Developing the S&OP process and its forecastability

Case: Product chain LPG

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Abstract

As a result of the rapidly changing environment, today's global and complex supply chains are constantly facing confrontations that challenge the efficient management of supply chains and the pre-eminent task of maximizing customer value. Better supply chain management can be achieved with support from the S&OP or Sales and Operations Planning process. S&OP is the process by which a company strives to balance supply and demand in order to execute profitable business.

The objective was to examine through the LPG product chain the case company S&OP process and its forecastability. The aim was to find and highlight development proposals to improve the S&OP process and short-term forecasts.

The research process was applied with a case study approach, utilizing both qualitative and quantitative methods. The research methods were a semi-structured interview, observation and time series analysis. The subjects of the semi-structured interview were selected from within the case company, which are representatives of the S&OP process and/or the production of the LPG chain. The field study of observation was targeted at the regular meetings of the S&OP process in the case company and process description documents. Based on the qualitative data collected, the time series analysis was implemented utilizing an alternative technique for SPSS. Time series analysis of the ARIMA model was executed with an open-source ecosystem.

The results presented an alternative method for implementing time series analysis for the commonly applied SPSS method, which may have an impact on how ARIMA models will be studied in the future. Based on the results, up-to-date and high-quality data, continuous improvement of the S&OP process, and the roles and responsibilities emerged as the most significant development findings. Based on the research results, suggestions for improving the S&OP process and its predictability were presented to the case company. In addition, further research and recommendations were presented to the case company.

Keywords/tags (subjects)

ARIMA, Forecasting, Python, S&OP Process, Time series analysis

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Tiivistelmä

Tämän päivän globaalit ja kompleksiset toimitusketjut kohtaavat nopeasti muuttuvan toimintaympäristön seurauksena jatkuvasti vastainkäymisiä, jotka haastavat toimitusketjujen sujuvaa hallintaa ja ensisijaista tavoitetta eli asiakkaiden arvonlisäyksen maksimointia. Toimitusketjun parempi hallinta voidaan saavuttaa S&OP -tai Sales and Operations Planning-prosessin tuella. S&OP on prosessi, jolla yritys pyrkii tasapainottamaan kysynnän ja tarjonnan kannattavan liiketoiminnan toteuttamiseksi.

Tutkimuksen tarkoituksena oli tutkia tapausorganisaation S&OP-prosessia ja sen ennustettavuutta nestekaasujen tuoteketjun kautta. Tavoitteena oli löytää ja tuoda esille kehitysehdotuksia S&OP-prosessin kehittämiseksi ja lyhyen aikavälin ennusteiden parantamiseksi.

Tutkimus toteutettiin tapaustutkimuksena, jossa hyödynnettiin niin laadullisia kuin määrällisiä menetelmiä. Tutkimusmenetelmät olivat puolistrukturoitu teemahaastattelu, havainnointi ja aikasarja-analyysi. Teemahaastattelun kohteet valittiin tapausorganisaation sisältä, jotka ovat keskeisiä S&OP prosessin ja/tai nestekaasuketjun tuotannon kanssa. Havainnoinnin kenttätutkimus kohdistettiin S&OP prosessin säännöllisiin kokouksiin kohdeorganisaatiossa, sekä prosessikuvauksen dokumentteihin. Kerättyjen laadullisten tietojen perusteella toteutettiin ARIMA-mallille aikasarja-analyysi avoimen lähdekoodin ekosysteemiin perustuvalla menetelmällä.

Tutkimuksen lopputuloksina esiteltiin vaihtoehtoinen tekniikka aikasarja-analyysin toteuttamiseksi yleisesti käytetylle SPSS-menetelmälle, millä voi olla vaikutusta miten jatkossa tutkitaan ARIMA-mallia. S&OP prosessin merkittävimmiksi kehittämiskohteiksi tulosten perusteella nousivat ajantasainen ja laadukas data, prosessin jatkuva parantaminen, sekä prosessin vastuut ja valtuudet. Tutkimustulosten perusteella esiteltiin parannusehdotuksia, joiden avulla S&OP prosessin toimintaa ja sen ennustettavuutta olisi mahdollista parantaa. Lopuksi esiteltiin jatkotutkimusehdotuksia kohdeorganisaatiolle.

Avainsanat (asiasanat)

ARIMA, Aikasarja-analyysi, ennustaminen, Python, S&OP prosessi

Muut tiedot (salassa pidettävät liitteet)

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Glossary

Term	Definition
AIC	The Akaike Information Criterion (AIC) is a measure used to compare how good different statistical models fits in the given set of data
AVEVA Unified supply chain	Planning tools for optimizing and steering operations
ARIMA	Stands for Auto Regressive Integrated Moving Average
CDU	Crude oil Distillation Unit
Coefficient of determination	Commonly utilized to describe how well a linear regression model fits the data.
Crude oil assay	Compilation of data on properties and composition of crude oils
Curve fitting	Curve fitting regression in time series analysis is used when data is in a non-linear relationship.
Data	Refers to digitally stored, machine-readable information consisting of signs and symbols, which can form, for example, documents and databases
Dependence	Refers to the association of two observations of the same variable at prior time periods.
Differencing	Differencing is used to make the series stationary and to control the autocorrelations. There may be some cases in time series analyses where we do not require differencing and over-differenced series can produce wrong estimates.
ERP	Enterprise Resources Planning. A software that enables an organization to manage business processes.
Forecastability	A measure of the degree to which something may be forecast with accuracy.
Hydrocarbon	Organic compound which consists of carbon and hydrogen. When burned, releases substantial amount of energy.
Information	Interpretable structured data that can be processed into information.
Knowledge	Information processed and interpreted by humans
LPG	Liquefied petroleum gas
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MSD	Mean Squared Deviation
MSE	Mean Squared Error
MRP	Material Requirements Planning
Naive method	The observed value of the previous period is used when forecasting the next period.

Nelson Complexity Index	The Nelson Complexity Index (NCI) is a measure of the sophistication of an oil refinery, where more complex refineries are able to produce lighter, more heavily refined and valuable products from a barrel of oil.
NIST	National Institute of Standards and Technology
NTP	Normal temperature and pressure NIST defines NTP conditions as follows: The pressure is 1 atm = 101,325 Pa, the temperature is 20 °C = 293.15 K.
OP	Oil Products
OP SCM	Oil Products Supply Chain Management
Predictability	Consistent repetition of a course of action, behavior, or something similar, making it possible to know in advance what to expect.
Residual	This is used to describe how well or poorly the selected model describes the observational data.
RMSE	Mean Absolute Percentage Error
RP	Renewable Products
SAP	ERP system
SC	Supply Chain
SCM	Supply Chain Management
sMAPE	Symmetric Mean Absolute Percentage Error
Specification	It may involve the testing of the linear or non-linear relationships of dependent variables by using time series models such as ARIMA models.
Stationarity	Denotes the mean value of the series that remains constant over the time period. If past effects accumulate and the values increase towards infinity then stationarity is not met.
S&OE	Sales and Operation Execution
S&OP	Sales and Operation Planning
Vapor pressure	The pressure of saturated steam, is the partial pressure of the steam at which the steam and liquid are in equilibrium.
Volatility	The standard deviation of the financial instrument's return over the given time horizon. Most commonly, the number is calculated from the standard deviation of daily returns and is expressed as a percentage per year.

1 Introduction

Digitization and digital transformation are comprehended as one of the greatest enablers in managing future supply chains. One of the key factors of digitization is information or data, and its proper harnessing for the company's use. The amount of data is increasing constantly, and finding, utilizing, and modifying the right data into a usable form is the core of digitization. The collected and applied data improves competitiveness of the company's, reduces uncertainties, and particularly facilitates decision-making within the company. Digital transformation is a larger entity that practically changes the way a company operates holistically – towards Supply Chain 4.0.

The entire value network is titled the supply chain, which consists of the customer's need all the way to the delivery of the commodity to the customer, including all functions and actors between these two points. Each function must additionally add value in the chain (Logistiikan maailma [The world of logistics], 2022b). Today's supply chains are extremely complex, and demands for low inventory, capacity and working capital challenge the reliability, flexibility, availability of the supply chain. (Logistiikan maailma [The world of logistics], 2022a.) The more complex the supply chain, the more vulnerable and prone to disruption it is. Disruptions often have the effect that the company is incapable of fulfilling, for example the promise of delivery time to the customer and customer satisfaction and return on value suffer.

Better management of the supply chain can be achieved with the support of the S&OP process. S&OP, or Sales and Operations Planning, is a process by which a company aims to balance supply and demand to execute profitable business. Hence, the S&OP process is the best forecasting tool to respond to customers' changing needs. (Logistiikan maailma [The world of logistics], 2022a.) Sheldon (2006, chapter 3) defines that a well-functioning S&OP process can even influence the customer's behavior. The COVID-19 pandemic is a significant example of what can occur to global supply chains and how different it can develop from the usual and safe – without overlooking the increasing speed of change. From a narrow-minded point of view, it is highly recommended to exchange to a more open-minded perspective no later than this stage – the time for transformation is now. (Dufva & Rowley, 2022.)

2 Neste Oyj

Neste was founded in 1948 and the purpose of the company was to secure Finland's oil supply. The first refinery was built in Naantali in 1957 and the second in Porvoo in 1965. The latter has been expanded various times and Porvoo refinery is one of the most complex refineries globally (Nelson's complexity index 12.1). Neste became Finland's largest company in the 1970s, which played a very significant role in balancing the Russian trade. In the mid-1990s, Neste was listed on the stock exchange and in 1997 Neste was merged with Imatran Voima to become Fortum Oyj. The merged electricity and oil company continued until 2005, when the operations were separated into independent companies and the oil business Neste Oil was listed on the Helsinki Stock Exchange. With the transformation in strategy, the Neste Oil name shifted back to Neste in 2015 to indicate the change towards renewables. The change in direction towards renewables started already in 1996, when Neste patented the NEXBTL refining technology, where for example animal and vegetable fats can be converted into molecules and used as a raw material instead of fossil raw materials in fuel production. In 2007, the production of renewable diesel started at the Porvoo refinery, and in order to increase the production capacity of renewables, Neste started new production plants in Rotterdam (Netherlands) and Singapore in 2010 and 2011. (Neste, n.d.a)

Neste's objectives have always been high in terms of human rights, sustainability and supply chains. Neste has therefore been selected almost 20 times on the Global 100 list of the most responsible companies in the world as well as the Dow Jones sustainability indices. (Neste, n.d.c.) Today, Neste is the world's leading producer of renewable diesel, sustainable aviation fuel (SAF) and renewable raw material solutions. The aim is to become a global leader in renewable and circular solutions. The growth rate in renewable products will accelerate even more when the Singapore refinery expansion is ready early 2023 and the joint venture with Marathon Petroleum in the United States starts. The Singapore expansion alone will increase renewable production capacity by 1.2 million tons. In the next few years, the capacity of renewables will continue to increase when Rotterdam expansion of nearly 2 billion investment is completed. (Lähteenmäki, 2022.)

The Porvoo refinery shown in Figure 1 has four different production lines and more than 40 production units and is one of the most versatile and efficient refineries in Europe. The refining capacity is around 206,000 barrels of crude oil per day and the total production capacity is around

12.5 million tons annually. The most important products are traffic fuels, base oils and marine fuels. The Porvoo refinery also has a harbour and a distribution terminal. Approximately 1100-1400 ships pass through Neste's harbour of Porvoo every year, and it is the largest harbour in Finland in terms of tons. (Neste, n.d.b.) In 2022, Neste launched an ambitious strategic study of transitioning the Porvoo refinery into Europe's most sustainable refinery by 2030 (Neste, 2022b). This denotes that existing fossil crude oil is exchanged for renewable and circulating materials.

Figure 1. Porvoo refinery in Kilpilahti (Neste, 2022b)

The following chapters will give a rough overview of the oil refining process in addition to various petroleum products and what their qualities are based on. From the point of view of the study, LPG will be reviewed in more detail as a separate chapter. This study does not cover the processing of renewable products or related processes. Chapter 2.2 establishes an overview of the process of the end-to-end supply chain for Neste oil products.

2.1 Refinery basis & products

In this study, oil refining is covered only at a rough level in this section. Oil refining is a petrochemical process in which crude oil is converted into a variety of valuable products. There are not many uses for crude oil as such and to add value in the process, the objective is to convert more valuable and economically viable derivatives such as gasoline, liquefied petroleum gas and lubricants – with minimal environmental impact. These different derivatives consist of hydrocarbon fractions of different lengths, which should be separated as efficiently as possible.

This can also be considered a fundamental principle of oil refining. Crude oil therefore consists mainly of various hydrocarbon fractions and impurities such as nitrogen, oxygen, sulfur and various metals. Obviously, a higher amount of impurities increases the challenges of refining and is thus a lowering factor in crude oil prices. The characteristics of crude oils vary from region to region, and therefore the planning of the crude oil slate is the prime issue to refineries. The profitability of refineries is directly based on their ability to maximize the yields of high value – added derivates. (da Silva, 2022, chapter 1.1, 2, 7.)

The operation of the refinery can be improved through the conversion process by increasing its complexity — by growing different process units to increase the quantity of derivatives and improve their quality. Although the investments are substantial and expensive, the increased yields and the improved quality of derivatives are often sufficient to increase the refining margin and thus offset the additional costs of investments. In order to ensure a benchmark basis for oil refineries, the Nelson Complexity Index has been created for this purpose. This can be utilized to compare the conversion capacity of refineries with distillation capacity or crude oil capacity. Different refining processes can be exploited to increase the yields of high value products such as diesel and petrol, for example. As previously mentioned in the study, the Nelson's complexity index in Neste's Porvoo refinery is 12.1, and according to Table 1, the refinery is one of the most complex refineries in the world. Table 1 displays the established complexity indices that are utilized to calculate the Nelson complexity index by means of the following equation

$$Nelson\ Complexity\ index = \sum_{i=1}^{N} Fi \times \frac{Ci}{CD} \tag{1}$$

where F_i = Complexity index of the process unit

C_i = Capacity of the process unit

CD = Capacity of the crude distillation unit

(da Silva 2022, chapter 7, 7.1.)

Table 1. Complexity Index for Crude Oil Refining Processes (da Silva, 2022, chapter 7, adapted)

Refining Process	Complexity Index
Atmospheric distillation	1
Vacuum distillation	2
Delayed coking	6
Catalytic cracking	6
Catalytic reforming	5
Hydrocracking	6
Alkylation	10
Aromatics/isomerization	15
Lubricating production	10
Oxygenates production	10

Figure 2 illustrates the crude oil distillation unit, or CDU, which defines the processing capacity of the entire refinery. The yields from the CDU determine and thus also limit the running of the following process units. Crude oil is fed from crude oil caverns by pumps and is first preheated between 120–160 ℃, where it is subjected to salting by water before feeding to the distillation unit. Desalting is a significant process to avoid corrosion problems. After desalting crude oil is further heated in the furnace near to 350–400 ℃ and fed to the lower part of the distillation unit and the feed is divided into steam and liquid phases. The liquid partition flows downward in the trays under the action of gravity, and the vaporized part towards the top of the tower. The temperature decreases in the distillation unit the higher the tower is advanced. When condensing, the steam gives off the amount of thermal energy required for vaporization, and the liquid draining from the upper bottom binds thermal energy when vaporized. At the same temperature, both steam and liquid appear, the power demand of which changes in opposite directions. Different hydrocarbon fractions are separated according to different boiling point cuts. The CDU is like a tall tower with several overlapping intermediate bases. Only gases and gasoline reach a vaporous state and are discharged from the upper parts of the column for further processing. Heavier hydrocarbons named middle distillates are withdrawn from the side-outputs. These include, for example, kerosene and diesel components. The heaviest hydrocarbons are withdrawn through the bottom of the unit to the next process. Bitumen, for example, is made from this base oil. In general, it can be said that the more volatile the product in question, the lower the distillation temperature and the higher the vapor pressure. By matching distillation profiles, the refinery can increase the desired product characteristics and thus improve its profitability, since all fractions are always produced to some extent. (da Silva, 2022, chapter 7.2.1; Kaiser, Klerk, Gary & Handwerk, 2019, chapter 22.2.1; Rautanen, 2015, 6, 7, 14.)

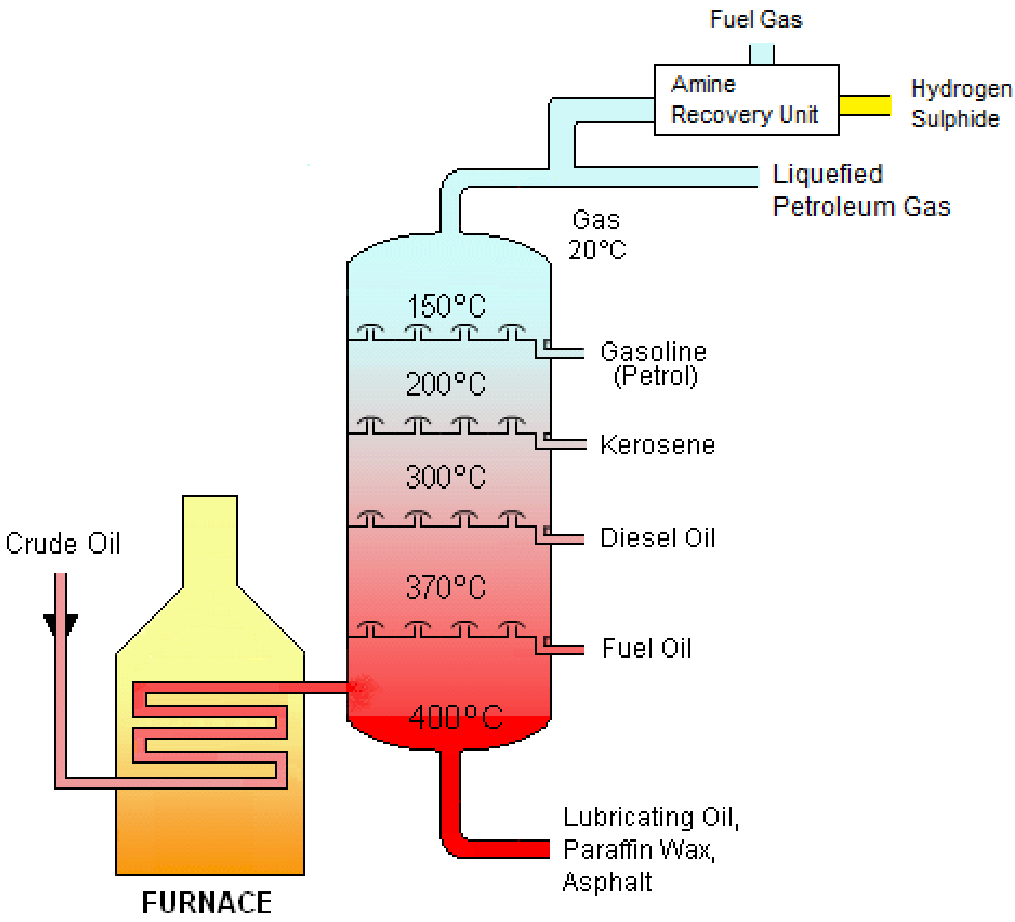


Figure 2. Fractional distillation in CDU (EnggCyclopedia, n.d.)

In oil refining, products can be divided, for example, on the basis of the widest fractions, into three product groups, and the fourth group comprises all the remaining products produced at the refinery. These three groups are light distillates, middle distillates, and heavy ends and the fourth group is often referred to as specialty products. The most profitable products are gasoline and light fuel oils, and refineries aim to maximize these fractions. The different products are divided by fractions in Table 2. In the table, when moving down, the density and volatility of products increases. (Kaiser et al., 2019, chapter 2.)

Table 2. Refined products and fractions (Kaiser et al., 2019, chapter 2.1, adapted)

Wide Fractions	**Narrow Fractions**	**Refined Products**
Petroleum gases	Natural gas	Methane
	Natural gas liquids	Ethane
		Propane
		Butanes
		Normal butane
		Isobutane
Light distillates	Naphthas	Light naphtha
		Heavy naphtha
	Gasolines	Motor gasoline
		Aviation gasoline
Middle distillates	Kerosenes	Jet fuel
		Kerosene-type jet fuel
		Naphtha-type jet fuel
		Gas turbine fuel
		Kerosene
	Light fuel oils	Diesel fuels
		Automotive diesel
		Marine diesel
		Light fuel oil (burner fuels)
		Home heating oil
		Industrial light fuel oil
Heavy ends	Heavy fuel oils	Residual fuel oil (burner fuels)
		Bunker (marine) fuel
		Heavy (industrial) fuel oil
	Specialty products	Base oil and lubricants
		Waxes
		Bitumen
		Asphalt
		Road oil
		Emulsion fuels
		Petroleum coke
		Carbon black

The price of crude oil is formed for the refining market by a wide variety of factors, including producers, processors, traders, OPEC and speculators. The market is also highly sensitive to various political and socio-economic actions, such as wars and natural disasters. Thus, they also play a major part in the price formation of crude oil. Given all the possible factors, it is clear that it is very difficult to reliably predict the price of crude oil. The same is true for processed products since their prices are mainly derived from crude oil prices. The price of crude oil depends on the transaction and the timing of the pricing. In spot pricing, the price of the raw material is the price of the moment in question, payment is made in cash and the cargo is delivered immediately. (Kaiser et al., 2019, chapter 4.1.) A forward contract, i.e. a derivative contract, commits parties to sell and buy at a predetermined price, for example, a cargo of crude oil. This can be used to protect against possible price changes, in addition, it is also possible to make a profit. In forwards, the terms of trade are always agreed between the parties. Futures are very much like forwards, but contract terms are standardized, and prices are constantly changing because futures trading is continuous. (Inderes, 2023.) The pairing of the price of crude oil is the refining margin. This indicates that if the margin is positive, there will be demand and the negative processing margin will denote a drop in demand.

The Nelson complexity index allows one to understand further refining margin formation – the more complex the process, the greater the margin, and the more traditional the refining method, the weaker the margin. The refining margin is influenced by many different factors such as

- total demand and supply of refined products, feedstocks and crude oil
- relative and absolute price of processed products (affecting realized sales prices and cash flow for that period)
- relative and absolute price changes in raw materials
- changes at refineries, for example in capacity and efficiency and operating costs
- availability of logistics services
- utilities such as electricity, steam and hydrogen
- emissions trading.

In addition to the above, the refinery's ability to maximize lower cost feedstocks while maximizing higher processing value product distribution has a key impact on refining margin. (Neste, n.d.e.)

2.1.1 Liquified petroleum gas

A mixture of gases containing propane, isobutane, n-butane and/or butene as main components are named liquefied petroleum gases i.e. LPG, which is gaseous under atmospheric conditions and normal pressure. However, they can be transformed into a liquefied state for transport and storage, thereby reducing their space requirement many times over. Liquefied petroleum gases are the lightest products in the oil refining process and can mainly be produced by processing natural gas or by distilling crude oil or from renewable raw materials. The Rotterdam refinery produces 40 tons of renewable propane per year from renewable raw materials such as sustainably produced vegetable oils and waste. Renewable propane can be used like fossil propane in all current applications and can also be mixed with each other (Neste, n.d.d; Neste Oyj, 2021, 8–12; Speight, 2019, chapter 3.)

Note that the properties of gases can vary significantly, as each gas is a by-product of the refining process. This is based on the fact that the properties of natural, manufactured and mixed gases can already vary significantly in themselves. Therefore it is not possible to determine on the basis of a single specification. Thus, the requirements for LPG are defined on the basis, for example, of the maximum sulphur content, the minimum heat content, or the performance of appliances, for example, burners. Table 3 compares the general properties of these different LPG's. One of the key characteristics of gases in terms of energy use is their calorific value. Effective calorific value refers to the lower calorific value, where combustion occurs under constant pressure and the resulting water vapor does not condense into water. As a product of combustion of liquefied gases, water and carbon dioxide are mainly formed. Therefore, due to their uniform and clean combustion results, LPGs are widely used in a variety of applications in a variety of industries, such as paper, chemical, metal, engineering, food and greenhouse farming. LPG is utilized, for example, in the following applications:

- fuel for forklifts
- greenhouse heating systems
- frying ovens and deep fryers in the food industry
- infrared dryers in paper industry
- different combustion processes
- defrosting processes
- flame cutting
- space heating

(Alakangas, Hurskainen, Laatikainen-Luntama & Korhonen , 2016, 186–187; Neste Oyj, 2021, 8–12; Speight, 2019, chapter 3.)

Table 3. General properties of liquefied petroleum gases (Alakangas et al., 2016, 186–188; International Labour Organization (ILO) & Finnish Institute of Occupational Health, 2023; Kaiser et al., 2019, table 2.3; Neste, 2019; Speight, 2019, table 3.2; table 9.8)

Hydrocarbon	Carbon Number	Density NTP (kg/m3)	Boiling Point atm (°C)	Melting Point (°C)	Lower Heating Value (kWh/m3)	Flash point (°C)	Vapour pressure at 20°C (kPa)	Auto-ignition temperature (°C)	Flammable limits (vol % at 25 °C)	
									Upper	Lower
Methane	1	0,72	−161,5	−183,0	10,0	−188	150	537	5,0	15,0
Ethane	2	1,35	−88,6	−183,0	16,9	−135	3850	472	3,0	12,4
Propane	3	2,01	−42,1	−189,7	28,8	−104	840	450	2,1	9,5
Normal butane	4	2,71	−0.5	−138,4		−60	210	365	1,8	8,4
Iso butane	4	0,25	−12,0	−160,0		−83	304	460	1,8	9,0
Natural gas		0,73	−162,0	−182,0	10,0	−188	150	600-650		

Liquefied gases form a combustible mixture with air and combustion is possible only in the accurate mixture ratio. For example, the vol% of propane is required to be between 2,1 and 9,5 in the entire mixture of gas/air in order for the mixture to ignite. Auto-ignition temperature refers to the temperature in a normal atmosphere at which the gas ignites on its own without an external source of ignition. The flash point is, again, the lowest possible temperature at which a volatile liquid can vaporize to form a flammable mixture in the air. There are several international standards for defining a flash point, but most advocate that when the flash point is below 43°C refers to inflammable liquids and above temperature are combustible. Due to the characteristics, LPG is subject to very specific legislation and regulations have laid down very detailed provisions for the treatment, storage and use of LPG. (Neste Oyj, 2021; Speight, 2019, chapter 5.5.)

Sales of Liquefied Petroleum Gases (LPG) in Finland are strictly regulated as well, and Statistics Finland (Tilastokeskus) produces comprehensive statistics on the sales of petroleum products — including liquefied petroleum gases. Figure 3 establishes domestic LPG sales in recent years. Sales are quite steady, there are no major fluctuations excluding August 2022, which is completely exceptional compared to other months. The decline in Russian natural gas could be one of the reasons for this increase, as companies have been forced to look for replacement in energy sources to replace it.

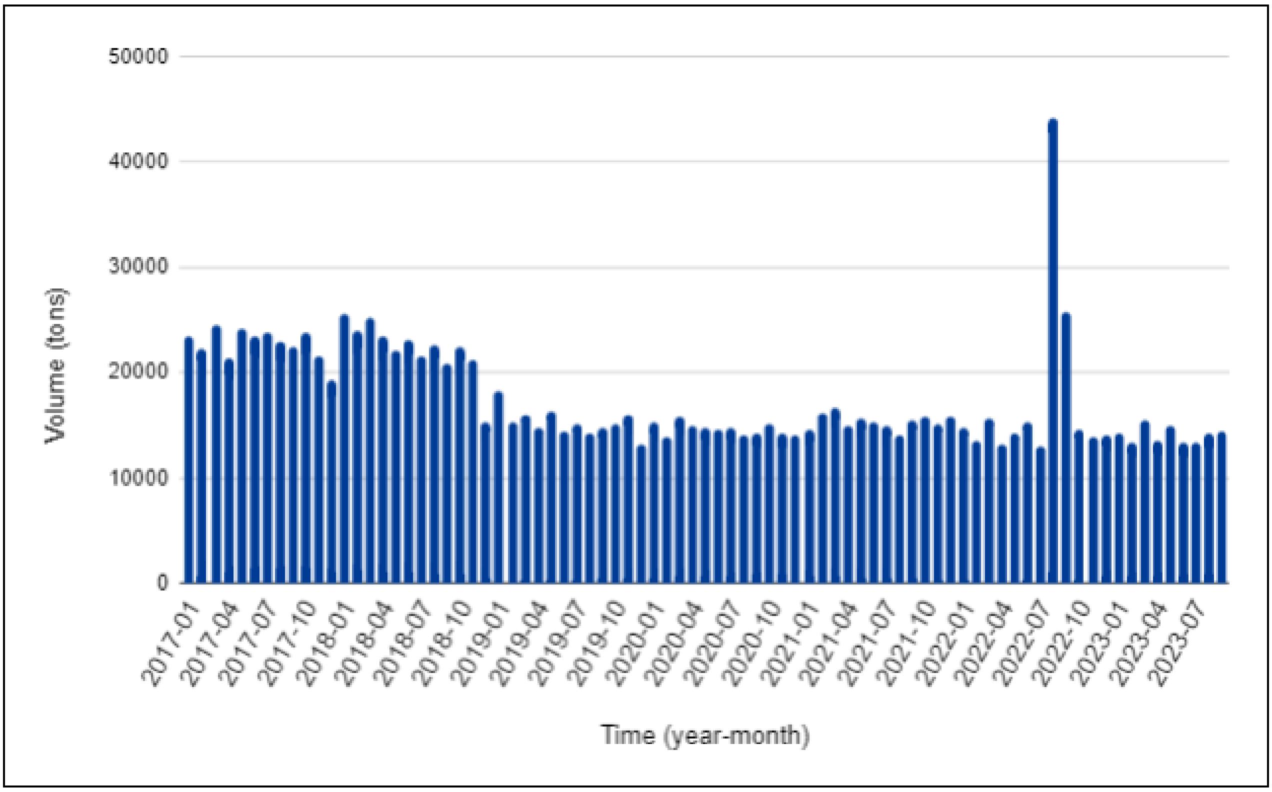


Figure 3. Domestic sales of LPG products in years 2017–2023 (Tilastokeskus, 2024, adapted)

2.2 Neste Oil Products End-to-end Supply Chain

In Neste, Oil Products Supply Chain Management (OP SCM) business unit optimizes, plans and steers long-, medium- and short-term business decisions and operations to ensure maximal profitability and customer delivery performance. The main responsibility of the OP SCM is to deliver the best optimal way to operate and execute the most optimal plan. To ensure this, the potential of the entire supply chain is required to be utilized, and processes and tools constantly improved. (Neste End-to-End Optimization, 2024.)

Neste started utilizing the AVEVA Unified Supply Chain tools in 2010 to optimize and schedule the Neste end-to-end supply chain. Currently the tools are utilized for example, in S&OP planning and strategic optimization and the daily operations of the refineries and logistics. With the planning tools, unified data sources can be utilized, and with flexible data integration mechanisms, data can be transferred to external business systems and between different business processes, for example. (AVEVA, 2022, 2–3; Falck, 2022.)

3 Research objectives

The challenges of supply chains have increased significantly over the past few years, especially because of the COVID-19 pandemic and the war in Ukraine. These two weak signals have become significant, and as the complexity of supply chains continues to grow, it is necessary to challenge both the development of operations and the changing of thinking models. According to the definition of futurist Elina Hiltunen, a weak signal indicates the first symptom of certain change that may be significant in the future (Dufva & Rowley, 2022). In addition, forecasting, complex and fast supply chains today require faster decision-making, responding to constantly changing conditions as promptly as possible, and maintaining a flexible end-to-end supply chain. With an efficient S&OP process, companies are able to advance their own strategy. In addition, value generation in the supply chain may increase.

There is significantly more research literature on supply chain development and development of the S&OP process at the general level, than there is on developing the forecastability in the S&OP process. The objective of the study is to examine through the LPG product chain the Neste OP SCM S&OP process and the forecastability there, and to find development proposals to improve the short-term S&OP process and forecasts. The S&OP plan is regularly updated once or twice a month, which is rarely enough at present considering the ever-changing circumstances of the whole end-to-end supply chain. Today, it is possible that forecasts should be updated weekly, even in cycles of a few days – depending on the requirements. In addition, finding the correct data and information, converting it into a functional format today, requires plenty of automation, configuration and knowledge of the company's information and data systems. On the other hand, various AI technologies can be increasingly utilized to respond to the accelerating and changing environment.

3.1 Research questions

Considerable time should be consumed on the theories and interpretations related to the perspective and the research topic, as well as on previous studies, so that the research has a better chance of success. In the study process, the research objectives, research problems and research questions are frequently defined first. Based on them, the entire purpose of scientific research is created. Kananen (2013) clearly points out that without a defined problem it is not a scientific thesis. The research questions determine how the empirical literature is selected, which approach is utilized, and which research methods are applied to solve the research problem. In addition to research questions, the size and nature of the research data samples also affects the selection of research methods. The suitability and selection of each method for research must be justified. (Kananen, 2013, 129–131; Tähtinen, Laakkonen & Broberg, 2020, 18–20.)

The aim of this study is to find answers to the following questions:

1. Does the S&OP process have to be developed and the forecastability there? If yes, how?
2. What causes the forecast errors in product chain LPG?
3. Is it possible to define relevant variables to improve forecasts in product chain LPG?

3.2 Research limitations

After the objectives and questions for the research are defined, study limitations should be addressed as well. In the S&OP process, forecasts are frequently produced at the strategic long-term and short-term planning level. The objective of the study is to examine through the LPG product chain the Neste OP SCM S&OP process and the forecastability there, and to find development proposals to improve the short-term S&OP process and forecasts. The time frame in the short-term planning level is usually less than three months. It is justified to limit the study to a certain part of the S&OP process, because the whole process is broad, and it is not possible to describe everything regarding one topic. In addition, limiting the study to a certain area of the process supports the researcher to create a reasonable ensemble from the implementation of the study (Kallinen & Kinnunen, 2021). In addition, the study was limited to a single product chain – Liquified petroleum gas. The scope of the thesis is not sufficient to manage the whole operation of the refinery, because it is an extremely complex and large entity. These research limitations have been defined together with the client. Furthermore, to ensure that development measures and solutions that may occur in this study can be utilized as rapidly as possible and thus support the company’s decision-making.

4 An overview to research methods

Development work is constantly required in order for companies to remain competitive. In order to be successful, companies require continuous development work in the following areas, for example

- to increase growth and/or improve profitability
- to keep up with developments
- for the development of new products and services
- to improve customer service
- to intensify performance
- to develop processes
- to develop the organizational structure
- for the well-being and motivation of employees
- change management and adaptation to changing conditions.

(Ojasalo, Moilanen & Ritalahti, 2018, 12–13.)

