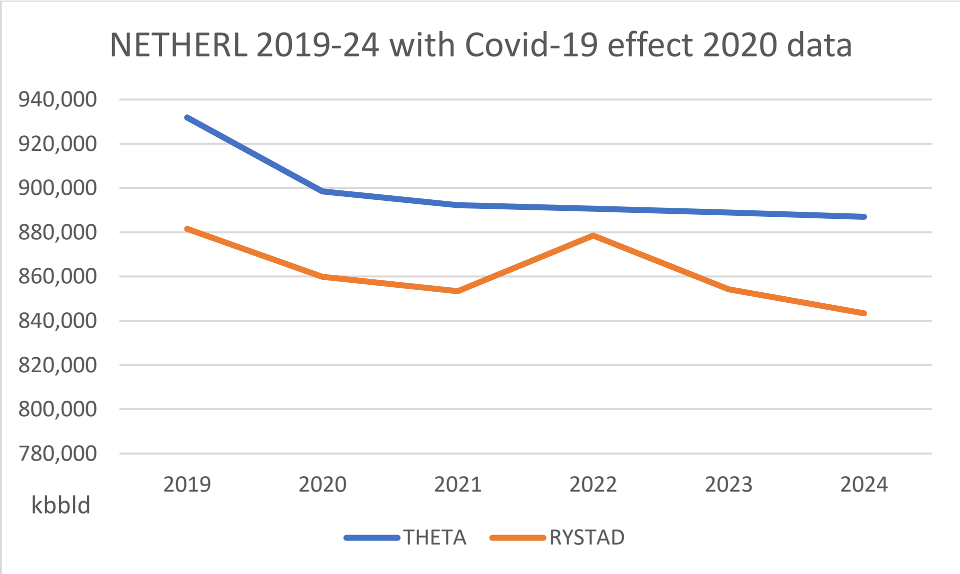
Theta	sMAPE vs Rystad
2019-2024	9,6770
2021-2024	9,0826
2022-2024	8,2755

Theta with Covid 2020	sMAPE vs Rystad
2019-2024	7,9908
2021-2024	6,5534
2022-2024	6,3726

7.1.2.6 NETHERLANDS



Plot 18 Netherlands Oil demand Optimised Theta model vs Rystad forecast to 2024

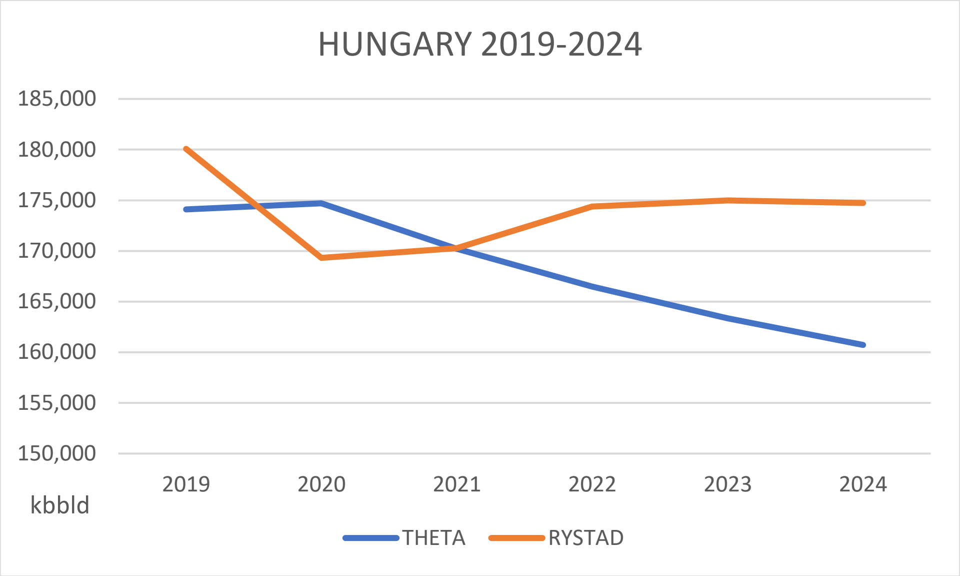


Plot 19 Netherlands Oil demand Optimised Theta model vs Rystad forecast to 2024 with Covid effect 2020 data

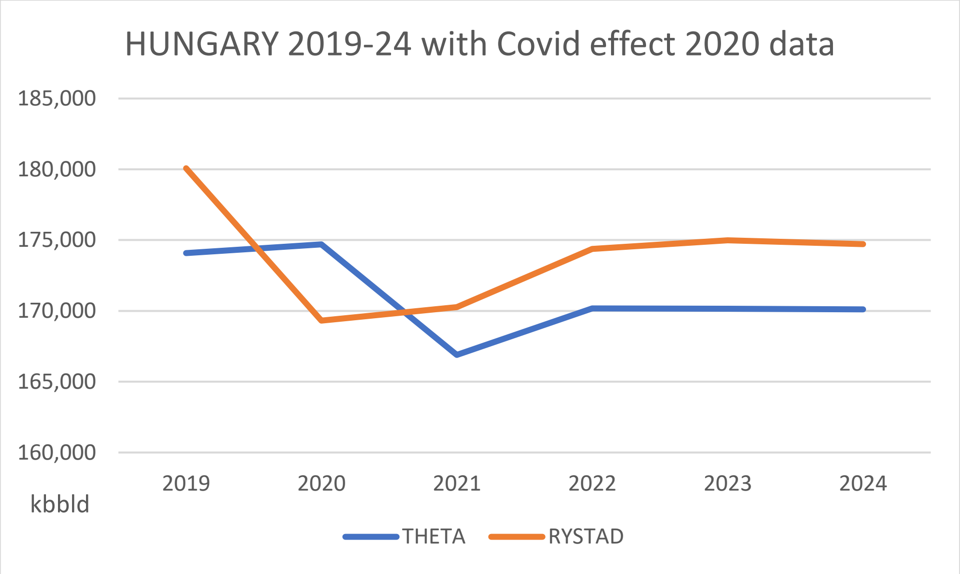
Theta	sMAPE vs Rystad
2019-2024	4,5389
2021-2024	4,3239
2022-2024	4,0908

Theta with Covid 2020	sMAPE vs Rystad
2019-2024	4,1319
2021-2024	3,7135
2022-2024	3,4703

7.1.2.7 HUNGARY



Plot 20 Hungary Oil demand Optimised Theta model vs Rystad forecast to 2024

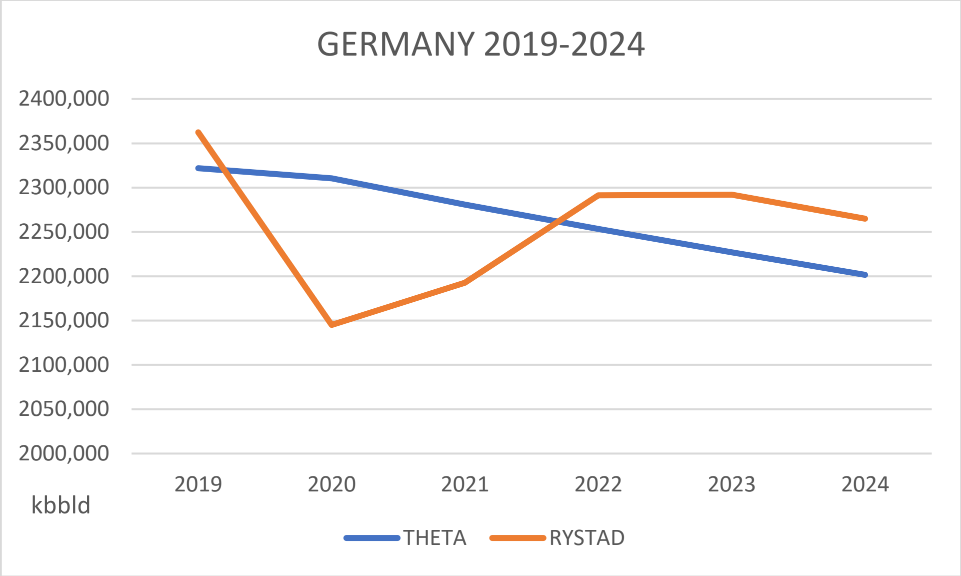


Plot 21 Hungary Oil demand Optimised Theta model vs Rystad forecast to 2024 with Covid effect 2020 data

