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GRADUATE SCHOOL OF SOCIAL SCIENCES
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MARITIME SECURITY, SAFETY AND ENVIROMENTAL
MANAGEMENT PROGRAM
MASTER'S THESIS

FORECASTING DRY CARGO HIRE RATES AND SEASONALITY EFFECTS

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İZMİR – 2021

THESIS APPROVAL PAGE

DECLARATION

I hereby declare that this master's thesis titled as "FORECASTING DRY CARGO HIRE RATES AND SEASONALITY EFFECTS" has been written by myself in accordance with the academic rules and ethical conduct. I also declare that all materials benefited in this thesis consist of the mentioned resourses in the reference list. I verify all these with my honour.

15/09/2021

Harun Caliskan

ABSTRACT

Master's Thesis

Forecasting Dry Cargo Hire Rates and Seasonality Effects

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One of the main transportation methods for global trade is Shipping with vessels. 90% of traded goods are carried over the seas. Therefore, Shipping business is one of the main pillars for economy and international transportation. Government policies, global economy, and seaborn trade are not easily predictable factors, and this makes shipping business very volatile and high risky. This high risk and volatility create a major problems and concern for investors at shipping business. Shipowners always look for a useful instrument to forecast the market levels. This helps them to move at the right time for optimizing the profit. Seasonality also another important element of maritime transportation when making decisions. Hence for several decades seasonality in Freight Market also has been investigated by scholars.

The aim of this study, to understand the seasonality effect in the dry bulk ship market and to make future forecasts by examining the daily hire rate in the handy size dry cargo ship market between 2017-2021. Time series models for example Trend Analisis, Exponential Smoothing and ARIMA is employed to make the prediction. In this research, it is aimed to assist companies such as shipowners, charterers, operators, operating in the field of ship chartering etc. to determining the right time to charter in or out their vessels.

Keywords: Handy size, Hire Rates, Dry bulk, Arima, Forecast, Seasonality

ÖZET

Yüksek Lisans Tezi

Kuru yük gemi kiralarının tahmini ve Mevsimsellik Etkisi

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Sosyal Bilimler Enstitüsü

Deniz Ulaştırma İşletme Mühendisliği Anabilim Dalı

Denizcilikte Emniyet, Güvenlik ve Çevre Yönetimi Programı

Küresel ticaret için ana taşıma yöntemlerinden biri gemilerle nakliyedir. Ticareti yapılan malların %90'ı deniz yoluyla taşınmaktadır. Bu nedenle deniz taşımacılığı, uluslararası ticaretin ve küresel ekonominin bel kemiğidir. Küresel ekonomi, deniz yoluyla yapılan ticaretin hacmi ve yapısı ve hükümet politikaları gibi öngörülemeyen faktörler nedeniyle, denizcilik piyasası yüksek risk ve oynaklık ile tanımlanmaktadır. Bu yüksek risk ve oynaklık, denizcilik sektöründeki yatırımcılar için büyük bir sorun ve endişe yaratmaktadır. Armatörler karar verirken piyasa seviyelerini anlamalarına, stratejik bir hamle yapmak için doğru zamanı belirlemelerine ve dolayısıyla kazançlarını optimize etmelerine yardımcı olacak etkin araçlara ihtiyaçları vardır. Ayrıca Mevsimsellik deniz taşımacılığında karar verirken önemli bir unsurudur. Bu nedenle, son yıllarda navlun piyasasındaki mevsimsellik bilim adamları tarafından da araştırılmıştır.

Bu çalışmanın amacı, 2017-2021 yılları arasında Kuru Yük gemi piyasasında oluşan günlük kira rakamlarını inceleyerek kuru dökme gemi pazarında mevsimsellik etkisini anlamak ve geleceğe yönelik tahminlerde bulunmaktır. Tahmin yapmak için Trend Analizi, Üstel Düzeltme ve ARIMA (BOX-JENKINS) modelleri gibi zaman serisi modelleri kullanılmıştır. Bu araştırmada armatör, kiracı, işletmeci, gemi kiralama vb. alanlarda faaliyet gösteren firmalara, gemilerini kiraya alma veya kiraya vermek için doğru zamanı belirlemelerinde yardımcı olmayı hedeflemektedir.