Development activities are performed in practically every position of the company and offers several opportunities for the comprehensive development of the company including for example the creation and implementation of new products, operating methods and processes. The variety of different industries and products today is huge, and therefore numerous different research methods have also been developed, and their correct use, i.e. methodological expertise, is key to high-quality development work. Ojasalo et al. (2018, 11) emphasize that methodological competence is more than the management of data methods and the ability to create, for example, a good survey for research. Methodological knowledge begins already with the identification of the research object and the existing knowledge of the research topic, which is a prerequisite for delimiting the topic and creating a conceptual framework. Not to mention a wide range of information acquisition skills and the ability to distinguish relevant information from a research perspective. Both innovative and systematic skills are needed, as well as the ability to produce proposed solutions and finally to work the results into the presented format. Development work offers a great opportunity to learn both new information and various skills needed in working life, such as problem solving, cooperation and interaction skills. In the best situation, it is possible to find development targets independently and collaboratively create solutions for them and evaluate the activities of others throughout the development process. Condensed in development work, it is possible to learn how to perform various projects in a determined and planned manner. Research is strongly associated with development work, which is characterized by the systematic, critical and analytical progress of research. Hence, research results are easier to justify and get rid of incorrect beliefs based on everyday thinking that may not have been evaluated critically enough. Thus, it may have been erroneously assumed that the company's services are in order and there are no requests for development needs. (Ojasalo et al., 2018, 11–21.)

Holopainen and Pulkkinen (2015, 18) explain that research is a systematic action that provides more information about the research object, and Kananen (2013, 22) specifies that research information is essential for decision-making. In addition to the previous ones, Nummenmaa, (2021,34) defines the aim of the research as making conclusions about the regularity of phenomena. Scientific research is often divided into empirical and theoretical research. Theoretical research can be done without observations and experiences or measuring devices. (Nummenmaa, 2021, 35.) Empirical research is defined as based on observations and experiences, and empirical material includes, for example: interviews, texts, pictures and observation diaries (Kallinen & Kinnunen, 2021). When writing a study, researcher should consider that the reader of the research is unable to identify the researcher's level of substance knowledge, therefore the entire suitability of all methods, analyzes and the selection of research approach must be justified (Kananen, 2013, 131).

The selection of approach is related to the objective of the research, in other words, to obtain a solution to the presented research problem. Developing an issue or creating a change can also be a research problem. Kananen (2013) perceives an approach or a research extract as a specific type of philosophical umbrella, under which the methods of analysis, data collection and interpretation that are characteristic of each research extract are included. The research methods are connected one after the other by forming a chain, the first part of which defines the tools and methods to be applied. Research methods are traditionally divided into qualitative and quantitative research based on their specific characteristics. Table 4 examines the differences and special characteristics of the quantitative and qualitative research extracts. In quantitative research, theory is applied to explain the phenomenon, in contrast with qualitative research, which pursues discovering a theory for the phenomenon. (Kananen, 2013, 22, 25.) In research, theory can therefore be used in two ways – by creating or testing it. Induction refers from practice to theory, i.e. theories are developed, or generalizations are made through individual cases. Deduction, on the other hand, aims to draw conclusions about cases based on theory. (Kananen, 2013, 49–50.)

Table 4. Comparison of quantitative and qualitative research approaches (Dahlberg & McCaig, 2010, Table 2.1; Kananen, 2013, 24; Mack, Woodsong, MacQueen, Guest & Namey, 2005, 3, adapted)

Factor	Research approaches	
	Quantitative research	Qualitative research
Theory development	Deductive	Inductive
Purpose of the reseach	Generalizing, predicting, explaining the phenomenon	Understanding the phenomena
Examples of methods	Surveys, observations, questionnaires, analysis of content	Observations, diaries, interviews, analysis of content, focus group
Research questions	Structured	Open-minded
Researcher role	An outside observer	External participant
Analytical perception	Measuring the variation	Describing the variation, relationship, individual experiences
Conclusions/ explanation	Numerical, quantitatives	Descriptive, textual

According to Mack et al. (2005), the main differences between research approaches are established in their flexibility. In quantitative research questionnaires are often applied as a research method, in which participants are questioned the identical questions in the similar order. Thus, the answer categories are closed and not open, for example. In qualitative research, interview is used as a method in which it is possible to obtain a comprehensive knowledge and understanding of the phenomenon. (Mack et al., 2005, 3.) Often, the researcher brings out in research that the research approaches are opposites of each other. Dahlberg and McCaig (2010, chapter 2) disagree on the topic and Kananen (2013, 22) likewise share their view that approaches are rather different continuums. Thus, it can be thought that both methods are complementary to each other in research, where approaches that are most useful in different parts of research can be utilized. Nevertheless, there are methods suitable for both qualitative and quantitative research, such as content analysis and observation. In practice, most studies have both qualitative and quantitative elements. (Dahlberg & McCaig, 2010, chapter 2.) In order to provide in-depth and diverse knowledge regarding the operation of the S&OP process for example, it is recommended to utilize qualitative research methods. On the other hand, for studying the variables of demand forecast, for example, historical data is crucial, applying the use of quantitative research methods is preferable.

Researching a particular phenomenon, it is highly justified to apply both qualitative and quantitative methods. On the other hand, Case study, development research and action research are perceived more as research strategies rather than as methodologies since they do not have their own methodology. The methodology thus includes all the methods and tools by which knowledge is acquired, formed and justified in research. The aforementioned view is further supported by the fact that these research strategies utilize both qualitative and quantitative research methods as illustrated by Figure 4.

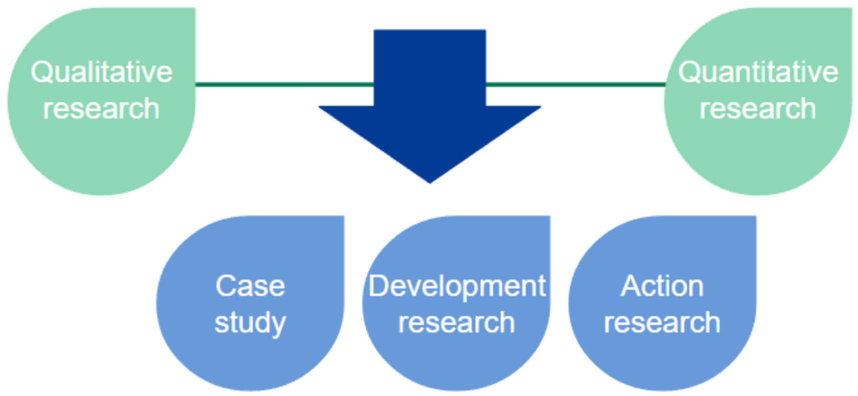


Figure 4. Example of the description of research approaches and the insertion of multiple-excerpt methods between them (Kananen, 2013, 22, adapted)

Action research typically actively involves company personnel in development work and often methods are those that allow active participation of employees and usage of common interaction in research (Ojasalo et al., 2018, 37). Hence, methods of analysis and data collection of other extracts are not excluded in action research and therefore, in the context of action research, a strategy for obtaining information about the phenomenon and selecting an approach to the study of the phenomenon is often discussed. The most essential issue in action research is to produce a change. The role of the researcher in development research is inclusive in the implementation of change, whereas in development research the researcher is not involved in the transformation process. According to Kananen (2013), the differences between development research and action research can be described therefore that in development research the object of change is products or technical processes. The action research focuses on the development of operations and processes involving employees. (Kananen, 2013, 28–29.)

Indicating to the definition of Case study, research is based on the present, research is not implemented from a past phenomenon. In order to provide a deep understanding of the phenomenon, it is needed to build a knowledge base on past events, or written documentaries on the subject. (Kananen, 2013, 54–58.) Primary data, i.e., empirical data, is direct information about the research object and is collected by the researcher themself. The material collected by others is secondary data. Materials collected by others must be linked to one's own research, thus applying them directly as such is not appropriate. All secondary data should be approached critically, and the reliability of the material should be carefully evaluated. The finished materials often require editing in order to be comparable. The best practice for secondary data is, for example, explaining an issue or describing a phenomenon. (Hirsjärvi et al., 2009, 186–189.)

In case study, several sources of information are applied, and research is comprehended on the phenomenon in its inherent environment. In case study, research questions are formed to answer questions such as why and how. Case studies include several different subspecies and can be classified on the basis of distinct characteristics, for example, an instrumental case study that pursues to create generalizations to other studies in question or intrinsic case study focusing on one case in-depth. Case study varies from qualitative research slightly. In qualitative research the answer to the research problem is discovered through a single qualitative method, while case study utilizes multiple methods to benefit. Case study is a highly demanding research strategy that requires the thesis author to have extensive knowledge of methodology, data collection and analysis methods. (Kananen, 2013, 54–58.)

Case study is similar to triangulation as shown in Figure 5, as it aims to gain a holistic understanding of the phenomenon utilizing a multi-method approach. In triangulation, the research problems are frequently multi-caused and significant, so one research method is not sufficient to obtain extensive information. Triangulation is not a research method in itself, but rather consists of the cohesion of qualitative and quantitative research methods varying on the precondition. It is best applied as a research strategy to comprehensive research projects such as AIDS research. (Kananen, 2013, 33.)

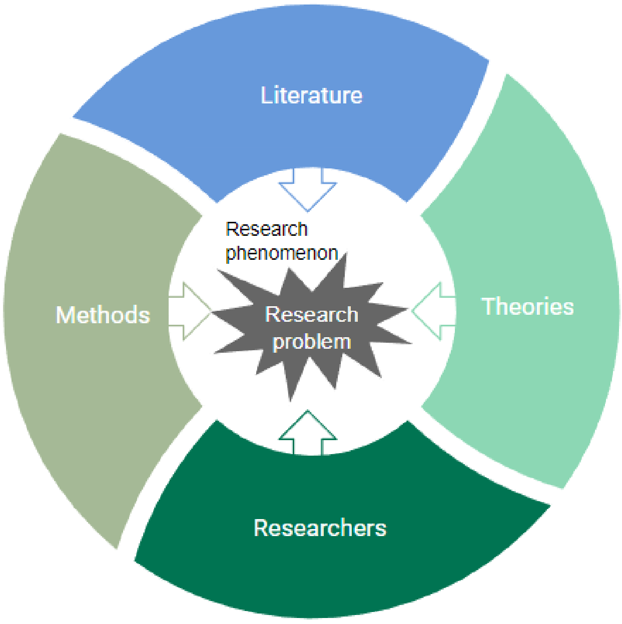


Figure 5. Triangulation and case study conceptual similarity (Kananen, 2013, adapted)

The S&OP process is wide-ranging and is a relatively complex process.The case study utilizes many different sources of information to achieve a holistic study, therefore it offers an excellent approach to answer research questions in study. Case study provides a suitable approach to understand the company's situation, for example the S&OP process, in its natural environment. (Kananen, 2013, 28, 33.)

Qualitative and quantitative research is not appropriate to be interpreted as mutually exclusive methods, but rather as complementary research methods. The qualitative approach always has quantitative features and, conversely, the quantitative has qualitative elements. In qualitative research, quantitative methods may be utilized in the analysis of the data. In both cases, the study extracts of both can therefore be treated, as well as methods. (Saaranen-Kauppinen & Puusniekka, 2006.) Qualitative and quantitative research has its own characteristics and chapter 4.1 examines the specifics of qualitative research and several data collection methods. Chapter 4.2 explores the features of quantitative research and methods of data collection.

4.1 Qualitative research methods

The objective of qualitative research is to find wealth of information about a narrow object and thus gain a broader understanding of the phenomenon (Ojasalo et al., 2018, 105). Hirsjärvi et al. (2009) presents the typical features of qualitative research as follows:

- Comprehensive data collection
- Human as an element of gathering data
- Use of inductive analysis
- Qualitative methods in the acquisition of literature
- Objective selection of the target group
- As the research progresses, the research plan adapts
- Unique treatment of cases and interpretation of substance based on it.

(Hirsjärvi et al., 2009, 164.)

The basis of qualitative research is the description of real life because people interpret phenomena often based on what they are interested in at any time, and what kind of perspective they select on a phenomenon or issue at any given time. From this, it can be concluded that real life is extremely diverse, therefore it is justified to study the phenomenon extensively, utilizing the human being for the benefit. (Hirsjärvi et al. 2009, 160–161.) The next two paragraphs present two commonly used qualitative methods – interview and observation, highlighting their advantages and, in contrast, also disadvantages.

4.1.1 Interviews

To survey the current situation, interviews are a good method to clarify and deepen information about the organization's processes. The advantages of interviews are that you can easily ask additional questions and inquire for justifications for the statements presented. The downsides of interviews are that they are often time-consuming and require regular preliminary preparation and familiarization with the interview. Interviews and data related to it are always situational and context bound. This indicates that the subjects can be stated differently in interviews than otherwise. The researcher has an important responsibility at this point in forming an interpretation and generalizing the results. (Hirsjärvi et al. 2009, 205–207.) With the assistance of interviews, the demands of the users in the process, the desired goals, and comprehensive in-depth information about the current state of a process can be bracketed. Interviews are also a valuable method for disclosing the requests of users and thus obtaining significant information for the process development process. A researcher can be thought of as a developer or change agent during the research, whose objective is to convey information, encourage, function as an instance in change with the power of a positive attitude and maintain a positive and developing atmosphere (Ilmakangas, 2018).

The interview question should be pretested before actual use, in order to avoid confusions and false reactions regarding the questions in the interview occasion. The primary objective of the interview is to produce crucial material for the research, i.e., to be effective, so that each party to the interview understands each other correctly. The planning of questionnaire design should not be approached lightly, because superficially produced questions can cause inaccurate information and thus the reliability of the study can suffer. (Wilson, 2018, chapter 7.) Interviews can be divided into structured, semi-structured and open interviews based on the questionnaire concept. In a structured interview, the same questions are questioned in the same order for each interviewee. In a semi-structured interview, the concept of questions phrasing can vary significantly during the interview. Thus, questions inappropriate to the situation can also be left out. Correspondingly, new questions can also be questioned during the interview if someone answers partially to the question or brings up a new topic of interest. In an open interview, as the name indicates, the phenomenon or problem is discussed freely. Both parties are equal in the interview and participation is active. (Ojasalo et al., 2018, 108–109; Dahlberg & McCaig, 2010, chapter 8; Yin, 2018, 118–119.)

In a semi-structured interview, the exact order or format of the questions is not particularly significant, but instead of an interview, pre-selected themes, i.e., subject areas, are discussed. The topic is considerably broader than the questions and can’t be answered especially briefly. In a semi-structured interview, the structure of the interview is generally freer, and the discussions often lead to new issues, problems and themes. Roles involved with the phenomenon are generally selected for the interview. Individuals who know substantially about the phenomenon can also be selected, if those who are involved by the phenomenon are not available. In qualitative research, the number of interviewees is not defined in advance, because the research problem and the amount of information determine this adequacy. The sufficiency of the interviews often reveals itself as saturation when the answers start to repeat themselves and the additional interviewees rarely bring additional information to the phenomenon after this point. Naturally, saturation is not used in situations where there are only several cases. The semi-structured interview performs best when it produces a broad understanding of a phenomenon about which the researcher has no prior knowledge, models or theories explaining the phenomenon. The aim of the semi-structured interview is often to increase the holistic understanding of the phenomenon, i.e., by exploring for answers to issues related to research problems. Therefore, the semi-structured interview is one of the most utilized data collection methods in case studies. (Kananen, 2013, 93–95.)

4.1.2 Observation

Observation is suitable as a method for a wide variety of research — in practice it is suitable for all development work, both qualitative and quantitative research. By observing real events physically on the spot, it is possible to gain useful information that may not be apparent with surveys or interviews. (Ojasalo et al., 2018, 42.) Observation is a particularly recommended method for different processes, i.e., functions in the organization. Operations in companies are often described using different processes. In addition, these described processes are documented, therefore by observing the different roles operating in the process, it is possible to determine whether the work is performed as described. The complexity of describing the performance of the work task and reaching tacit information can be difficult to expose in other ways than observation. The advantage of observation is that the issues occur in a natural environment, that is, within the phenomenon's own context. The disadvantages of observation are mainly related to the presence of the researcher — subjects can change their behavior in the observational situation, secondly, the researcher can emotionally join the group of subjects and the objectivity of qualitative research suffers. (Kananen, 2013, 88–91; Saaranen-Kauppinen & Puusniekka, 2006.)

Reactivity refers to the researcher's impact on the research results, and the greater the impact, the smaller the researcher's objectivity becomes. Particularly, quantitative research aims to minimize reactivity. In terms of objectivity, it is beneficial that the subjects are not aware of the researcher's presence. From an ethical point of view, the above-mentioned technique of action is not in accordance with acceptable research practice, because participation in research should always be voluntary. Observation can be conducted to different degrees, and the role of the researcher in observation has its own influence, as presented in Figure 6. Technical observation is the most assured method because the phenomenon can be recorded in its entirety, for example by videotaping and thus the data can always be returned repeatedly. Different data collection methods are used in the observation, such as a research diary, video recording and description. (Kananen, 2013, 88–91; Saaranen-Kauppinen & Puusniekka, 2006.)

Researcher is not involved in the process	Researcher involved in the process		Researchers influence
Technical observation	Indirect observation	Direct observation	No
	Participatory observation	Participating observation	Yes

Figure 6. Different degrees of observation (Kananen, 2013, 88, adapted)

Observation can be performed either directly or indirectly. In direct observation, the actors of the target phenomenon can perceive the observation, whereas in indirect observation the researcher is hidden, and the target actors are not aware of the observation. In general, the selection is influenced by whether the subjects of observation change their behavior in the study condition. In participatory observation, the researcher is present in the condition and participates in the activity, thus the advantage of the method is the opportunity to reveal the core of the phenomenon under study and obtain versatile information about it. (Kananen, 2013, 89.) The roles of “participant as observer” and “observer as participant” may seem quite similar in terms of actions to be taken, but in the former the researcher participates as a member of that group during observation and in the latter observation, the researcher's activity is passive, i.e., does not participate in the course of events. (Saaranen-Kauppinen & Puusniekka, 2006.)

The basic starting point for the observations is a research diary, in which the observations about the research object are recorded. In qualitative research, it is crucial to operate on observation and analysis at the same time. With this, the researcher is able to direct the observation to issues that are valuable in solving the research questions. Observation is performed unstructured or structured. In a structured observation, the researcher recognizes which objects require observation. For this purpose, a form can be prepared in advance to facilitate observation. Unstructured observation does not necessarily contain information about the object of the observations. It is more difficult to implement predictive work for unstructured observation. It is often beneficial to save unstructured observations, hence certain situations can be returned to, countless times if necessary, and thus ensure the reliability of the observation. (Kananen, 2013, 90–93.)

Observation as a research method is appropriate for both qualitative and quantitative research, and the researcher can perform observations on relatively different levels, in accordance with the requirements of the study. In qualitative research participatory observation is more often utilized than systematic observation, it provides the researcher a beneficial option of being present in the situation and in particular to obtain a holistic understanding of the activities in the group and the lives of the subjects. Participatory observation allows the researcher to select the level of observation, i.e., how precisely the observation is performed, and it can be limited and focused on specific objects. Systematic observation is thoroughly structured and various methods have been developed for its implementation, such as checklists. (Hirsjärvi et al., 2009, 214–217.) For example, to calculate how many speeches each participant will use in a meeting.

4.2 Quantitative research methods

In quantitative research, according to Hirsjärvi and others (2009, 140), the following, for example, are essential

- definition of concepts
- previous theories
- conclusions of previous studies
- the data is suitable for numerical measurement and can be processed statistically.

In quantitative research, the aim is to describe the phenomenon numerically and it is interpreted using statistical methods. A deductive approach is essential for quantitative research, where previous theories and the conclusions of previous studies provide the starting points for the research. Quantitative research is therefore an excellent choice for testing theories and creating generalizations based on the observation of connections between measured variables. One of the substantial advantages of quantitative research is the objectivity of data collection and analysis, which increases the reliability of the study and makes it possible to avoid assumptions. (Dahlberg & McCaig, 2010, chapter 2.) In quantitative research, the material can be very extensive, for example the actual sales volume of a product over several years. This variety of data is about a typical time series set, in which the set of data points has been obtained in a sequential time interval. The following chapters explore time series analysis, the ARIMA model, and highlight the benefits of producing time series analysis with Python.

4.2.1 Time Series Analysis

Time series can essentially be utilized to study almost any phenomenon because time progresses continually, and the frequency of distinct phenomena varies over time. By measuring the phenomenon repeatedly similarly, the temporal change of variables can thus be described with a time series. Utilizing time series, it is obvious to detect variations and review the development trends of processes, likewise develop forecasts. The development of forecasts is established on the assumption that a number of regularities observed in the past will be repeated in the future. (Nummenmaa, 2021, 461.) According to the definition, a time series is named an observation sequence y_t, where the values of the variable y are recorded consecutively at time points t. Time series can be continuous or discrete, i.e., discontinuous. In the discrete case, the interval between consecutive observations is usually the same length for the entire time series, and the observations are taken at equal intervals at certain points in time. (Bousqaoui, Slimani & Achchab, 2021.) A continuous time series is frequently used when the measurement and recording of observed values is continuous, for example automated process monitoring. (Holopainen & Pulkkinen, 2015, 305). When analyzing time series, the order of the observations can't be ignored, and the use of regression analysis methods is thus excluded. Moreover, observations are often interdependent. Such correlation between observations as a function of time is called autocorrelation. In practice, it signifies the correlation of the time series with itself. (Nummenmaa, 2021, 461–469.) In time series methods, the only independent variable is time.

Stationary refers to a time series in which no trend or seasonality is observable. In this case, the time series is in place and its mean and standard deviation remain constant over time. If the time series data is non-stationary, it must first be converted to stationary by decomposing the time series into different components. Converting a time series to a stationary one is important in order to analyze the time series and apply it, for example, with forecast models. Next, one of the most common graphical representations of a time series is presented, as well as how regularities can be distinguished by applying different components in a time series. (Auffarth, 2021, chapter 1; Krispin, 2019, chapter 11.)

Time series are often depicted graphically in such a way that the time is presented on the X axis and the values of the time series on the Y axis, as explained in Figure 7. The points of the time series values are often combined with straight lines to make it easier to understand the regularities of the graph and the passage of time. (Nummenmaa, 2021, 463.)

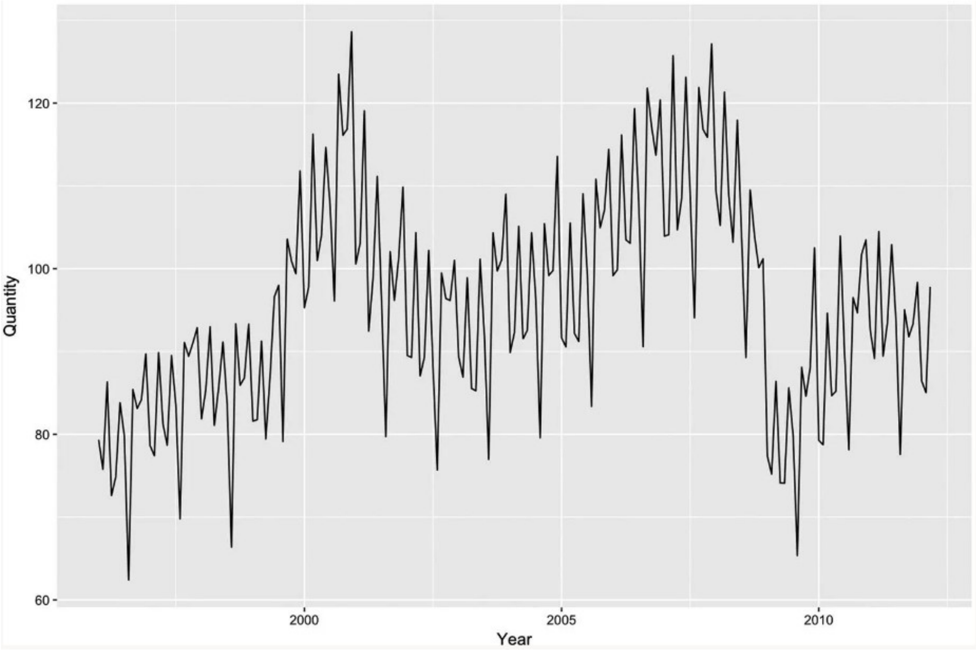


Figure 7. An example of time series (Kotu & Deshpande, 2018, chapter: Taxonomy of Time Series Forecasting)

As mentioned above, different components, i.e., features can be distinguished from the time series, such as level, trend, seasonal variation, cyclical variation and random variation. With the benefit of these behavioral components, various regularities can be revealed from the time series. The purpose of the level (M) is to describe the magnitude of the observation in the time series. For example, the sales of a product are 12,000 units per year, in which case the level of the time series measured monthly is 12,000 units / 12 = 1,000 units. A level is an attractive feature when there is no cyclical variation and/or significant variations in values in any direction. (Nummenmaa, 2021, 464–465.)

The trend (T) describes a long-term change in the same direction, although during the review period the observed values can vary significantly. There can be numerous trends in a time series, and they can also be in different directions, but in the longer term the direction is the same. Figure 8 points out that there are two trends in the time series of the Brent crude oil price – the rising trend covers the entire review period (five years), and the falling trend ends at the end of April 2020. By looking at these trends, one can try to estimate significant changes in time series. (Nummenmaa, 2021, 464–465.) The price of oil products fell in the spring of 2020 due to the collapse of demand, which was a consequence of the COVID-19 pandemic.

Figure 8. Brent oil futures historical data (Fusion Media Ltd, 2023, adapted)

Seasonal (S) variation describes the periodic variation of values on both sides of the trend in a time series and it appears as repeated patterns in a time series. Seasonal variation can occur at frequent time levels in a time series. (Nummenmaa, 2021, 466.) For example, the winter quality of diesel is sold more in the winter months than in the summer months. The seasonal period (L) can be divided into different time windows, such as yearly, quarterly, monthly et cetera (Kotu & Deshpande, 2018, chapter 12.1). Although diesel sales in the long term may be on an overall level occasionally decreasing and periodically increasing, the seasonal variation repeats itself. Seasonal variation can occur in a time series without a trend component, i.e., it is not a necessity (Nummenmaa, 2021, 466). Figure 9 displays frequently used AirPassangers dataset (available for example in https://www.kaggle.com/datasets/abhishekmamidi/air-passengers) in which the monthly passengers' number of US Airline from 1949 to 1960 is represented. On the Y axis is the number of passengers and on the X axis is time. Seasonality is easily discovered in the figure and the rising trend can be observed in the growth of passenger numbers over time.

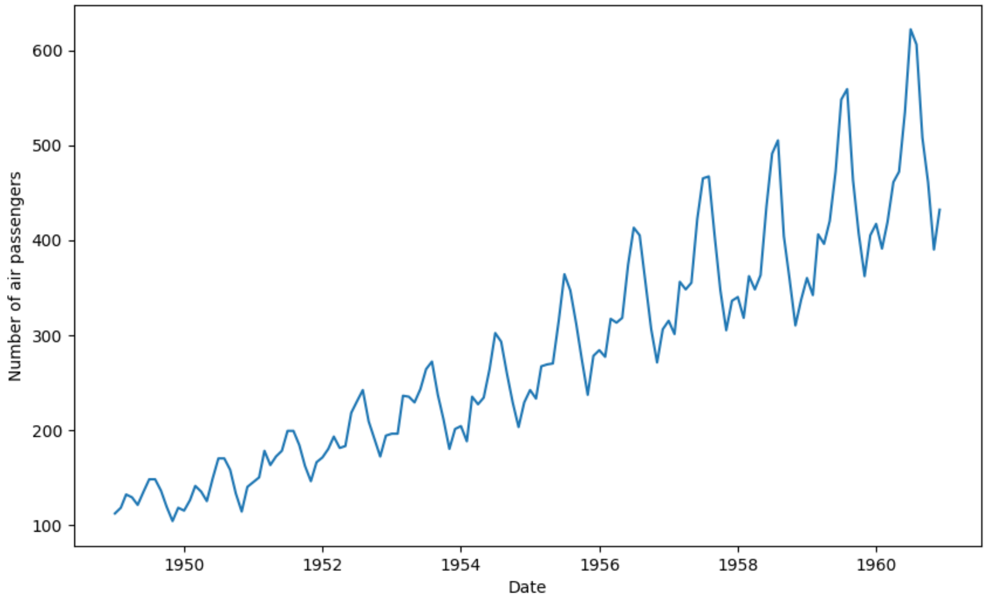


Figure 9. An example of seasonal variation (Banerjee, 2020a, adapted)

Cyclical (C) fluctuation represents a longer-term fluctuation in which growth and decline alternate. The frequency and amplitude of cyclical fluctuations generally vary from one period to another – thus cyclical fluctuations are not as regular as seasonal fluctuations. Cyclical fluctuations are especially used to describe the economic condition and progress. For example, GDP (Gross domestic product) is an economic indicator which changes can be described in a time series. When a boom is prevalent, it can be interpreted as being above the trend, and in a recession, below the trend. (Nummenmaa, 2021, 466).

Noise can be described as something that can't be explained in time series with the aforementioned components. Thus, everything else in the time series that is not explained by level, trend, seasonal or cyclical variation is noise, i.e. random variation (I). Trend and seasonality components are systematic components and predictable. The noise is non-systematic and can't be forecasted. (Kotu & Deshpande, 2018, chapter 12.1.)

As presented above, often the time series illustrates different characteristics such as trend, cyclical, seasonal, and/or random variation. Based on this empirical observation, it is desirable to decompose the time series, specifically, divide it into parts or similar components as part of a statistical analysis. The objective of decomposition is to describe and analyze the time series and eliminate seasonal variation to facilitate the interpretation of the time series. The time series decomposition can be utilized for example in forecasting if something is known about the behavior of the product. In the simplest time series model, additive model, variable y_t can be solved by adding the components of the time series together. The additive time series decomposition can be represented by the following equation:

$$y_t = T_t + S_t + C_t + I_t \tag{2}$$

where y_t = Series observation at time t
T_t = Trend
S_t = Seasonal
C_t = Cyclical
I_t = Random variation

The unit of measurement of all components is the same as the original time series. For example, if measuring the sales of products in euros, the unit of components is also euro. Additive model is recommended when the seasonal and cyclical fluctuations and random variation in time series are steady. (Kotu & Deshpande, 2018, chapter 12.1; Nummenmaa, 2021, 467–468.)

The multiplicative time series decomposition using the following equation:

$$y_t = T_t \times S_t \times C_t \times I_t \tag{3}$$

where T_t = Trend
S_t = Seasonal
C_t = Cyclical
I_t= Random variation

In the input model, the components of the time series are multiplied together, and the model operates best in situations where the magnitude of the components decreases or increases as the values of the time series increase. However, often the selection between these two models is made by experimentation and more suitable is chosen. (Nummenmaa, 2021, 467.) Multiplicative time series can be converted to additive form by applying logarithmic function, as below:

$$\log(y_t) = \log(T_t) + \log(S_t) + \log(C_t) + \log(I_t) \tag{4}$$

(Kotu & Deshpande, 2018, chapter 12.1.1.)

The decomposition of the time series to different areas was presented above. To facilitate the interpretation of a time series, it is often smoothed out by trend as well as random variation. For example, when monitoring the change in domestic sales of LPG, it may be necessary to filter out seasonal noise to better reflect the changes overall from the time series. One of the most used methods is to take advantage of the moving average. At its simplest, a moving average in a time series calculates the sum of the consecutive value of n, which is divided by n, and moves on to the next value in the time series and repeat the process. (Hopp & Spearman, 2011, 444–445.) The MA process can be defined by the following expression:

$$MA_n = \frac{\sum_{i=1}^{n} A_i}{n} \tag{5}$$

where MA_n = Moving Average

n = Number of periods

i = Time period (e.g., Months)

A_i = Actual data in period

Example: Calculate the moving average of three- and five-month domestic sales of LPG. This can be executed by summing the sales of previous months with a defined value of n while it serves as the denominator, as below:

$$MA_3 = \frac{23404 + 22150 + 24508}{3} = 23354\ tons$$

The values applied in the calculation of the moving average are included in Annex 1 and it can be visualized from Figure 10, how the moving averages with defined values equalize sales compared to actual sales. The variation in the time series can be smoothed by moving the time window forward according to the defined standard term n. A suitable value of n may not always be recognized at the beginning, and different values are required to establish before a beneficial one is discovered. In the example case n=3 or n=5, it is not very easy to decide which of the values is beneficial. However, it can be seen from the graphs that, as a rule, the trend is downward, and the moving average model does not predict an upward or downward trend. Thus, generically, the following conclusions can be drawn:

- the moving average model is generally higher than future demand in line with the declining trend and, conversely, lower than growing sales
- higher n values equalize the model in a more stable direction, then again, weaken the responsiveness to changes in the process.
  (Hopp & Spearman, 2011, 446–447.)

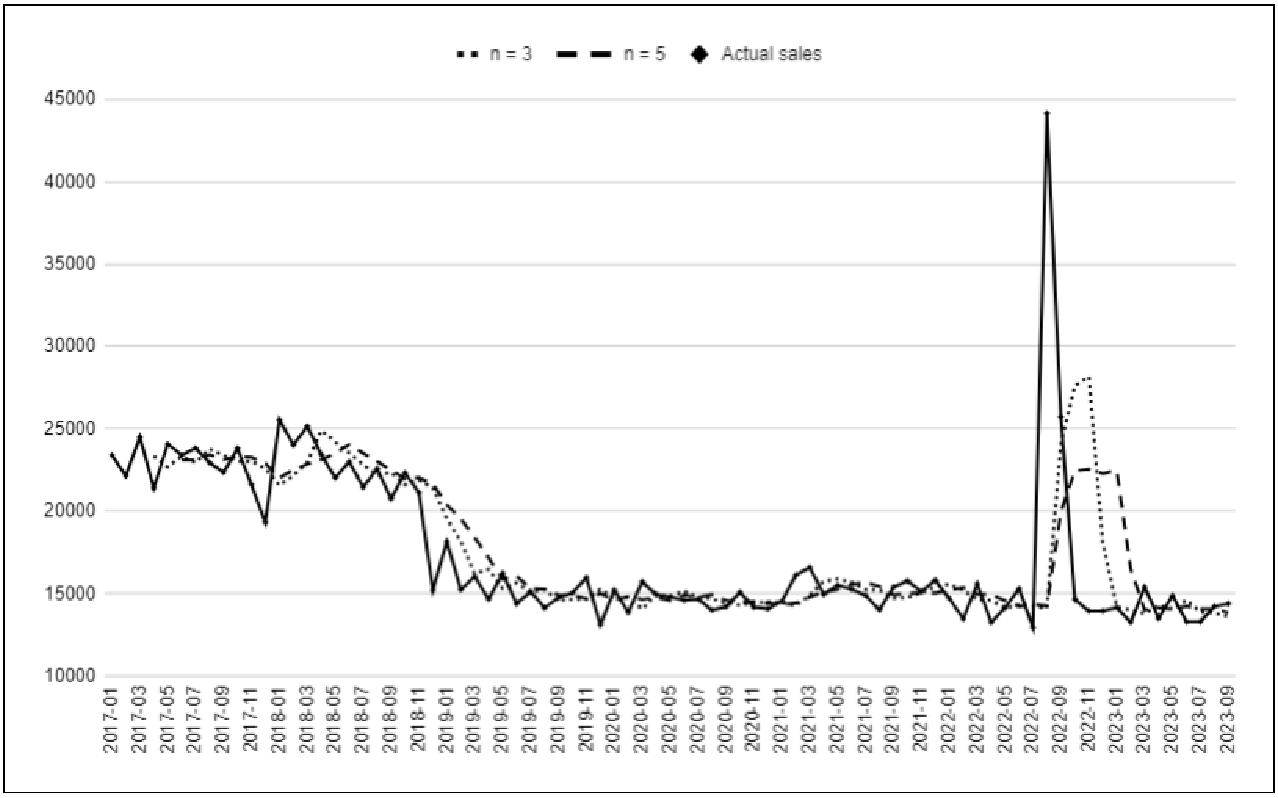


Figure 10. Moving average with *n* = 3, 5.