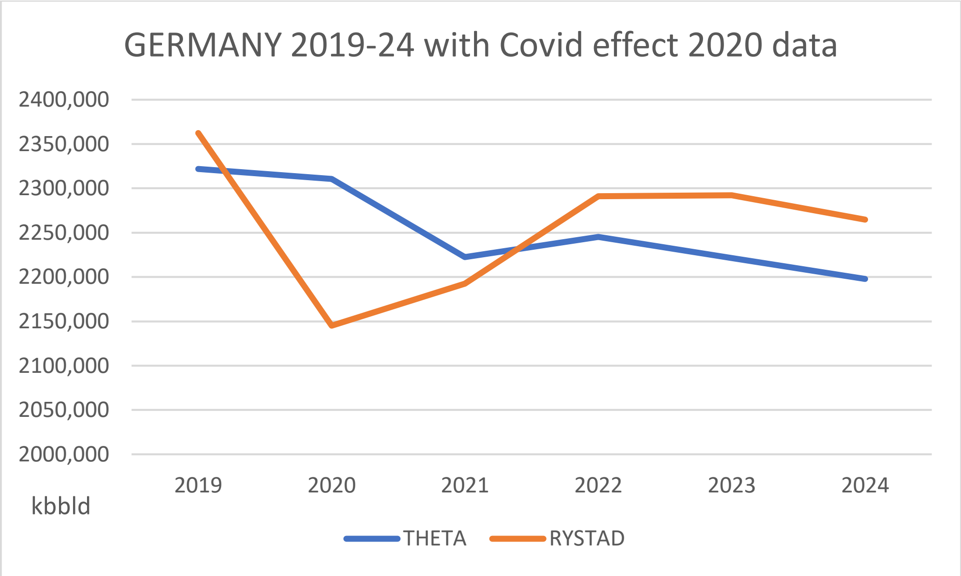
Theta	sMAPE vs Rystad
2019-2024	4,4013
2021-2024	4,9738
2022-2024	6,6207

Theta with Covid 2020	sMAPE vs Rystad
2019-2024	2,7371
2021-2024	2,4774
2022-2024	2,6343

7.1.2.8 GERMANY



Plot 22 Germany Oil demand Optimised Theta model vs Rystad forecast to 2024

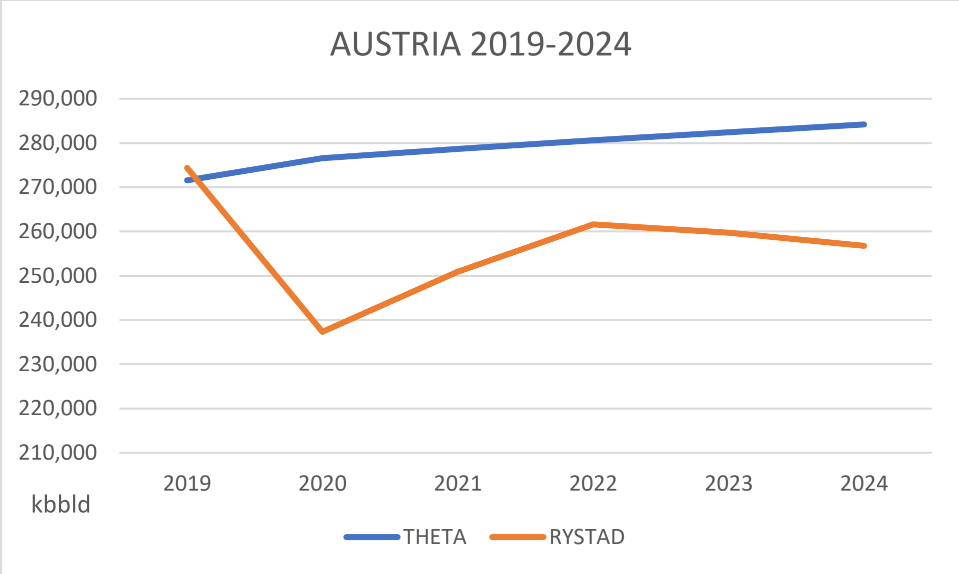


Plot 23 Germany Oil demand Optimised Theta model vs Rystad forecast to 2024 with Covid effect 2020 data

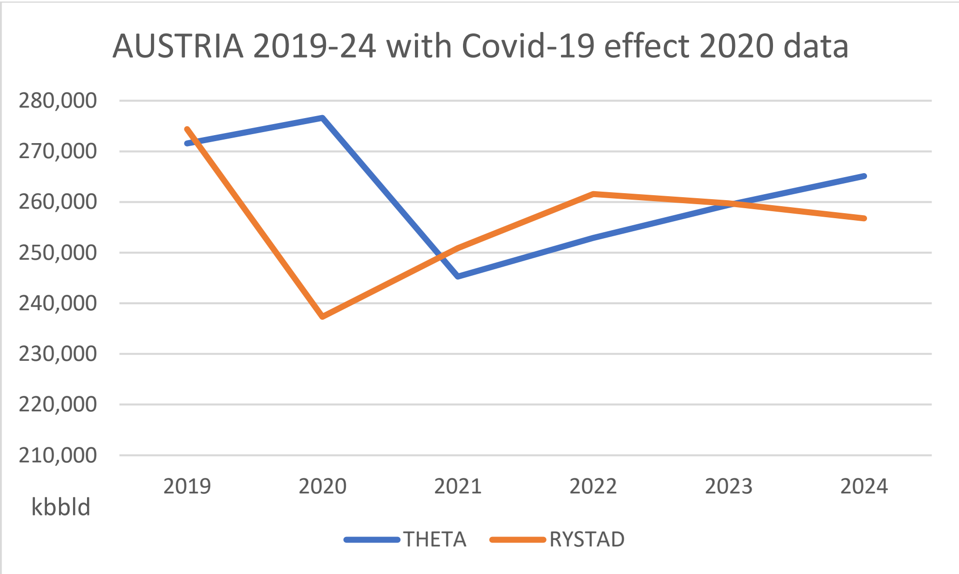
Theta	sMAPE vs Rystad
2019-2024	3,4163
2021-2024	2,8356
2022-2024	2,4651

Theta with Covid 2020	sMAPE vs Rystad
2019-2024	3,1136
2021-2024	2,3815
2022-2024	2,7267

7.1.2.9 AUSTRIA



Plot 24 Austria Oil demand Optimised Theta model vs Rystad forecast to 2024

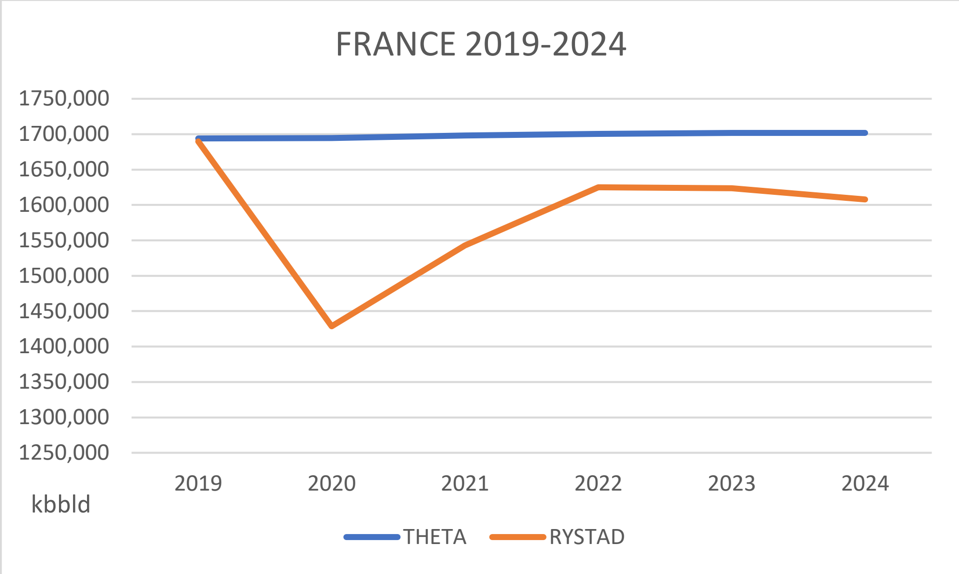


Plot 25 Austria Oil demand Optimised Theta model vs Rystad forecast to 2024 with Covid effect 2020 data