Anahtar Kelimeler: Handysize, Kira, Kuru Yük, Arima, Tahmin, Mevsimsellik

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ABBREVIATION

ASBA	The Association of Ship Brokers and Agents Inc.
BCI	Baltic Exchange Capesize Index
BDI	Baltic Dry Index
BFI	Baltic Freight Index
BHS 1	Baltic Handysize Route 1
BHS 2	Baltic Handysize Route 2
BHS 3	Baltic Handysize Route 3
BHS 4	Baltic Handysize Route 4
BHS 5	Baltic Handysize Route 5
BHS 6	Baltic Handysize Route 6
BHS 7	Baltic Handysize Route 7
BHS 7 TC	Baltic Handysize 7 Routes Average
BHSI	Baltic Exchange Handysize Index
BIMCO	Baltic and International Maritime Council
BPI	Baltic Exchange Panamax Index
BSI	Baltic Exchange Supramax Index
CoA	Contract of Affreigment
FFA	Forward Fregiht Aggrement
GDP	Gross Domestic Product
GDTCE	Gross Daily Time charter Equivalent
ICS	Institue of Chartered Shipbrokers
IFO	Intermediate Fuel Oil
LNG	Liquefied natural gas
LOA	Length overall
LPG	Liquefied petroleum gas
MAD	Mean absolute deviation
MAPE	Mean absolute percentage error
MDO	Marine Diesel Oil
MSD	Mean squared deviation

NOAA	National Oceanic and Atmospheric Administration
OECD	The Organisation for Economic Co-operation and Development
RMT	Review of Maritime Transport
S & P market	Sale and Purchese Market
SAC	Sample Autocorrelation Function
SPAC	Sample Partial Autocorrelation Function
SPSS	Statistical Package for the Social Sciences
TPC	Ton per centimeter
UNCTAD	The United Nations Conference on Trade and Development

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INTRODUCTION

This thesis is about understanding of dry bulk market. Especially concentrates on Handysize vessel. Main focus is trying to forecast Handysize market hire rates and seasonality. This will enable ship owners or operators to change their tonnage from spot market to time charter or vice versa to get ideal profit.

This thesis is organized Four main chapters, plus introduction and the conclusion.

In the Introduction, background of thesis and the objective of the study are expressed.

Chapter one explains relation between world economy and shipping. Definition of pattern of maritime trade, characteristic of the four-shipping market, and factors effecting shipping market are expounded.

Chapter two focuses on shipping organizations, what is shipping routes, types of charter parties and seasonality.

Chapter three aims to describe types of forecasting methods and which methods used in shipping researchers. Also review of literature added to this chapter.

In Chapter four, aim of study and methodology are mentioned. Finding of analysis and evaluation of this analysis provided.

In the final section, Recap of the analysis and studies are reviewed. Suggestions for the further studies are pointed out.

CHAPTER ONE
SHIPPING MARKET

1.1 WORLD ECONOMY AND SHIPPING

Maritime is the one of the primary necessities for progress of the civilization. The best way to transport large quantities of the goods was using boats on the rivers or seas. This solution is continuing for long distances (United Nations, 2017:1-2).

Trade between countries started because of several reasons. Impact of climate on agricultural products, places of natural resources, and unable to produce sufficient commodities are some of the motives for international trade. Hence demand for goods and transportation of goods was created need for international shipping trade (Branch, 1998:1-2).

Beginning of the 19th century steamships were introduced to the shipping world. These vessels were gamechanger and increased amount of several orders of world trade. Gradually globalisation has been begun (United Nations, 2017:1-2).

In 1948, steam ships accounted for 68% of the ships in the fleet and 79% of the fleet tonnage, while motor ships accounted for 29% of ships and only 20% of the tonnage; sail still powered for 4% of vessels, but only 1% of registered ship tonnage. By 1970, motor ships dominated the fleet both in terms of ships and cargo tonnage, with 85% and 64%, respectively. After fuel conversion was implemented and engines turned to more efficient marine diesel engines, engine efficiencies increased from 35% to 40% in 1975 to more than 50% today. This and other technological advancements allowed maritime shipping to meet the transportation demands driven by a growing globalized economy (OECD, 2010).

Need for international shipping created modern industries such as insurance for finance, some of engineering, and inventions for safe of navigation (United Nations, 2017:1-2).

It looks as if that commercial progress creates international business, which in return generates request for shipping (Lun et al., 2010:2).

As per UNCTAD (2020) report 11.08-billion-tons of cargo shipped world widely. It makes world economy a leading influencer on the demand for seaborne goods transportation. Ban Ki-moon (Former Secretary-General of the United Nations) revealed that “Maritime transport is the backbone of the global trade and the global economy” (B. Ki-Moon, 2016). Over 80% of all cargo, in terms of volume, is carried by sea, accounting for 70% of the total value of international trade (Hoffman et al., 2017).