An autoregressive model, or AR model, can be used as a model input to predict the value of the next time period. This is based on the assumption that previous observations are assumed to be beneficial in predicting values for the next time period. A positive correlation occurs when variables change in the same direction. Thus, it can be stated that values changing in different directions (one decreases and the other increases) indicate a negative correlation. (Gupta, 2021, 227.) The AR model can be defined by the following expression:

$$AR(p) : y_t = c + \sum_{i=1}^{p} \emptyset_i y_{t-1} + e_t \tag{6}$$

where $AR(p)$ = Notation for an AR process with p-order

y_t = Current value of the series

c = constant

p = number of lags

$\emptyset_i$ = coefficient of the i lag of the series

y_{t-1} = i lag of the series

e_t = error term

(Krispin, 2019, chapter 11.)

One technique to turn a non-stationary time series into a stationary one is to apply the differencing method, where the differences of consecutive observations are calculated in the time series. This can be written in the form

$$y'_t = y_t - y_{t-1} \tag{7}$$

Figure 11 establishes the differences between consecutive observation values calculated in Appendix 1 in relation to domestic sales of LPG. It can also be noted from the Appendix 1 that series with order differencing can only have $T - 1$ values, because from the first observation no calculation can be performed. (Hyndman & Athanasopoulos, 2018, chapter 8.1.)

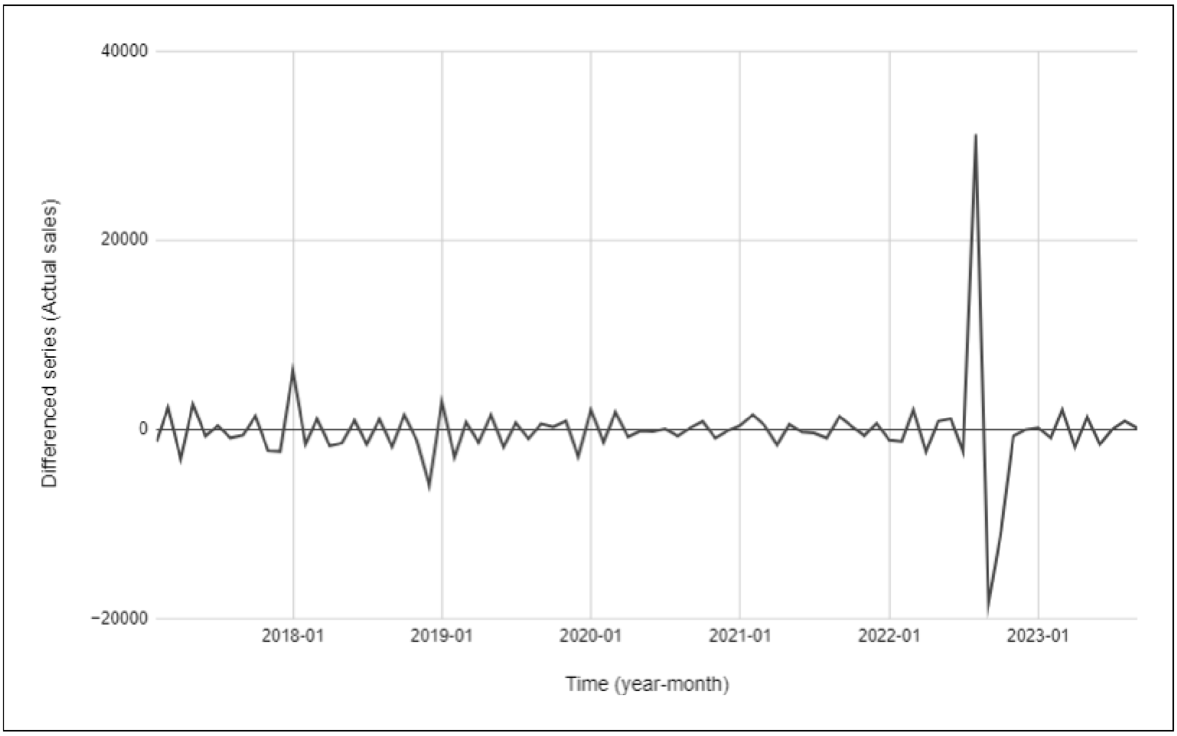


Figure 11. The change of consecutive observed values for domestic sales of LPG

The stationarity of the time series and residuals can be measured applying various test quantities, such as the Augmented Dickey–Fuller test or ADF-test. The ADF-test is one of the most popular statistical tests to determine whether the time series is stationary or not. This can be accomplished through the null hypothesis as well as an alternative hypothesis. The null hypothesis can in general be rejected if the p-values are less than 0.05 or 5 %. It can be assumed that the time series has a unit root (p-value ≥ 0.95) and conclude that the process is only weakly stationary. (Auffarth, 2021, chapter 5.)

The dependence between a time series and its laps can be measured by the autocorrelation function (ACF). The purpose for the ACF plot is to explain how time series factors are correlated. The closer the coefficient is to ±1, the better the correlation between them. ACF can be applied to identify seasonality in a time series, it can likewise classify the process type. (Krispin, 2019, chapters 5, 7, 11; Chase, 2013, chapter 7.) In the example, the relationship between LPG current sales y_t and delayed sales y_{t-k} can be described by the value r_k. The autocorrelation coefficient r_k can be written as follows:

$$r_k = \frac{\sum_{t=k+1}^{T}(y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^{T}(y_t - \bar{y})^2} \tag{8}$$

(Hyndman & Athanasopoulos, 2018, chapter 2.8.)

A time series where no autocorrelation is observed is called white noise. The expectation for a white noise series is that 95 % of the AFC values are within $\pm\frac{2}{\sqrt{T}}$, where T is the length of the time series. Figure 12 establishes the autocorrelation of the domestic sales of LPG data set for 20 lags. The data set can be discovered from Appendix 2. In the example case, $T = 81$, thus the limits for white noise are $\pm\frac{2}{\sqrt{81}} = 0{,}22$. Obviously can be discovered in the figure that not until at lag 10 the autocorrelation coefficients of the series reach into the limits of $\pm 0{,}22$, which confirms that the data set is not white noise. (Hyndman & Athanasopoulos, 2018, chapter 2.9.)

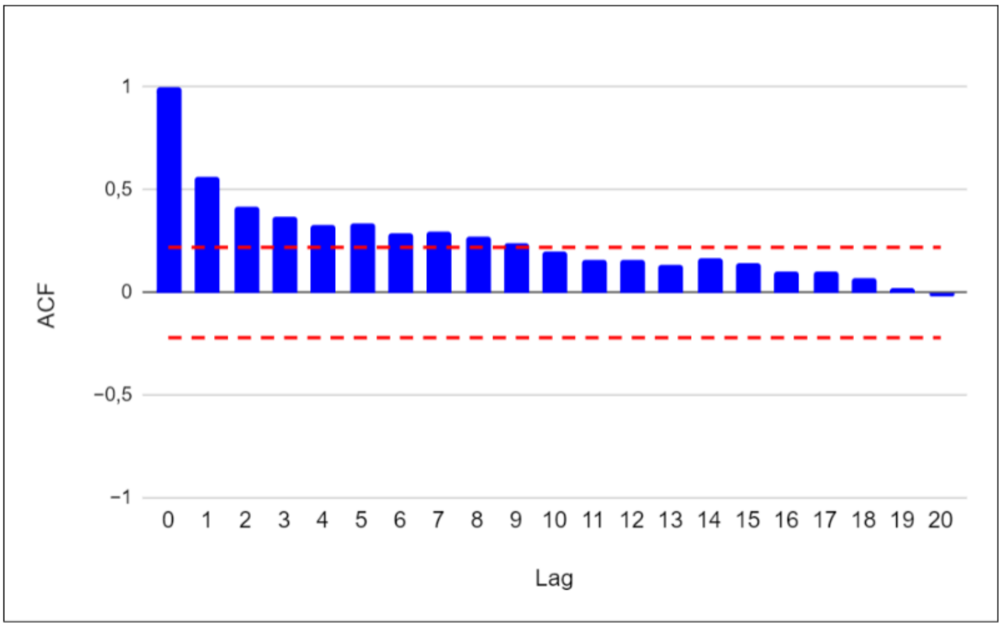


Figure 12. Autocorrelation Function (ACF) plot of the domestic LPG sales dataset

AFC therefore measures the correlation between y_t and y_{t-k} with different values of k. This denotes when y_t and y_{t-1} are correlated, y_{t-1} and y_{t-2} can also be assumed to be correlated. Thus, y_t and y_{t-2} may be correlated additionally. Therefore, AFC is not functional in all cases. As a solution to this, PACF, i.e., partial autocorrelation function, has been developed, which takes into account the aforementioned problem by eliminating the effect of delay $k-1$. Grounded on the above, the first value of PACF is equal to ACF because nothing removable occurs between them. In the autoregressive or AR model (presented above), each partial autocorrelation can be estimated as the last coefficient. (Hyndman & Athanasopoulos, 2018, chapter 8.5.) ACF and PACF perform a significant role in adjusting the parameters of the ARIMA model. In the next chapter, the ARIMA model will be more explained and its usability in time series analysis.

4.2.1.1 ARIMA

The ARIMA model or method is one of the commonly utilized methods in time series modeling, which was developed by Box and Jenkins in 1976. The advantage of the ARIMA is that it includes the integrated (I) process, therefore no separate preprocessing is required transforming the time series stationary. The differencing process can be represented as follows:

$$Y_d = (Y_t - Y_{t-1}) - \cdots - (Y_{t-d+1} - Y_{t-d}) \tag{9}$$

where $Y_d =$ the d difference of series Y_t

(Krispin, 2019, chapter 11, The ARIMA model.)

The ARIMA model is most often displayed as ARIMA (*p, d, q*), where *p* denotes the order of the autoregressive model part (AR process), *d* refers to the degree of integration (I) and *q* indicates the order of the moving average (MA process). The ARIMA (*p, d, q*) can be represented as follows:

$$ARIMA(p, d, q): \; Y_d = c + \sum_{i=1}^{p} \emptyset_i \, Y_{d-i} + \sum_{i=1}^{q} \theta_i \in_{t-i} + \in_t \tag{10}$$

where $Y_d =$ the d difference of series Y_t

$c =$ constant

$p =$ number of lags to regress against Y_t

$\emptyset_i =$ coefficient of the i lag of the series

$Y_{d-i} =$ the d difference of the i lag of the series

$q =$ the number of past error terms utilized in the equation

$\theta_i =$ corresponding coefficient of $\in_{t-i}$

$e_t =$ error term, which is white noise

(Krispin, 2019, chapter 11, The ARIMA model.)

In summary, it can be presented that ARIMA model can be fitted in a time series exploiting the following basic steps:

1. Preprocess the data, which includes removing outliers, data transformation to stationery, and differencing the data to eliminate the trend and seasonality.
2. The model parameters estimation and diagnostics. Parameters for the model can be utilized by variety methods like AIC (Akaike's information criterion)
3. Model fitting. Once the ARIMA model parameters have been selected, the model is needed to check whether it fits the data.
   (Chase, 2013, Chapter 7; Krispin, 2019, chapter 11, Forecasting with ARIMA Models section.)

Once the parameters of the ARIMA model have been selected, the ability of the model in terms of forecasting accuracy can be tested. Model parameters are generally entered into statistical software or software platforms to produce the analysis as simple as possible. (Chase, 2013, Chapter 7.) One of the most general method to implement the forecasting accuracy is applying error metric to quantify the overall accuracy of the forecast, such as:

- the mean squared error (MSE)
- the mean absolute error (MAE)
- the root mean squared error (RMSE)
- the mean absolute percentage error (MAPE).

In MSE, a residual is calculated for each point which is squared. The values obtained are taken as an average. MAE is practically the same as MSE, the absolute values of the error are applied instead of residuals. The differences between MSE and MAE appear when outliers or extreme values are treated in the series. This appears in such a way that the quadratic function gives a greater weight to deviant values. Therefore the distribution of errors is of great importance when evaluating the error metric suitable for the model. RMSE indicates the root mean square distance between predicted and actual values, hence RMSE can be thought of as a scaled version of MSE. In addition, RMSE corresponds to the standard deviation or error. MAPE measures the average percentage of absolute error. Errors reported as a percentage have their advantages, for instance they are unit-free and are generally used in connection with comparing the effectiveness of forecasts. The same as time series, different metrics have been developed for different applications. After all, the objective of metrics is to capture the performance of a time series, in order to train and develop the model to meet the defined objectives and forecasts. (Auffarth, 2021, chapter 4; Hyndman & Athanasopoulos, 2018, chapter 3.4; Krispin, 2019, chapter 8.)

ARIMA is a powerful tool for forecasting time series data. However, it is crucial to be aware of the advantages and disadvantages of ARIMA models before using them. Below is a summary of some of the advantages and disadvantages of the ARIMA model.

The advantages of the ARIMA model:

- are able to capture a variety of temporal patterns, including trends, seasonality, and noise
- relatively easy to fit and interpret
- flexibility and modularity
- can be utilized to generate forecasts with a high degree of accuracy, especially short-term forecasts.

The disadvantages of the ARIMA model:

- can be sensitive to outliers and missing data
- can be computationally expensive to fit
- requires statistical knowledge to develop
- may not be appropriate for forecasting non-stationary time series.

(Chase, 2013, chapter 7; Krispin, 2019, chapter 11.)

The following chapter presents the benefits of implementing time series analysis with Python – a free and an open-source programming language.

4.2.1.2 The advantages of implementing time series analysis with Python

Python is one of the most established and widespread programming languages. Its popularity is based on its beginner-friendly operating environment – even if never been programmed before, Python syntax and structure are easy to follow and read. In addition, Python is free, open-source software, allowing anyone to extend its functionality and benefit from these extensions. R and Python are the most generally applied programming languages in time series. According to Auffarth (2021), Python has overtaken R as a programming language in recent years. (Auffarth, 2021, chapter 1; Gupta, 2021, chapter 1.)

In order to utilize Python in data analytics, a suitable programming environment is required to be downloaded, such as Anaconda or use cloud-based services like Google Colab. After this, coding can be started, for example in Jupyter Notebook, which is an open-source web application where programming languages as Python scripts can be run. The data can be easily downloaded to a notebook, where it can furthermore be pre-processed. In addition, both visualization and model training can be processed rapidly, without forgetting the evaluation of the model. Python code is written in code segments which can be executed one or all at a time. Moreover, descriptive text can be written in code segments, for example reporting purposes. Figure 13 summarizes the implementation of the system architecture, as well as some of the libraries to be utilized, both in terms of data preparation and visualization of the results.

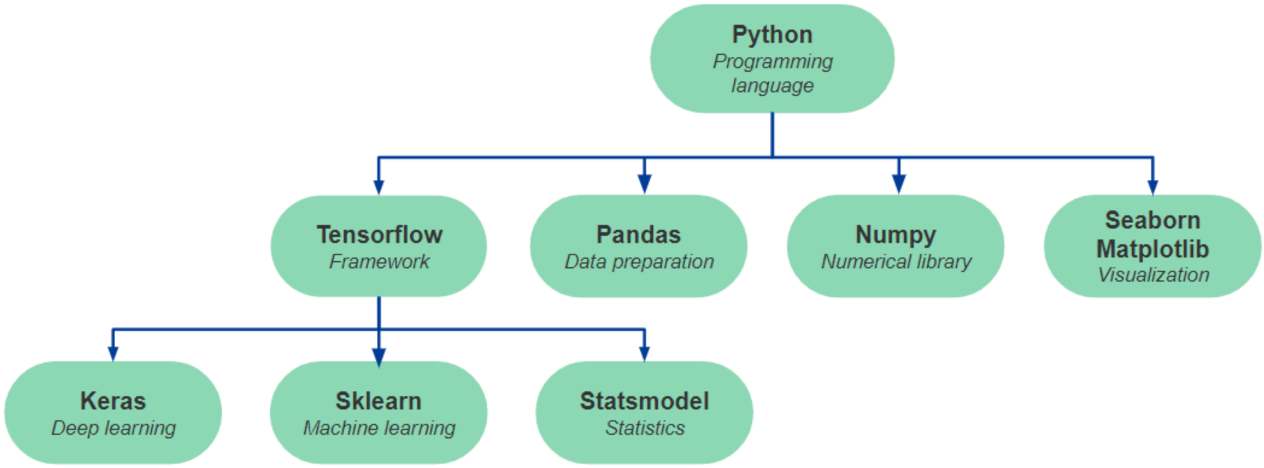


Figure 13. Principle on the system architecture (Moroff et al., 2021, 45, adapted)

To run the script and visualize the data, a variety of programming libraries are required such as NumPy (Numeric Python), Pandas (the basic library for data analytics) and the Statsmodel library, with tools for building ARIMA models, for example. The libraries can be easily implemented in Jupyter Notebook using a couple of code commands as discovered in Figure 14. In summary, it can be stated that utilizing the Jupyter Notebook, data analytics can be implemented in many different ways and information can be shared more effortlessly with stakeholders. (Auffarth, 2021, chapter 1; Gupta, 2021, chapter 2, 5.)

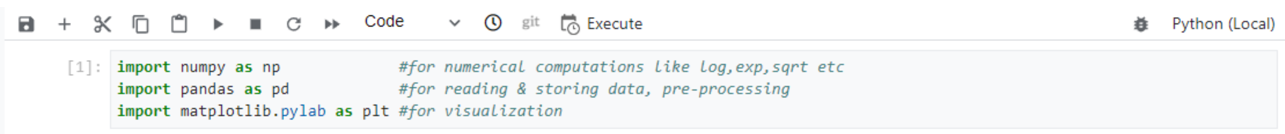


Figure 14. Importing library packages in Jupyter Notebook

Therefore, Python can be applied to implement a wide range of statistical functions and to deliver key concepts in statistics, such as normal distribution and Pearson's correlation coefficient, or to manage more challenging statistical analyses. Time series data analysis and implementation of forecasts, for example, can be implemented in a notebook environment by the following basic steps

- Importing the data and libraries
- preprocessing the imported data
- data visualization
- data transformation
- building and fitting the models, for example ARIMA
- using and evaluating the forecasting model

(Gupta, 2021, chapters 8, 9, 10, 15; Hyndman & Athanasopoulos, 2018, chapter 1.6.)

Rapid implementation of analyzes and results can be considered mandatory today. Time series can contain a very large number of data points. An increase in the number of data points can often result in an increase in computational time and resources – especially in the case of AI and ML methods and tools. Given these circumstances, utilizing Python in time series analysis allows predictions to be created relatively effortlessly and easily. In addition, according to Nguyen, Adams and Miller (2023, chapter:preface), the production of traditional statistical analyses does not necessarily require a great number of computational resources. This is also explained more in chapter 5.3, which explains more about forecasting and its methods.

Statistical software platforms such as SPSS (Statistical Product and Service Solutions) calculate the model and often display the results as a table. Due to the ease of the low-level user interface, SPSS has been particularly widespread with social scientists for years. However, several software require a license and are therefore not free to use. In addition to the license, e.g., SPSS may require the use of educational institution equipment in order to operate, which may not be possible, e.g. from a student taking online studies due to the location. (Tilasto-ohjelmat [Statistical software’s], 2021.)

"Python is one of the most commonly used tools for quantitative analysis, data science and machine learning. Software based on an open-source ecosystem is widespread e.g. due to extensive method libraries (various machine learning methods, traditional time series and regression methods) and the repeatability of script-based implementations. These libraries regularly give the author the opportunity to expand their analysis further and in new directions faster than to be attached to a roadmap for the publications of a particular software house.
(Ahma-aho, 30.4.2024.)

The main difference between script-based tools is especially the repeatability of the process, compared to systems based on graphical user interfaces. This indicates the code is understandable and the analysis is feasible by another person based on the script. In graphical interfaces, however, the description of the process is commonly left to the description of the performed action. For example as follows: “the button X was pressed, after which the XY parameter was chosen...” While, for example, analysis with a syntax editor could be studied, less often such tools have a mode of operation to produce syntax out with analysis. Based on the above, it is highly justified to implement quantitative analysis with script-based tools based on an open-source ecosystem. (Ahma-aho, 30.4.2024.)

5 Literature review

In this chapter, the essential theory related to the research is reviewed, which is applied to explain and clarify the existing practice, in other words, the real world. With the benefit of the theory, it is simpler to understand the research problem, in addition to this the aim is to find dependencies both between and within phenomena. With the help of different theories, the problem is possible to view through many different lenses and thus see the same phenomenon from a different perspective. According to Kananen (2013), theories provide tools that enable the understanding and discovery of phenomena. (Kananen, 2013, 46.)

5.1 Operations management

It can be said that operations include all the activities that perform the goods out the door as cost-effectively as possible. Figure 15 presents functions that are most commonly included in operational management. Operations management is a broad entity and, depending on the perspective, it can include many other additional functions. Production management is therefore the core of managing the entire operation. Hopp and Spearman (2011) present an attractive view of a leader who understands the principles of factory physics and is able to intuitively observe and empirically interpret their own environment, is able to recognize changes occurring more rapidly in the system and thus react more rapidly to changing conditions. (Hopp & Spearman, 2011, 693.) For this reason, the knowledge, experience and continuous development of this leader or function owner are the core of continuous improvement and development.

Figure 15. Functions of Operation Management (WallStreetMojo, n.d., adapted)

According to Hopp and Spearman (2011), three major trends can be observed in current manufacturing management, which contain valuable elements of an integrated solution. The first to quote is Six Sigma, which offers a methodology for improvement that engages both employees and upper management. The second trend is the lean philosophy, which aims to eliminate activities that prevent increasing customer value return. The third trend is IT systems (for example ERP) that provide data to generate reliable decisions. These methods in isolation have no value if no information has been obtained about manufacturing and methods related to it, not to mention information about the company itself and its industry. Previously mentioned, as several other methods, have been frequently sold as turnkey solutions for companies. Instead, from the customer perspective, cursory assumptions are adopted about the functionality of the method and disappointment occurs when perfect solutions are not discovered. The most vital action is to create a strategy with which the company is able to continuously improve and develop its activities within the framework of its own resources, and to produce policies and processes according to which it is able to perform over time. (Hopp & Spearman, 2011, 180.)

The organization strategy is obliged to be sufficiently clear and concrete – one that allows each employee to identify their own role. This study does not cover strategy planning in-depth, but the company's strategy requires it to be agreed and coordinated with other functional areas when decision-making is practiced by the supply chain, for example in production and logistics. The company's top management is responsible for defining the strategy, i.e., what needs to be done, when and how widely. To support this activity, according to Silver et al. (2016), the organization has often defined different levels of strategy, which are utilized to guide and implement the action. The levels of the strategy can be delimited as shown in Figure 16, from the highest to the lowest level. (Silver et al., 2016, chapter 1.2.)

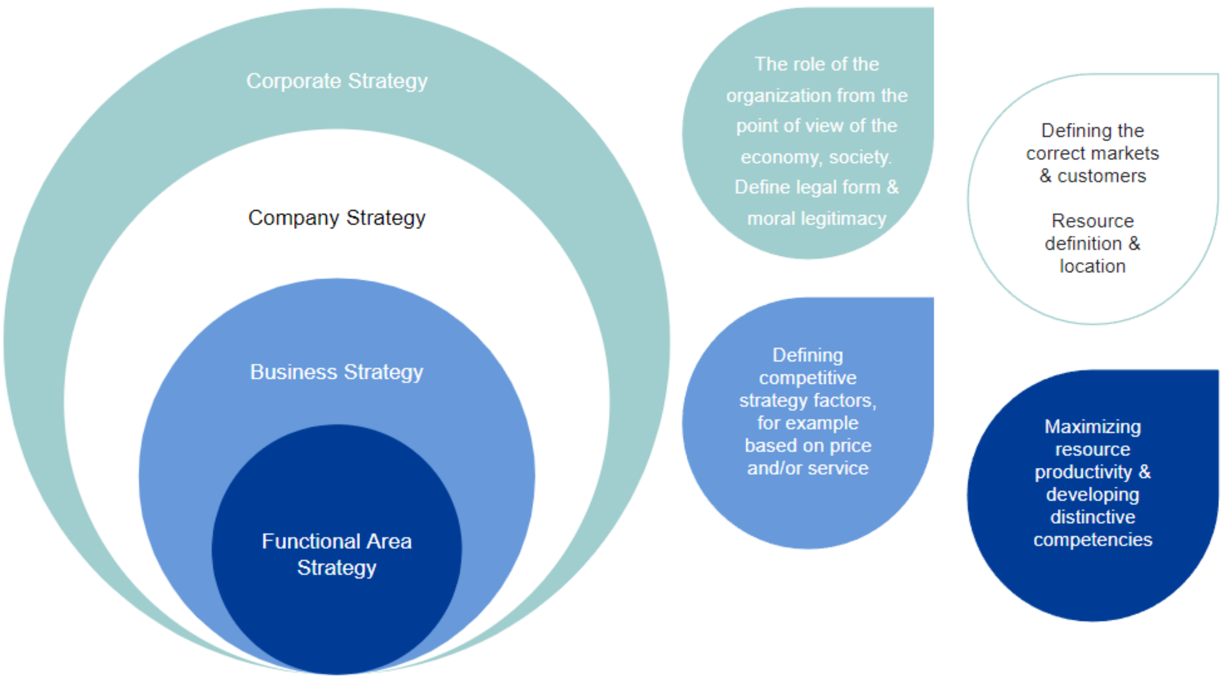


Figure 16. The four levels of strategy (Silver et al., 2016, chapter 1.2, adapted)

Operations strategy is one of the organization's strategies alongside marketing, finance, and human resources. According to Silver et al. (2016), operations strategy can be divided into three parts: mission, objectives and management. The purpose of a mission is to define the direction of operations. It is important for the mission description to be a particularly interesting statement of direction so that the company attracts excellent employees. Therefore, the mission should represent the excellence of the company and contain the thrill of the top management to convey the desired image to investors, customers, and employees. The objectives of the operation are much more precisely defined than the mission and are clearly measurable in contrast to the mission. With the help of objectives, operations define how a company achieves its mission. When defining objectives, it is essential to make the determination carefully and also to put them in order of priority. Although the purpose is always to improve operations, there are frequently conditions where compromises are executed, for example, as a result of raw materials delivery is delayed. (Silver et al., 2016, chapters 1.4.1–1.4.2.)

> *"Those who cannot remember the past are condemned to repeat it. Statement strongly emphasizes the point of view, that various companies are performing the same issues at the same time and repeating the same mistakes at the current rate of data growth."* (Santayana, 1905)

Transition to the next industrial revolution and to survive also in the near future, requires companies to coordinate operations according to customer needs, but also to remember the events and lessons of history, which Santayana already brought out at the beginning of the last century and is still relevant as heralded by Hopp and Spearman (2011, 44). The advantage of open data integration is that it can be educated from the mistakes made by others and save time, increase value generation in addition improve the customer experience. The open data economy is a significant opportunity for companies to cooperate. With the benefit of a wider network, it is achievable to gain, for example, the results of innovations in a shorter time invested and thus achieve better competitiveness significantly earlier than performing solo (Karppala, 2022). Currently, on a global level, each company has common challenges to tackle, such as reducing the carbon footprint and preserving biodiversity. Several companies have already started various cooperation projects decades ago, for example to reduce carbon dioxide emissions. Neste's many cooperation projects include the following, Neste has started cooperation with Brightlands

Venture Partners, 4 Impact VC and Asahi Kasei to invest in the Circularise startup software company to boost the transition in the polymer and chemical industry towards the circular economy and the usage of more sustainable materials. In this cooperation, blockchain-based digital solutions are offered, the purpose of which is to improve traceability and transparency throughout the whole value chain. (Neste, 2022a.) The best opportunities for success are acting proactively, i.e., acting on your own initiative and taking responsibility. It is absurd to preserve information that can be utilized to save natural resources and increase diversity – harnessing such information for everyone's use is a common interest. Ultimately, with the help of legislation, companies can be guided to develop in the right direction with everyone's interests in mind.

One cooperation strategy is co-opetition, which denotes cooperation with a competitor. This approach achieves significant benefits for common goals, for instance learning from others, spreading risks and cooperation has a significant impetus to generate, for example legislative changes. (Brandenburger & Nalebuff, 2021.) Layered thinking and the diversity of the organization offer a suitable growth platform for new innovations and the development of development. In order for the growth medium to remain rich and vibrant, it demands to be fertilized at intervals – to provide opportunities for ideas to collide from the edges of the evolution of thinking (Saarinen, 2014). Transparency and the sharing of information offer improved opportunities for these fruitful encounters most frequently – in other words, for the development of operations.

5.2 Supply chain management

The core of the supply chain is to balance supply and demand and produce added value at each stage of the chain. To increase the return on value and to prepare beforehand for future conditions, it is according to Moroff, Kurt and Kamphues (2021, 1) critical to increase the accuracy and efficiency of forecasting, especially when reducing short-term changes in the supply chain. In order to manage changes in the supply chain, coordination of effective information exchange is the fundamental basis (Silver et al., 2016, chapter 12.2.1). Today's supply chains are extremely challenging to manage, partly due to their complexity and partly due to constantly changing requirements. Supply chain complexity can be the result of many different sources and combinations and according to Christopher (2011) some of the most general origins are listed below in random order:

- Network complexity
- Supplier complexity
- Organizational complexity
- Process complexity
- Information complexity
- Range complexity
- Product complexity
- Customer complexity

(Christopher, 2011, 161–165.)

As Sakki (2014, 1) already states in his preface, supply chains have a large amount of untapped potential that companies can utilize to improve their competitiveness and outcome. For example, with the S&OP process it is possible to improve internal cooperation and thus harness existing potential and improve value returns and the competitiveness of the company. Figure 17 establishes McKinsey's (2016) view of the six most important value drivers for operational efficiency towards Supply Chain 4.0. From the representation, it is possible to perceive rapidly in which direction the development of the supply chain can proceed in the coming years in different areas, and especially to understand the development status from the perspective of the company and to identify potential development targets.

> *“Supply Chain 4.0 is the highest maturity level, leveraging all data available for improved, faster, and more granular support of decision making.“*
> (McKinsey, 2016.)

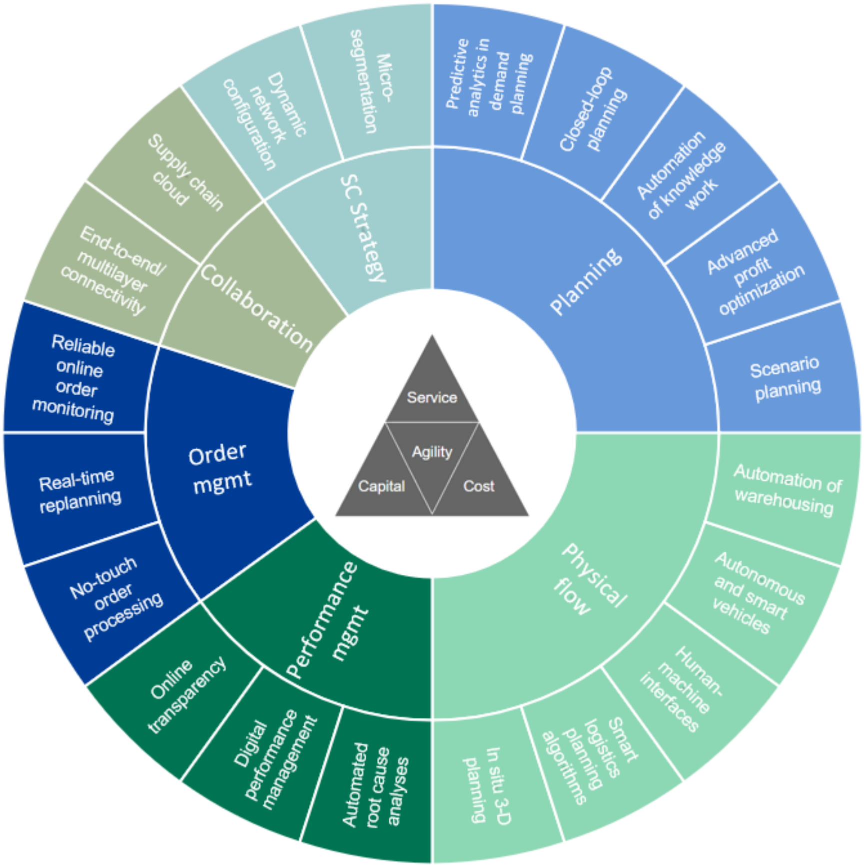


Figure 17. McKinsey’s view of the core value drivers in Supply Chain 4.0 improvement (McKinsey, 2016, adapted).

Managing the supply chain is frequently making different decisions and selections based on continually variable data. The most important mission is to gather the relevant data to execute the best solution for the current situation in terms of the company and the customer. The decisions are overly complex and challenging, and related issues have to be examined from several different perspectives simultaneously. Therefore, finding and utilizing the right data is one of the most crucial missions of supply chain management (Silver et al., 2016, chapters 2.1–2.2.) The right data is often difficult to discover, and the search has to be executed from the company’s various systems and combine the collected data to the system where it is in use. The data may still have to be cleaned and converted into a usable format. Tacit knowledge or experiential knowledge is often information which is not often documented or stored in any form in the organization's data systems. For example, with personnel turnover, it is possible to lose crucial information for the development of the organization rapidly. (Ahlavuo, Hyyppä & Haggrén, 2011, 54.)

One of the greatest developments in the last decades in the field of supply chain is the widespread use of enterprise resource planning systems (ERP). The systems have several modules that generate it more efficiently to operate on the optimization of production planning and inventory management, for example. In these ERP systems, such as SAP, it is possible to integrate the third-party software company's own modules and to have data transferred in the chain efficiently both upstream and downstream. (Silver et al., 2016, chapter 17.3.) The data is also available to every department and provides real-time status, for example, factory operations at all times (Silver et al., 2016, chapter 13.2.3.) The following chapters introduce a few typical phenomena in the supply chain and address the challenges of production planning and inventory management.