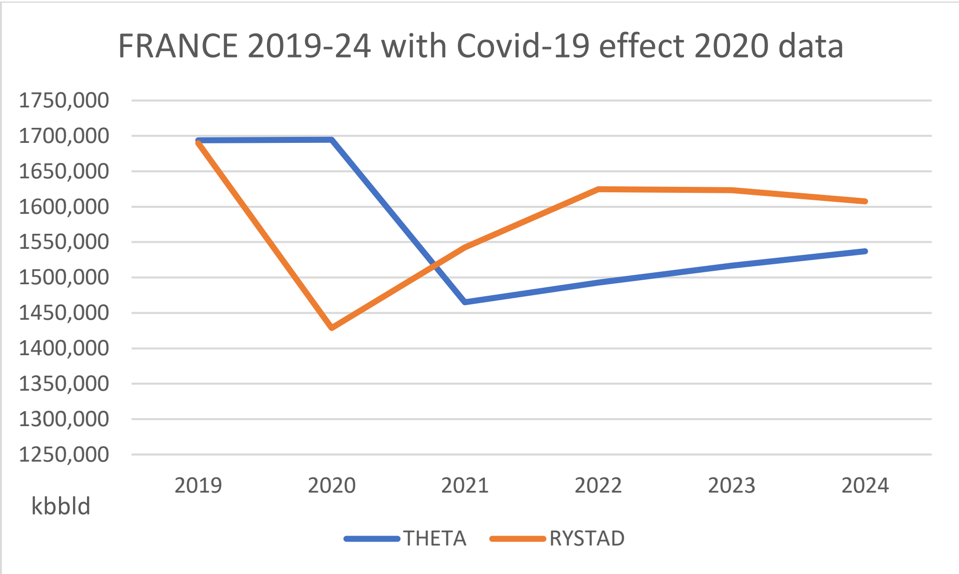
Theta	sMAPE vs Rystad
2019-2024	8,7202
2021-2024	9,0018
2022-2024	8,5061

Theta with Covid 2020	sMAPE vs Rystad
2019-2024	4,2099
2021-2024	2,2364
2022-2024	2,2289

7.1.2.10 FRANCE



Plot 26 France Oil demand Optimised Theta model vs Rystad forecast to 2024



Plot 27 France Oil demand Optimised Theta model vs Rystad forecast to 2024 with Covid effect 2020 data

Theta	sMAPE vs Rystad
2019-2024	6,9715
2021-2024	6,1368
2022-2024	4,9825

Theta with Covid 2020	sMAPE vs Rystad
2019-2024	7,0328
2021-2024	6,2288
2022-2024	6,5856

7.1.3 Results of all 10 Countries' Oil Demand vs Rystad (Covid Absence scenario)

Year	UNITED KINGDOM		GERMANY		NETHERLANDS		AUSTRIA		SWITZERLAND		FRANCE		SPAIN		ITALY		GREECE		HUNGARY	
	RYSTAD	THETA	RYSTAD	THETA	RYSTAD	THETA	RYSTAD	THETA	RYSTAD	THETA	RYSTAD	THETA	RYSTAD	THETA	RYSTAD	THETA	RYSTAD	THETA	RYSTAD	THETA
2019	1.568,32	1.592,26	2.362,38	2.321,90	881,54	931,88	274,39	271,57	227,93	223,15	1.689,78	1.694,00	1.336,65	1.348,04	1.205,18	1.259,29	312,62	303,21	180,08	174,09
2020	1.225,77	1.558,88	2.145,10	2.310,57	859,90	898,45	237,34	276,61	191,97	226,20	1.428,66	1.694,64	1.090,79	1.345,13	1.016,95	1.197,07	259,55	315,35	169,32	174,70
2021	1.354,89	1.549,12	2.192,58	2.280,87	853,42	897,39	250,88	278,66	203,78	225,79	1.542,64	1.698,20	1.213,33	1.361,43	1.095,16	1.186,67	295,32	317,63	170,28	170,22
2022	1.498,87	1.539,11	2.291,28	2.253,21	878,46	896,09	261,60	280,59	222,18	225,29	1.624,81	1.700,49	1.286,91	1.376,93	1.155,33	1.174,07	314,18	319,49	174,38	166,48
2023	1.492,19	1.528,91	2.292,17	2.226,94	854,28	894,52	259,73	282,43	223,59	224,73	1.623,46	1.701,65	1.282,47	1.391,72	1.143,41	1.159,56	314,54	320,96	174,98	163,34
2024	1.479,79	1.518,55	2.264,90	2.201,63	843,36	892,70	256,79	284,20	223,42	224,10	1.607,62	1.701,81	1.273,29	1.405,86	1.133,33	1.143,38	313,14	322,11	174,72	160,72
Year	sMAPE		sMAPE		sMAPE		sMAPE		sMAPE		sMAPE		sMAPE		sMAPE		sMAPE		sMAPE	
2019	1,5148		1,7284		5,5525		1,0323		2,1216		0,2495		0,8488		4,3911		3,0547		3,3822	
2020	23,9247		7,4272		4,3853		15,2818		16,3734		17,0322		20,8824		16,2712		19,4120		3,1303	
2021	13,3766		3,9471		5,0230		10,4888		10,2446		9,5998		11,5040		8,0205		7,2787		0,0334	
2022	2,6492		1,6754		1,9870		7,0068		1,3911		4,5518		6,7590		1,6087		1,6763		4,6349	
2023	2,4306		2,8866		4,6021		8,3770		0,5076		4,7031		8,1707		1,4023		2,0231		6,8776	
2024	2,5857		2,8333		5,6834		10,1345		0,3023		5,6926		9,8969		0,8821		2,8231		8,3495	**AVRG ALL**
AVRG 2019-24	7,7469		3,4163		4,5389		8,7202		5,1568		6,9715		9,6770		5,4293		6,0446		4,4013	6,2103
AVRG 2021-24	5,2605		2,8356		4,3239		9,0018		3,1114		6,1368		9,0826		2,9784		3,4503		4,9738	5,1155
AVRG 2022-24	2,5552		2,4651		4,0908		8,5061		0,7337		4,9825		8,2755		1,2977		2,1742		6,6207	4,1701

Table 6 All Oil demand Optimised Theta model vs Rystad forecast to 2024 with data till 2018, Covid absence

In this case, it is seen what our Optimised Theta Model would forecast until 2024 from data available until 2018. Compared to Rystad's data, as expected, the 2020 and 2021 forecasts have big errors, as the model could not have been aware of the pandemic that was about to hit. Nevertheless, the forecasts from 2022 to 2024 have satisfying sMAPE and are closer to the respective ones of Rystad. This means that when demand recovers to previous levels and regain the trend and dynamic it had, our model can perform well, and the forecasted values do not differ significantly from Rystad's.

This can be seen by the average sMAPE of 2022-24 forecasts from all countries, which falls below 5% to 4,1701%, when the respective one for 2021-24 period is 5,1155% and 2020-24 period even worse, 6,2103%, embedding the 2020 (Covid effects) forecast error along with the 2021 forecast error.