One of the major influencers of the demand for seaborne transport is the global economy. Since high income is likely to be related with more domestic consumption and less export, economic expansion in developing countries seems negative impact on ocean transportation. Another positive impact to maritime industry is shocks in GDP (world). Each category of shipped goods is affected with magnitude of specific (Nektarios, 2020:7).

Also, earlier findings (Alizadeh et al., 2014:445-461), (Baser et al., 2019:1-17), support the idea that world economy have impact on demand in the maritime industry.

1.2 GLOBAL PATTERN OF MARITIME TRADE AND AREAS

The goods are shipped among more than thousands commercial ports. Understand what for and where these cargoes are move is needed for understanding this economic system (Stopford, 2009:347). Table 1 and Table 2 shows volume of cargoes imported and exported by continents.

Table 1 Volume of cargoes imported (percentage)

		YEAR					
	REGION	2015	2016	2017	2018	2019	2020
IMPORT	Africa	3.37	3.08	2.90	2.95	3.02	2.86
	America	22.58	22.20	21.52	21.25	21.34	21.01
	Asia	37.36	36.73	37.66	37.97	37.74	37.99
	Europe	35.15	36.48	36.36	36.33	36.45	36.69
	Oceania	1.54	1.51	1.57	1.49	1.45	1.45

Source: UNCTAD.

Table 2 Volume of cargoes exported (percentage)

		YEAR					
	REGION	2015	2016	2017	2018	2019	2020
EXPORT	Africa	2.38	2.26	2.42	2.55	2.48	2.14
	America	17.13	17.03	16.70	16.37	16.55	15.79
	Asia	41.47	40.91	41.11	41.20	41.08	42.15
	Europe	37.61	38.32	38.18	38.28	38.18	38.21
	Oceania	1.41	1.48	1.60	1.59	1.71	1.71

Source: UNCTAD.

In 2020, Asia imported about 38 pct of cargoes, Europe imported about 37pct of cargoes, America imported about 16 percentage of cargoes. Remaining continents imported only 9 percentage of cargoes. Although Africa and Oceania have very large areas, portion of importations is minor compared to others. In 2020 Exporter continents were Asia about 42 percentage, Europe about 38 percentage and America about 16 percentage. Asia, Europe, and America generated largest part of the world trade. Therefore, main trade routes formed between these continents which helped by the Panama and Suez canals.

The oceans and seas are at the centre of maritime trade and cover more than 70% of the globe. Largest one is Pacific Ocean, secondly Atlantic Ocean and thirdly Indian Ocean. Each has a unique character and specific trading centres/areas with major ports.

1.2.1 Atlantic Ocean Maritime Areas

Atlantic Ocean with linked seas and rivers has important economic role of the world trade. Baltic, Mediterranean, Black Sea, the Mexico Gulf, and the Caribbean giving wide range for trade. Rivers like Rhine, Elbe, the St Lawrence, Mississippi, Orinoco, Amazon and Parana provide water transports deep into Countries. Atlantic Ocean connected with other oceans via the Suez Canal to the Indian Ocean and via the Panama Canal to the Pacific Ocean (Stopford., 2009:356).

1.2.2 Pacific Ocean Maritime Areas

Pacific Ocean Maritime Areas briefly can be described Canal of Panama in the West, Malacca strait in the East, Bering strait in the north and Antarctica in the south (Stopford, 2009:359). According to National Oceanic and Atmospheric Administration (NOAA) “Pacific Ocean is the biggest water area on the earth and covers more than 30 percent of the World`s surface. It contains roughly half of the World's open water source and have two times more water than the Atlantic Ocean” (NOAA, 2021).

Countries of east coast of Pacific Ocean as China, Indonesia, Taiwan, South Korea, the Philippines, Singapore, Malaysia, Hong Kong, Thailand, Vietnam, and Japan produces seaborne market of food, energy, steels, raw materials, cement, general cargo, and vehicles. These areas also have the world`s busiest of container transportation. New Zealand, Papua New Guinea, Australia, and several islands are the key providers of raw materials and energy to Asian countries, with main exports of coal, grain, iron ore, bauxite, gas, and forest products (Stopford, 2009:361).

1.2.3 Indian Ocean Maritime Areas

Borders of the Indian Ocean are Pakistan, Iran, and India in the north, east part of Africa in the west, Antarctic continent in the south, Indonesia, and Commonwealth of Australia in the east. This ocean also contains Red Sea, the Arabian Gulf and sea, the Bay of Bengal, the Timor Sea, and the Arafura (Stopford, 2009:362).