5.2.1 Supply chain challenges in inventory management and production planning

The management of inventory and production throughout the supply chain can’t be overemphasized, as they can be an obstacle for a company to maintain or achieve a competitive advantage. This is not always clear to the top management. Therefore, supply chain and warehouse management executives must participate in strategic planning, in order to gain an overall nature of the company's operating strategy and understand the effects of supply chain decisions on other functions. (Silver et al., 2016, chapter 1.2.) Inventory management can operate in various different practices because inventories can differ significantly from each other based on the manufacturing and storage of the products and product qualities (Silver et al., 2016, chapter 2.1). Figure 18 displays several variables that should be taken into account when making inventory management decisions. In the refinery, a number of products and components are stored in caverns and tanks. In addition, since there is always some inaccuracy in forecasts, safety stock is used to hedge inventories (Sakki, 2014, 99.) For example, ABC analysis is a classification method which is utilized to manage inventories by categorizing value and/or importance of the product or item.

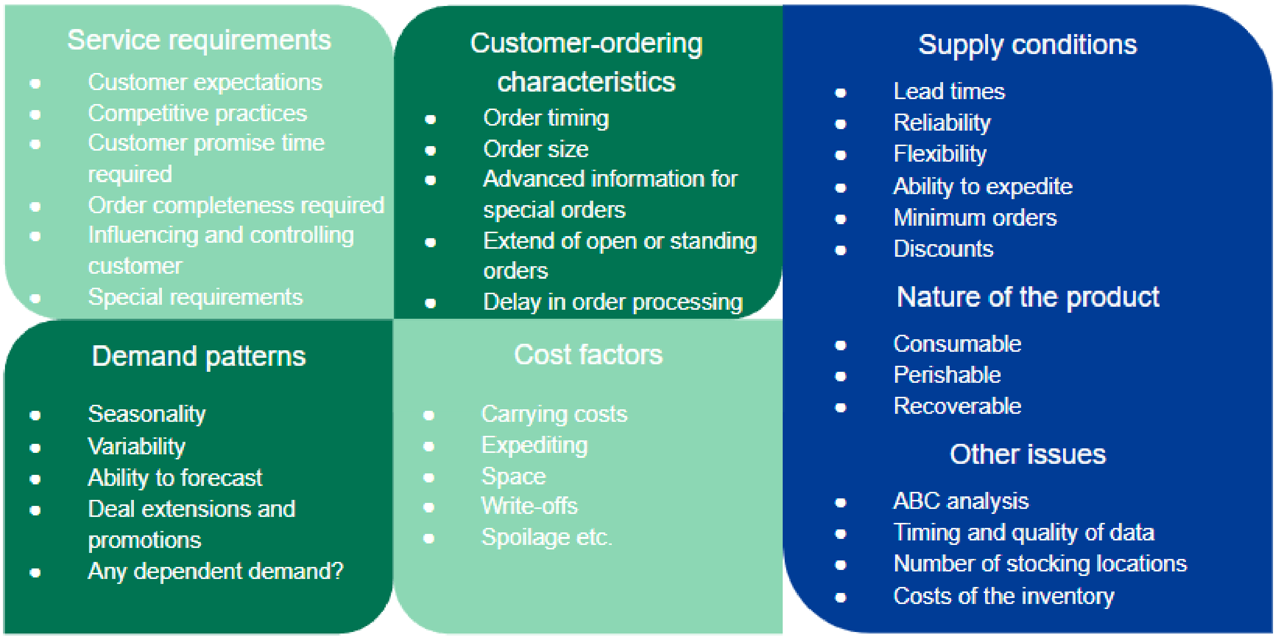


Figure 18. Variables in inventory planning decisions (Silver et al., 2016, chapter 2.6.2.1, adapted)

Master production planning is the foundation of all planning and serves as the interface between production and sales. In order to create a successful production plan, one of the most significant advantages is to understand the wide-ranging entity and in which planning horizon which information is used to support decision-making. The framework established in Figure 19 brilliantly describes the field of production planning, how the sub-areas are linked to it and how information and/or data flows between interfaces. The framework includes an MRP closed loop that was developed with the assembly industry in mind but is likewise usable for other process types. MRP differs from ERP quite a bit, one can think of ERP as an extension of MRP. MRP is a production tool, so to speak, and in ERP, all functions of the company use the same database. The development of ERP systems has enabled real-time information flow and visibility of the factory status for all departments. For example, driving changes and delays in production are supported by these common databases and integrations and are immediately available to everyone and coordination becomes easier. The arrows in the frame describe the direction of the information flow. Information flow and feedback are vital in production planning and control, so that changes can be reacted to and, if necessary, re-planned. (Silver et al., 2016, chapters 13.2, 14.3, 15.7–15.8.)

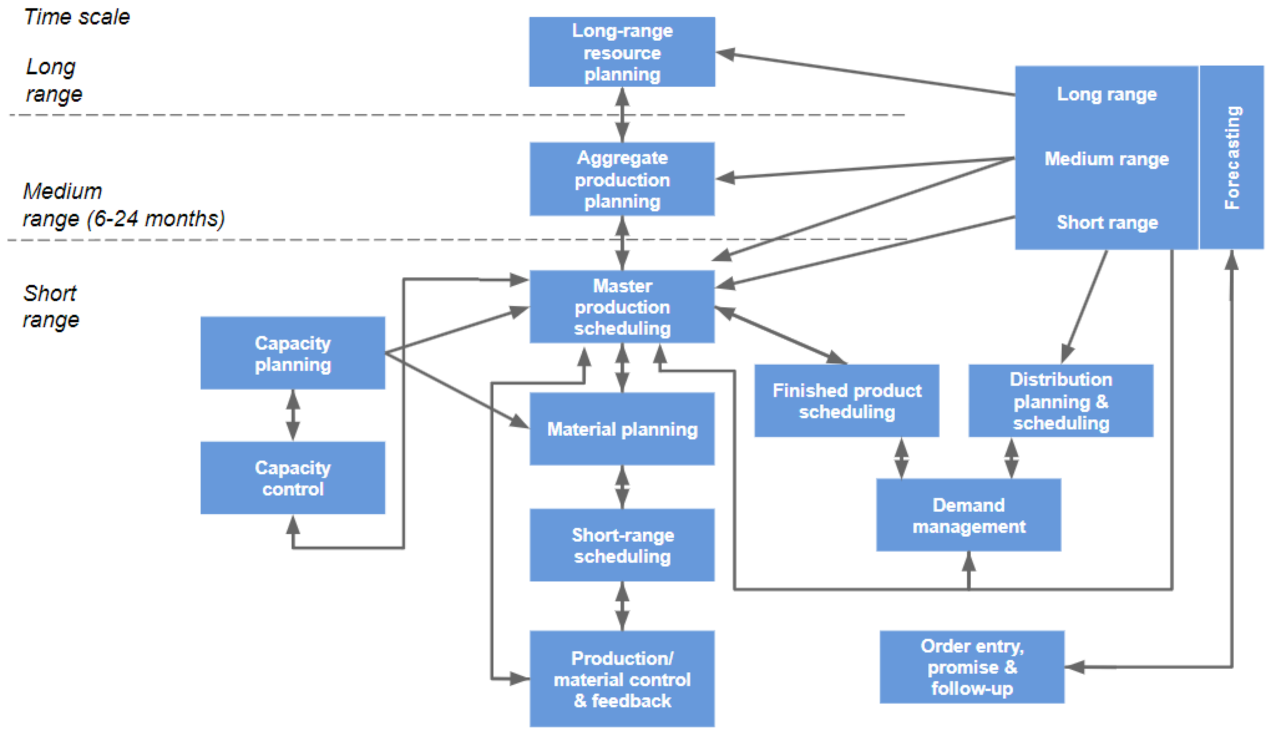


Figure 19. Framework for production decision-making (Silver et al., 2016, chapter 13.2, adapted)

Production planning can use a wide variety of systems and models to plan, optimize and simulate different scenarios, and run alternative plans from which to choose the best feasible plan. One of the many production planning systems used is the Aggregate Production-Planning System, where the plan deals with inventories, production volumes, labor levels based on each type of product. Especially when referring to continuous process production, such as an oil refinery, there is a requirement to have discussions about the production plan between several operators and stakeholders. Therefore, such decisions are often part of the S&OP process. (Silver et al., 2016, 13.3, 14.5.)

In the case of oil refineries, the planning models are often tailored, which brings challenges in terms of maintenance and usability of the models and requires special expertise. In addition, in long-term or short-term planning, the emphasis can be on different subjects, which can indicate that different models, even several different models on the same planning horizon, are used in production planning. The size of the models should also be given importance because the speed and efficiency of the models directly indicates in practice how many different scenarios can be implemented. One option for customized modeling is Linear Programming (LP) models. The variation of LP models' formulations is huge, according to Silver and others (2016) practical LP models can most commonly be parsed as follows:

- Demand is considered to be deterministic
- costs in regular production can be described by track with linear or convex functions
- costs is linear (usually) in the change in production rate
- certain markets are served by a specific production plant
- lower and upper limits of inventories and production volumes are defined
- Inventory accounting costs can vary
- lost sales and after-orders are not allowed in most formulations.

(Silver et al., 2016, chapter 14.6.)

This study does not cover the mathematical formulation of LP models, but rather highlights the usability, accessibility and limitations of models on a general level. One of the best features of LP models is that product categories, as well as various constraints, such as the usability of production units or inventory levels, can be included in the formulation. In contrast, the main weakness of LP models is the assumption of deterministic demand, which undermines reliability from long-term forecasts. However, according to Silver and others (2016), simulation tests by Dzielinski, Baker and Manne (1963) denote that under stochastic conditions, a deterministic model can operate favorably, as long as the solution is implemented according to a rolling forecast. (Silver et al., 2016, chapter 14.6.)

Although ERP systems and different models have significantly improved the flow of information over the past decades, information about deviations from the production plan must be communicated as quickly as possible to initiate corrective actions. Getting the right information from the system rapidly is not always that easy. In addition, this often requires the trained use of the system and planning models to implement fast problem solving. In addition to the above, the information may become outdated or damaged. Maintaining the master data of the ERP system and preserving the integrity of the data are the biggest challenges that can be classified as disadvantages of the ERP system. (Silver et al., 2016, chapters 12.5, 15.7.)

5.2.2 Bullwhip effect

One of the most well-known phenomena of lack or distortion of information in the supply chain is named the Bullwhip effect. In the Bullwhip effect, minor changes downstream can cause massive fluctuations upstream of the supply chain, which can be observed in Figure 20. The bullwhip effect causes various disadvantages in the supply chain. It leads, for example, to lost sales, back deliveries, extra production, and transportation, and performs incorrect capacity decisions – all of which lower the customer's service level. (Logistiikan maailma [The world of logistics], 2022c; Silver et al., 2016, chapter 12.1.)

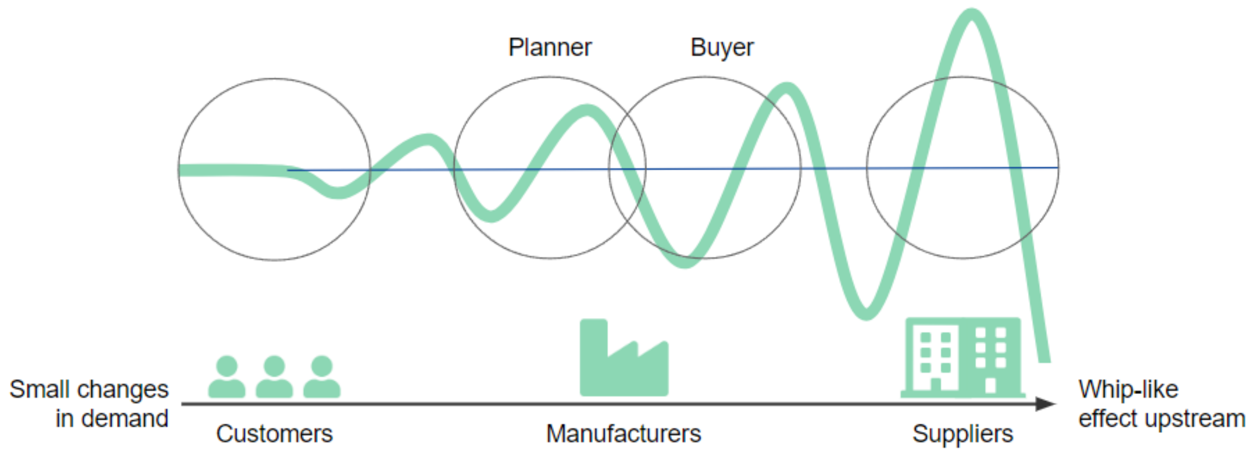


Figure 20. Bullwhip effect from end customer to raw material supplier (Baker, 2022, adapted)

Hsiao and Shieh highlight the Bullwhip effect and the importance of information sharing in the supply chain. The study explains the trend of the bullwhip effect from the point of view of sharing information using the ARIMA model. Hsiao and Shieh (2005, 604) introduce qualitative studies done by Lee (1997) in addition Baganha and Cohen (1998), where it is observed, one way to eliminate or mitigate the impact of the Bullwhip effect, is to increase information sharing. It can consist, for example, about the information of customers or information sharing between the supplier and the manufacturer. (Hsiao & Shieh, 2005, 604–605.)

As a result of the research, it was found that the Bullwhip effect decreases when information is shared and increases when information is not shared. Regardless of whether information is shared or not, the Bullwhip effect is always present. The longer the delivery times are, the greater is the Bullwhip effect. (Hsiao & Shieh, 2005, 608–609.) As a result of the corona pandemic, global supply chains were significantly disrupted, and the impact of the Bullwhip effect grew tremendously. Therefore, for example, bottlenecks emerged in harbors and as a result, container ships started to navigate irregularly all over the globe. Thus, the car factories had a shortage of components, and accordingly, human resources had to be furloughed and fired, even if order backlog existed for many years further.

5.2.3 Houlihan effect

Kristianto, Helo, Jiao and Sandhu (2011) introduce an adaptive fuzzy VMI control for supporting inventory management, particularly vendor managed inventory (VMI) to mitigate the Bullwhip effect in supply chains. A phenomenon termed the Houlihan effect – a shortage causes an increase in safety stocks, and this usually leads to large order quantities. As a result of which the orders do not correspond to the real demand. This results in an increase in production batch sizes, to manage the promised delivery time, known as the Burbidge effect. (Kristianto et al., 2011, 345.)

The simulation results of the study reveal that by eliminating the Burbidge and Houlihan effects in the VMI control model, the Bullwhip effect is reduced. According to Kristianto and colleagues with the steering of VMI, it is feasible to obtain more accurate production plans and the levels of safety stocks can also be reduced by lowering the standard deviation from the relative stock levels. In addition to the phenomena mentioned above, their study likewise highlights the effect of information sharing, the importance of which was presented in the study by Hsiao and Shieh as well. (Kristianto et al., 2011, 354.)

5.3 Forecasting

Forecasting is the starting point for practically all production planning. So far, no one has a crystal ball to predict the future, thus the best solution for success in the future is to select the most excellent information in the present. According to Moroff and colleagues (2021, 41), the uncertainty factors in forecasts are often due to incorrect information or a lack of knowledge, and partly to information related to sales. Practically everything depends on the future and therefore forecasting can be approached in many different directions. Hence, there are numerous different methods and approaches to forecasting. Forecasting can be divided based on methods, for example, as in Figure 21 the methods are divided into quantitative and qualitative methods. (Hopp & Spearman, 2011, 440.)

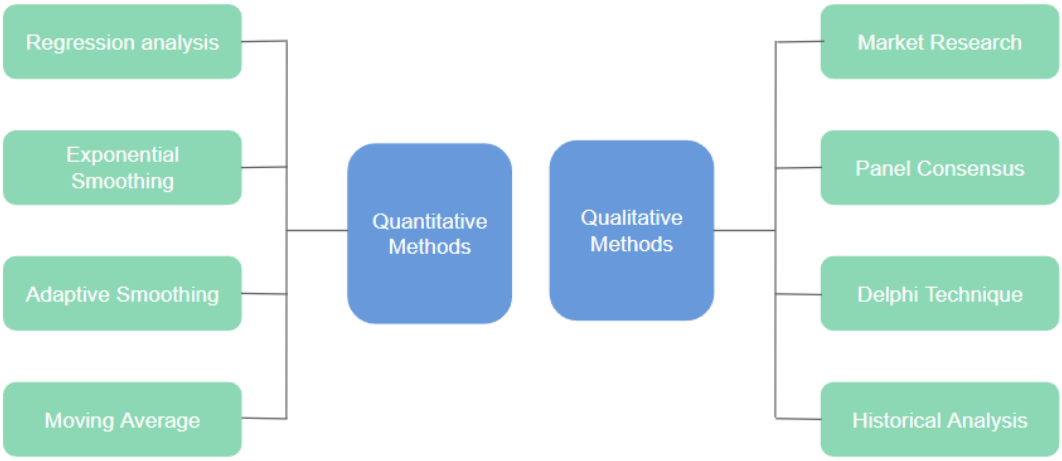


Figure 21. Quantitative & Qualitative Forecasting Methods (Bhola, 2021, adapted).

Qualitative forecasting methods are based, for example, on the interpretation and empirical knowledge of experts – hence the methods are subjective. Whereas quantitative forecasting methods are based on objective numerical data. There is no single acceptable way to produce forecasts to provide a holistic view and knowledge, therefore it can be valuable to use both forecasting methods when creating forecasts. Numerical methods can be considered more stable but are not suitable for estimating demand forecasts for a new product, for example. The advantages of qualitative methods are the experience and insight brought by experts. Then again, opinion or judgment may not always gain support among stakeholders. Quantitative forecasting methods are based on the assumption that using numerical historical data, future parameters can be forecasted, e.g. demand for a product. (Bhola, 2021; Reflex, 2022; Hopp & Spearman, 2011, 440–441.) For example, quantitative time series forecasting techniques can be classified on the basis of Figure 22.

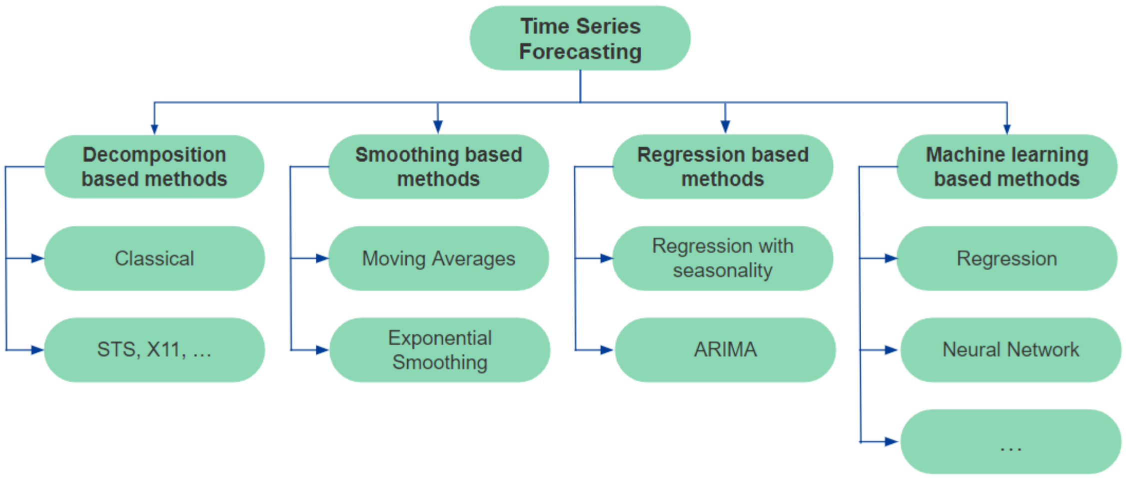


Figure 22. Classification of time series forecasting techniques (Kotu & Deshpande, 2018, adapted).

The theory behind the second research question is presented by Hopp and Spearman (2011, 441) according to the first law of forecasting:

> *"First law of forecasting: Forecasts are always wrong."*

Even if you have the best mathematical forecast models and the prime expert in question, it can be stated that a 100 % forecast is not possible to achieve, and this is one of the most significant subjects to recognize about forecasts. The planning horizon often denotes how far into the future, for example, forecasts are utilized to support decision-making. However, the forecasts become more imprecise as the horizon grows, because the models for demand forecasts are not known completely accurately. One fundamental grounds of forecast inaccuracy is the bullwhip effect presented in chapter 5.2.2. This is shown by the fact that each level of the supply chain updates its demand forecast from its own perspective – as they observe it, instead of actual demand. According to Hopp and Spearman (2011), the solution for this is sharing the demand data, vendor-managed inventory, and reducing lead times. Thus, in order to support the company's decision-making as best as possible, minimizing forecasting errors is the subject to focus on, or forecasts should be updated according to actual demand. (Hopp & Spearman, 2011, 441, 636; Silver et al., 2016, chapter 14.3.)

The preparation of forecasts is based on scenarios, i.e. created models. An attempt is made to explain and describe the phenomenon under consideration with the support of a mathematical model. According to Holopainen and Pulkkinen (2015) the most important attribute of using a mathematical model is the simple preparation of forecasts, so that based on the utilized initial data and the operated vision, several different scenarios can be modeled, and the beneficial one can be selected. (Holopainen & Pulkkinen, 2015, 266.) The application of the model with the most significant prediction value requires observation of its characteristics before executing it. Various methods have been developed to evaluate it, such as coefficient of determination, t-value, and residual. (Holopainen & Pulkkinen, 2015, 277–282.)

In order to study and describe the connections between variables using statistical methods, it is needed systematically to collect data about the phenomenon. With the advantage of statistical reasoning, we can select a part of this data, i.e. a sample, and examine the variables relevant to the research from this smaller set, model them using the selected method and find causal connections between phenomena, and based on that, draw conclusions and create forecasts. (Nummenmaa, 2021, 24–27). To produce forecasts, it is crucial to know how to create effective forecasts – it is essential to identify the mechanism by which forecasts are generated, as well as how they can be influenced and how to adjust them. For example, oil market prices are level two chaotic system. This indicates that forecasts are affected all the time by different variables, and this has a major impact on forecasting. In their study, Chinn, LeBlanc and Coibion (2005) highlighted the challenge of forecasting crude oil because price is influenced by market data that has a direct impact on price. The spot price of crude oil is also affected by storage and transportation costs. (Chinn et al., 2005, 6–9.)

One of the most common ways to predict future demands is time series analysis, which was presented in chapter 4.2.1. Product demand is one most commonly predicted parameter in time series models. This is based on the fact that demand for a product is influenced by competition, customer appeal and marketing. Although the above variables are difficult to model unequivocally, over time they will generally persist in history and future demand can be predicted based on them. (Hopp & Spearman, 2011, 441.) Silver and colleagues (2016) advocate utilizing deductive mathematical modeling for decision-making, especially in cases involving uncertainty—such as forecasting. Modeling is not constantly feasible, therefore simulation is an exceptionally viable option in these cases. Simulation, however, requires a model of the system, for example process units from a refinery. By simulating over time, for example, the operation of a unit, the process and its behavior can be discovered substantially. (Silver et al., 2016, chapter 2.8.)

The paper by Bousqaoui and colleagues compares the performance of four different forecasting methods which are: ARIMA, the multi-layer perceptron (MLP), the long short-term memory model (LSTM) and the convolutional neural network, known as CNN or ConvNet. In terms of this study, the most valuable results were the comparison of different forecasting methods, the performance evaluation of utilized methods and a more in-depth review at the ARIMA model. (Bousqaoui et al., 2021, 3319, 3323.)

Artificial neural networks, or ANN, are based on machine learning methods which consist of an input and output layer and one or more hidden layers in between. This is a powerful way to discover linear/non-linear relationships between input and output. MLP is a feed-forward neural network where data is fed from multiple layers from input to output. The LSTM network is used in deep learning, and it is a frequent neural network with feedback connections. According to Thanki and Borra (2019) emphasized by Bousqaoui and colleagues (2021), the basic structure of CNN is similar to that of MLP, but there are two types of hidden layers. The second layer performs learning functions such as convolution, and the others are classification layers. The second layer performs the learning operations such as convolution and others are classification layers. (Bousqaoui et al., 2021, 3321–3322.)

Mishra, Morisetty and Sarawagi (2022) presents a study utilizing time series algorithms in production forecasting in distillate fuel oil refinery and propane blender net production. Mishra and colleagues study compares three different time series methods (Seasonal Naive method, Exponential Smoothening and ARIMA) for creating forecasts for the next two years. (Mishra et al., 2022, 4). Variations in the demand and supply of crude oils are very closely related to price changes, hence cost efficiency is key in the oil industry and oil distillation, and the importance of forecasting should not be underestimated. In this study likewise, the final result is that the ARIMA algorithm performs better than other algorithms in terms of both performance and accuracy.

The prediction accuracy and performance of the models is evaluated using RMSE, i.e. Root Mean Square Error, which is one of the most general metrics used with forecasting methods. RMSE is calculated by subtracting the observed value from each predicted value and squaring the difference. All the squared differences are added together, which form the average, and this is called MSE, or Mean Square Error. By taking the square root of the MSE, RMSE is acquired. Although in the study by Bousqaoui and colleagues, CNN gives more accurate results in terms of forecasting accuracy, its training time and energy consumption are more than double compared to the ARIMA model. The study also raised that when the model is large, it is likely preferable to utilize a simpler method such as the ARIMA model. (Bousqaoui et al., 2021, 3326–3327.)

Makridakis, Spiliotis and Assimakopoulos (2018) examined the performance and forecasting accuracy of machine learning (ML) methods and compared them to traditional statistical prediction methods. Symmetric mean absolute percentage error, or sMAPE, can be utilized to express a percentage of the accuracy of a forecast method. Percent-based accuracy can compare the accuracies of the representations of different methods, since it has upper and lower limits, moreover, it is scale independent. The lower the sMAPE value prediction model gains, the more accurate it is. Figure 23 explains the methods used in Makridakis and colleagues' study and their prediction accuracy based on sMAPE. It can be established that the most accurate methods are statistical methods. (Makridakis et al., 2018, 1, 15–17.)

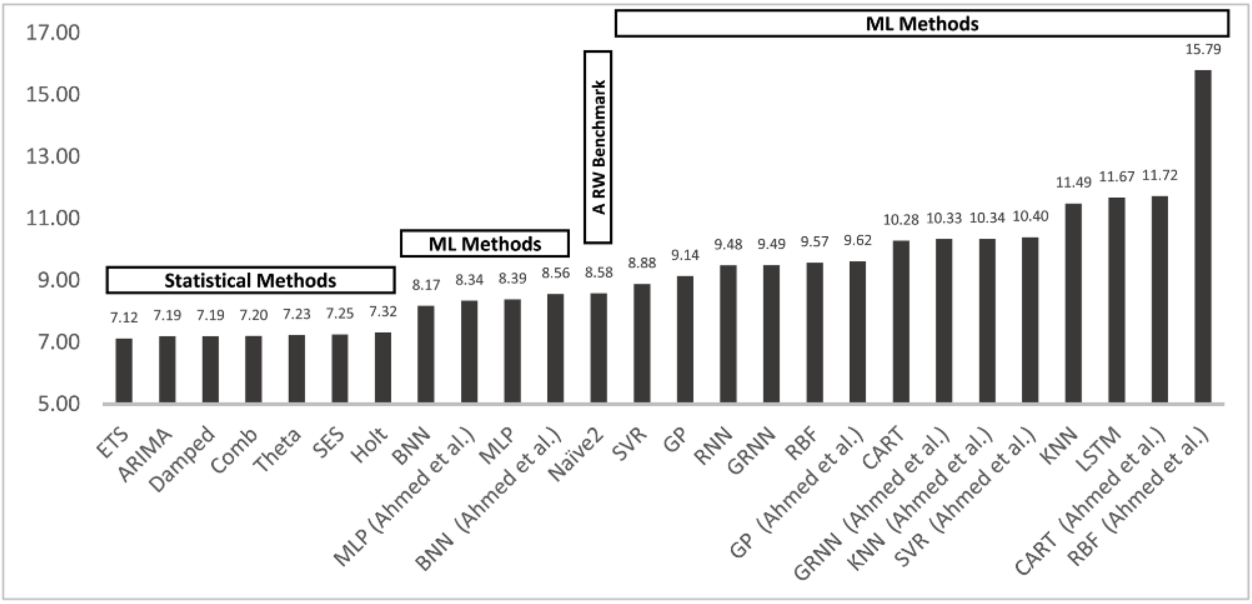


Figure 23. Forecasting performance (sMAPE) of the statistical and ML methods (Makridakis et al., 2018, 15).

According to Makridakis and colleagues (2018, 6) the Computational Complexity (CC) denotes the relative time it requires to train and extrapolate a prediction model compared to the time corresponding to the Naive method to complete the same task. CC is defined simply as follows

$$Computational\ Complexity\ (CC) = \frac{Computational\ Time\ Model}{Computational\ Time\ Naive} \tag{10}$$

It can be noted from Figure 24 that a more advanced model does not produce a more accurate forecast compared to statistical methods. When creating forecasts, the computational time used by the model is a critical factor, hence it is crucial to discover a forecasting method whose accuracy and computational time are at an acceptable level. Obviously, prediction models can be lightened in different ways, thus reducing computational time, but the computational time of ML models is however significant compared to statistical methods. Study by Makridakis and colleagues pointed out that with less computational effort, it is possible to achieve excellent accuracy, thus statistical methods are still feasible. The reasons for the ML methods underperformance were not clearly stated in Makridakis and colleagues' study. In terms of ML methods, the most critical objective would be to discover the reasons behind underperformance, in order to exploit ML methods' huge potential in the field of forecasting. On the other hand, it is good to insist that statistical methods have been studied for decades and there is a significant amount of empirical evidence. In Makridakis and colleagues' study, the accuracy of the ARIMA model has improved considerably compared to the 1982 M-competition. In conclusion, in order to improve the forecast accuracy and performance of ML models, the causes of underperformance should be defined, and empirical research data to be available. (Makridakis et al., 2018, 19.)

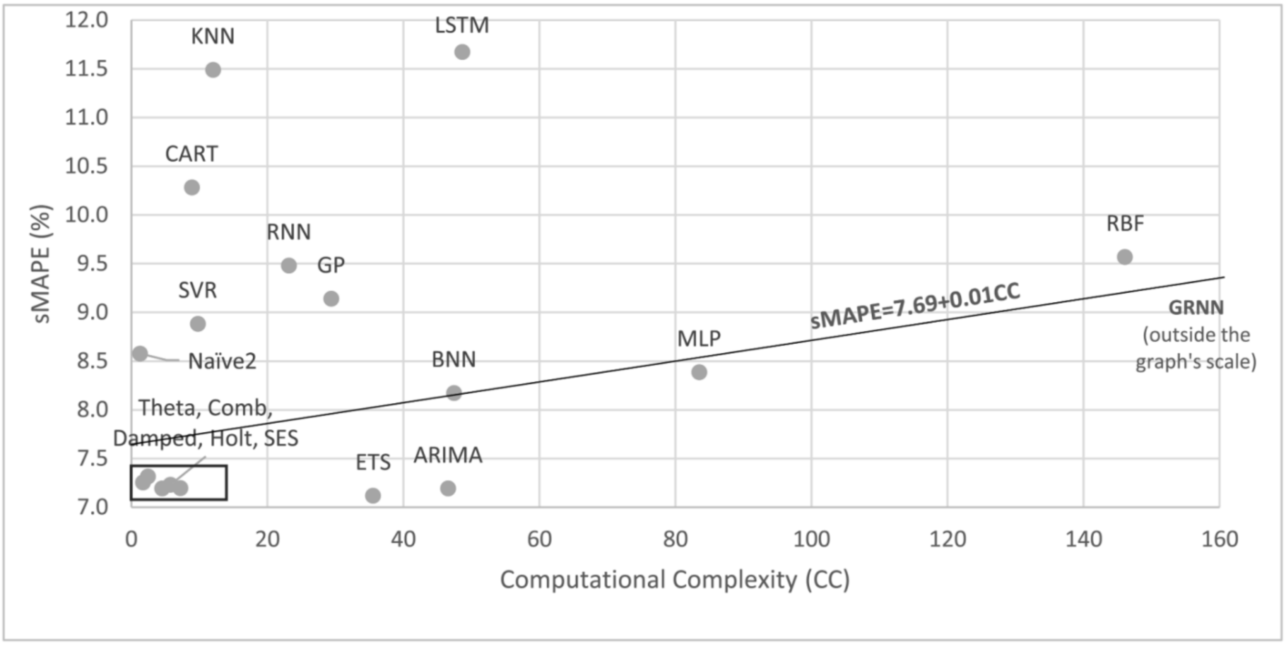


Figure 24. Computational complexity versus forecasting performance between different forecasting methods (Makridakis et al., 2018, 18).

In the former studies, the aim was to compare different time series models from the point of view of forecasting and to find the best model in terms of both accuracy and efficiency. In the aforementioned studies the performance of the ARIMA model was one of the most efficient than other time series models. Hence, there are a number of forecasting methods that utilizes history as their data source, as has been noted. Many ERP software today has features that allow historical data to be organized and combined in a variety of ways to achieve the desired outcome. Therefore it is crucial to raise the fact that historical data can also be manipulated in different ways. Software allows forecasting equations to be weighted in different ways and thus obtain the desired outcome. As a final remark, it should be pointed out that history can be utilized to produce a significant amount of valuable information, as long as it is used wisely. (Sheldon, 2006, chapter 4.)

5.4 Sales & Operations Planning Process

S&OP stands for Sales & Operations Planning, a process that allows a company to bring demand and supply into balance. This is crucial, because imbalances often result in a detrimental business and the value of the supply chain deteriorates. Sheldon (2006, chapter 4) defines S&OP as a high-performance process that bonds the handshake between operations and the demand side of businesses. S&OP gathers the essential decision-makers and experts of the company together and the goal is to produce the most cost-effective plan for several months in the future. One common frequency for the S&OP is a 12-months rolling plan, but other views can be found as well. For example, in Neste's Oil Products business unit S&OP process is a 15-month rolling plan divided into two rounds — a monthly S&OP and simpler mid-month S&OP in mid-process rotation. The S&OP process, as its name indicates, is a process which competence relies specifically on performing issues at the right stage of the process, in the accurate order, and on top of everything correct. All significant data and up-to-date information from inter alia sales, forecasts, markets, inventories, production capacity, unit outages and modifications are gathered to the monthly meeting of the S&OP process – a huge amount of information is collected together at least once every month. (Sheldon, 2006, chapter 1, 5–6; Silver et al., 2016, chapter 12.) Figure 25 displays the steps of the monthly S&OP process according to Frolov, Iliashenko and Ershova (2021, 950) towards an approved demand and supply plan which can be executed by operations.