7.1.4 Results of all 10 Countries' Oil Demand vs Rystad (Covid 2020 real scenario)

Year	UNITED KINGDOM		GERMANY		NETHERLANDS		AUSTRIA		SWITZERLAND		FRANCE		SPAIN		ITALY		GREECE		HUNGARY	
	RYSTAD	THETA	RYSTAD	THETA	RYSTAD	THETA	RYSTAD	THETA	RYSTAD	THETA	RYSTAD	THETA	RYSTAD	THETA	RYSTAD	THETA	RYSTAD	THETA	RYSTAD	THETA
2019	1.568,32	1.592,26	2.362,38	2.321,90	881,54	931,88	274,39	271,57	227,93	223,15	1.689,78	1.694,00	1.336,65	1.348,04	1.205,18	1.259,29	312,62	303,21	180,08	174,09
2020	1.225,77	1.558,88	2.145,10	2.310,57	859,90	898,45	237,34	276,61	191,97	226,20	1.428,66	1.694,64	1.090,79	1.345,13	1.016,95	1.197,07	259,55	315,35	169,32	174,70
2021	1.354,89	1.292,82	2.192,58	2.222,29	853,42	892,20	250,88	245,28	203,78	202,18	1.542,64	1.465,07	1.213,33	1.130,18	1.095,16	1.033,30	295,32	263,24	170,28	166,89
2022	1.498,87	1.546,65	2.291,28	2.245,07	878,46	890,73	261,60	252,89	222,18	219,14	1.624,81	1.492,83	1.286,91	1.167,99	1.155,33	1.183,15	314,18	317,48	174,38	170,18
2023	1.492,19	1.534,73	2.292,17	2.221,38	854,28	888,99	259,73	259,44	223,59	218,98	1.623,46	1.516,67	1.282,47	1.202,93	1.143,41	1.167,48	314,54	319,19	174,98	170,15
2024	1.479,79	1.523,05	2.264,90	2.197,83	843,36	886,98	256,79	265,11	223,42	218,72	1.607,62	1.537,04	1.273,29	1.235,29	1.133,33	1.150,29	313,14	320,55	174,72	170,12
Year	sMAPE		sMAPE		sMAPE		sMAPE		sMAPE		sMAPE		sMAPE		sMAPE		sMAPE		sMAPE	
2019	1,5148		1,7284		5,5525		1,0323		2,1216		0,2495		0,8488		4,3911		3,0547		3,3822	
2020	23,9247		7,4272		4,3853		15,2818		16,3734		17,0322		20,8824		16,2712		19,4120		3,1303	
2021	4,6891		1,3458		4,4431		2,2590		0,7892		5,1584		7,0957		5,8121		11,4872		2,0068	
2022	3,1378		2,0375		1,3871		3,3856		1,3782		8,4668		9,6880		2,3792		1,0448		2,4326	
2023	2,8106		3,1367		3,9819		0,1110		2,0843		6,8014		6,4002		2,0833		1,4687		2,7983	
2024	2,8813		3,0060		5,0418		3,1900		2,1244		4,4886		3,0296		1,4852		2,3359		2,6721	**AVRG ALL**
AVRG 2019-24	6,4931		3,1136		4,1319		4,2099		4,1452		7,0328		7,9908		5,4037		6,4672		2,7371	5,1725
AVRG 2021-24	3,3797		2,3815		3,7135		2,2364		1,5940		6,2288		6,5534		2,9400		4,0841		2,4774	3,5589
AVRG 2022-24	2,9432		2,7267		3,4703		2,2289		1,8623		6,5856		6,3726		1,9826		1,6165		2,6343	3,2423

Table 7 All Oil demand Optimised Theta model vs Rystad forecast to 2024 with Covid effect 2020 data

Having taken into account the up-to-date 2020 data, where demand collapsed in most of the cases due to Covid, the model is witnessed to adapt to the dumping and reduction from 2021 forecast and predicting with greater accuracy the yearly oil demand till 2024. Compared to Rystad, the average sMAPE of all 2021-24 period average sMAPEs from all countries, is calculated at 3,5589%, giving us more than 30% improvement compared to the previous case (5,1155%).

If the period is narrowed and forecasts are examined for the 2022-2024 period when countries hope to have fully recovered from Covid effects or be very close to achieving it, it is spotted even better forecasting accuracy. Compared to Rystad, the average sMAPE of all 2022-24 period average sMAPEs from all countries, is calculated at 3,2423%, giving us more than 22% improvement compared to the previous case (4,1701%).

7.2 Gas Demand Time Series Forecasting

7.2.1 Introduction

Moving on with the Gas Demand Time Series, the Optimised Theta Model is applied for each country to forecast until 2024 as before. It is not available the equivalent data from Rystad as in the Oil Demand, so our forecasts will be presented and let the future show their accuracy.

7.2.2 Scenarios

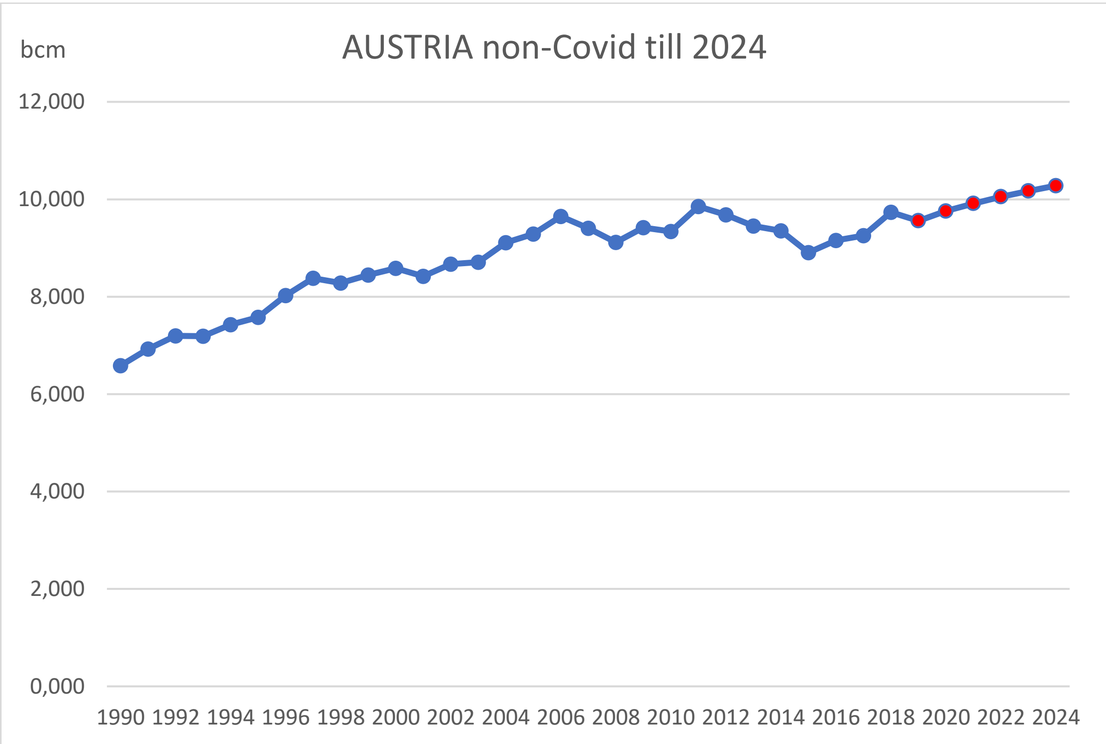
Three different scenarios are presented: the non-Covid scenario that would project our forecasts from 2019 to 2024 if they were performed in the end of 2018 with the respective data till then. The steady-Covid scenario that (as applied before in the Oil Demand Series) after taking into account the 2020 value and forecasting the 2021 value (correction of the time series with damping except few exception countries), it sets the 2021 forecast demand as data for 2021 to proceed with the Optimised Theta Model and so on until the 2024 annual demand value is forecasted. The recovery-Covid scenario, which sets the 2020 forecast demand (the one our Optimised Model generated before comparing it to the actual 2020 data) as data for 2021 to proceed with the Theta Method. This is a fast recovery scenario, as after the 2021 forecast, which reflects the effect of Coronavirus from the comparison with the 2020 actual data, it is assumed that our time series would proceed as it was forecasted before, meaning catching up the trend, level and dynamic it had before the 2020 Coronavirus correction.

7.2.3 Evaluation

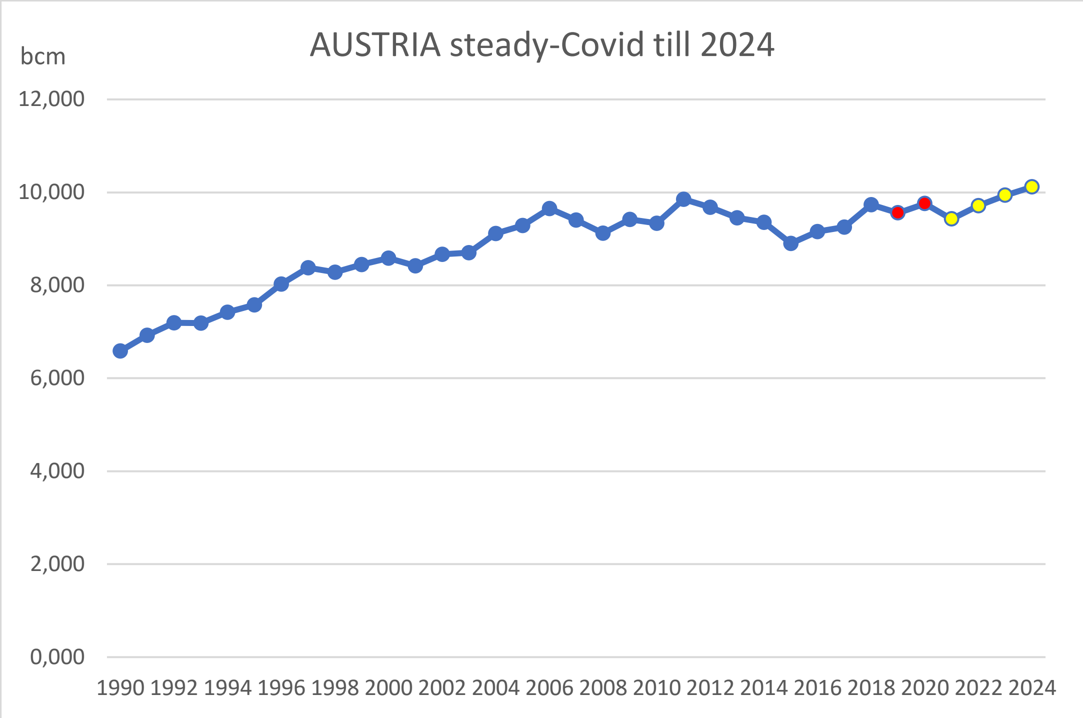
The actual forecasts to be compared and evaluated are the ones of the steady and fast recovery Covid scenario for 2022, 2023 and 2024, as they use data until 2020, they "correct" the 2021 forecasted value and apply the Optimised Theta Model that has been calculated for each country. The non-Covid scenario is the way our model would forecast the future, that as proven before in the Oil demand series through the comparison with Rystad's forecasts, could be also trusted as is for the 2022-24 period forecasts.