In the Indian Ocean despite its size the East African coast have little impact on the shipping market. The Red Sea is very busy Seaway for traffic because of the Suez Canal linking the Mediterranean Sea and the Indian Ocean. Myanmar (Burma), Bangladesh, Pakistan, India, and various smaller countries produce cereals, coal, and iron ore. Also, half volume of the cargos imported are crude oil and oil products due to lack of resource (Stopford, 2009:364).

1.2.4 BIMCO Geographical Ranges

BIMCO also published definitions of geographical ranges to minimise the risk of becoming entangled in disputes. Accordingly geographical ranges are (BIMCO, 2021):

- Scandinavia: Shall mean ports or places situated in Norway, Denmark, Sweden, and Finland, including islands within the Baltic Sea.
- Baltic: Shall mean ports or places situated in the Baltic and adjacent waters south of a line drawn from Falsterbo to the 55-deg. latitude on the east coast of Moen, following the 55-deg. latitude west to the east coast of Jutland.
- U.K.: Shall mean ports or places situated in Great Britain and Northern Ireland.
- Continent: Shall mean ports or places located on the Coast of the European Continent, from Hamburg in the north to Bordeaux in the south, both inclusive, also including Rouen.
- A.R.A. ("Amsterdam-Rotterdam-Antwerp"): Shall mean the ports of Amsterdam, Rotterdam, and Antwerp.
- Skaw/Cape Passero: Shall mean ports or places situated on the Coast of the European Continent, including Rouen, from Skaw in the north to Cape Passero in the southeast, Cape Passero being the easternmost point, thus including Western Mediterranean ports, Balearics, Sardinia, Corsica, and Malta, but excluding the North African Coast and the Adriatic Sea.
- Mediterranean: Shall mean ports or places situated in the Mediterranean Sea from the Strait of Gibraltar in the west to the Dardanelles in the northeast, thus including the Adriatic Sea and Aegean Sea, but excluding the Suez Canal. The dividing line in the west shall be a line drawn from Gibraltar in the north to Ceuta in the South, both inclusive. The dividing line in the northeast shall be the western entrance of the Dardanelles.
- West Med. ("West Mediterranean"): Shall mean ports or places situated in Mediterranean, from Gibraltar strait in the west to Cape Passero in the east. The dividing line in the west shall be a line drawn from Gibraltar in the north to Ceuta in the south, both inclusive. The dividing line in the east shall be a line drawn from Cape Passero in the north to, and excluding, Misurata in the south, thus including the north coast and the southwest coast of Sicily.
- East Med. ("East Mediterranean"): Shall mean ports or places Situated in the Mediterranean Sea, from Cape Passero in the west to the Dardanelles in the northeast. The dividing line in the west shall be a line drawn from Cape Passero in the north to, and including, Misurata in the south, thus including the east coast of Sicily and the Adriatic Sea. The dividing line in the northeast shall be the western entrance to the Dardanelles, thus including the Aegean Sea.

- West Coast Africa: shall mean ports or places located on western coast of Africa, from Dakar in the north to Douala in the south, both inclusive, including Fernando Po, but excluding Cape Verde Islands.
- East Coast Africa: Shall mean ports or places situated on the East Coast of Africa, from Cape Guardafui in the north to, and including. Maputo in the south, including Zanzibar.
- Southern Africa: Shall mean ports or places situated on the South Coast of Africa, from Maputo in the east to Lüderitz in the west, both exclusive.
- Red Sea: Shall mean ports or places situated in the Red Sea, from Suez in the north to the Strait of Bab el Mandeb in the south, thus including Suez gulf and Aqaba gulf.
- PG ("Persian Gulf") or AG ("Arabian Gulf"): Shall mean ports or places situated in the Persian (Arabian) Gulf, including Shatt Al Arab, not above Basrah. The dividing line in the south shall be a line drawn from, and including, Bandar Abbas to the northernmost point of the Musandam Peninsula.
- West Coast India: Shall mean ports or places situated on the West Coast of India, from, and including, Kandla in the north to Cape Comorin in the south.
- East Coast India: Shall mean ports or places situated on the East Coast of India, from, and including, Calcutta in the north to Cape Comorin in the south, excluding Sri Lanka.
- Far East: Shall mean ports or places situated on the Mainland Coast, from Myanmar in the southwest up to, and including, Vostochny in the northeast, thus including Singapore and including the whole of Japan, The Philippines, China (Taipei), Malaysia, Brunei, Indonesia and Papua New Guinea.
- Singapore/Japan: Shall mean ports or places situated in the Far East, from Singapore in the south through the South China Sea to Japan in the north, thus including Singapore, the Philippines, China (Taipei) and the whole of Japan, but excluding Mainland Ports, Malaysia, Brunei, Indonesia and Papua New Guinea.
- ECCAN ("East Coast Canada"): Shall mean ports or places on the East Coast of Canada situated on the Coast facing the Bay of Fundy, the Atlantic Ocean, the St. Lawrence River not above Montreal, and the Gulf of St. Lawrence from, and including, Battle Harbour in the north to Oak Bay in the south, also including Anticosti, Prince Edward, Magdalen, Cape Breton and New Foundland.
- USNH ("United States North of Hatteras"): Shall mean ports or places situated on the United States' East Coast, from Cape Hatteras in the south up to, and