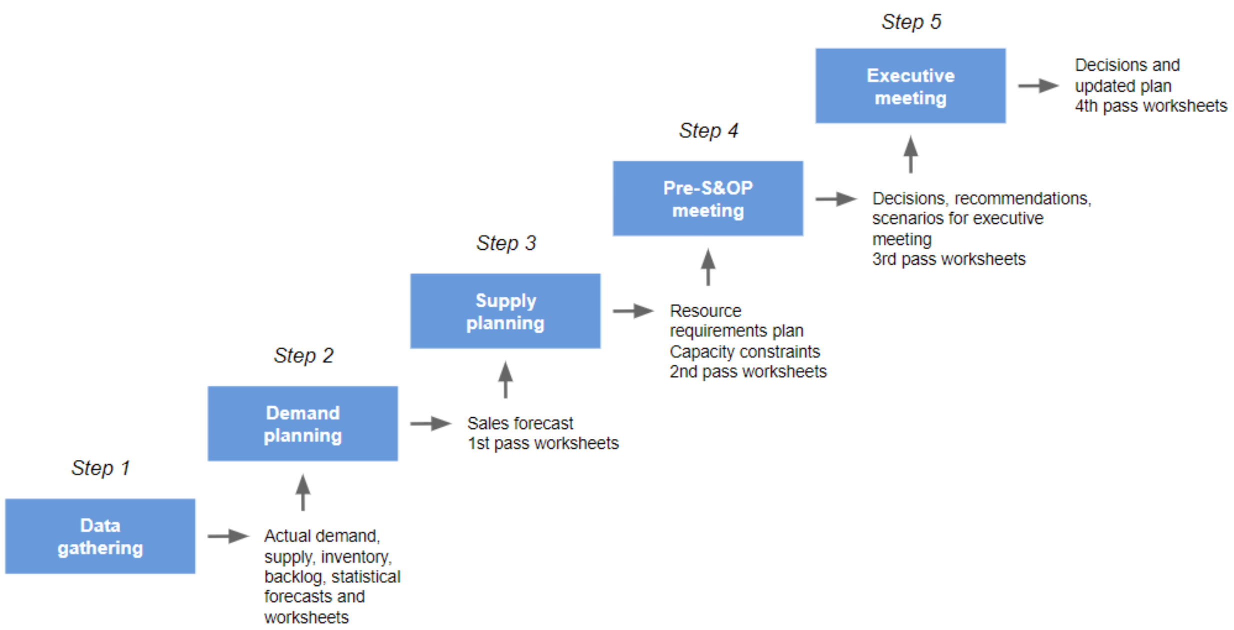


Figure 25. Sales and Operations Planning process (Frolov et al., 2021, 949, adapted).

Participants in the S&OP process can vary significantly, and the amount might be dependent, for example, due to the size of the company. However, most often the participants are the person responsible for the entire S&OP process, the planner responsible for the master production plan and the managers responsible for demand and supply. In addition, managers in charge of finances and engineering are usually required. On the other hand, an organization can be so large that the entire S&OP process can be its own operating unit – as part of the end-to-end supply chain management. Sheldon (2006) indicates that the main responsibilities of the functions of operations are low cost, quality, capacity, resilience and responsiveness. Thus, the S&OP process can be seen as the culmination of the entire potential of the operations, covering customer service, costs and inventories. In addition, the S&OP process has the potential to improve both internal information flow and collaboration within the company and external information sharing across company boundaries. The benefits of the S&OP forum are the development of cooperation and the sharing of tacit knowledge, which can be used to discuss and learn inter alia from various measures, opportunities and risks. (Sheldon, 2006, chapter 1, 5–6; Silver et al., 2016, chapter 12.)

The meeting structure plays a significant part in the S&OP process and Sheldon (2006) points out its importance. When the structure is consistent and identified to all stakeholders, it is effortless for process owners to participate prepared for the meeting when they know what is expected of them and thus are able to fill performance gaps in the plan and share their knowledge. The most important task of the S&OP process owner is to support and ensure smooth cooperation in the process. Listed below are a few of the actions and tasks of the S&OP process owner in the monthly S&OP meeting

- Monitors and executes meeting schedules
- Lead the meeting
- Prioritize actions
- Keeps attendance high
- Maintains a consistent agenda
- Demonstrates accountability at the meeting
- Ensures follow-up actions are documented and distributed

As an integral part of the meetings, various risks are also identified, such as the transfer of the production line, the launch of a new product and related marketing, or the seasonality of the product. Any new information about markets or strategic planning, for example, is important to highlight at these meetings so that it can be included in the plan at the right time and their effectiveness can be assessed. For example, the timing of the introduction of new production lines may change well from the original plan, due to various reasons – for example, parts of certain devices may have to wait longer, and the project will be delayed as a result. (Sheldon, 2006, chapter 6, 8.)

Hulthen, Naslund and Norrman (2016) present in their study a description of the S&OP process, according to which it can be described as interdisciplinary and its approach to increasing both the effectiveness and efficiency of the company. This indicates, among other factors, that from the customer perspective, the manufacturer is excellent and reliable, and the products can be manufactured with high quality, minimizing manufacturing costs. One of the most significant objectives of their study was to identify the challenges of measuring the performance of the S&OP process. According to Hulthen and colleagues there is not enough research evidence based on the identification of challenges related to the systematic measurement of the S&OP process. Hulthen and others confirm that challenges occur even in mature S&OP processes and the dismantling of even functional silos presents challenges in creating more cross-functional and process-oriented organizations. Thus it is not surprising that the scientific community emphasizes the necessity of measuring the S&OP process. (Hulthen, Naslund & Norrman, 2016, 5, 14.) Sheldon (2006, chapter 10) furthermore underlines the importance of measuring the process, a new S&OP round should always start from the evaluation of the previous plan.

Parravicini (2015) lists 12 principles which are beneficial to keep in mind when developing and implementing the S&OP process. Three of these principles are selected for this study, which are part of the literature review. The first principle is that forecast is not the goal. According to Parravicini (2015) this indicates that the goal and the forecast should not be confused – they are not consistent subjects. Mixing these together results in trying to hide the problem, rather than solving it. According to the second principle, the result of the S&OP process is a range forecast. As mentioned above, Parravicini also confirms the following that the S&OP process is a cyclical process, where the created and approved forecast is always used to create the basis for the next S&OP plan. Risks, assumptions, and opportunities are retained and stored for later reference and/or comparison. The third principle is that the S&OP process is a process of continuous improvement. (Parravicini, 2015, chapter 8.) One of the most established continuous improvement models is PDCA, which consists of four development phases and its name consists of the initial letters of each phase: P=Plan, D=Do, C=Check, A=Act (PDCA model and continuous improvement, 2020). The idea is that the organization's operations focus on process-oriented operations to serve the customer better and more seamlessly, because obstacles and tensions between different functions can be removed. (Silver et al., 2016, chapter 1.2.)

> *"Corresponding to the Finnish Standards Association SFS standard SFS-ISO 10005:2005, according to the process model shown in Figure 26, quality management system planning applies to the entire model."*

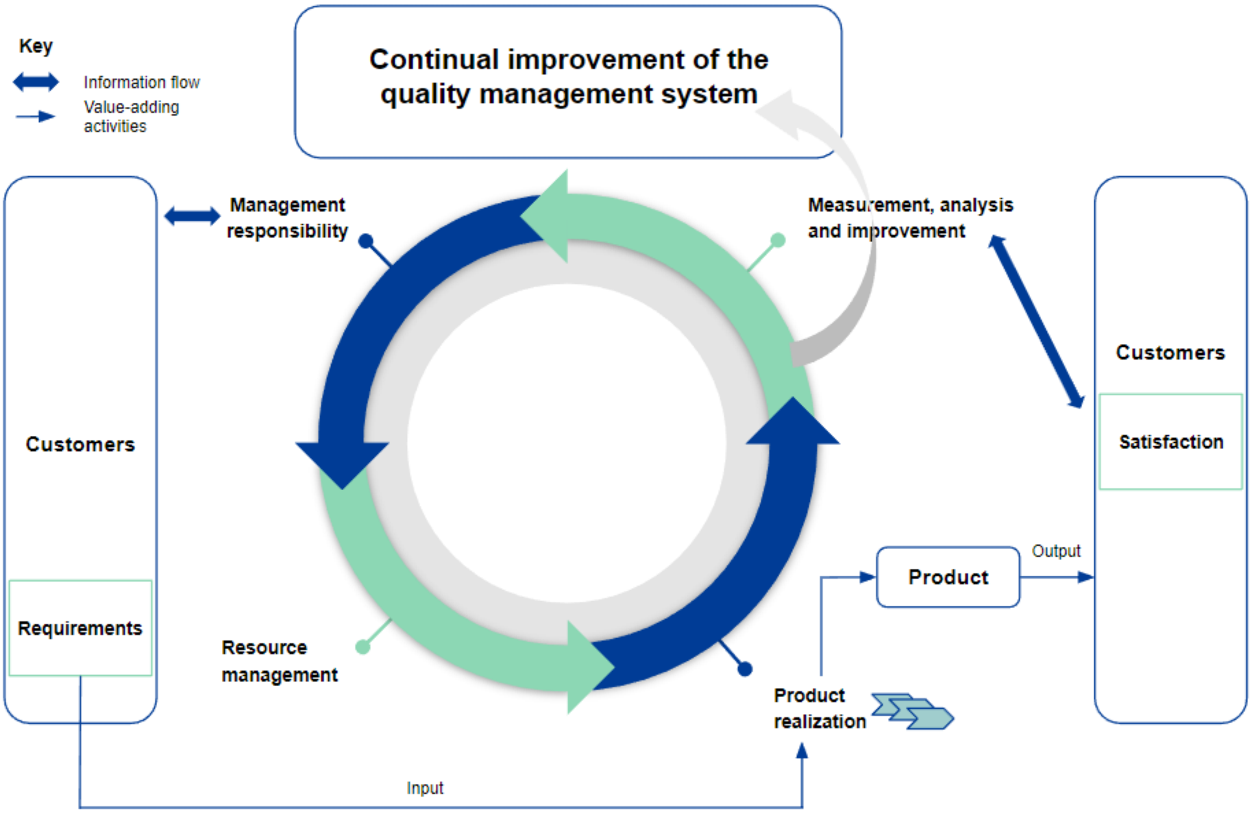


Figure 26. Model of a process-based quality management system (SFS-ISO 10005:2005, 6, adapted).

5.4.1 Short term Sales & Operations Execution

The purpose of the S&OE, which stands for Sales & Operations Execution, is to execute the S&OP plan in the most economical and optimal way. For example, the demand review and -gap reconciliation and inventory planning are included in S&OE. S&OE ensures that in the event of a disruption, for example a vessel being late, corrective actions are implemented fast and as cost-effectively as possible. The planning and execution window is shorter than in S&OP and regularly the monthly supply and sales are divided into smaller periods such as weeks and days. (Neste End-to-End Optimization, 2024.)

S&OP focuses on long-term high-level planning and optimization, while S&OE focuses on the execution of operations and addresses the subjects of real demand and supply in a shorter planning horizon – from a week to a couple of months. Tools and processes that support decision-making in different planning processes can less frequently be similar. For example, short- and long-term planning emphasizes different starting points, requirements, goals as well as implementation. As a rule, S&OP meets once a month, and this meeting frequency is not sufficient for the S&OE process to respond to operational questions for scheduling. In her article, Hippold emphasizes an interesting standpoint of Gartner's Vice President, Marko Pukkila, to exclude operational topics from S&OP meetings altogether. According to Pukkila, only when the impact of operational topics extends to break the annual production plan, they can be raised to S&OP meetings. Thus, it is recommended to organize a separate meeting for the main objectives of the S&OE process, where the focus is only on responding to S&OE topics. This enables an effective checkpoint to compare and measure the execution plan created by S&OP. All of the above aspects support the S&OE process differentiation from the S&OP process. However, rarely has the S&OE process been separated from the S&OP process into its own process. (Hippold, 2019.)

5.5 Data streams and competence in the company

The refinement of knowledge is formed on the basis of observations into various models and theories, which can be utilized in operations at both an individual and organizational level. Knowledge can be illustrated by applying different concepts such as competence, knowledge, data and information. Knowledge is insightful learning, which reflects the level of knowledge. Knowledge is formed when information is interpreted. According to Ahlavuo and colleagues (2011), knowledge is a combination of knowledge, experience, information and values. Again, information can be divided into different categories, such as tacit knowledge and explicit knowledge. Competence consists of the application of values, experience, beliefs, knowledge, expertise and the entire network of available stakeholders to solve a problem or a task. According to Ahlavuo and others (2011), information and communication streams are information transferred through processes, for example, between different organizations, groups, individuals and data resources. These streams can be one-way or two-way. Exploiting data streams correctly, as well as combining megatrends and weak signals, companies can identify changes earlier and thus observe potential opportunities to support profitable business. (Ahlavuo et al., 2011, 54, 56.)

The concept of tacit knowledge originated as early as the 1940s as a result of Michael Polanyi's development work. Tacit knowledge is difficult to define and store, because it is a skill and/or knowledge created through learning, which contains rooted assumptions and how an individual perceives and understands the surrounding reality. In order for tacit knowledge to be utilized as an asset of the company, it must be made visible - visualized as words and/or numbers, for example. Conceptual knowledge is systematic and defined, which can be represented for example, as numbers, texts, metadata, or scientific formulas. These include, for example, user manuals, operating instructions, or meeting notes. Conceptual information can therefore be processed and stored and forwarded. (Ahlavuo et al., 2011, 56–57.)

Ahlavuo and colleagues (2011) propose that companies should invest in documenting knowledge capital and exploit more experience-based capability in developing the company's operations. They also challenge for a vision and strategy to be presented exoterically enough so that everyone has the opportunity to understand what goals have been set and how to achieve them. Ståhle and Laento (2000, 28) emphasizes that 95 % of a company's data capital is tacit knowledge and only 5 % is documented. In addition, as the amount of data increases all the time, it is worth pointing out the difficulty of distinguishing the essential from the data overload. This chapter can be concluded in the proposal of Ahlavuo and others to update the expression to the present day, for example as follows:

> *” Knowledge is power when one is able to separate essential knowledge from information chaos into one's own productive activity.”*

When tacit knowledge is produced visible, it can be placed authentically as a company's asset and competitive advantage. (Ahlavuo et al., 2011, 62–65.)

6 Data collection

Literature review, official documents and instructions, and various documents are commonly used data collection methods in research. They allow researcher to collect existing data as well as previous scientific publications on their research topic from various archives, collections and data banks. The researcher should always accurately assess the use and application of the material collected by others in their research. In particular, in the use of documents made in a company, subjectivity and source criticism is always in place, because the documents are produced for a specific purpose. (Saaranen-Kauppinen & Puusniekka, 2006.)

The data search for the study literature review was implemented from Aalto-Primo, Google, Google Scholar, Janet Finna, Lukki Finna, Perlego, Theseus electronic databases and the databases of the target organization. The keywords used are listed in Table 5. Searches were performed in the timeframe from 26 June 2022 to 20 April 2024. The basic premise of the case study is that in order to increase the holistic understanding of the research phenomenon, research lives and evolves continuously. Therefore the data is collected almost throughout the study. Data search was attempted to perform systematically, and saturation utilized to inform about the adequacy of the data.

Table 5. Search keywords

Search key words	
ARIMA	Predictability
Bullwhip	Python
Cooperation	Quantitative and qualitative forecasting
CNN	Supply chain
Crude oil distillation	Supply chain management
Data streams	S&OE
Forecast	S&OP
Forecastability	S&OP process
Forecastability vs predictability	Sales and operations planning process
Forecasting	Statistical analysis
Houlihan	Statistical analysis python
Liquefied petroleum gases	Statistical forecasting methods
LPG	Time series
MLP	Time series analysis
Operations management	Time series python
Predict	

In the acquisition of material from scientific sources, the focus was on essential literature, both for references and the latest research evidence. Even though the search for information emphasized recent studies and literature, no clear limit was set for new research. As a general rule, however, most of the scientific research evidence utilized in the study is at most five years old. Special attention was conducted to the author and publisher of the material and selected material was validated for example by exploring the author further. Various sources were likewise found as a secondary source through other research. Some of the material used in the study was lent from, for example, the Aalto University library and others from a digital library, for instance Perlego. The advantage of digital libraries is certainly the effortless availability of the material, and searches can filter based on time and keyword targets, for example, which can be exploited to reduce the reference parameter and thus minimize the quantity of applicable material. Ethical principles were followed in the acquisition of material from scientific sources.

7 Implementation of the study

The objective of the study was to examine through the LPG product chain the Neste OP SCM S&OP process and the forecastability there, and to find development proposals to improve the short-term S&OP process and forecasts. The starting point of the study was an idea that a well-functioning S&OP process could produce more valuable forecasts. Thus, the company could make more profitable business. The research started by exploring multidimensionally different aspects of relevant theory, such as operations and supply chain management, and thus examined inherent into the S&OP process and definitions of forecasting and the methods applied in them. In addition to the above, expanding the basic principles of oil refining brought additional depth to the context of the study. Thus, the literature-based approach initiated a strong foundation for the study and the target was to utilize versatile literature in the research. The advantage of extensive and diverse data can be identified in its convenience in research analysis to strengthen development proposals and conclusions in study. Both traditional books and electronic libraries were employed in literature, which enabled enhanced accessibility for some works. The key words applied in the research were formed relatively simply when creating the table of contents. The keywords were collected alphabetically in an Excel file, and it was effortless to further refine them from there. Chapter 6 discussed how the implementation of data collection was performed in the study.

Yin (2018, 15) defines case study as follows:

“A case study

- *is an empirical method that investigates a contemporary phenomenon (the “case”) in depth and within its real-world context, especially when*
- *the boundaries between phenomenon and context may not be clearly evident*
- *relies on multiple sources of evidence, with data needing to converge in a triangulating fashion.”*

Thus, case study selected as a research strategy provides an appropriate starting point for an in-depth picture of the subject. (Kananen, 2013, 28, 33.) According to Yin’s definition and the complexity of supply chains, a qualitative research method is not sufficient for this study. The main limitations to utilize only qualitative methods is the definition of the research problem clearly and the solution of the research problem through a single qualitative method. A single method of research clearly fails to solve the research problems in this study. Therefore, more methods are crucial in solving the research problems, both in the analysis of the data and in the data collection. This definition alone is not adequate to explain the selection of a case study. According to Kananen (2013) the object, that is, the case should additionally be defined in the research. (Kananen, 2013, 56–59.)

In order to provide in-depth and diverse knowledge regarding the operation of the S&OP process for example, it is recommended to utilize qualitative research methods. On the other hand, for studying the variables of demand forecast, for example, historical data is crucial, applying the use of quantitative research methods is preferable. Since the data collection methods of a case study are not limited to one method, but in order to achieve a comprehensive description and reliable research, empirical data collection was implemented in this study by utilizing both qualitative and quantitative data collection methods which are presented in Figure 27.

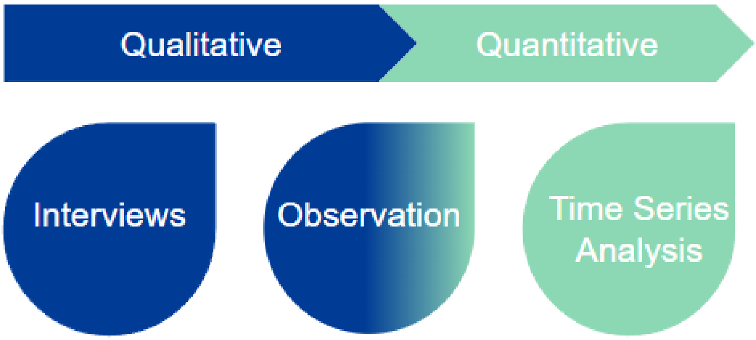


Figure 27. Research methods utilized in the study

Through interviews, experts included in the S&OP process provided comprehensive information about the current state of the process – both challenges and well-controlled entities. The objective of the study was to examine through the LPG product chain the Neste OP SCM S&OP process and the forecastability there, and to find development proposals to improve the short-term S&OP process and forecasts. Observations were applied to gather information about the functionality of the S&OP process and decision-making. The purpose of utilizing secondary data in the study was to create a holistic view of the S&OP process and related phenomena and challenges, forecasting and verification of research results. There is no requirement for a special analysis of the written material because the researcher validates her claims based on the material (Kananen, 2013, 85).

For the purpose of defining and studying variables, the use of a quantitative research method was justified. One of the advantages of the ARIMA model is that its implementation and learning is relatively rapid compared to many other forecasting methods and does not require significant resources regarding information systems. Furthermore, it is quite accurate and competitive based on its efficiency. Besides, the ARIMA model is greatly researched and utilized, which supported its selection as a quantitative research method. The thesis process is described in Figure 28.

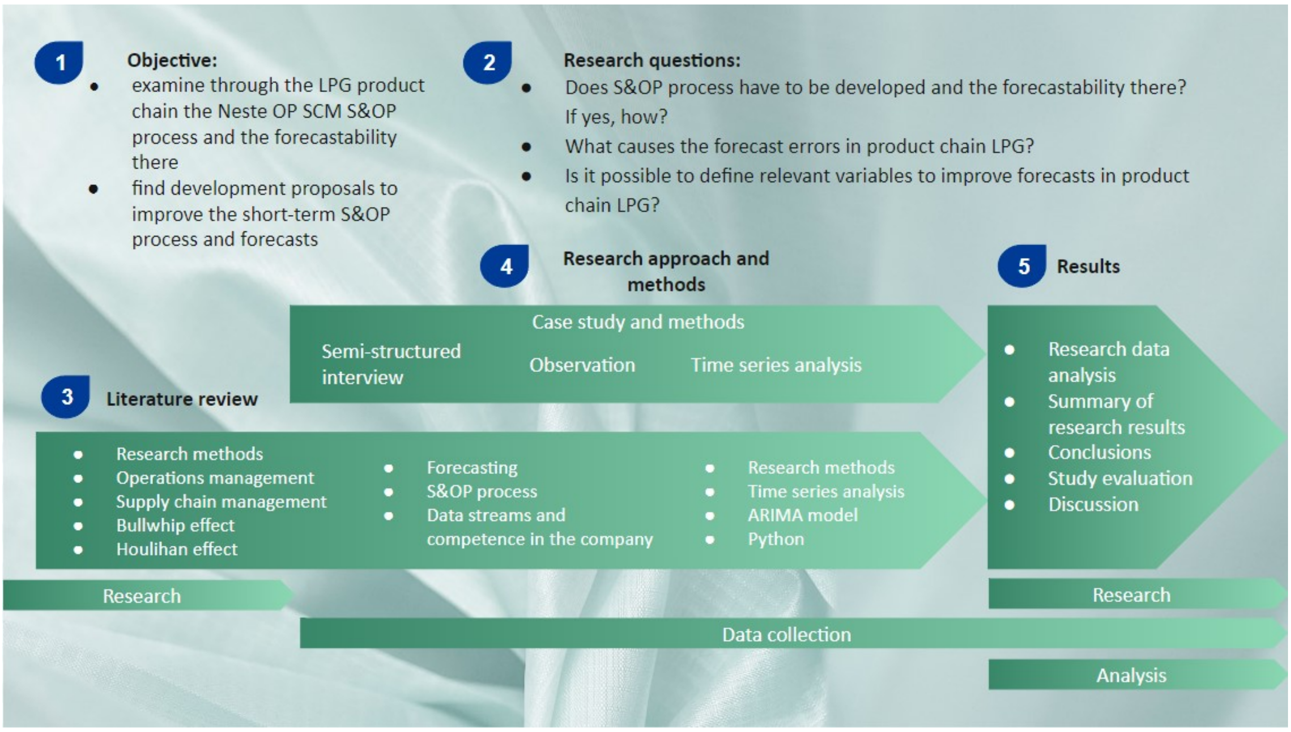


Figure 28. Thesis process

7.1 Research data and methods

This case study applied both qualitative and quantitative research methods to solve the research problems. Interviews and time series analysis were the primary sources of empirical data. The interviews were utilized to provide comprehensive information about the current state of the S&OP process – both challenges and well-controlled entities limited to the perspective of the LPG product chain. Observation was used as a supporting research method for the S&OP process, utilizing to expand knowledge of the process, especially during the most active planning phase. Observation also sought to verify the process in addition to the actions of individuals in their natural environment. The following chapters examine the implementation of the research methods utilized in the study.

7.1.1 Semi-structured interview

A semi-structured interview method was utilized in this study which is an intermediate form between an open and a form interview. In a semi-structured interview, according to Hirsjärvi and others (2009, 208), the topics are identified in advance, but the formulation of the question is not precise, and the order of the questions does not necessarily follow the equivalent pattern. The advantages of a semi-structured interview are that questions can be performed in a different order, allowing to proceed in accordance with the interviewee and it is possible to maintain the conversation pleasant from the subject's point of view. Based on the theory, eight themes had been defined in advance, which were

- S&OP Process
- Forecasts
- Liquified petroleum gases
- Refinery
- Information flow and collaboration
- Optimizing
- Chain steering
- Scheduling

In order for a researcher to increase their holistic understanding of the research problem, it is highly justified to allot it into themes in order to create information that is sufficiently comprehensive in the interviews to solve the research problem. This enabled researcher to focus on different areas more deeply with the interviewees who had the most comprehensive expertise in, for example, forecasting and the S&OP process.

The main target group of the development work is the representatives of Neste’s OP supply chain, but the S&OP process is at its best with the cooperation of many different departments. In this study, it was essential to collect knowledge from at least the following functions which are related to the S&OP process:

- Domestic sales
- Forecasting
- Logistic planning
- Operative planning
- Refining and executing production plan
- Supply and demand
- Supply chain finance
- Supply chain planning

A purposive sampling technique was applied in the selection of interviewees for the study. Based on the approach, critical cases were used for the selection of suitable individuals to represent. The rationale is that relevant participants are selected through a defined research problem that is central to the S&OP process and/or LPG production. These aim is to ensure that the areas relevant to study are covered and to ensure sufficient diversity in the criteria. Criteria applied for this study included following:

- Role is a participant in the S&OP process
- The role is related to the LPG product chain

(Ritchie, Lewis, Nicholls & Ormston, 2013, chapter 5.)

Literature review was utilized as the foundation for creating interview questions, and the questions sought to obtain answers to research questions, observe the functionality of the S&OP process in its own environment and broaden understanding of the phenomenon. A comprehensive quantity of interview questions took shape and in the pre-testing of the questions the researcher was challenged to consider the relevance of all questions to the objective of the study. In pre-testing, some of the original questions were removed, new ones were added, some questions were refined, and a section edited to be clearer. An abundant amount of questions were produced in advance so that the researcher could plan prematurely the frame of each interview to fit precisely with the expert's substance competence in mind. In the case of a semi-structured interview, not all predefined questions were expected to be presented but rather the interview was allowed to proceed spontaneously, as best as possible considering the interviewee. Therefore as a result, new subject areas arose, and several more specific questions could be examined about these new subject areas.

The interviewees were contacted in advance, and the interview pre-release presented the study with its subject, as well as contact information of the researcher in case potential interviewees essential to be in contact with the researcher and inquire about the study for further information if necessary. The pre-release about the study was emailed two weeks before the researcher had further contact with the interviewees. This aimed to give interviewees time to communicate with the researcher as well as to reflect on their own willingness to research. The researcher was afterward in contact with the interviewees to agree on the time of the interview. All interviewees were sympathetic, and interview schedules were quickly agreed. Overall, 11 interviews were agreed upon and conducted over a three-week period. Interviews were thus accumulated for the researcher three or four interviews a week.

Interviews were conducted face-to-face where possible, nevertheless some of the interviews were held remotely. Regardless of the location of the researcher and interviewee, the interviews were conducted using the Google meet tool, which was additionally applied to record the interviews for further action and analysis. The tool allowed automatic recording of the interview on the researcher’s personal cloud storage service. The application performs transcription directly, but the languages supported by the software did not cover Finnish. Therefore another tool was chosen for transcription, Microsoft Word with the Dictate feature. At the beginning of each interview, the researcher's presentation and the subject of the study, the ethical practices of the interview and the general procedure of the interview were presented. At the end of the interview, an effort was made to leave some time for the interviewee to highlight their own views and knowledge on the subject, which they considered essential in relation to the research topic. Interviews were also recorded on the phone's voice recorder through an application that served as a backup. Medium quality was selected from the application so that the entire interview could be recorded in one attempt. All applications were pre-tested to ensure that the interviews were conducted without interruption.

The interviews were scheduled between March 20 and April 6, 2023, and the total number of interviews were 11. The interview material was all 9 h 57 min and the average interview duration was 52 min 28 s. The duration of the shortest interview was 34 min 11 sec and the longest was 1 h 29 min. Prior to the start of the interview round, 10 questions were defined that were questioned to all participants. These questions can be discovered in Appendix 5. Based on the literature review presented in chapter 5 and the researcher's expertise, these general interview questions were defined as relevant to provide answers to the research questions, or they were used to obtain as comprehensive a sample as possible. Diverse themes were selected from different questions for different experts to improve holistic knowledge and understanding of the phenomenon.

The first transcribed version of the interview material was produced using Microsoft Word Dictate feature, in which the speech was transformed into text during the interview. However, rarely do people speak clearly and slowly enough, so it was profitable to listen to interviews once more and improve the first transcribed version into a more accurate format to advance the reliability of the research. In addition, the interviews applied words related to, for example, the units of the refinery, and for these the software feature was challenging to discover the correct word. Overall, software development and digitalization make it possible to facilitate the research process, for example saving significant time in transcribed interviews and speeding up analysis of results. There is no material on the exact duration of transcriptions, because it depends on various different issues such as experience, level of transcription, quality of audio in the interview, number of interviewees. On a general level, it is recommended to set aside one full working day for transcribing a one-hour interview. Transcriptions of the material started instantly after the first interview and the work continued throughout the interview round. The last transcript of the interview was completed on 21 April 2023.

After transcribed, the interview material was segmented. In segmentation, the material is separated and divided into its own factual content, i.e., segments. The purpose of segmenting the raw data, i.e., the interview material, is to form individual issues or variables into their own classes or categories and collect the material belonging to the same category from the entire interview material. The data can be classified theory- or material-based, as well as a combination of these in a case study. (Kananen, 2013, 104.) The classification simplifies the data-analysis, and this ensures that the entire interview data has been processed in the study.

7.1.2 Observation

As Hirsjärvi and colleagues (2009, 214) point out, observation is a laborious and time-consuming method, furthermore, it is not feasible to spend a great number of time collecting material in thesis-level study. Thus, observation was not the main research method in this study and observation was performed as a lighter research method. The observation was implemented as a passive observation because the objective of the study was not to change the activity, but to find development proposals and increase comprehensive information about the current state of the S&OP process and the activities of the subjects involved. One of the most valuable benefits of observation is that observation can be applied to determine whether subjects are performing as stated in the interview (Hirsjärvi et al., 2009, 212). Observation can be recorded, with the advantages of being able to observe a great amount of nonverbal activities such as gestures and facial expressions that would otherwise remain largely unobserved (Saaranen-Kauppinen & Puusniekka, 2006). However, the use of recordings was not considered essential for this study, because more than half of the participants in the meetings were generally remote and the cameras were turned off. In addition, nonverbal activity was not perceived to provide answers to the research questions themselves, therefore it was justified to consume the resources in other areas of the study.

An observation diary for providing the research method was created in advance in Excel, the structure of which can be examined from Appendix 6. The table was used to facilitate the observation of the implementation phase, the aim was to provide for the observer the opportunity to focus on the observation itself as much as possible during the execution. Simultaneously, this activity was aimed at increasing the reliability of observation. The observation diary is not published as a supplement to the study because it contains confidential information about the client. The purpose of the observation was to validate interviews, as well as the functioning of the S&OP process and to compare it with existing process descriptions.

In the observation, attention was given to the distribution of speeches among the participants in the meetings, in order to investigate whether different roles have a different influence on the S&OP process. In the table, subjects were defined by numbers, making it relatively easy to calculate the number of speeches by different subjects at the respective meeting. In the column 'Number', the number corresponding to the subject in question (applied numbers between 1 to 20) was entered in a new row when the subject spoke in the meeting. Thus, it was possible to automatically set up the calculation of the speeches in the column 'Number of speeches' for each subject separately, in addition to the total number of speeches in different meetings. The 'Notes' column was used to write various comments and remarks. The presence of different roles in the meetings was also recorded in the table. A pull-down menu was created to select a subject's status from three different options: present, remote, or absent. The purpose of the presence status was to clarify whether a person's interaction changes whether they are physically present at the meeting or not. During the analysis phase, data from the observation diary were grouped and combined for the purpose of summarizing the observation results.

7.1.3 Time series analysis with Python in Google Cloud Vertex AI platform

Time series analysis was selected as the quantitative research method for the study based on the researcher's expertise, literature review and empirical data from the semi-structured interview in order to obtain answers for the research questions. Time series analysis is a commonly applied research method, and the ARIMA model has been utilized in demand forecasting since the 70s. When considering a suitable statistical software platform for the implementation of the ARIMA model, it became clear rapidly that there are other options for a low-level user interface than SPSS. Google Vertex AI Workbench is a Jupyter-based machine vision-based platform which can be used to implement, for example, a forecast model based on time series – from data management to forecasts, thus covering the entire process. With the help of built-in AutoML, the data can be studied, a forecasting model can be developed, and its effectiveness can be evaluated. After the evaluation, the forecasting model can be implemented and utilized to support decision-making in the supply chain. In addition, the environment is scalable, creating beneficial solutions for businesses. (Google Cloud, 2022.) The selection for the ARIMA model implemented with Python in Google Cloud Vertex AI Workbench environment, was particularly supported that Python is a free, open-source programming language. Python has significantly increased its popularity as a tool for statistical analysis. In addition, cloud-based environments based on machine vision with data processing and learning models create very competitive conditions for companies to produce statistical analyzes in prompt. In conclusion, the implementation of the ARIMA model with Python is not a commonly used method in theses. Thus, the starting point was to present an alternative technique to perform time series analysis to the commonly used SPSS method. The review of Python's code structure and various commands has been excluded from this study, therefore those will not be reviewed. Scripts from Gupta’s (2021) work, as well as notebooks published in the Kaggle community, were used as a reference or an example for the use of Python codes applied in this study. Kaggle is one of the largest communities of data scientists and machine learners with millions of users around the world. In addition, the scripts used in the research have been reviewed together with the client's data scientists.