Below three countries are presented (Austria, United Kingdom, Italy) as example, showing the plot of our Optimised Theta Model from 1990 to 2024 for each one of our three different scenarios. The red dots represent the forecasts from 2019 to the future and the yellow dots the forecasts from 2021 to 2024 in the two actual Covid scenarios, where 2019 and 2020 data has been taken into consideration. Values in billion cubic meters.

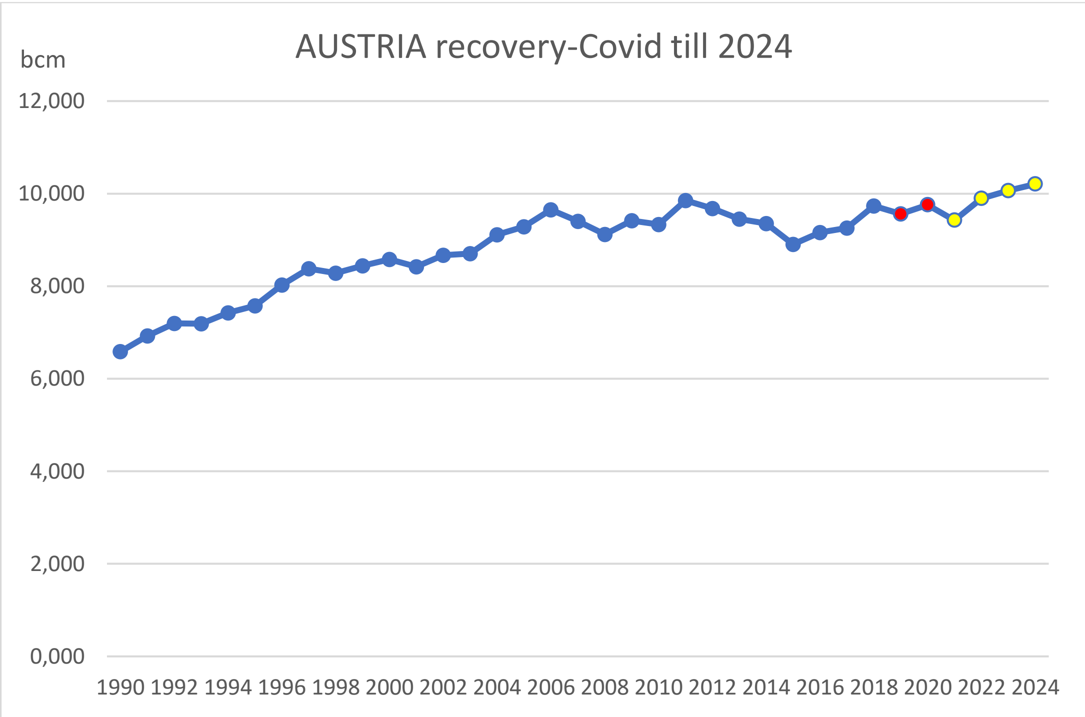
7.2.3.1 AUSTRIA



Plot 28 Austria Gas demand Optimised Theta Model forecast to 2024, hypothetical non-Covid scenario



Plot 29 Austria Gas demand Optimised Theta Model forecast to 2024, steady Covid scenario



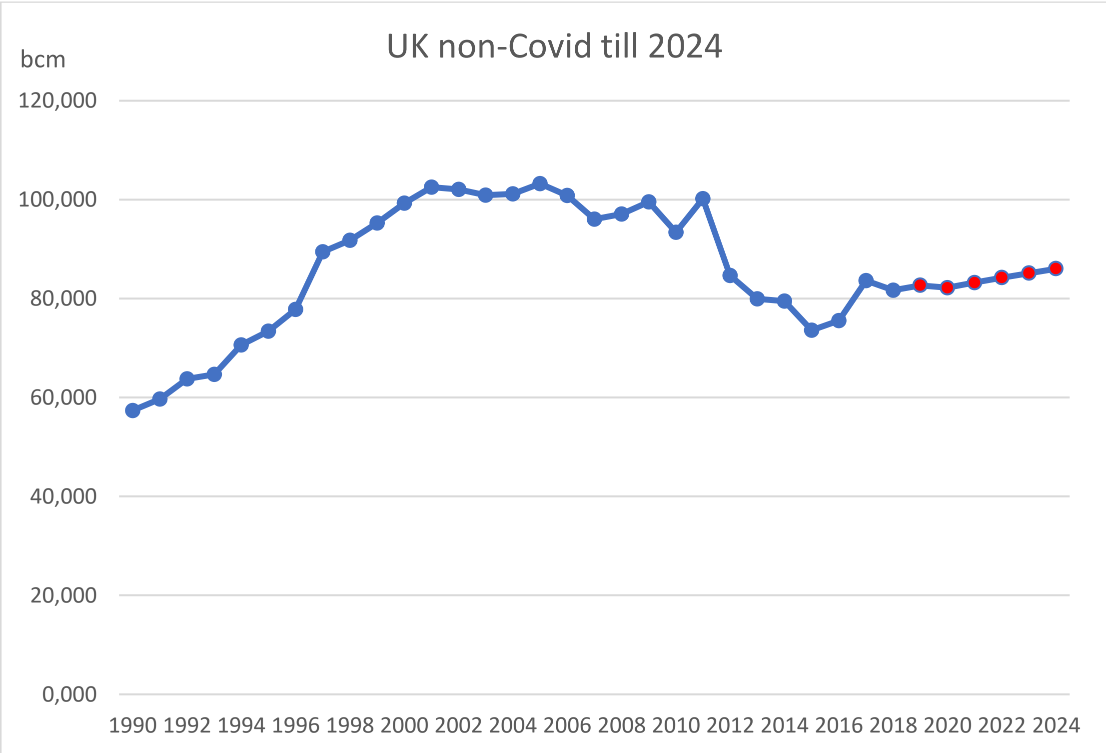
Plot 30 Austria Gas demand Optimised Theta Model forecast to 2024, recovery Covid scenario

AUSTRIA GAS DEMAND FORECAST TILL 2024 (bcm)			
	non-Covid	steady-Covid	recovery-Covid
2019	9,5592		
2020	9,7569		
2021	9,9144	9,4255	
2022	10,0497	9,7117	9,8962

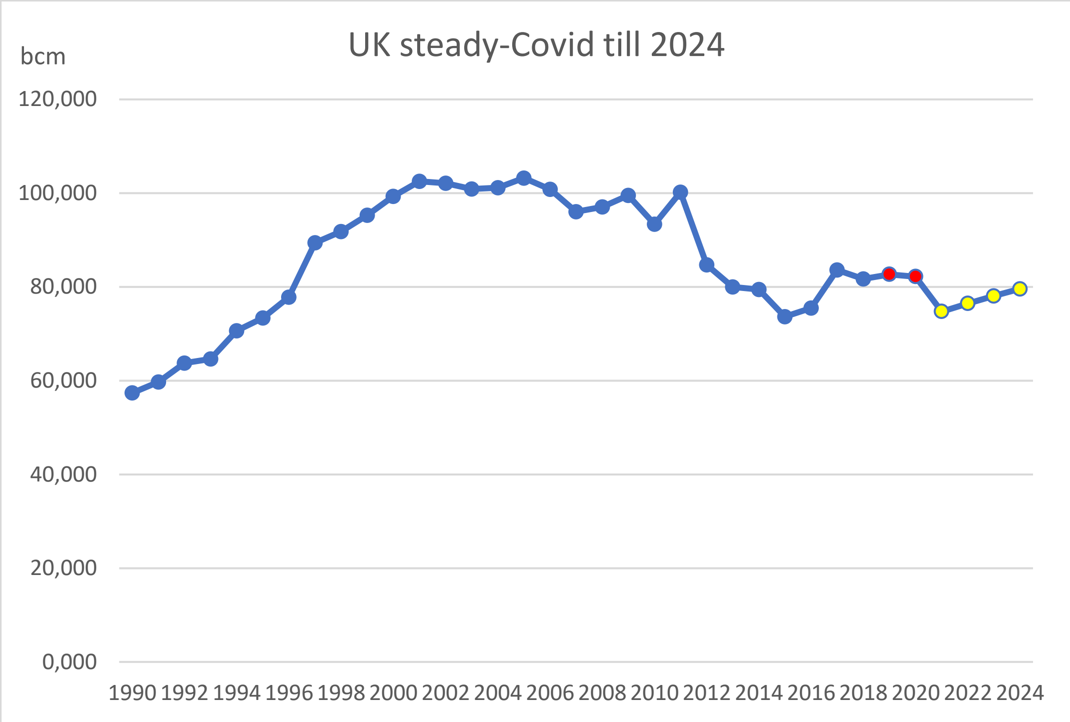
2023	10,1697	9,9360	10,0636
2024	10,2791	10,1175	10,2057

Table 8 Austria Gas demand Optimised Theta Model forecast to 2024, three scenarios

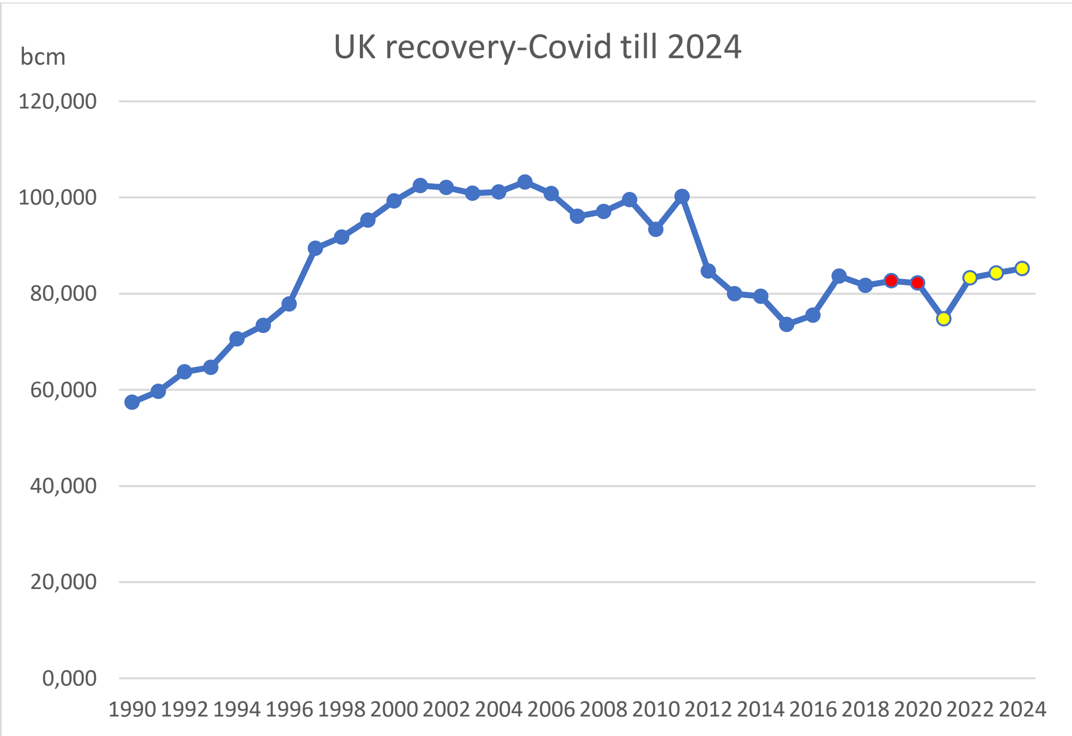
7.2.3.2 UNITED KINGDOM



Plot 31 UK Gas demand Optimised Theta Model forecast to 2024, hypothetical non-Covid scenario



Plot 32 UK Gas demand Optimised Theta Model forecast to 2024, steady Covid scenario



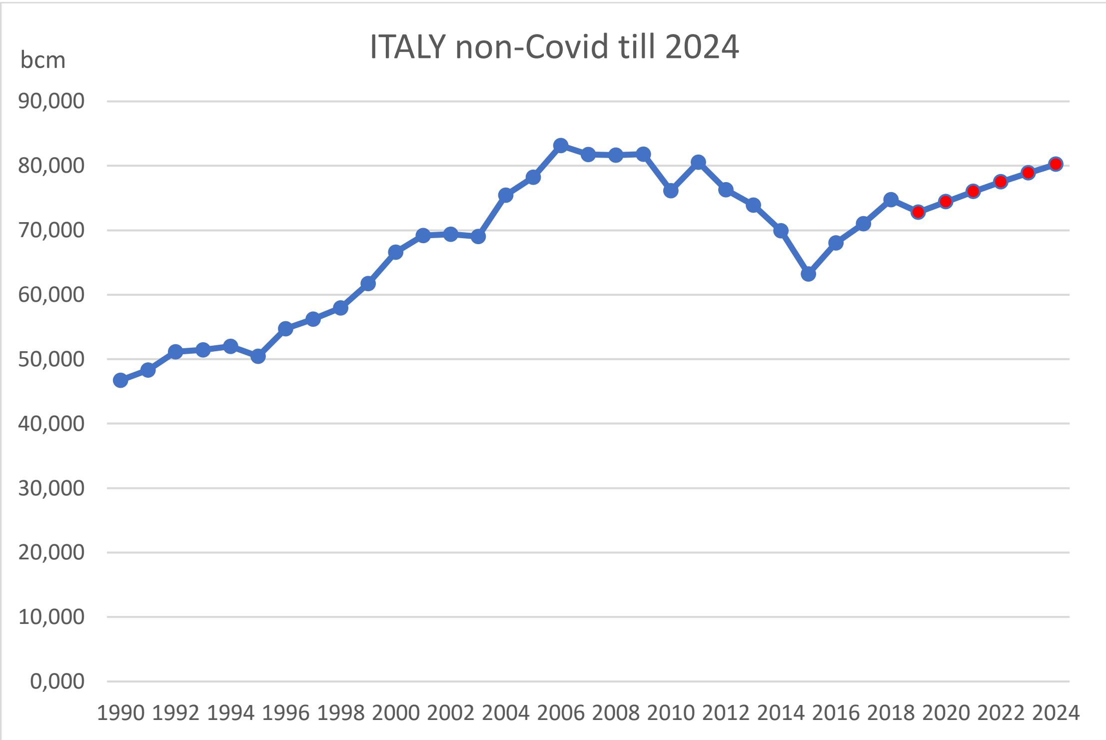
Plot 33 UK Gas demand Optimised Theta Model forecast to 2024, recovery Covid scenario

UK GAS DEMAND FORECAST TILL 2024 (bcm)			
	non-Covid	steady-Covid	recovery-Covid
2019	82,6754		