The ARIMA model can be built effortlessly with Python, for example in the notebook environment, and is thus useful compared to, for example, the SPSS tool. For different statistical analysis, tailored programming library packages are available, which can be implemented in notebook with only a couple of code commands. Statistics Finland produces various databases, that can be retrieved from the API interface in formats such as .xlsx, .csv or JSON. In this study the Statistics Finland's free-of-charge databases for the domestic sales of petroleum products was utilized as dataset for ARIMA model. The search parameters of the table, i.e. the variables, were the monthly-based domestic sales of LPG (tons). As a result of the search, Table View 1 was selected and the table was loaded in comma-separated and titled .csv format. The data required to yet preprocess by removing the unnecessary information in Excel, in order to facilitate further refinement in the notebook.

Input data was uploaded in the Jupyter notebook programming environment. Data processing started with pre-processing and importing libraries in accordance with Figure 29. To run the script and visualize the data, a variety of programming libraries are required, such as NumPy (Numeric Python), Pandas (the basic library for data analytics) and the Statsmodel library, with tools for building ARIMA models, for example. This chapter does not describe all Python scripts used in the study. The complete Python code applied in the study can be examined in Appendix 7.

```
[1]: from datetime import datetime
     import numpy as np            #for numerical computations like log,exp,sqrt etc
     import pandas as pd           #for reading & storing data, pre-processing
     import matplotlib.pylab as plt #for visualization
     #for making sure matplotlib plots are generated in Jupyter notebook itself
     import statsmodels.api as sm
     %matplotlib inline
     from statsmodels.tsa.stattools import adfuller
     from statsmodels.tsa.stattools import acf, pacf
     from statsmodels.tsa.seasonal import seasonal_decompose
     from statsmodels.tsa.arima.model import ARIMA
     from statsmodels.graphics.tsaplots import plot_predict
     from sklearn.metrics import mean_squared_error, r2_score
     from matplotlib.pylab import rcParams
     rcParams['figure.figsize'] = 10, 6
     import seaborn as sns
     pd.set_option('display.max_columns', None)
     pd.set_option('display.max_rows', None)

[2]: df = pd.read_csv("Domestic_monthly_sales_01_2017-09_2023.csv")

[3]: #path = "Domestic_monthly_sales_01_2017-09_2023.csv" #For local
     path = "Domestic_monthly_sales_01_2017-09_2023.csv"
     dataset = pd.read_csv(path)
     #Parse strings to datetime type
     dataset['Month'] = pd.to_datetime(dataset['Month'],infer_datetime_format=True) #convert from string to datetime
     indexedDataset = dataset.set_index(['Month'])
     indexedDataset.head(5)
```

Figure 29. Programming library import and start of preprocessing the imported dataset

Next step was to clean and preprocess the imported data. In the time series process it denotes separating the time series into its components – trend , seasonality, and residuals. Decomposition simplifies the visualization of the series' components and evaluates its stationarity. Figure 30 displays the seasonal additive decomposition of this case study dataset. In the case of monthly data, the value 12 is used for the period (Chase, 2013, chapter 7).

```
[5]: decompose = seasonal_decompose(df['#Tonnes'],model='additive', period=12)
decompose.plot()
plt.show()
```

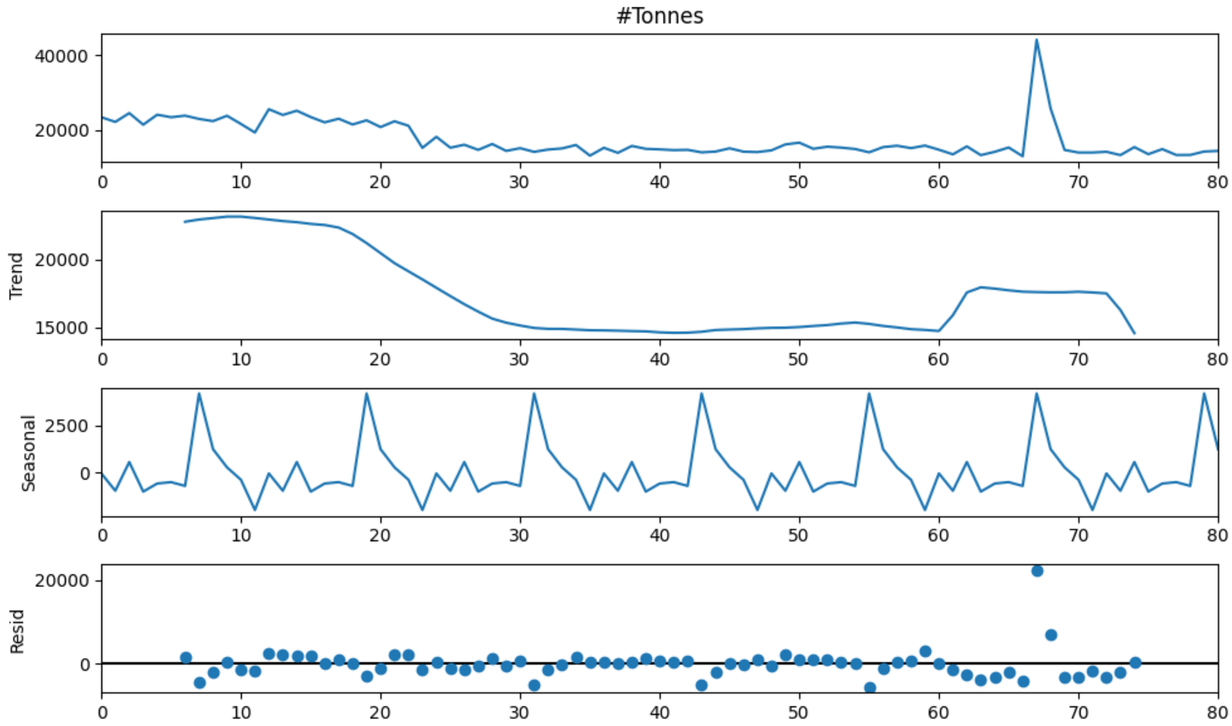


Figure 30. Seasonal decomposed dataset with additive model

Based on the previous decomposition, it can be visually stated that the trend and seasonal component exists in the series. However, this is not always directly visible, hence it is valid to apply statistical tests when evaluating the properties of a time series more. The stationarity of a time series is commonly tested by the Dickey-Fuller test (DF-test) or the Augmented Dickey-Fuller test (ADF-test). The stationarity of the time series was tested in the study applying the ADF-test, in which case the null hypothesis and the alternative hypothesis were utilized. If the p-value is less than the significance level 0,05; the null hypothesis can be rejected. Thus, it can be assumed that the time series has a unit root (p-value ≥ 0,95) and conclude that the process is only weakly stationary or non-stationary. (Auffarth, 2021, chapter 5.)

The script for performing the ADF-test is explained in Figure 31. In this function, autolag='AIC' is used to automatically determine the lag length and it will choose the number of lags which generates the lowest AIC (Seabold, Skipper & Perktold, 2010). From the ADF-test results, few assumptions can be discovered. The test statistic of -4,700490 indicates the presence of a unit root, and the p-value is 0,000084 which is significantly lower than the common significance level of 0,05 (Critical value 5 %). Based on the above, the null hypothesis can be rejected and assume the time series is stationary with 99 % confidence.

```
[8]: #Perform Augmented Dickey-Fuller test:
print('Results of Augmented Dickey-Fuller Test:')
dftest = adfuller(indexedDataset['#Tonnes'], autolag='AIC')

dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','Lags Used','Number of Observations Used'])
for key,value in dftest[4].items():
    dfoutput['Critical Value (%s)'%key] = value

print(dfoutput)
```

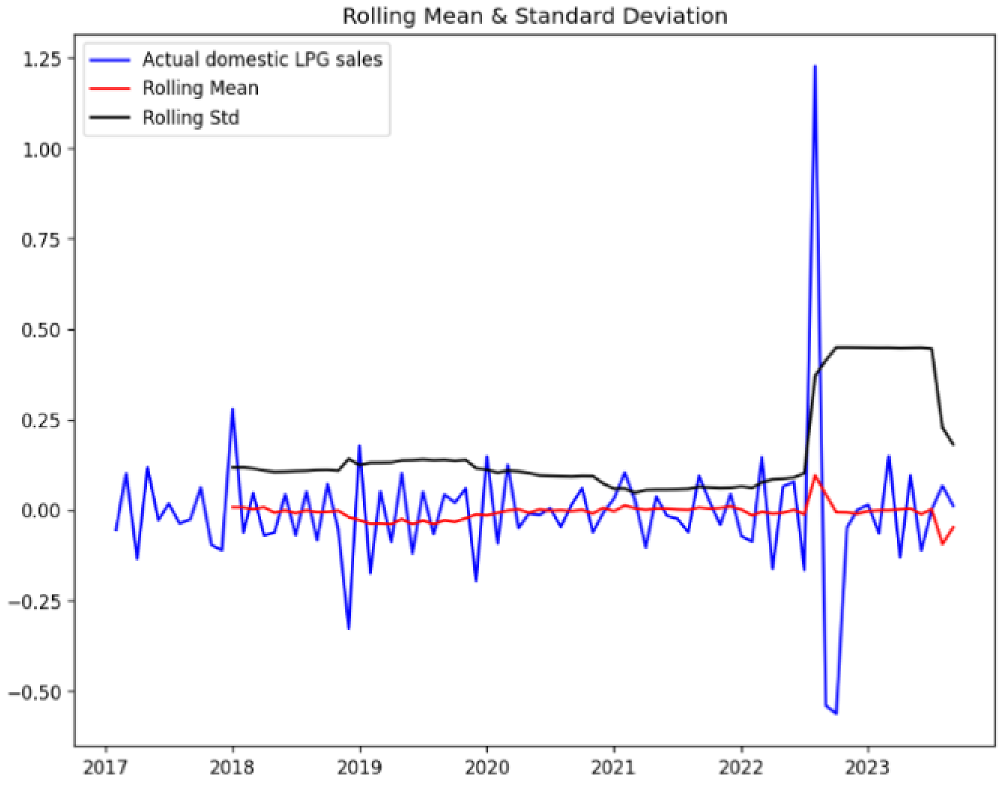
```
Results of Augmented Dickey-Fuller Test:
Test Statistic                  -4.700490
p-value                          0.000084
Lags Used                        0.000000
Number of Observations Used     80.000000
Critical Value (1%)             -3.514869
Critical Value (5%)             -2.898409
Critical Value (10%)            -2.586439
dtype: float64
```

Figure 31. Augmented Dickey-Fuller test attempt 1 using Python to evaluate test set stationarity

Based on the above, it could be assumed that the dataset does not require higher order differencing, and directly could be shifted to the selection of the ARIMA model parameters. However, various manipulations are performed to remove the trend from the dataset. These can be reviewed from the Python Input scripts in Appendix 7. Figure 32 explains the final ADF-test result of the last run. To achieve stationarity, the dataset was applied through following data transformation for removing the trend

- log scaling
- log scaled minus moving average
- removing NaN (Not a Number) values.
- time shifting

By applying the previous transformations, it denotes that in ARIMA, the value for term d = 1. It can be established that the rolling mean has simply small variations. Larger shifts occur at a point with an exceptional value relative to the time series, therefore a small trend can be observed. In the original dataset, this was an exceptional, single month sales spike. The results of the ADF-test statistic have decreased and are less than the 1 % Critical value, therefore the dataset is stationary with 99 % confidence. (Banerjee, 2020a; Chatterjee, 2018.)




```
Results of Dickey Fuller Test:
Test Statistic                -6.763206e+00
p-value                        2.758574e-09
Lags Used                      3.000000e+00
Number of Observations Used    7.600000e+01
Critical Value (1%)           -3.519481e+00
Critical Value (5%)           -2.900395e+00
Critical Value (10%)          -2.587498e+00
dtype: float64
```

Figure 32. The 4th attempt of the ADF-test to evaluate the dataset stationarity

The definition for the order of differencing continued, to ensure the valid order is applied for the time series. The dataset was tested by both methods (AFC and PAFC) because AFC does not apply in all cases, as we have stated in chapter 4.2.1. Figure 33 exhibits the AFC and PAFC plot results with first order differencing. The results for the log-modified original series exposed the series' plots were strongly correlated. This generally indicates that the series requires a higher order of differencing. Thus, first order differencing was executed. From the AFC pattern, instantly can be discovered during the first lag, the value quickly drops to the negative side. This usually occurs because the non-seasonal differencing reduces autocorrelation. The following can be considered a rule of thumb for over-differencing: If lag – 1 is more than –0,5; 0 or negative, the series does not require a higher degree of differencing. (Chase, 2013, chapter 7.)

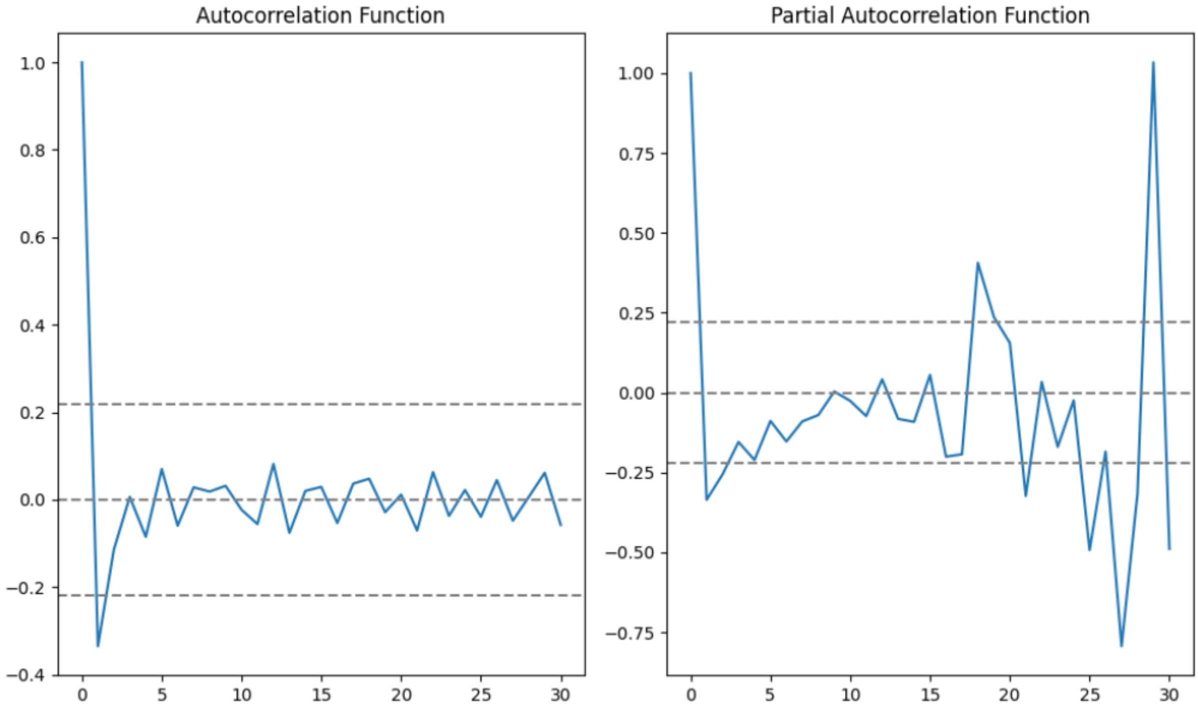


Figure 33. ACF and PAFC plots with first order differencing

Tentatively it showed the model might contain an AR(1) or even AR(2) term, since 1 plot is outside from the 95 % the confidence interval, from plot 2 onwards the AFC plot remains within the limits. Based on the ACF and PACF plot, testing of several ARIMA models was necessary to identify the best forecasting model.

Next, the evaluation of different ARIMA models was implemented, where different model options were executed in the notebook and their results were compared. This aimed to find the best possible ARIMA model for the dataset of this case study. The main characteristics on the basis of which the goodness of the models was evaluated are presented in chapter 9 in Table 6. The resulting parameters are numerous, therefore the most relevant parameters have been selected in the table to validate the selection or rejection of the model. One of the key parameters were RSS and AIC and minimizing the values was stepwise search for ARIMA model evaluation.

Residuals of selected models were examined by an ACF-test to ensure that the density plot of residual errors reflects white noise. Based on the above analysis, the best model was chosen, based on which a forecast for the series was created. Once the suitable parameters for the ARIMA model had been selected, the next phase was model fitting to check whether it fits the data.

Model evaluation can be done for example based on MSE, MAE and RMSE values. Model was evaluated based on RMSE values which is one of the most general metrics used with forecasting methods.

8 Research data and analysis

Each data collection method has its individual analysis method, and this creates additional challenges to the researcher from the point of view of data management. Data analysis can be accomplished in several ways and there are no precise rules or restrictions, which is especially evident in the analysis of qualitative data. (Hirsjärvi et al., 2009, 223–225.) A sufficient amount of data in a case study is often when the data starts to repeat itself, which is called saturation. An additional sign of a sufficient amount of material is evidence, i.e., the phenomenon can be presented reliably. (Kananen, 2013, 79.) Chapter 8.1 examines the analysis of qualitative data, how the data has been collected and utilized for this study. The quantitative data analysis, collection methods and data utilization is covered in chapter 7.1.3, because in time series analysis the analysis, testing, making hypothesis, modeling and so forth is the core for the research method. Thus, time series analysis, research data and analysis are incorporated into the research implementation phase. The results of the quantitative method are discussed in chapter 9.

8.1 Qualitative research data analysis

Qualitative research data analysis is frequently utilized for understanding and explaining the research data, to create conclusions reliably. Analysis is a large-scale and complex process. It can be feasible with a good strategy and a consistent approach to work. From the point of view of the reliability of the study, it is paramount to ensure the data has been carefully processed in order to establish reliable conclusions. (Hirsjärvi et al., 2009, 221–223.) In this study, the interview material was recorded on two different devices, transcribed twice, and at the same time reviewed and supplemented the data. Afterwards, the transcribed material was categorized according to predefined themes and the data identified for the same theme was combined. This ensured that the entire interview material was reviewed in the study.

The interview process started by validating the interview questions by pre-testing them. Validation aims to reduce various disturbances in the interview situation and minimize ambiguities and misunderstandings arising from the questions. Thus, it is possible to make the interview as smooth as possible, both from the perspective of the interviewer and the subject. Finally, through validation it is possible to improve the quality of the data and the reliability of the study. Preliminary testing was conducted based on one person. The research questions were given to the pre-tester and after a couple of days the questions were reviewed together and openly discussed the interview questions and corrective actions were taken to improve, for example, the understanding of the questions.

It is not precisely determined that the number of interviewees is sufficient, because the case investigation is valid only in its own context and a particular case can only be produced once in the circumstances and in the environment. In order for statistical methods to be applied, sampling must be performed randomly. The purpose of this is to provide an equitable opportunity for each unit within the population to be elected. Based on the above, it can be noted that the number of interviewees is always determined on a research basis and the selection of subjects is thoughtful and not random, unlike in quantitative research. Thus, statistical methods such as sample representability or sampling ratio cannot be applied in this context. This study interviewed 11 people covering the S&OP process for the LPG product chain for 91,7 % of the target population. The selected persons were actual members of the operations, and they were found to be provided with the best possible information in terms of the phenomenon under the study. This is termed discretionary sampling and the method elite sampling. Thus, discretionary sampling can be stated to be comprehensive. (Kananen, 2013, 94–95; Nummenmaa, 2021, 65; Saaranen-Kauppinen & Puusniekka, 2006.)

The researcher was interested in the transcribing phase to make a comparison of whether the dictate feature of system software, such as the Dictate feature in Microsoft Word mentioned in paragraph 6.1.2, would be beneficial in the study in terms of time management and whether transcriptions can be performed faster than producing a full text. Among all 11 interviews, the researcher drew four interviews, to which the time consumed on transcribing was measured. Most of the transcriptional work was paused in order to maintain the high quality of the material. The break time was not included at the time of the transcription. The number of words in the transcribed interviews varied between 4304 and 10472 words and the layout of all transcribed interviews repeated the same pattern in order to be comparable with each other. Based on the sample, the following conclusions were obtained: it takes about 260 minutes to write an interview lasting about 53 minutes. The average number of words in the Finnish language is about 7260 and nearly 13 pages are formed with applied settings. Based on these, approximately 4,9 hours can be calculated for the transcription of an hour's interview. In general, it is beneficial to reserve one full working day for the transcript of a one hour-long interview. Based on the trial in this study, it can be concluded that the Microsoft Word Dictate feature facilitates transcription and can save almost 30 % of daily working time.

The purpose of the observation was to validate the topics emerged in the interviews – to determine whether subjects are performing as stated in the interview. In addition, S&OP process descriptions and other relevant internal documents were reviewed to verify that the operations are as described, and the documentation is up to date. The distribution of speeches among the participants in the meetings were under examination, in order to investigate whether different roles have a different influence on the S&OP process. A calculation was created on the observation table in the background so that the calculation of the speeches was as far automated as possible. The purpose was to increase the reliability of the research data. During the analysis phase, data from the observation diary were grouped and combined for the purpose of summarizing the observation results.

9 Results

The objective of the case study was to examine through the LPG product chain the Neste OP SCM S&OP process and the forecastability there, and to find development proposals to improve the short-term S&OP process and forecasts. The research work began by deep diving into theoretical themes, through the top level of operations management, towards supply chain management, approaching the S&OP process. Another approach towards the S&OP process was forecasts and their usage in decision-making. Through the theory of forecasting, a third research method was initiated quickly, a time series analysis, which was selected for the study in the middle of the research process.

> *"I have to say that mainly we will get in time, in a way the best information of that moment will be brought into the S&OP. But the problem is that information changes really fast, or when topics occur really fast in the markets or at the refinery, then in a way it affects it."*

In general, based on interviews, the best possible information for a given time is received in time for S&OP. However, the problem is that there can be changes in the market and the refinery can change in fast frequency and the information becomes outdated fast. This is especially emphasized in short-term planning, Scheduling and the S&OE process. A solution to this could be to develop simpler optimization and simulation models in which plans could be updated faster based on changed data. If necessary, scenarios can be implemented with these models, which require less computing power, faster and with fewer resources. The most important topic would be, to evaluate the changed conditions with easy modeling, which could be applied in decision-making on the implementation of the new production plan. The mid-month S&OP that is currently in use isas well laborious and time-consuming.

> *"Different so-called input data occurs too late. In particular, the discrepancy of inventories in schedule has now emerged, which has had significant effects on middle distillates."*

The optimization time utilized for the S&OP model is not precisely defined, which means that it depends occasionally on how long it takes to finalize the runs. If the model has a lot of errors, it takes a lot of time to discover them, which reduces the time spent running scenarios, for example. Efforts have been made to respond to this by increasing resources, for example. The development and maintenance team of the model will be present when S&OP is ongoing. In addition, there is an effort to increase the responsibility of supply chain planners when it comes to running scenarios. If changes are required to apply to the model, then the implementation of the scenarios can be accelerated. Thus, it can be assumed that by reducing errors in the model input data, the cost-effectiveness of the S&OP process can feasibly be improved. There are some performance metrics used in the S&OP process. Generally, they are applied for reporting the major differences in terms of purchases, sales and inventories. The manual reporting tool was excluded from the study because of an ongoing development project related to it.

Appendix 3 presents the current S&OP process description with a few points' delineation, as they contained the company's sensitive information. The omitted items do not add much value, mainly by using a few items to refine the steps in the process. The interviews revealed the S&OP process is partly unclear, who is responsible for which area and the schedule of various procedures in the process was not clear in all respects. The review of the S&OP process should be increased so that the clarification and understanding of participants' roles and responsibilities are clear. There are aconsiderable number of stakeholders related to the S&OP process, hence a cross functional description of the process might be in order. The current S&OP process description in Appendix 3 was last updated in October 2019, and some of the practices have changed in some respects, therefore the process should be updated and regularly evaluated. The best method to implement an update is to continually improve the process, then the update will be done regularly. Above all, it will be implemented.

Observation was executed between 23.3.20203 and 31.3.2023, with the official month S&OP running. From the occasion, the S&OP input meeting, daily iteration meetings and the official S&OP result meeting were selected as objects for observation. While S&OP is running, the same meeting room is reserved for the entire time and the observation was selected to be executed in the meeting room present. S&OP scheduling is pre-calendared, therefore it can be easily checked in what phase of the process is ongoing and what data is required in the files or planning model before the Input data meeting. In general, it was possible to execute the observation in nine meetings. In the target organization, English and Finnish are used as the official languages, hence the observed meetings were conducted in English. Generally, Finnish was applied as the language of the observation diary. The meetings were conducted in hybrid form, with some of the participants physically present and others remotely.

The objective of the observation was to validate the topics that emerged from the interviews, i.e. to validate the S&OP process, whether subjects are performing as told in the interviews. In addition, the S&OP process descriptions were examined to verify that the operations are as described, and the documentation version is the latest. Process descriptions are secondary data, that is, not primary data produced by researcher. The distribution of speeches among the participants in the meetings were under examination, to investigate if different roles have different influences in the S&OP process. A calculation was created on the observation form in the background, hence the calculation of the speeches was automated as much as possible. This was aimed to increase the reliability of research data. As a result, comparable calculation data was obtained by four meetings, based on which the summary of the distribution of speeches was formed.

The S&OP round starts with the Input meeting, where sales (term and spot), purchases, refinery restrictions and units' yields and inventories are reviewed in accordance with the agenda, i.e. the status of the data to be entered in the planning model. In other words, all the possible data required to start running the new plan. Production planners then start creating a production plan for the refinery for the next 15 months. Several data must be updated and/or integrated into the planning model, so that the latest data exists in the production model and the new plans are also based on the latest data in order to make the plan as accurate and realistic as possible. As a result, forecasts for the coming months will improve, data can be relied on and data from the planning model can be used to support decision-making.

Generally, the official S&OP lasts about a week. In the daily iteration meetings, the current level of the plan is reviewed and how far the production planners have been able to run the upcoming monthly plan forward. This can only be achieved after all the essential input data has been integrated into the model. The first iteration meeting was delayed because not all relevant information had been integrated into the planning model, for example the refinery inventories were still missing in the model. In general, during S&OP iteration days, information is updated and shared very actively to start model runs as quickly as possible. Information is shared, for example, in self-calendared meetings, in separate calls and on chat channels. Iteration meetings repeat the same agenda – product chains, inventories, purchases, restrictions, etc. are reviewed according to the agenda and discuss whether the situation corresponds to the view of the supply chain planner. If someone has something to point out or update, these will be noted at this point and the necessary changes to the model will be agreed. The observation diary in S&OP day 4 highlights a significant topic, with a group of 10 people working full days in the light of false S&OP input data. It turned out that errors related to inventories had been detected in the schedule model, on the basis of which the S&OP production plan already made could not be utilized as such, but major changes would have to be made to the model before further progress could be made. This significantly increased the working time spent on the S&OP process for many experts and, for example, the next iteration meeting had to be moved forward.

In the S&OP results meeting, the most important results are discussed among a larger group of stakeholders. The results meeting starts by reviewing the most crucial results, the lessons learned related to the S&OP continuous improvement and the highlights of the S&OP round. After these, each product chain is reviewed one by one by the supply chain planner. Finally, general topics can be reviewed through such as the market, other commercial or general topics. Figure 37 presents the percentage of the total number of speeches used by the participants in S&OP meetings. The objective for the distribution of speeches among the participants was under investigation to examine whether different roles have a different influence on the S&OP process. From this small sample of 4 meetings, no significant or generalized conclusions could be drawn about the influence of individuals. Consequently, in this study, this distribution of speeches is not given much weight.

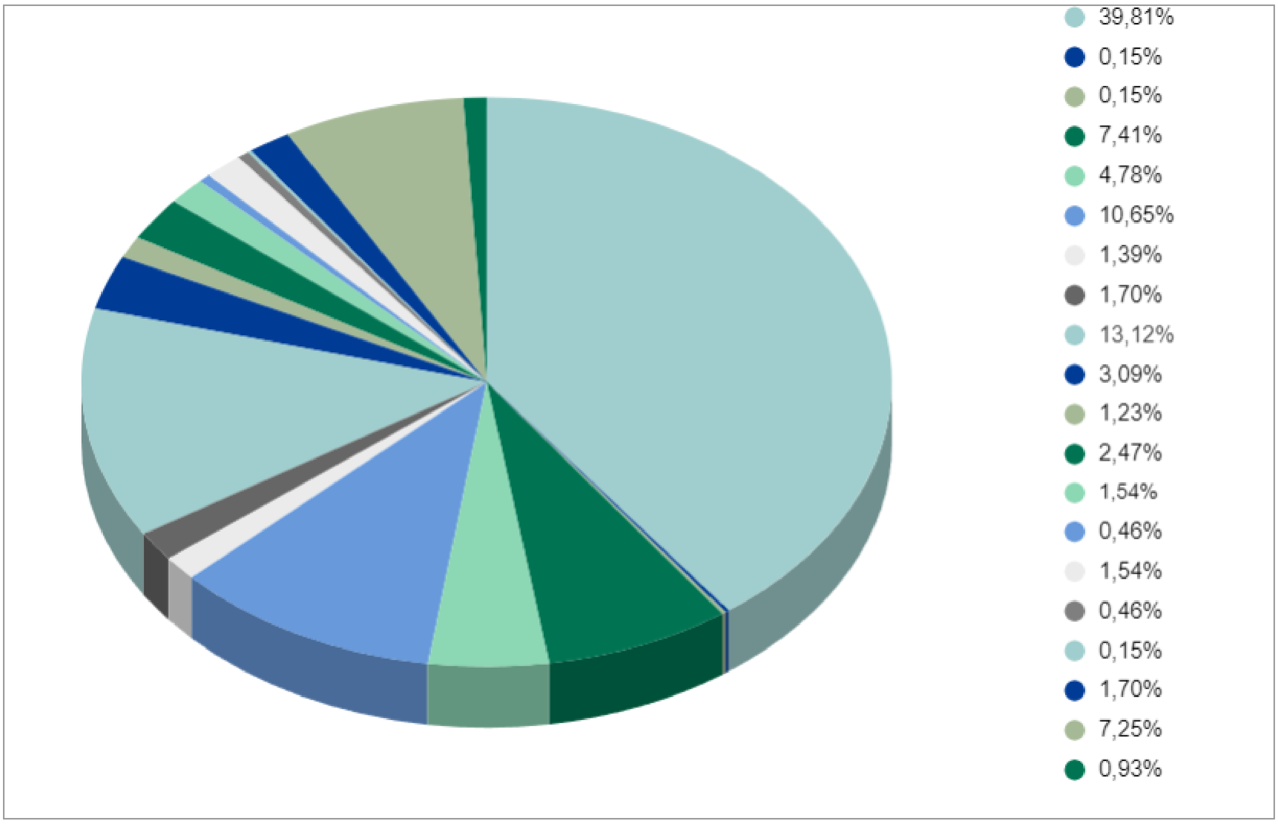


Figure 34. Distribution of speeches by participants in the S&OP meetings in the period 23.3.2023–31.3.2023

Originally, the intention was to utilize the ARIMA model in the SPSS environment for time series analysis. However, during the study it was revealed that the client has an environment more suitable for the business, which made it extremely reasonable to apply it. Therefore, the study presents an alternative technique to the commonly used SPSS method for implementing time series analysis. Furthermore, Google Vertex AI as a platform enables developers and companies to build, train and deploy AI and ML applications in the cloud (Google Cloud, 2023). Based on the empirical semi-structured interview, the results showed that the demand for LPG and actual sales are one of the most essential variables for improving forecasts. This was evident in a total of 63 % of the interviews. Thus, historical actual sales data were chosen as variables to forecast future sales based on historical data. The time series analysis was executed in the Google Vertex AI environment with Python.

In the case study, multiple different ARIMA models were examined based on the applied dataset. The dataset was decomposed and manipulated through several steps to remove the trend from the time series and convert it stationary. To achieve stationarity, the dataset was applied through several data transformation (log-scaled, log-scaled minus moving average, removing NaN, time shifted) for removing trend.

When time series was transformed into stationary, a comparison of the ARIMA models was performed to identify the most beneficial forecasting model for this dataset. The comparison for evaluating different ARIMA models is presented in Table 6. Ones of the most significant performance statistics in evaluating the goodness of the ARIMA model are RSS, AIC and Ljung-Box. RSS measures the variance of the value of the observed data compared to the predicted value according to its regression model, which indicates whether the model fits the actual dataset or not. The goal is to obtain as low a value as possible. Zero indicates in practice that the model is perfect. AIC can be applied to determine which of several models is most likely the best model for a particular set of data. Therefore AIC-points can't be applied with different order of differencing, since one data point is lost through each order of differencing. Ljung-Box is a t is a statistical test that determines whether the residuals are independent. According to the null hypothesis, the residuals are independently distributed. If the likelihood value is above a significant level 0,05, residuals are independent and the model fits well. (Auffarth, 2021, chapter 5; Nguyen et al., 2023, chapter 10.)

Table 6. Different ARIMA models evaluation based on AIC, RSS and Ljung-Box test parameters

ARIMA model:	AIC:	RSS:	Ljung-Box:
ARIMA(1,0,0)	-43.696	2,5109	0,65
ARIMA(2,0,0)	-46.989	2,3469	0,16
ARIMA(3,0,0)	-46.857	2,2911	0,11
ARIMA(0,0,1)	-53.492	2,2092	1,48
ARIMA(0,0,2)	-54.882	2,1159	0,00
ARIMA(0,0,3)	-52.964	2,1136	0,00
ARIMA(1,0,1)	-54.976	2,1131	0,00
ARIMA(2,0,1)	-52.996	2,1127	0,00
ARIMA(3,0,1)	-50.996	2,1127	0,00
ARIMA(1,0,2)	-52.997	2,1126	0,00
ARIMA(1,0,3)	-51.007	2,1125	0,00
ARIMA(2,0,2)	-51.032	2,1115	0,00
ARIMA(3,0,3)	-47.312	2,1039	0,00

The table reveals the most relevant results and characters of the ARIMA models, in order to compare the models and justify why some of the models are rejected in this case study. If result for Ljung-Box was below the significance level, model was rejected. Therefore four models reached the second round of evaluation. The value for Ljung-Box test in single order differenced ARIMA(0,0,1) model is 1,48, which is above the significant level of 0,05. This indicates that the remains are white noise, and the model can be accepted. In addition, selecting the model with the lowest possible values for RSS and AIC, the suitable model based on the above was ARIMA(0,0,1) with this dataset. The chosen ARIMA model is therefore ARIMA(0,1,1) because of the first order of differencing. Results for the ARIMA(0,1,1) model can be established in Figure 35.