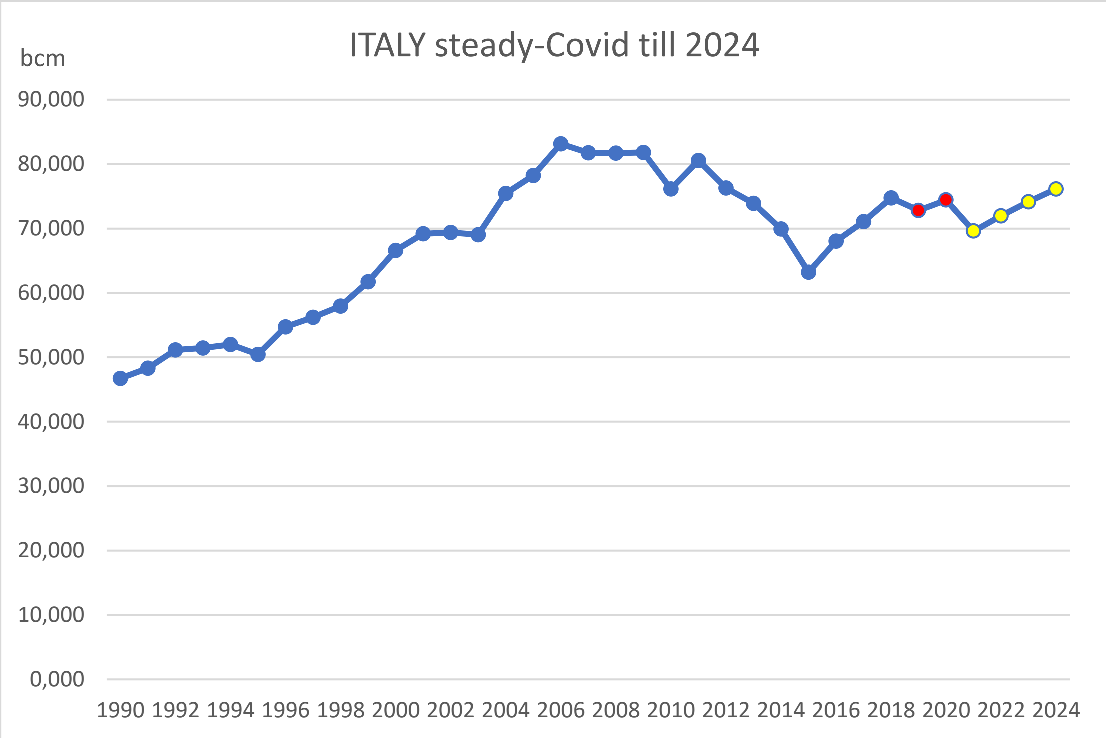
2020	82,1848		
2021	83,2323	74,7457	
2022	84,2187	76,4656	83,2618
2023	85,1493	78,0663	84,2751
2024	86,0290	79,5582	85,2303

Table 9 UK Gas demand Optimised Theta Model forecast to 2024, three scenarios

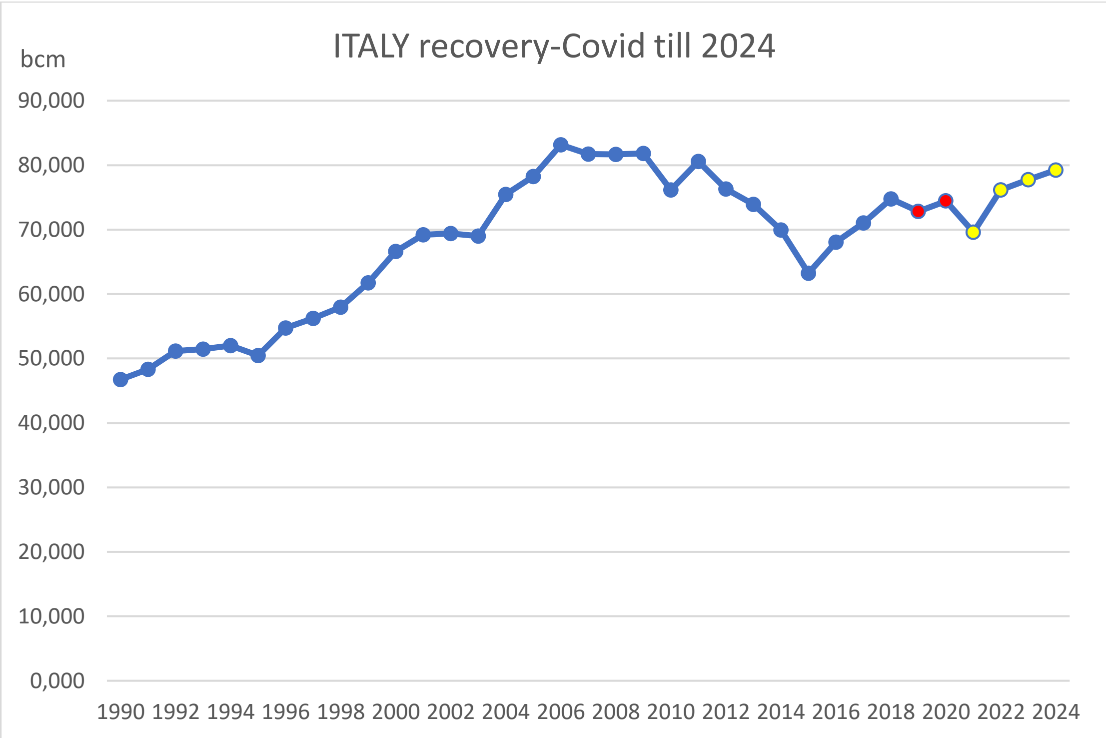
7.2.3.3 ITALY



Plot 34 Italy Gas demand Optimised Theta Model forecast to 2024, hypothetical non-Covid scenario



Plot 35 Italy Gas demand Optimised Theta Model forecast to 2024, steady Covid scenario



Plot 36 Italy Gas demand Optimised Theta Model forecast to 2024, recovery Covid scenario

ITALY GAS DEMAND FORECAST TILL 2024 (bcm)			
	non-Covid	steady-Covid	recovery-Covid
2019	72,8027		
2020	74,4250		
2021	76,0018	69,5906	

2022	77,4890	71,9596	76,1290
2023	78,8988	74,1300	77,7259
2024	80,2419	76,1291	79,2303

Table 10 Italy Gas demand Optimised Theta Model forecast to 2024, three scenarios

7.2.4 All Rest European Countries' Three Scenarios Forecasts to 2024

For the rest 21 European countries, below are presented our forecasted yearly Natural Gas demand values till 2024, in the same context of the three scenarios introduced. Time will show which of the two, between steady-Covid and fast recovery-Covid scenario will prove more accurate (as the non-Covid scenario is hypothetical).

Of course, a combination of these two is also possible. Their forecasts could be simply combined with 50% weight contribution for each, generating a new forecast that would stand in the middle between them as a "moderate recovery-Covid scenario" with its value being equal with the average of the other two.

The forecasts of Gas Demand till 2024 in billion cubic meters for the rest European countries can now be put together:

BELARUS GAS DEMAND FORECAST TILL 2024 (bcm)			
	non-Covid	steady-Covid	recovery-Covid
2019	19,3883		
2020	20,3026		
2021	20,3891	20,1742	
2022	20,5167	20,3656	20,4330
2023	20,6730	20,5668	20,6142
2024	20,8496	20,7749	20,8083

BELGIUM GAS DEMAND FORECAST TILL 2024 (bcm)			
	non-Covid	steady-Covid	recovery-Covid
2019	20,4006		
2020	20,5635		
2021	20,9802	19,7470	
2022	20,5167	20,355	21,0320
2023	20,6730	20,9115	21,4718
2024	20,8496	21,4238	21,8880

BULGARIA GAS DEMAND FORECAST TILL 2024 (bcm)			
	non-Covid	steady-Covid	recovery-Covid
2019	2,8954		
2020	2,6986		
2021	2,5665	2,9733	
2022	2,4405	2,7346	2,5360
2023	2,3190	2,5316	2,3880
2024	2,2007	2,3544	2,2506

CZECH GAS DEMAND FORECAST TILL 2024 (bcm)			
	non-Covid	steady-Covid	recovery-Covid
2019	8,2571		
2020	8,5550		
2021	8,5953	8,7291	
2022	8,6336	8,7505	8,6121
2023	8,6704	8,7724	8,6516
2024	8,7057	8,7947	8,6893

DENMARK GAS DEMAND FORECAST TILL 2024 (bcm)			
	non-Covid	steady-Covid	recovery-Covid
2019	3,5107		
2020	3,3651		
2021	3,4671	2,6756	
2022	3,5632	2,8926	3,4686
2023	3,6537	2,9739	3,5660
2024	3,7390	3,1090	3,6578

FRANCE GAS DEMAND FORECAST TILL 2024 (bcm)			
	non-Covid	steady-Covid	recovery-Covid
2019	45,4848		
2020	46,0551		
2021	47,0074	42,1461	
2022	47,8860	4,9816	46,4299
2023	48,7027	4,9528	47,4768
2024	49,4672	4,9205	48,4351

GERMANY GAS DEMAND FORECAST TILL 2024 (bcm)			
	non-Covid	steady-Covid	recovery-Covid
2019	90,7478		
2020	91,0743		
2021	91,8086	89,4988	
2022	92,5081	90,8083	91,9677
2023	93,1819	91,9311	92,7843
2024	93,8369	92,9165	93,5443

HUNGARY GAS DEMAND FORECAST TILL 2024 (bcm)			
	non-Covid	steady-Covid	recovery-Covid
2019	10,2814		
2020	10,3042		
2021	10,3880	10,7025	
2022	10,4540	10,7176	10,4349
2023	10,5050	10,7260	10,4891
2024	10,5436	10,7288	10,5302

LATVIA GAS DEMAND FORECAST TILL 2024 (bcm)			
	non-Covid	steady-Covid	recovery-Covid
2019	1,3609		
2020	1,2994		
2021	1,2321	1,0249	
2022	1,1713	1,0274	1,2180
2023	1,1149	1,0151	1,1474
2024	1,4374	0,9924	1,0843

IRELAND GAS DEMAND FORECAST TILL 2024 (bcm)			
	non-Covid	steady-Covid	recovery-Covid
2019	5,8425		
2020	5,5803		
2021	5,6741	5,2262	
2022	5,7693	5,3597	5,6835
2023	5,8658	5,4913	5,7874
2024	5,9635	5,6211	5,8919

Table 11 Gas demand of rest European countries Optimised Theta Model forecast to 2024, three scenarios (1)

SERVIA GAS DEMAND FORECAST TILL 2024 (bcm)			
	non-Covid	steady-Covid	recovery-Covid
2019	2,3493		
2020	2,2341		
2021	2,1324	2,5373	
2022	2,0562	2,3036	2,1183
2023	1,9954	2,1467	2,0334
2024	1,9441	2,0366	1,9674

SLOVENIA GAS DEMAND FORECAST TILL 2024 (bcm)			
	non-Covid	steady-Covid	recovery-Covid
2019	0,8997		
2020	0,9091		
2021	0,9204	0,9190	
2022	0,9299	0,9287	0,9204
2023	0,9379	0,9369	0,9299
2024	0,9446	0,9438	0,9378

[illegible] GAS DEMAND FORECAST TILL 2024 (bcm)			
	non-Covid	steady-Covid	recovery-Covid
2019	[illegible]		
2020	[illegible]		
2021	[illegible]	[illegible]	
2022	[illegible]	[illegible]	[illegible]
2023	[illegible]	[illegible]	[illegible]
2024	[illegible]	[illegible]	[illegible]

Table 12 Gas demand of rest European countries Optimised Theta Model forecast to 2024, three scenarios (2)

SWEDEN GAS DEMAND FORECAST TILL 2024 (bcm)			
	non-Covid	steady-Covid	recovery-Covid
2019	1,2536		
2020	[illegible]	1,2951	
2021	[illegible]	1,2486	
2022	1,3651	1,3018	1,3780
2023	1,3702	1,3373	1,3769
2024	1,3806	1,3635	1,3841

7.3 Limitations of Our Approach

Our research has certain limitations, that could be addressed or overcome in future research. The basic limitations of the above presented study and results are:

- Access could not be gained to all European countries' yearly data for oil and gas demand
- Forecast fit was tested upon several data but forecasting error was tested to one year ahead forecasting horizon
- For the evaluation of our long-term forecasts to 2024, 10 countries were compared with Rystad and not all 37
- Only simple and ready to use in Excel methods were tested as benchmark to beat
- In time series with non-linear trend, particularly exponential ones, Theta produces unreasonable forecasts
- Only one metric of forecasting error was evaluated (sMAPE)

7.4 Discussion

In the content of continuous decarbonization and covid-recovery planning, our model offers a ready to use excel tool that requires only data entry by the user and a hit of a button ("Solve") for Solver to give us a reliable forecast.

The following research questions were answered:

- Theta Model was optimised using only Excel and Solver

  ->Resulting in ready to use forecasting tool with simple data entry.

- All benchmark methods were outperformed

  ->Resulting in more than 30% improvement in point forecast accuracy across 37 oil&gas data sets.

- Forecasting horizon was expanded effectively

  ->Resulting in close to 3% sMAPE compared to Rystad's forecasts from 2021-24

Overall, it is recommend the use of our Optimised Theta Model for oil&gas country demand yearly data, except for time series of non-linear trends.

Although randomness is present in yearly oil&gas demand forecast and seasonality is absent, the Optimised Theta Model proposed can act as a general useful forecasting tool for predicting demand in this sector.

This is done via a simple excel spreadsheet with only requirement the data entry by the user.

In case of ignorance or no alternative, the safest thing is to take the most recent data available as next year's forecast.

CHAPTER 8_CONCLUSION-KEY FINDINGS-FUTURE WORK

It was witnessed the performance of the Optimised Theta Model for 37 European countries' oil and gas annual demand time series. Our model outperformed all other benchmark methods used in this thesis in forecasting accuracy, measured with sMAPE, by adapting to the specific parameters and characteristics of each country, extrapolating the trends in the future using simple math with no need for other complex calculations.

In terms of forecasting fit, it achieved 4,3388% in total (across all data-set from 1990 to 2018) average of all countries sMAPE, which is a 16,14% improvement over the second best performing, naive method with 5,1736%. In terms of point yearly forecast that evaluates the forecasting accuracy, it achieved 2,3653% in 2019 average of all countries sMAPE, which is a staggering 30,12% improvement over the second best performing, Exponential Triple Smoothing function of excel with 3,3850%.

In addition, our forecasts till 2024 generated from our model, compared to the respective ones of Rystad for the 10 countries there were data available in the Oil demand category, were very promising, with average sMAPE of 3,5589% for 2021 to 2024 period and 3,2423% for 2022 to 2024 period, with similar trends at the same time in most of the cases, compared to Rystad.

These, along with all other forecasts that were performed for the rest of the countries with three different COVID-19 related scenarios, would be very interesting to see in the future how they performed and which scenario will prove more accurate, compared with the actual data, when they will become known in the future (with four years patience).

As annual oil&gas demand and energy demand forecasting in general, are, and will continue to be very important for every country, especially in the content of continuous decarbonization and covid-recovery planning, our model offers a ready to use excel tool that requires only data entry by the user and a hit of a button ("Solve") for Solver to give us a reliable forecast.

Our analysis also came up with a surprising finding, as the naive method performed very good every time and if someone is asked to do a forecast in annual level and does not know how, the safest thing is to just take the data available from the previous year. Of course, this would not be the case if there is a bigger forecasting horizon, like it was done with our model to forecast till 2024, as the naive method will give the same 2019 forecasted value as the forecast for all next yearly demands, forming a straight line. Neither for quarterly or monthly forecasts, where seasonality is present and the naive method fails triumphally to capture it.

In fact, this bring us to the first future prospect for our model, as if there are the data available, our model can work for monthly or other forecasts with a simple addition in the initial calculations in Excel on the data, in order to deseasonalize them. The deseasonalization is performed using the classical multiplicative decomposition by moving averages [97], provided that a significant seasonal pattern has been identified at the (1−a) % confidence level [56]. It can then simply be performed the Theta Forecast calculated on the seasonally adjusted data in the same exact way and finally seasonality is added again to take the final results. Besides, over the years and upon the data sets tested, in this category, the Theta Method has proven to perform its best, whereas in our current thesis case (yearly data), Theta has presented its worst performance [92].

As future work, it would be also very insightful to apply our Optimised Theta Model to all of the rest European countries' oil and gas time series and see in this more complete, larger number of data sets how the accuracy of our Optimised Theta Model holds up.

It would be also feasible and valuable to compare the accuracy of our Model with more complex methods or the benchmarks of M3 or/and M4 Forecasting Competitions.

As a more advanced work, since the latest results of M4 competition prove the dominance and superiority of hybrid models, that combine statistical methods with Neural Networks, it could be examined the determination of the critical parameters (α, w, θ) coming from a black-box pure machine learning or/ and neural network forecasting engine.

In any case, it was possible to optimise (with the clever construction of the model in Excel and the help of Solver add-in) and test the well-established Theta Method in oil and gas annual demand data of European countries and witness its usefulness in this sector also.

The results were promising, and our Optimised Theta Model can be widely applied through the use of the excel file for annual oil and gas demand forecasting at national level and even for monthly or quarterly forecasts on deseasonalized data, instead of using simple conventional methods or ready to use functions of Excel.

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