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                #Tonnes   No. Observations:                   80
Model:                 ARIMA(0, 0, 1)   Log Likelihood                  29.746
Date:                Sat, 11 May 2024   AIC                            -53.492
Time:                        15:43:18   BIC                            -46.346
Sample:                    02-01-2017   HQIC                           -50.627
                         - 09-01-2023
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0065      0.010     -0.665      0.506      -0.026       0.013
ma.L1         -0.6810      0.062    -11.045      0.000      -0.802      -0.560
sigma2         0.0276      0.002     14.864      0.000       0.024       0.031
===================================================================================
Ljung-Box (L1) (Q):                   1.48   Jarque-Bera (JB):              2827.17
Prob(Q):                              0.22   Prob(JB):                         0.00
Heteroskedasticity (H):               6.18   Skew:                             3.97
Prob(H) (two-sided):                  0.00   Kurtosis:                        31.02
===================================================================================
```

Figure 35. Results for ARIMA (0,1,1) model

The different ARIMA models were compared using root mean squared error (RMSE) values based on the dataset's values against the forecasted values. These accuracy metrics were applied to test all four models that reached the final evaluation round. The results exposed the best fitted model was ARIMA(0,1,1). The RMSE score for this dataset was 0,904 and it can be considered as an acceptable score with utilized dataset, this can be established from Figure 36. Within applied dataset, the individual outlier data point can affect the forecast accuracy with the model and thus have bigger influence for the accuracy and model is overfitted. From the results in Figure 36, it can be visualized that the forecast accuracy is progressing constantly better, thus the moving average model appears to be suitable for this dataset. In conclusion, as stated in section 4.2.1.2 the model has disadvantages in terms of its sensitivity to outliers' data and requires statistical expertise from the user in order to be able to fit the model properly and apply it to support decision-making.

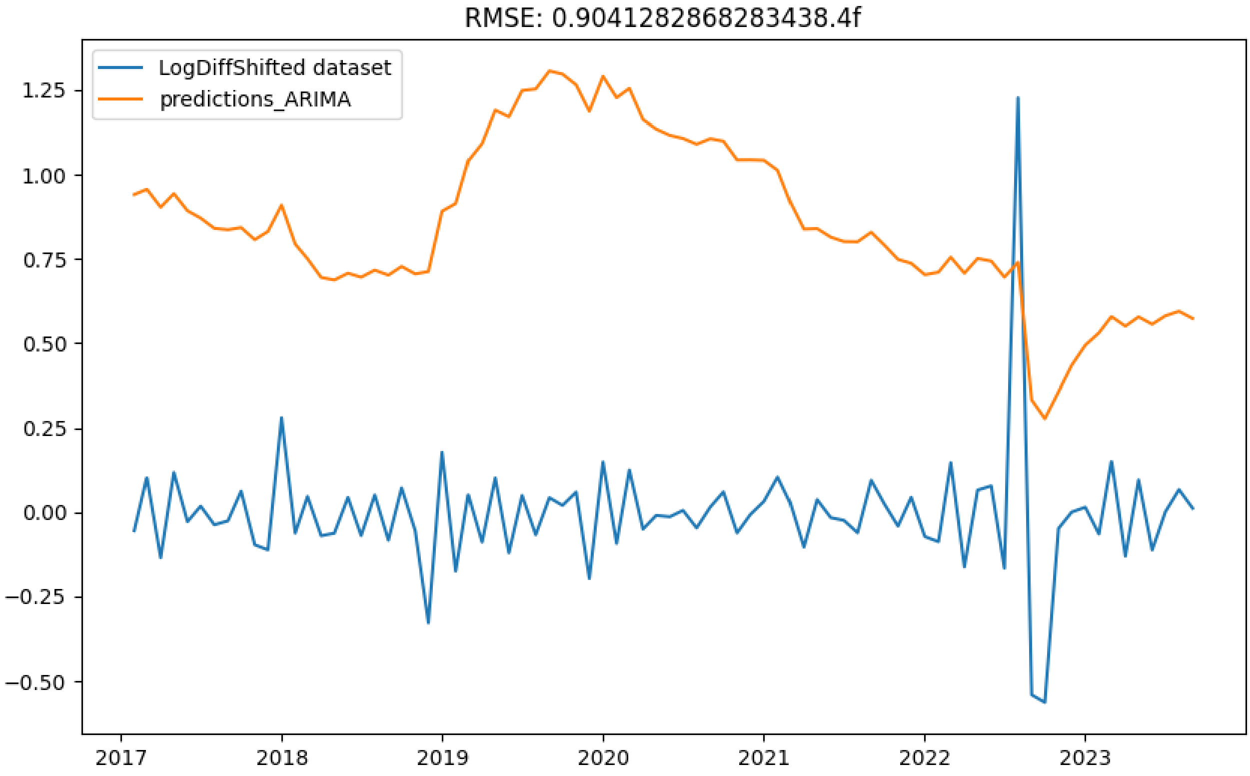


Figure 36. Results for testing RMSE

ARIMA forecasting can be processed at least in couple of different ways with Python, it depends on which libraries are utilized and what method. In Figure 37 the forecast has been created in different coding and by adjusting the utilized dataset, ARIMA parameters and time, in addition with 95 % confidence intervals the forecast can be executed. Obviously, it can be stated in the graph that the forecast follows a significantly better manipulated dataset and moving average model seems to suit the dataset. From the pattern can be clearly observed the prediction of dampening close to zero very quickly, because the model does not get to update itself.

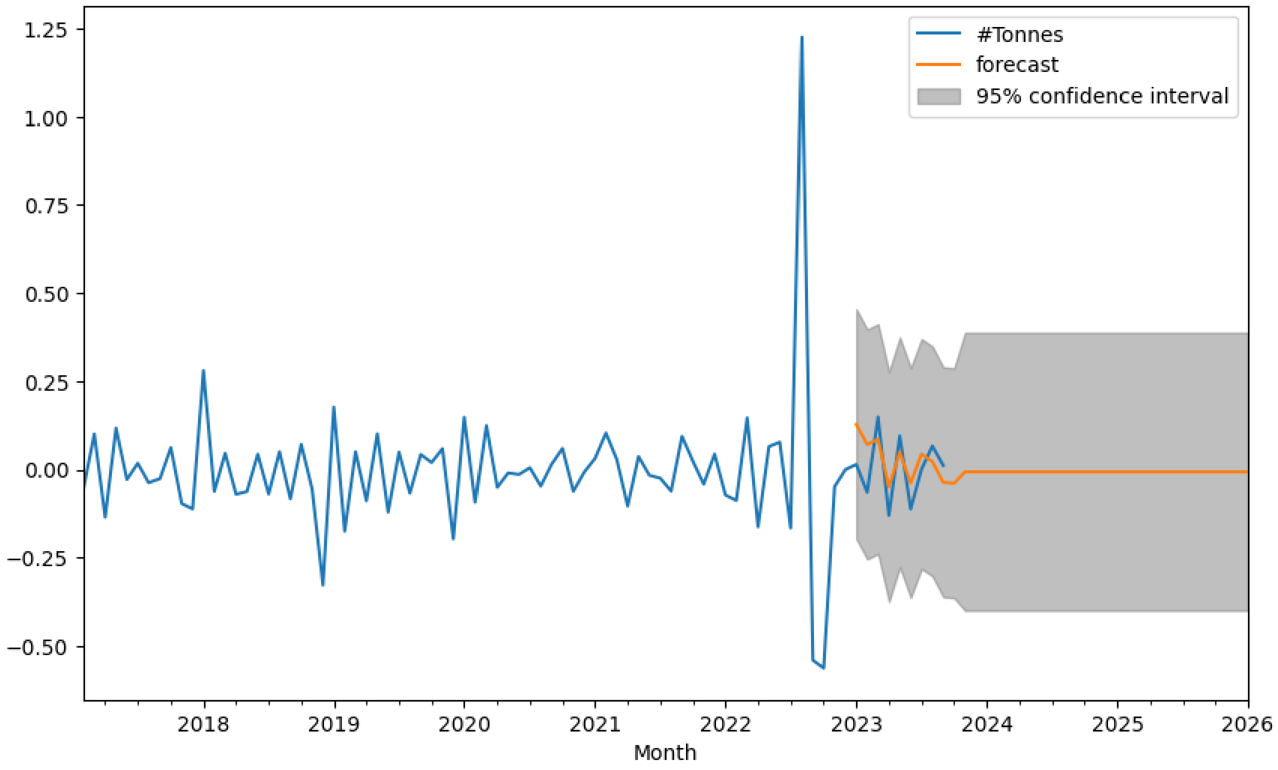


Figure 37. Generated Forecast by applying forecast() method in Notebook with Python

9.1 Reliability of the results

The case study should consider if qualitative or quantitative parts of the study are used, the reliability review should be carried out according to the requirements of each extract (Kananen, 2013, 122). In other words, take a stand on the research methods used and how they have been used. There are no specific criteria or methods for qualitative data analysis on how to increase the quality of research. Saaranen-Kauppinen and Puusniekka (2006) advise that the reliability of research can be increased by, among other things, describing the material, pre-testing interview questions, and investing in the categorizing and coding of the text throughout the analysis phase of the interview material. According to Saaranen-Kauppinen, Puusniekka and Kananen, critical and reflective work approach and documentation are prerequisites for assessing the reliability of the study. If there is no documentation of the selections, solutions or factors influencing the solutions made during the study, it is extremely difficult to evaluate the study. (Kananen, 2013, 116; Saaranen-Kauppinen & Puusniekka, 2006.)

All respondents who were sent a request for an interview accepted it. This may indicate that research data is highly valued both in the company and its employees, and there is hardly concern about being identified, or expectation in anonymity is at adequate level. 11 individuals were interviewed in the study, which covered the S&OP process for the LPG product chain in 91,7 % of the target population. Interview questions were themed, as well as pre-tested. The interview material was recorded with two devices, transcribed twice, segmented and categorized under each research question in the table. Finally, the material was analyzed, interpreted and summarized into a synthesis.

In the case of observations, systematic documentation is the key element. An observation diary was created for the observation, which made it informal to observe the implementation phase by, among other things, automating the calculation of contributions to the table for the people attending the meeting.

Research data and the conduct of research, such as changes and additions, were utilized by keeping a research journal, the implementation of which was maintained in connection with the study versioning. Among the versions of the study can be observed the course of research and its formation over time. The comments obtained bring more depth to the study, for example by writing ideas or linking the appropriate article to the correct chapter, highlighting observations and forming synthesis during the implementation phase of the research. (Dahlberg & McCaig, 2010, chapter 10.) Special attention was given to the use of sources. In-text citations were added simultaneously as the text was produced to create it simple to return to it during the next writing session. References were immediately added to the list of references when they were first referenced in the study.

File formats and software in line with commonly used standards were used in the study. With these actions, it can be ensured the material is accessible, reusable, and technically compatible. The data management plan for the study has been compiled into an Excel table, from which the data formats are used, and the sizes of the data can be observed. It can be established from Figure 38 how the data management plan has been implemented. Quantitative data has been transferred from the source straight to an Excel table, in which the data was preprocessed to .xlsx and .csv format. Next step was to implement the preprocessed source data into the Google Vertex

AI Workbench and utilize in Jupyter Notebook. Data management was defined on specified locations, on the researcher's personal computer. An effort was made to name the files clearly using a similar naming principle and dates, as can be seen from the image. A backup of the data files was also created on the researcher's PC.

Name (includes date)	File format	Size (KB)	Usage Rights	
	.docx		Secret	granted by the client
	.xlsx		Confidential	licence/access right
	.tif		Internal	collected/produced
	.txt		Public	
	.csv			
ARIMA mallin muokatut komennot	.txt	2	Confidential	Produced
Brent-öljyfutuurit historialliset tiedot_20230205	.xlsx	128	Public	Collected
Digital supply chain compass_20230219	.pptx	174	Public	Adapted
Domestic_monthly_sales_01_2017-09_2023	.csv	2	Public	Produced
Havainnointipäiväkirja_20230318	.xlsx	14	Secret	Produced
Havainnointipäiväkirja_20230729	.xlsx	357	Secret	Produced
Opinnaytetyo_YAMK_20221023	.docx	108	Confidential	Produced
Opinnaytetyo_YAMK_20221030	.docx	111	Confidential	Produced
Opinnaytetyo_YAMK_20221102	.docx	112	Confidential	Produced
Opinnaytetyo_YAMK_20221117	.docx	523	Confidential	Produced
Opinnaytetyo_YAMK_20221120	.docx	1128	Confidential	Produced
Opinnaytetyo_YAMK_20221126	.docx	1128	Confidential	Produced
Opinnaytetyo_YAMK_20221207	.docx	1129	Confidential	Produced
Opinnaytetyo_YAMK_20221211	.docx	1190	Confidential	Produced
Opinnaytetyo_YAMK_20221216	.docx	1195	Confidential	Produced
Opinnaytetyo_YAMK_20221220	.docx	1197	Confidential	Produced

Figure 38. Description of data management created in the study

The dataset utilized in the time series analysis are authentic and actual data on domestic LPG sales collected and maintained by Statistics Finland. The data is public and therefore it is possible for everyone to test and validate the research results. When the input data was implemented into the Google Vertex AI environment, it was processed with as minimum changes as possible, to ensure the input data quality. In addition, well-known statistical test methods were applied in the time series analysis with suitable characteristics.

The results are not generalisable, but apply to this study and can be exploit in this context. Obviously, the development proposals that have emerged in terms of the S&OP process and the flow of information can be utilized for other product chains. For example there are variations between different product chains and the aforementioned justifications should be carefully considered when evaluating the usability of development proposals in other contexts.

9.2 Ethics of the study

The objectives of the entire case study and the reporting and analysis of research results are in line with high morale in terms of confidence. Work-based development also adheres to the same standards as in scientific research. Thus, research was conducted precisely in accordance with good practices. (Ojasalo et al., 2018, 48–49.) The reliability of the case study can be improved, for example through adequate and comprehensive reporting together with clear implementation. Thus, it is significant to define the concepts of the research because they delineate, give them purpose and define the concept. The key concepts of the research were defined at the beginning, to understand the research problems and the research object more adequately. (Hirsjärvi et al., 2009, 149, 152.)

It is essential that the subjects of the study know the purpose of the study, its objectives and their role in the study. The above topics were discussed in the context of both qualitative methods, both in interviews and observation. The interviews were pre-tested, recorded and transcribed twice in order to collect and analyze all data reliably. Regarding research ethics, the anonymity of the individuals interviewed or observed was ensured consequently that the respondents were not identified and personal information such as names were not published in the study. (Ojasalo et al., 2018, 48.) The research material collected in the study is carefully stored in a password-protected method hence its privacy is not compromised. After a two-year retention period, the research material will be systematically and securely destroyed.

The calculations in this study are based on actual numbers, which are publicly available actual data collected by others. The data, figures, codes, calculations, graphs used in the time series analysis have been checked before the work is completed in order to avoid errors that may have arisen in the implementation. Permission has been requested for the use of other confidential information received from the client, for example process description.

10 Conclusions

In this chapter the research questions are answered based on the literature review, empirical research data and results, and the synthesis of their analysis. The objective of the study was to examine through the LPG product chain the Neste OP SCM S&OP process and the forecastability there, and to find development proposals to improve the short-term S&OP process and forecasts. In conclusion, it will be assessed whether the objectives established for the study were achieved.

1. Does the S&OP process have to be developed and the forecastability there? If yes, how?

When the S&OP process is ongoing, generally, information is shared in iteration meetings and at other times in different groups on chat channels and between individuals. Information is easily lost in these multiple different communication channels, and it can be challenging to return to them later, when a similar situation occurs again. One of the substantial challenges of data, and tacit knowledge in an information-intensive network economy, is preserving and utilizing it – to create a platform and/or system for all relevant data in which it is easy to add, search, connect, modify and analyze. By combining all the different layers of information, i.e. data (e.g. from IT systems), information and tacit knowledge, it is possible to achieve better reliability and less errors in forecasting. Thus supporting the company's decision-making ability in a more beneficial way and improving competitiveness.

> *“In my opinion, it actually goes so that when the S&OP process is developed, it improves forecastability and speeds up the process, so that just what time is freed up for everyone's analysis.”*

Competitiveness is created by a combination of expertise, collaboration and data. One of the greatest opportunities for collaboration is transparency and the sharing economy through several interfaces. By improving the flow of information and increasing transparency in interfaces, it is possible to increase process reliability and reduce errors. Above all, it is possible to see objects earlier than before. Rapid responsiveness and the detection of new opportunities require multidisciplinary expertise. (Törnblom, 2022.) In addition to the above, the continuous growth of personnel competence and research and development activities can significantly increase the invention of new innovations as long as they are performed correctly. For example, development work can start in a regular conversation with a colleague. However, in these circumstances, there is a risk of forgetting to record the documentation and thus even valuable ideas can r be briefly forgotten. In addition, the information overload also brings major challenges in today's information-intensive operating environment. Employees might start pruning some of the information because they can't handle that amount of information at a time. As a result, conversations in chat spaces, for example, are missed by relevant people because the information overload is too vast or in unsuitable form. In addition, there are a variety of different chat groups, leaving essential information either undistributed to potential employees or not reaching them in time.

> *"Actually, everything else works on the LPG side, except acquiring the sales numbers into SAP. Some minor deviations have been observed within the numbers, and there is a little improvement in the schedule of getting the sales numbers into SAP. They must be reminded to update the sales numbers, in order to get them ready for the S&OP round."*

Study also revealed weaknesses in the maturity of the process because on a monthly basis, others are reminded to take care of their work tasks on time. However, the monthly cycle of S&OP process is scheduled in calendars, which makes it easier to complete tasks on time. Such errors could be thought to be more of a fiddly nature, which can be corrected with little effort. Even if some information is crucial to pass on as late as possible, it should be delivered on time, so that the S&OP process can start on time with the next steps of the process.

In addition, the incoming input data from several different sources to the S&OP process causes a great amount of challenges in the process. Several data are added to systems manually, allowing various keystroke errors or missing sales volumes to cause even large errors that always consume resources ineffectively. This, in turn, decreases the value creation in the supply chain. In addition, customers may not report their own production shutdowns, which may affect consumption and cause large fluctuations in the upstream of the supply chain.

It was found quite unequivocally in the study that by developing the S&OP process, its process can be improved in several different ways. In order to improve the functionality and forecastability of the S&OP process, it is required to measure it with suitable metrics. During the observation, it emerged that there were not that many performance metrics related to the measurement of the S&OP process and the question also arises whether these existing performance metrics inform enough about the process and how the process itself works? Can they be used to continuously develop the process and evaluate why something happened and what can be done about it?

2. What causes the forecast errors in product chain LPG?

The first research question already revealed a number of difficulties that undermine the functioning of the process. Alike, several issues have been identified affecting forecast errors in the LPG product chain. It is clear that not all objects can be identified in advance, hence a 100 % forecast is not valid as such and is not worth pursuing. In addition, oil market prices are a level two chaotic system, which indicates that forecasts are affected all the time by different variables, and this can have a major impact on forecasting. Based on the research results, the information flow and the accuracy of the data – especially sales forecasts and the input data of the planning model were perceived as difficult. The aforementioned were exposed to be the major causes of errors in the LPG chain.

> *"We want to use the realized amounts of the product loadings, so create forecasts from the quantities loaded. The data in the Schedule model starts today. Then again, we need history data to forecast the product loadings in terminals."*

In the interviews, it was revealed that one of the best methods for forecasting variations in demand is using historical data. There are various reasons for applying historical data, but this study and in this context, particularly highlighted the challenges related to customers' annual contracts. The quality of annual contracts from customers have been observed and occasionally the forecasts indicate significant differences in relation to actual consumption. One reason might be that the forecasts provided by customers include a safety factor, for example 10 % more volume has been added on top of the actual need. Additional reason may be that the annual sales forecast is distributed evenly over 12 months, although the demand differences between months can significantly vary. The sales forecast for the domestic distribution is therefore closely monitored. For example, the actual figures for the previous week are examined and that data is applied in planning the manufacturing plan for the following week(s). Furthermore, in ERP systems, a substantial amount of information is still entered into the various fields and reports of the systems manually, thus various keystrokes or data copy errors can be major reasons that S&OP input data already has an inherently incorrect starting data for some of the sales. Automation can be utilized to reduce the above errors, where the error in itself is not necessarily very substantial, but its significance is emphasized in optimizing the plan specifically. In particular, such an error is highlighted in 24/7 production facilities such as refineries.

"Well, I guess the quality of the data in the sense of how exact the crude oil assays are in order, so that we understand the crude oil composition. Because that's where the LPG's comes from. Of course, the capacities of other process units also affect how much LPG is generated from other process units. But if there is a difference between the S&OP and reality, then it is cumulatively causing problems."

Sales forecasts are one part of S&OP input data. In addition, the quality of the data in the planning tool itself can be inaccurate. The planning model contains a huge amount of data and various calculations within, so that it is capable of optimizing a complex refinery such as the Porvoo refinery. Thus, continuous improvement and development of the planning model is likewise an essential part of high-quality overall optimization of supply chain management and maximization of value creation. It is extremely difficult to manually validate the planning tool. Thus, automatic checks should be implemented in the design model as much as possible to identify errors more systematically.

3. Is it possible to define relevant variables to improve forecasts in product chain LPG?

Based on the research's primary data, the most essential variables in the LPG product chain to improve forecasts are as follows:

- sales forecasts and their quality
- demand forecast
- sales volumes of other product chains, for example the gasoline chain
- input data of planning models and its quality
- system integrations
- system problems
- lack of documentation
- rapid obsolescence of information

To be able to react rapidly to changing conditions and to improve forecasts in LPG product chain, it is necessary to practice a combination of qualitative and quantitative forecasting methods. In which the experts' substantive knowledge of the product chain and the market is applied, and moreover script-based tools for creating quantitative analysis. With the support of the above, for example, in relation to the changed market condition, different scenarios can be instantly implemented, and different variables can be selected to create new plans and forecasts.

The benefits of the ARIMA model are more valuable in short-term forecasts, approximately within 1–3 months of the present. The advantages of the S&OE as an individual process can allow the S&OP process to step out from the creation and optimization of the short-term plan, and thus focus properly on optimizing a long-term plan. The benefits of separating the processes can be considered at least as decision-making in the S&OE process speeds up. For example, when trading crude oil cargo, it is vital to ensure the right moment for the purchase in order to maximize economical profitability. The benefits of the ARIMA model for short-term forecasting, combined with statistical analysis in the Google Vertex AI environment, provide a prompt solution to the need for supply chain planners. Furthermore, it can be utilized to support decision-making in a rapidly changing environment in various ways. Google Vertex AI as an operating environment is easy to learn but requires a knowledge of data analytics and understanding and smooth use of Python's code structure. On the other hand, a huge number of ready-made code structures are already available, hence the implementation of new functions can be effortless as long as the basic knowledge of Python scripts is in order.

Evaluation of the research process

When evaluating the process of the thesis, the following results emerged. More people could have tested the pre-testing of interview questions, thus the questions could have been reduced even more and form part of the questions clearer. This came up in a few interviews where the interviewer had to repeat the question in other words and direct the conversation more than was the aim. This may have had an impact on the responses, and in some interviews the response was shortened, and may not have given as beneficial an answer as researcher would have wished. In the field stage of observation, difficulties were caused by the transfer of the selected meetings and thus the decreased amount of research data to be utilized, which may be relevant in assessing the reliability of the research in terms of observation. However, observation was not the main research method, instead it was applied to validate interviews. Hence, the weight of the limited observation data is not considered to be that significant from the writer's point of view. However, the end result of the study was results that would enable the goal to be achieved. Thus, the objectives of the study were achieved.

Source criticism caused some difficulties, especially in terms of the S&OP process, forecasts and time series analysis. The primary obstacle was reducing the huge number of search hits and finding valid sources for study. Secondly, it was time-consuming to separate suitable source data. It might be possible that some more systematic way of going through the source material would have accelerated the activity. In addition, the extent of the source material challenged the research to remain within decent limits.

Extensive data and the lack of experience of the researcher in time series analysis, Python and programming in the environment of the Jupyter Notebook delayed the progress of the research, especially in the implementation and analysis phase. A considerable amount of time was spent on both the time series analysis and the structure of the Python code, including reading and understanding the scripts, which significantly delayed the progress of the study. In addition, the material of the time series analysis produced challenges, because all the test results were not continually completely clear for the author. The notebook itself and Google Vertex AI as an environment were extremely pleasant to apply and particularly easy for the author. Writing scripts, editing, transferring, importing new libraries is effortless and fast. The implementation of new models is handled in the blink of an eye and the results are obtained in a few seconds.

11 Discussion

One of the most significant responsibilities in the supply chain is to react rapidly to changing circumstances, especially in today's challenging and complex operational environment. In addition, the implementation of actions requires a lot from both experts and systems to increase economical profitability. The more complex the supply chain, the more vulnerable and prone to disruption it is. Disruptions often have the effect that the company is incapable of fulfilling promises for customers and customer satisfaction and return on value suffer.

The global challenges of the supply chain, together with the rapidly changing operational environment, often creates conditions in organizations where the information or data needed at a certain time can be problematic to access. Both due to the complexity of the data's multiple locations and the lack of documentation of employees' tacit knowledge. Therefore, it would be valuable to systematically document the tacit knowledge in order to continually improve efficiency. In addition to the above, it might be useful to develop a generic information retrieval system that primarily serves employees in finding the right information and can offer a large potential for organization to become more competitive.

Based on this research, further studies are proposed on the use of generative AI in the organization, to facilitate the identification of relevant data, and accelerate operations. With the assistance of the generative AI, it is possible to realize substantial resource savings, furthermore it is possible to develop the generative AI by using it. Thus, the resources of the employees could be utilized more beneficially, for example, of optimization of operations and thus generating more added value. Another target for AI exploitation could be the S&OP process itself. As digitization continues to increase, utilizing AI as part of the S&OP process could make sense to explore and analyze its potential in the process. Benefits from generative AI is that it can explore and find new patterns which could not be identified otherwise. Third, the S&OP process description should be updated to reflect the actual process, furthermore, adding process descriptions from the process interfaces between S&OP and S&OE in addition S&OE and Schedule. Additionally, include all other functions in the process descriptions, such as data processing and other associated systems. Finally, document the entire S&OP process with other planning processes including the roles and responsibilities of the process owners and other related participants.

Based on this study, several areas for development were found, and based on the research, it is proposed that the most essential development suggestions should be evaluated and produced into an action plan, by implementing them in the Jira Software used by OP SCM. In Jira, development requests can be assigned, for example, the right project, criticality level, schedule, and the right resources can be allocated for working on the development or investigation. In addition, the use of Jira increases transparency in the company.

Suggestions for future research

The study excluded the treating of performance metrics as a result of an ongoing development project related to the reporting tools. Based on the above, further research is proposed for the measurement of forecast accuracy. Moreover, it is suggested for future research for investigation and evaluation of the performance metrics and their use in the S&OP process.

Based on the study, further research on the co-integration of time series is proposed. It could be worthy of note, for example, the correlation between the output of the Porvoo refinery's CDU or KTO units to the LPG sales and create possible future scenarios towards bio transition. The interviews also revealed an interesting perspective of liquid gases towards the future bio transition: The CO2 reduction targets drive the manufacturing industry to evaluate future investments. For example in terms of fuel infrastructure - will bio- or co-processed propane be utilized in the manufacturing industry in the future, or some other renewable fuel? How can it be established that there is also a path to renewables in the future for propane and LPG in general?

References

Ahlavuo, M., Hyyppä, H. & Haggrén, H. (2011). *Tietovirrat akateemisessa tutkimusympäristössä [Information flows in an academic research environment].* The Photogrammetric Journal of Finland, Vol. 22, No. 3. Accessed on 3 Sep 2023. Retrieved from https://foto.aalto.fi/seura/julkaisut/pjf/pjf_e/2011/PJF2011_3_Ahlavuo_et_al.pdf

Ahma-aho, S. (2024). Digital lead. Google Chat 30.4.2024.

Alakangas, E., Hurskainen, M., Laatikainen-Luntama, J. & Korhonen, J. (2016). *Suomessa käytettävien polttoaineiden ominaisuuksia [Features of fuels used in Finland]*. VTT Technical Research Centre of Finland Ltd. Juvenes Print. Accessed on 3 Sep 2023. Retrieved from https://www.vttresearch.com/sites/default/files/pdf/technology/2016/T258.pdf

Auffarth, B. (2021). *Machine Learning for Time-Series with Python.* Packt Publishing. https://www.perlego.com/book/3040281/machine-learning-for-timeseries-with-python-forecast-predict-and-detect-anomalies-with-stateoftheart-machine-learning-methods-pdf

AVEVA. (2022). *AVEVA™ Unified Supply Chain Build knowledge, build process, and build profitability. Product datasheet*. Accessed on 12 Jan 2024. Retrieved from https://www.aveva.com/content/dam/aveva/documents/datasheets/Datasheet_AVEVA_UnifiedSupplyChain_22-06.pdf.coredownload.inline.pdf

Baker, A. (2022). *Managing the Bullwhip Effect: The Importance of Signals and Priority*. Accessed on 11 December 2022. Retrieved from https://www.leandna.com/blog/managing-the-bullwhip-effect/

Banerjee, P. (2020a). *Complete Guide on Time Series Analysis in Python.* Accessed on 27 March 2023. Retrieved from https://www.kaggle.com/code/prashant111/complete-guide-on-time-series-analysis-in-python

Banerjee, P. (2020b). *ARIMA model for Time Series Forecasting.* Accessed on 27 March 2024. Retrieved from https://www.kaggle.com/code/prashant111/arima-model-for-time-series-forecasting

Bhola, P. (2021). *Quantitative & Qualitative Forecasting Techniques For Your Supply Chain.* Accessed on 11 March 2022. Retrieved from https://fulfillment.shiprocket.in/blog/qualitative-and-quantitative-forecasting-methods/#What_Are_Quantitative__Qualitative_Forecasting_Techniques

Bousqaoui, H. Slimani, I. & Achchab, S. (2021). *Comparative analysis of short-term demand predicting models using ARIMA and deep learning*. International Journal of Electrical and Computer Engineering (IJECE) Vol. 11, No. 4, August 2021, pp. 3319~3328 http://doi.org/10.11591/ijece.v11i4.pp3319-3328

Brandenburger, A. & Nalebuff, B. (2021). *The Rules of Co-opetition*. Harvard Business Review. January–February 2021. Accessed on 11 December 2022. Retrieved from https://hbr.org/2021/01/the-rules-of-co-opetition

Chase, C. (2013). *Demand-Driven Forecasting* (2nd ed.). Wiley. https://www.perlego.com/book/999757/demanddriven-forecasting-a-structured-approach-to-forecasting-pdf

Chatterjee, A. (2018). *Time Series For beginners with ARIMA.* Accessed on 20 March 2024. Retrieved from https://www.kaggle.com/code/freespirit08/time-series-for-beginners-with-arima

Chinn, M., LeBlanc, M. & Coibion, O. (2005*). The predictive content of energy futures: An update on petroleum, natural gas, heating oil and gasoline*. Accessed on 16 November 2022. Retrieved from https://www.nber.org/system/files/working_papers/w11033/w11033.pdf

Christopher, M. (2011). *Logistics & Supply Chain Management*. 4th ed. Pearson.

Dahlberg, L. & McCaig, C. (2010). *Practical Research and Evaluation*. SAGE Publications. https://www.perlego.com/book/861597/practical-research-and-evaluation-a-starttofinish-guide-for-practitioners-pdf

da Silva, M. W. (2022). *Crude Oil Refining. A Simplified Approach*. CRC Press. https://www.perlego.com/book/3584576/crude-oil-refining-a-simplified-approach-pdf

Dufva, M. & Rowley, C. (2022). *Heikot signaalit [Weak signals] 2022*. An article on Sitra's website. Accessed on 26 June 2022. Retrieved from Heikot signaalit 2022 - Sitra

EnggCyclopedia. (N.d.). *Crude Oil Refining – Products.* https://enggcyclopedia.com/2011/05/crude-oil-refining-products/?utm_content=cmp-true

Falck, J. (2022). *AVEVA Unified Suply Chain tools in Neste.* Accessed on 21 February 2023.

Frolov K., Iliashenko V. & Ershova A. (2021). *Strategic Procurement of Resources for Transportation: Architectural and Methodological Issues*. Transportation Research Procedia 54:945-952. January 2021 http://dx.doi.org/10.1016/j.trpro.2021.02.149

Fusion Media Ltd. (2023). *Brent oil futures historical data 01/2018-01/2023.* Accessed on 5 February 2023. Retrieved from https://fi.investing.com/commodities/brent-oil-historical-data

Google Cloud. (2022). *Intro to data science on Google Cloud*. Accessed on 27 March 2023. Retrieved from https://cloud.google.com/blog/topics/developers-practitioners/intro-data-science-google-cloud

Google Cloud. (2023). *Introduction to Vertex AI.* Accessed on 6 May 2023. Retrieved from https://cloud.google.com/vertex-ai/docs/start/introduction-unified-platform

Gupta, P. (2021). *Practical Data Science with Jupyter* ([edition unavailable]). BPB Publications.

https://www.perlego.com/book/2660997/practical-data-science-with-jupyter-explore-data-cleaning-preprocessing-data-wrangling-feature-engineering-and-machine-learning-using-python-and-jupyter-pdf

Hippold, S. (2019). *How to set up S&OE in supply chain planning.* An article on Gartner website. Accessed on 18 February 2024. Retrieved from
https://www.gartner.com/smarterwithgartner/how-to-set-up-soe-in-supply-chain-planning

Hirsjärvi, S., Remes, P. & Sajavaara, P. (2009). *Tutki ja kirjoita [Research and write]*. 15th ed. Tammi.

Holopainen, M. & Pulkkinen, P. (2015). *Tilastolliset menetelmät [Statistical methods]*. 5th – 17th. ed. Sanoma Pro Oy.

Hopp, W.J. & Spearman, M.L. (2011). *Factory Physics*. 3rd ed. Waveland Press Inc.

Hsiao, J.M. & Shieh, C.J. (2005). *Evaluating the value of information sharing in a supply chain using an ARIMA model.*
https://doi.org/10.1007/s00170-004-2214-4

Hulthen, H., Naslund, D. & Norrman, A. (2016). *Challenges of Measuring Performance of the Sales and Operations Planning Process. Operations and Supply Chain Management: An International Journal*, 10(1), 4-16.
http://doi.org/10.31387/oscm0260176

Hyndman, R. J. & Athanasopoulos, G. (2018). *Forecasting: principles and practice*. 2nd ed. OTexts: Melbourne, Australia. Accessed on 1 October 2022. Retrieved from
https://otexts.com/fpp2/

Inderes. (2023). *Futuurit ja termiinit – Inderes Sijoituskoulu [Futures and forwards Inderes Investment School].* Accessed on 19 October 2023. Retrieved from
https://www.inderes.fi/fi/futuurit-ja-termiinit

Ilmakangas, V. (2018). *Muutosagentti – organisaation uusi tapa johtaa muutoksia esimiesten ja henkilöstön vahvalla tuella [Change agent – the organization's new way of leading changes with the strong support of managers and personnel].* Valmennustrio 3 October 2018. Accessed on 29 June 2022. Retrieved from
Muutosagentti – organisaation uusi tapa johtaa muutoksia esimiesten ja henkilöstön vahvalla tuella - valmennustrio.fi

International Labour *Organization (ILO) & Finnish Institute of Occupational Health. (2023). Kansainväliset kemikaalikortit [International Chemical Safety Cards (ICSCs)].* Accessed on 3 September 2023. Retrieved from
https://www.ilo.org/dyn/icsc/showcard.listcards3?p_lang=fi

Kaiser, M., Klerk, A., Gary, J. & Handwerk, G. (2019). *Petroleum Refining*. 6th ed. CRC Press.
https://www.perlego.com/book/2193884/petroleum-refining-technology-economics-and-markets-sixth-edition-pdf

Kallinen, T. & Kinnunen, T. (2021). Etnograghy. In opus by Jaana Vuori. *Laadullisen tutkimuksen verkkokäsikirja [Online Handbook of Qualitative Research.]*. Tampere: Yhteiskuntatieteellinen tietoarkisto [Social science data archive]. Accessed on 6.1.2023. Retrieved from https://www.fsd.tuni.fi/fi/palvelut/menetelmaopetus

Kananen, J. (2013). *Case-tutkimus opinnäytetyönä [Case study as a thesis].* Jyväskylän Ammattikorkeakoulun Julkaisuja -sarja. Juvenes Print.

Karppala, S. 2022. *Feedback instructions for study authors*. Message in the Moodle environment, 23 May 2022. Receiver Vesterinen, S. Digital supply chain lecturer's feedback guide for digital supply chain students at Jyväskylä University of Applied Sciences.

Kotu, V. & Deshpande, B. (2018). *Data Science*. 2nd ed. Elsevier Science. https://www.perlego.com/book/1829417/data-science-concepts-and-practice-pdf

Krispin, R. (2019). *Hands-On Time Series Analysis with R*. Packt Publishing. https://www.perlego.com/book/969857/handson-time-series-analysis-with-r-perform-time-series-analysis-and-forecasting-using-r-pdf

Kristianto, Y., Helo, P., Jiaob, J. & Sandhu, M. (2011). *Adaptive fuzzy vendor managed inventory control for mitigating the Bullwhip effect in supply chains*. http://dx.doi.org/10.1016/j.ejor.2011.07.051

Logistiikan maailma. (2022a). *S&OP – Sales and Operations Planning*. Accessed on 26 June 2022. Retrieved from
S&OP – Sales and Operations Planning – Logistiikan Maailma

Logistiikan maailma. (2022b). *Toimitusketjun kehittäminen [Supply chain development].* Accessed on 26 June 2022. Retrieved from
Toimitusketjun kehittäminen – Logistiikan Maailma

Logistiikan maailma. (2022c). *Kysynnän ja tarjonnan hallinta [Supply and demand management].* Accessed on 20 November 2022. Retrieved from https://www.logistiikanmaailma.fi/logistiikka/logistiikka-ja-toimitusketju/kysynnan-ja-tarjonnan-hallinta/

Lähteenmäki, P. (2022). *Nesteen uusi johtaja Matti Lehmus näkee tien eroon öljystä ja luotsaa yhtiötä hirmukasvuun: Kertoo nyt, millaisella autolla itse ajaa [Neste's new director Matti Lehmus sees a way to get rid of oil and steers the company to tremendous growth: Now tells what kind of car he drives]*. Talouselämä. News. Accessed on 14 October 2022. Retrieved from https://www.talouselama.fi/uutiset/nesteen-uusi-johtaja-matti-lehmus-nakee-tien-eroon-oljysta-ja-luotsaa-yhtiota-hirmukasvuun-kertoo-nyt-millaisella-autolla-itse-ajaa/c7087c95-d5ff-4fe5-93f1-141d02fb2a8c

Mack, N., Woodsong, C., MacQueen, K., Guest, G. & Namey E. (2005). *Qualitative Research Methods: A Data Collector's Field Guide.* Family Health International 2005. Accessed on 25 February 2023. Retrieved from https://batukarinfo.com/system/files/Qualitative%20research%20-%20datacollectorguideenrh.pdf

McKinsey. (2016). *Supply Chain 4.0 – the next-generation digital supply chain.* Accessed on 19 February 2023. Retrieved from https://www.mckinsey.com/capabilities/operations/our-insights/supply-chain-40--the-next-generation-digital-supply-chain

Makridakis, S., Spiliotis, E. & Assimakopoulos, V. (2018). *Statistical and Machine Learning forecasting methods: Concerns and ways forward.* PLOS ONE 13(3): e0194889. https://doi.org/10.1371/journal.pone.0194889

Mishra, A., Morisetty, R. & Sarawagi, R. (2022). *Forecasting the production of Distillate Fuel Oil Refinery and Propane Blender net production by using Time Series Algorithms*. Open-access archive. Research from the arXiv® platform. https://doi.org/10.48550/arXiv.2208.05

Moroff, N.U., Kurt, E. & Kamphues, J. (2021). *Machine Learning and Statistics: A Study for assessing innovative Demand Forecasting Models.* https://doi.org/10.1016/j.procs.2021.01.127

Neste. (N.d.a). *Our transformation journey*. About Neste. Accessed on 21 February 2023. Retrieved from https://www.neste.com/about-neste/who-we-are/strategy/transformation-journey#d310e7b2

Neste. (N.d.b). *Porvoo*. About Neste. Accessed on 21 February 2023. Retrieved from https://www.neste.com/about-neste/who-we-are/production/porvoo#d310e7b2

Neste. (N.d.c). *Sustainability indices*. Accessed on 3 March 2023. Retrieved from https://www.neste.com/sustainability/performance/sustainability-indices#d310e7b2

Neste. (N.d.d). *Uusiutuva propaani [Sustainable propane*]. Accessed on 23 September 2023. Retrieved from https://www.neste.fi/vastuulliset-ratkaisut/tuotteet/uusiutuvat-polttoaineet/uusiutuva-propaani

Neste. (N.d.e). *Nesteen kokonaisjalostusmarginaali [Neste's total refining margin].* Accessed on 24 September 2023. Retrieved from https://www.neste.fi/konserni/sijoittajille/markkinatietoa/nesteen-kokonaisjalostusmarginaali

Neste. (2019). *Käyttöturvallisuustiedote Propaani [Safety data sheet Propane].* Accessed on 23 September 2023. Retrieved from https://www.neste.fi/static/ktt/10588_fin.pdf

Neste End-to-End Optimization. (2024). Google slides. Accessed on 12 January 2024. Retrieved from Neste.

Neste Oyj. (2021). *Nestekaasu – puhdas ja taloudellinen energiavaihtoehto [LPG - clean and economical energy option].* Accessed on 13 June 2023. Retrieved from https://www.neste.fi/sites/neste.fi/files/Nestekaasu_esite_A4_0621_LR_0.pdf

Neste. (2022a). *Neste, Brightlands Venture Partners, 4 Impact VC and Asahi Kasei invests combined EUR 11 million into startup Circularise to accelerate a shift towards a circular economy*. Neste Corporation, News, 17 November 2022. Accessed on 18 November 2022. Retrieved from https://www.neste.com/releases-and-news/circular-economy/neste-brightlands-venture-partners-4-impact-vc-and-asahi-kasei-invests-combined-eur-11-million

Neste. (2022b). *Neste launches a strategic study on transitioning its Porvoo refinery to a renewable and circular site and ending crude oil refining in the mid-2030s*. Neste Corporation, Press Release, 19 September 2022 at 9 a.m. Accessed on 21 February 2023. Retrieved from https://www.neste.com/releases-and-news/renewable-solutions/neste-launches-strategic-study-transitioning-its-porvoo-refinery-renewable-and-circular-site-and

Neste. (2023). *Annual Report (2022).* Accessed on 3 March 2023. Retrieved from http://neste.com/annualreport

Nguyen, H. H., Adams, P. & Miller, S. (2023). *Building Statistical Models in Python*. Packt Publishing.
https://www.perlego.com/book/4237388/building-statistical-models-in-python-develop-useful-models-for-regression-classification-time-series-and-survival-analysis-pdf

Nummenmaa, L. (2021). *Tilastotieteen käsikirja [Handbook of statistics].* Tammi.

Ojasalo, K., Moilanen, T. & Ritalahti, J. (2018). *Kehittämistyön menetelmät – Uudenlaista osaamista liiketoimintaan [Development study methods – A new kind of know-how for business].* 3rd-5th. ed. Sanoma Pro Oy

Parravicini, M. (2015). *A Guide to Sales Management: A Practitioner's View of Trade Sales Organizations.* Business Expert Press, LLC.

Rautanen, J. (2015). *Krakkausprosessin tislausosan operoinnin tavoitemittaristo [Monitoring the distillation section of a cracking process].* Master's thesis. Aalto University. Department of Biotechnology and Chemical Technology. Accessed on 9 July 2023. Retrieved from https://aaltodoc.aalto.fi/bitstream/handle/123456789/15973/master_Rautanen_Jenni_2015.pdf?sequence=1&isAllowed=y

Reflex. (2022). *QUALITATIVE FORECASTING VS QUANTITATIVE FORECASTING – KNOWING THE DIFFERENCES & APPLICATIONS.* An article on the Reflex Business Planning website 20 June 2022. Accessed on 6 May 2023. Retrieved from https://forecastingsoftware.co.uk/qualitative-forecasting-vs-quantitative-forecasting/

Ritchie, J., Lewis, J., Nicholls, C. M. & Ormston, R. (2013). *Qualitative Research Practice (2nd ed.).* SAGE Publications.
https://www.perlego.com/book/1431388/qualitative-research-practice-a-guide-for-social-science-students-and-researchers-pdf

Saaranen-Kauppinen, A. & Puusniekka, A. (2006). *KvaliMOTV - Menetelmäopetuksen tietovaranto [KvaliMOTV - Method teaching].* Tampere: Social science data archive. Accessed on 18 March 2023. Retrieved from
https://www.fsd.tuni.fi/menetelmaopetus

Saarinen, E. (2014). *Jakso Ajattele rinnalla olevasti – alustus 3/7 2022 ja luentotallenne 7/2014. Filosofia ja systeemiajattelu [Think side by side - initiation 3/7 2022 and lecture recording 7/2014. Philosophy and systems thinking]-Aalto University lecture series* [Podcast]. Spotify music service. Accessed on 25 October 2022. Retrieved from https://open.spotify.com/episode/3RQY4Iw2WYXDn7Cpd5eyoq?si=vB3z9LW9Qw28Ivg5qf1A_Q&utm_source=copy-link

Sakki, J. (2014). *TILAUS–TOIMITUSKETJUN HALLINTA Digitalisoitumisen haasteet [ORDER - SUPPLY CHAIN MANAGEMENT The challenges of digitization].* 8th ed. Vantaa: Jouni Sakki Oy

Seabold, Skipper & Perktold, J. (2010). *statsmodels: Econometric and statistical modeling with python.* Proceedings of the 9th Python in Science Conference. Accessed on 20 April 2024. Retrieved from https://www.statsmodels.org/dev/generated/statsmodels.tsa.stattools.adfuller.html

SFS-ISO 10005:2005. (2005). *LAADUNHALLINTAJÄRJESTELMÄT. OPASTUSTA LAATUSUUNNITELMISTA. [Quality management systems. Guidelines for quality plans*]. Helsinki: Finnish Standards of Associations SFS. Accessed on 13 November 2022. Retrieved from: Nonpublic.

Sheldon, D. (2006). *World Class Sales & Operations Planning*. J. Ross Publishing. https://www.perlego.com/book/1355035/world-class-sales-operations-planning-a-guide-to-successful-implementation-and-robust-execution-pdf

Silver, E.A, Pyke, D.F. & Thomas ,D.J. (2016). *Inventory and Production Management in Supply Chains*. 4. Ed. CRC Press.

Ståhle, P. & Laento, K. (2000). *Strateginen kumppanuus : avain uudistumiskykyyn ja ylivoimaan [Strategic partnership: the key to renewal and superiority].* WSOY.

Tilasto-ohjelmat [Statistical software's]. (2021). *The Online Handbook of Quantitative Research*. Accessed on 20 March 2024. Retrieved from https://www.fsd.tuni.fi/fi/palvelut/menetelmaopetus/kvanti/spss/tilasto-ohjelmat/

Tilastokeskus. (2024). *Öljytuotteiden myynti kotimaahan. Muuttujina Tiedot, Kuukausi ja Öljytuote [Sale of petroleum products domestically. Variables by Data, Month and Petroleum Product].* Accessed on 15 March 2024. Retrieved from https://pxdata.stat.fi/PxWeb/pxweb/fi/StatFin/StatFin__ehk/statfin_ehk_pxt_11t2.px/

Tähtinen, J., Laakkonen, E. & Broberg, M. (2020). *Tilastollisen aineiston käsittelyn ja tulkinnan perusteita [Fundamentals of processing and interpreting statistical data].* Turku: Publication series of the Faculty of Education, University of Turku C, Learning materials 22.

Törnblom, V. (2022). *Kun tiedosta jalostuu arvoa - Tiedolla johtaminen on modernin organisaation menestystekijä [When information is refined into value - Knowledge management is a success factor for a modern organization].* An article on HR viesti website. Accessed on 29 December 2023. Retrieved from https://www.hrviesti.fi/natiivi/3639/kun-tiedosta-jalostuu-arvoa-tiedolla-johtaminen-on-modernin-organisaation-menestystekija

WallStreetMojo. (N.d). *Operations Management*. An article on WallStreetMojo's website. Accessed on 22nd January 2022. Retrieved from https://www.wallstreetmojo.com/operations-management/

Wilson, A. (2018). *Marketing Research*. 4th ed. Red Globe Press. https://www.perlego.com/book/2997202/marketing-research-delivering-customer-insight-pdf

Yin, R. (2018). *Case Study Research and Applications: Design and methods*. 6th ed. SAGE.

Appendices

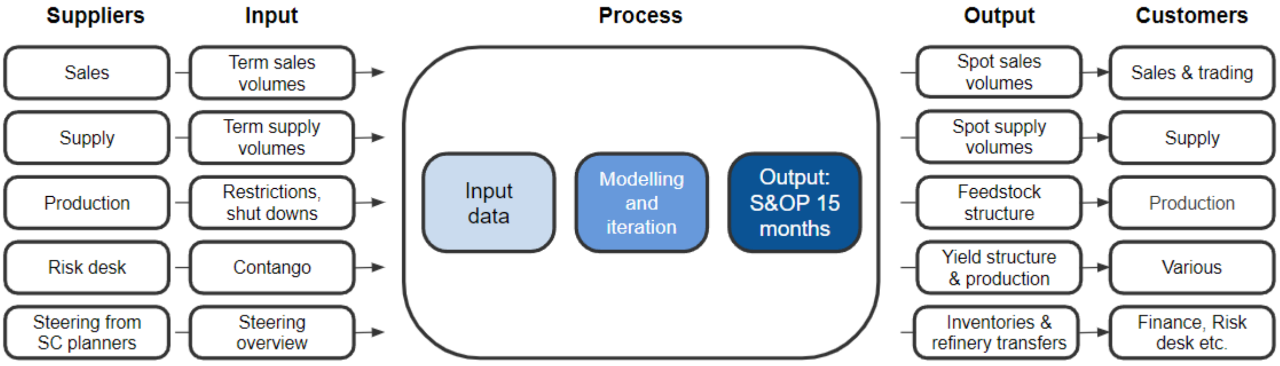
Appendix 1. Domestic LPG total sales in Finland 01/2017 - 09/2023, calculated data results for moving average and differenced series

Time (year-month)	Total LPG's (t)	Moving Average		Differenced series (Actual sales)	Time (year-month)	Total LPG's (t)	Moving Average		Differenced series (Actual sales)
	Actual sales	*n* = 3	*n* = 5			Actual sales	*n* = 3	*n* = 5	
2017-01	23404				2020-06	14597	15154	14911	−203
2017-02	22150			−1254	2020-07	14672	14780	14786	75
2017-03	24508			2358	2020-08	13999	14690	14946	−673
2017-04	21405	23354		−3103	2020-09	14210	14423	14602	211
2017-05	24078	22688		2673	2020-10	15089	14294	14456	879
2017-06	23404	23330	23109	−674	2020-11	14185	14433	14513	−904
2017-07	23825	22962	23109	421	2020-12	14080	14495	14431	−105
2017-08	22949	23769	23444	−876	2021-01	14535	14451	14313	455
2017-09	22360	23393	23132	−589	2021-02	16125	14267	14420	1590
2017-10	23797	23045	23323	1437	2021-03	16590	14913	14803	465
2017-11	21601	23035	23267	−2196	2021-04	14954	15750	15103	−1636
2017-12	19313	22586	22906	−2288	2021-05	15519	15890	15257	565
2018-01	25554	21570	22004	6241	2021-06	15266	15688	15545	−253
2018-02	24009	22156	22525	−1545	2021-07	14897	15246	15691	−369
2018-03	25151	22959	22855	1142	2021-08	14011	15227	15445	−886
2018-04	23447	24905	23126	−1704	2021-09	15400	14725	14929	1389
2018-05	22025	24202	23495	−1422	2021-10	15773	14769	15019	373
2018-06	23007	23541	24037	982	2021-11	15131	15061	15069	−642
2018-07	21458	22826	23528	−1549	2021-12	15812	15435	15042	681
2018-08	22577	22163	23018	1119	2022-01	14705	15572	15225	−1107
2018-09	20769	22347	22503	−1808	2022-02	13469	15216	15364	−1236
2018-10	22317	21601	21967	1548	2022-03	15597	14662	14978	2128
2018-11	21122	21888	22026	−1195	2022-04	13257	14590	14943	−2340
2018-12	15208	21403	21649	−5914	2022-05	14151	14108	14568	894
2019-01	18161	19549	20399	2953	2022-06	15297	14335	14236	1146
2019-02	15244	18164	19515	−2917	2022-07	12953	14235	14354	−2344
2019-03	16036	16204	18410	792	2022-08	44144	14134	14251	31191
2019-04	14670	16480	17154	−1366	2022-09	25716	24131	19960	−18428
2019-05	16238	15317	15864	1568	2022-10	14646	27604	22452	−11070
2019-06	14388	15648	16070	−1850	2022-11	13952	28169	22551	−694
2019-07	15119	15099	15315	731	2022-12	13954	18105	22282	2
2019-08	14136	15248	15290	−983	2023-01	14157	14184	22482	203
2019-09	14754	14548	14910	618	2023-02	13266	14021	16485	−891
2019-10	15051	14670	14927	297	2023-03	15403	13792	13995	2137
2019-11	15973	14647	14690	922	2023-04	13516	14275	14146	−1887
2019-12	13118	15259	15007	−2855	2023-05	14873	14062	14059	1357
2020-01	15220	14714	14606	2102	2023-06	13292	14597	14243	−1581
2020-02	13871	14770	14823	−1349	2023-07	13301	13894	14070	9
2020-03	15718	14070	14647	1847	2023-08	14224	13822	14077	923
2020-04	14944	14936	14780	−774	2023-09	14388	13606	13841	164
2020-05	14800	14844	14574	−144					

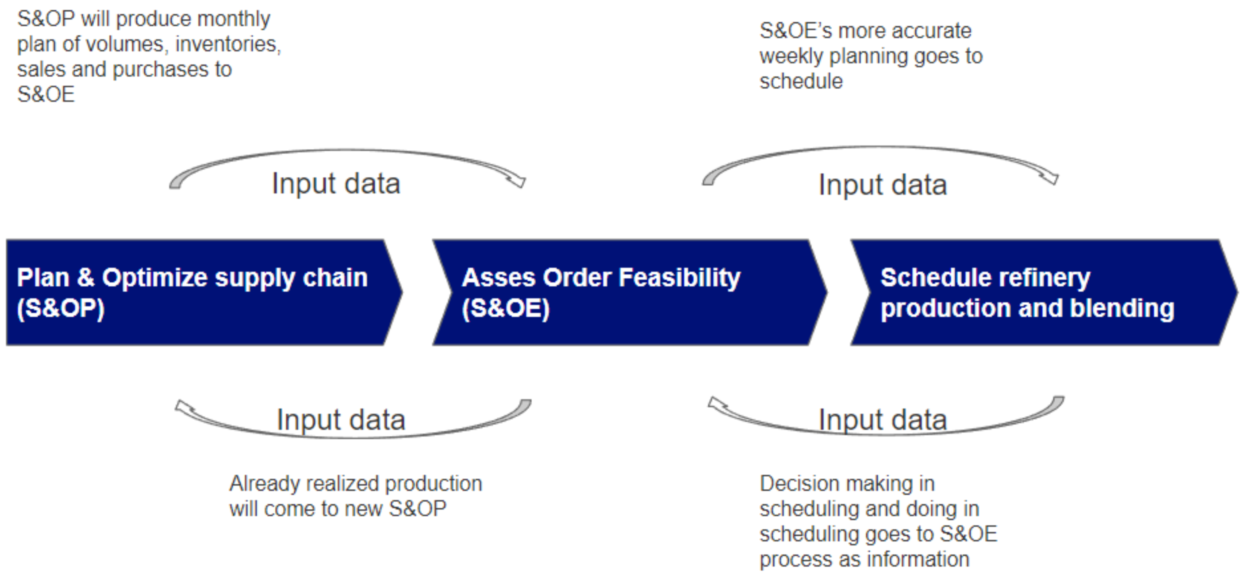
Appendix 2. ACF data set of the domestic LPG sales

Lag	ACF
0	1
1	0,562040312
2	0,4155896957
3	0,3680025875
4	0,3291521773
5	0,3377379873
6	0,2874323092
7	0,29647411
8	0,2694996568
9	0,2421138799
10	0,1954530281
11	0,1585293333
12	0,1607988863
13	0,133461242
14	0,1657459618
15	0,1398688926
16	0,1021052771
17	0,1008215014
18	0,06808683596
19	0,02057222745
20	−0,01823668146

Appendix 3. Description of the OP S&OP process



Appendix 4. Description of the S&OP process deliveries to S&OE and Scheduling



Appendix 5. Common questions in the semi-structured interview

1. How is the current S&OP process described?
2. Which stakeholders are part of the process?
3. Does forecastability need to be improved in the S&OP process to develop it, and if yes, how?
4. What are Liquefied Petroleum Gases (LPG)?
5. What kind of products are LPG and what peculiarities they have?
6. What factors influence the preparation of forecasts?
7. What factors/variables cause errors in the LPG product chain?
8. Which roles do you collaborate most with?
9. What factors improve the flow of information?
10. What is needed to develop the flow of information?

Appendix 6. Structure of the observation form

Number	Remote / Present	Name	Number of speeches		Number:	Name:	Notes:
1		Name 1	0				
2		Name 2	0				
3		Name 3	0				
4		Name 4	0				
5		Name 5	0				
6		Name 6	0				
7		Name 7	0				
8		Name 8	0				
9		Name 9	0				
10		Name 10	0				
11		Name 11	0				
12		Name 12	0				
13		Name 13	0				
14		Name 14	0				
15		Name 15	0				
16		Name 16	0				
17		Name 17	0				
18		Name 18	0				
19		Name 19	0				
20		Other persons	0				

Appendix 7. Time series analysis with ARIMA model in Jupyter notebook

Python script has been compiled in this appendix, based on which time series analysis with the ARIMA model has been executed in the study. Not all scripts and results of different models have been collected, because it would increase the length of this appendix particularly. First version of each script is written and on that basis the workflow in the study can be understood.

```
[1]: import numpy as np
     import pandas as pd
     import matplotlib.pylab as plt
     %matplotlib inline
     from statsmodels.tsa.stattools import adfuller
     from statsmodels.tsa.stattools import acf, pacf
     from statsmodels.tsa.seasonal import seasonal_decompose
     from statsmodels.graphics.tsaplots import plot_predict
     from statsmodels.tsa.arima.model import ARIMA
     from sklearn.metrics import mean_squared_error
     from matplotlib.pylab import rcParams
     rcParams['figure.figsize'] = 10, 6
     import seaborn as sns
     pd.set_option('display.max_columns', None)
     pd.set_option('display.max_rows', None)

[2]: df = pd.read_csv("Domestic_monthly_sales_01_2017-09_2023.csv")

[3]: #path = "Domestic_monthly_sales_01_2017-09_2023.csv" #For local
     path = "Domestic_monthly_sales_01_2017-09_2023.csv"
     dataset = pd.read_csv(path)
     #Parse strings to datetime type
      dataset['Month'] =
      pd.to_datetime(dataset['Month'],infer_datetime_format=True)
      #convert from string to datetime
     indexedDataset = dataset.set_index(['Month'])
     indexedDataset. Head()

[4]: plt.xlabel('Month')
     plt.ylabel('Domestic LPG sales (tonnes)')
     plt.plot(indexedDataset)

[5]: decompose = seasonal_decompose(df['#Tonnes'],
      model='additive', period =12)
     decompose.plot()
     plt.show()

[6]: decompose = seasonal_decompose(df['#Tonnes'],
      model='multiplicative', period=12)
     decompose.plot()
     plt.show()

[7]: rolmean = indexedDataset.rolling(window=12).mean()
     rolstd = indexedDataset.rolling(window=12).std()
     print(rolmean,rolstd)

[8]: #Plot rolling statistics
      orig = plt.plot(indexedDataset, color='blue', label='Original')
      mean = plt.plot(rolmean, color='red', label='Rolling Mean')
     std = plt.plot(rolstd, color='black', label='Rolling Std')
     plt.legend(loc='best')
     plt.title('Rolling Mean & Standard Deviation')
```

```
    plt.show(block=False)

[9]: def test_stationarity(timeseries):

      #Determine rolling statistics
      movingAverage = timeseries.rolling(window=12).mean()
      movingSTD = timeseries.rolling(window=12).std()

      #Plot rolling statistics
       orig = plt.plot(timeseries, color='blue', label=
      'Actual domestic LPG sales')
      mean = plt.plot(movingAverage, color='red', label='Rolling Mean')
      std = plt.plot(movingSTD, color='black', label='Rolling Std')
      plt.legend(loc='best')
      plt.title('Rolling Mean & Standard Deviation')
      plt.show(block=False)

      #Perform Dickey-Fuller test:
      print('Results of Dickey Fuller Test:')
      dftest = adfuller(timeseries['#Tonnes'], autolag='AIC')
     dfoutput = pd.Series(dftest[0:4], index=['Test Statistic',
     'p-value','Lags Used','Number of Observations Used'])
     for key,value in dftest[4].items():
       dfoutput['Critical Value (%s)'%key] = value
     print(dfoutput)

[10]: test_stationarity(indexedDataset)

[11]: indexedDataset_logScale = np.log(indexedDataset)
      plt.plot(indexedDataset_logScale)

[12]: movingAverage = indexedDataset_logScale.rolling(window=12).mean()
     movingSTD = indexedDataset_logScale.rolling(window=12).std()
     plt.plot(indexedDataset_logScale)
     plt.plot(movingAverage, color='red')
     plt.title('Dataset manipulation removing trend')
     plt.legend(['log-scaled dataset','Rolling Mean'])

[13]: datasetLogScaleMinusMovingAverage = indexedDataset_logScale
     - movingAverage
     datasetLogScaleMinusMovingAverage.head()

     #Remove NAN values
     datasetLogScaleMinusMovingAverage.dropna(inplace=True)
     datasetLogScaleMinusMovingAverage.head()

[14]: def test_stationarity(timeseries):

      #Determine rolling statistics
      movingAverage = timeseries.rolling(window=12).mean()
      movingSTD = timeseries.rolling(window=12).std()

      #Plot rolling statistics
      orig = plt.plot(timeseries, color='blue',
      label='Actual domestic LPG sales')
      mean = plt.plot(movingAverage, color='red', label='Rolling Mean')
      std = plt.plot(movingSTD, color='black', label='Rolling Std')
      plt.legend(loc='best')
      plt.title('Rolling Mean & Standard Deviation')
      plt.show(block=False)

      #Perform Dickey-Fuller test:
      print('Results of Dickey Fuller Test:')
      dftest = adfuller(timeseries['#Tonnes'], autolag='AIC')
      dfoutput = pd.Series(dftest[0:4], index=['Test Statistic',
     'p-value','Lags Used','Number of Observations Used'])
```

```
    for key,value in dftest[4].items():
      dfoutput['Critical Value (%s)'%key] = value
    print(dfoutput)

[15]: test_stationarity(datasetLogScaleMinusMovingAverage)

[16]: exponentialDecayWeightedAverage = indexedDataset_logScale
     .ewm(halflife=12, min_periods=0, adjust=True).mean()
     plt.plot(indexedDataset_logScale
     plt.plot(exponentialDecayWeightedAverage, color='red')

[17]: datasetLogScaleMinusExponentialMovingAverage
     = indexedDataset_logScale - exponentialDecayWeightedAverage
     test_stationarity(datasetLogScaleMinusExponentialMovingAverage)

[18]: datasetLogDiffShifting = indexedDataset_logScale
     - indexedDataset_logScale.shift()
     plt.plot(datasetLogDiffShifting)

[19]: datasetLogDiffShifting.dropna(inplace=True)
      datasetLogDiffShifting.head()

[20]: datasetLogDiffShifting.dropna(inplace=True)
      test_stationarity(datasetLogDiffShifting)

[21]: decomposition = seasonal_decompose(datasetLogDiffShifting)

      trend = decomposition.trend
      seasonal = decomposition.seasonal
      residual = decomposition.resid

      plt.subplot(411)
      plt.plot(indexedDataset_logScale, label='Original')
      plt.legend(loc='best')

      plt.subplot(412)
      plt.plot(trend, label='Trend')
      plt.legend(loc='best')

      plt.subplot(413)
      plt.plot(seasonal, label='Seasonality')
      plt.legend(loc='best')

      plt.subplot(414)
      plt.plot(residual, label='Residuals')
      plt.legend(loc='best')

      plt.tight_layout()

[22]: def test_stationarity(timeseries):

      #Determine rolling statistics
      movingAverage = timeseries.rolling(window=12).mean()
      movingSTD = timeseries.rolling(window=12).std()

      #Plot rolling statistics
      orig = plt.plot(timeseries, color='blue', label='Original')
      mean = plt.plot(movingAverage, color='red', label='Rolling Mean')
      std = plt.plot(movingSTD, color='black', label='Rolling Std')
      plt.legend(loc='best')
      plt.title('Rolling Mean & Standard Deviation')
      plt.show(block=False)

      #Perform Dickey-Fuller test:
      print('Results of Dickey Fuller Test:')
      dftest = adfuller(timeseries['#Tonnes'], autolag='AIC')
```

```
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic',
    'p-  value','Lags Used','Number of Observations Used'])
    for key,value in dftest[4].items():
      dfoutput['Critical Value (%s)'%key] = value
    print(dfoutput)

[23]: test_stationarity(datasetLogDiffShifting)

[24]: #ACF & PACF plots

    lag_acf = acf(datasetLogDiffShifting, nlags=30)
    lag_pacf = pacf(datasetLogDiffShifting, nlags=30, method='ols')

    #Plot ACF:
    plt.subplot(121)
    plt.plot(lag_acf)
    plt.axhline(y=0, linestyle='--', color='gray')
    plt.axhline(y=-1.96/np.sqrt(len(datasetLogDiffShifting))
    ,linestyle='--', color='gray')
    plt.axhline(y=1.96/np.sqrt(len(datasetLogDiffShifting))
    ,linestyle='--', color='gray')
    plt.title('Autocorrelation Function')

    #Plot PACF
    plt.subplot(122)
    plt.plot(lag_pacf)
    plt.axhline(y=0, linestyle='--', color='gray')
    plt.axhline(y=-1.96/np.sqrt(len(datasetLogDiffShifting))
    ,linestyle='--', color='gray')
    plt.axhline(y=1.96/np.sqrt(len(datasetLogDiffShifting))
    ,linestyle='--', color='gray')
    plt.title('Partial Autocorrelation Function')

    plt.tight_layout()

[25]: #ARIMA Model
    #making order=(0,0,1)
    # With differencing (log-diff-shifted dataset)
    model = ARIMA(datasetLogDiffShifting, order=(0,0,1), freq='MS')
    results_ARIMA = model.fit()
    plt.plot(datasetLogDiffShifting['#Tonnes'])
    plt.plot(results_ARIMA.fittedvalues[1:], color='red')
    plt.title('ARIMA(0,1,1) model -
    RSS:%.4f'%sum((results_ARIMA.fittedvalues[1:] -
    datasetLogDiffShifting['#Tonnes'][1:])**2))
    print('Plotting ARIMA model')

[26]: #ARIMA Model
    #making order=(0,1,1)
    model = ARIMA(datasetLogDiffShifting, order=(0,0,1), freq='MS')
    results_ARIMA = model.fit(transformed=False)
    # Print the model summary
    print(results_ARIMA.summary())

[27]: predictions_ARIMA_diff
    = pd.Series(results_ARIMA.fittedvalues,copy=True)
    print(predictions_ARIMA_diff.head())

[28]: predictions_ARIMA_diff_cumsum
    =  pd.Series(results_ARIMA.fittedvalues, copy=True)
    print (predictions_ARIMA_diff.head())

[29]: predictions_ARIMA_diff_cumsum = predictions_ARIMA_diff.cumsum()
    print(predictions_ARIMA_diff_cumsum.head())

[30]: indexedDataset_logScale.head()
```

```
[31]: #  add them to base number

      predictions_ARIMA_log = pd.Series(datasetLogDiffShifting
      ['#Tonnes'].iloc[0], index= datasetLogDiffShifting.index)
      predictions_ARIMA_log =
      predictions_ARIMA_log.add(predictions_ARIMA_diff_cumsum,fill_value=
      0)
      predictions_ARIMA_log.head()

[32]: predictions_ARIMA = np.exp(predictions_ARIMA_log)
      plt.plot(datasetLogDiffShifting)
      plt.plot(predictions_ARIMA)
      plt.title('RMSE:
      {0}.4f'.format(np.sqrt(mean_squared_error(datasetLogDiffShifting,
      predictions_ARIMA))))
      plt.legend(['LogDiffShifted dataset','predictions_ARIMA'])

[33]: # fit MA model (0,1,1)
      model = ARIMA(datasetLogDiffShifting, order=(0,1,1), freq='MS')
      model_fit = model.fit(transformed=False)
      # print model summary

      # Plot residual errors
      residuals = pd.DataFrame(model_fit.resid)
      fig, ax = plt.subplots(1,2)
      residuals.plot(title="Residuals", ax=ax[0])
      residuals.plot(kind='kde', title='Density', ax=ax[1])
      plt.show()
      print(residuals.describe())

      # plot residual histogram
      residuals = pd.DataFrame(model_fit.resid)
      residuals.hist()
      plt.show()

[34]: res = ARIMA(datasetLogDiffShifting, order=(0,0,1), freq='MS').fit()
      fig, ax = plt.subplots()
      ax = datasetLogDiffShifting.loc['2017':].plot(ax=ax)
      forecast = plot_predict(res, '2023', '2026', ax=ax)
      plt.show()
```