including, Calais in the north, including Chesapeake Bay, Delaware Bay, the Delaware River not above Philadelphia and the Hudson River not above Albany.

- USEC (“United States’ East Coast): Shall mean ports or places situated on the United States’ East Coast from Miami in the south to Calais in the north, both inclusive, including Chesapeake Bay, Delaware Bay the Delaware River not above Philadelphia and the Hudson River not above Albany.
- USNOPAC (“United States’ North Pacific Coast”): Shall mean ports or places situated on the United States’ North Pacific Coast, from Brookings in the south to Blaine in the north, both inclusive, including the Columbia and Willamette Rivers and Puget Sound.
- USPAC (“United States’ Pacific Coast”): Shall mean ports or places situated on the United States Pacific Coast, from San Diego in the south to Blaine in the north, both inclusive, including the San Francisco Bay Area, the Columbia and Willamette Rivers and Puget Sound.
- U.S. Gulf: Shall mean ports or places in the United States situated on the Coast facing the Gulf of Mexico, from Key West in the east to, and including, Brownsville in the west, including the Mississippi River not above Baton Rouge.
- ECCA (“East Coast Central America”): Shall mean ports or places in Belize, Guatemala, Nicaragua, Costa Rica, Honduras, and Panama situated on the East Coast facing Caribbean, including the Panama Canal.
- WCCA (“West Coast Central America”):Shall mean ports or places in Honduras, Guatemala, Nicaragua, Costa Rica, El Salvador, and Panama situated on the Pacific coast, including the Panama Canal.
- Caribs (“Caribbean Sea”): Shall mean ports or places situated on Dominican Republic, Cayman, Haiti, Puerto Rico, Jamaica, Virgin, Leeward, Windward and Barbados.
- West Indies: Shall mean ports or places situated on Cuba, Pinos, Bahamas, Great Inagua, Turks and Caicos.
- NCSA (“North Coast South America”): Shall mean ports or places situated on the North Coast of South America, from Turbo in the west to Georgetown in the east. both inclusive, including the Orinoco River not above Matanzas and including Lake Maracaibo and Aruba, Curacao Bonaire, Margarita, Trinidad, and Tobago.
- ECSA (“East Coast South America”): Shall mean ports or places situated on the East Coast of South America, from, and including Georgetown in the north to Punta Dungeness in the south including the Amazon River not above Macapa, the

River Plate, the River Parana not above San Lorenzo and the Uruguay River not above Fray Bentos.

- WCSA (“West Coast South America”): Shall mean ports or places situated on the South American Pacific Coast, from Jurado in the north to Punta Arenas the south, both inclusive.

1.2.5 Key Trade Routes

According to the Baltic Exchange (2021) the largest trade routes for major bulk cargoes are:

- For Iron Ore:
  - ➢ Major Exporters are Australia, India, South Africa, Brazil, Norway, Black Sea and Chile
  - ➢ Major Importers are Far east, Europe, and Argentina
- For Coal
  - ➢ Major Exporters are Australia, South Africa, Indonesia, Colombia, USA East Coast and West Coast of Canada.
  - ➢ Major Importers are Far east, Europe, Brazil, India and Argentina
- For Wheat
  - ➢ Major Exporters are North America, Australia, East coast of South America, UK/Continent, Black Sea
  - ➢ Major Importers are Far east, Middle East, Europe, and North Africa
- For Soya Beans
  - ➢ Major Exporters are USA gulf, USA West Coast, Brazil, and Argentina
  - ➢ Major Importers are Far east, Middle East, and Europe

1.3. FOUR SHIPPING MARKET

1.3.1. Definition of Market

Basically, market is where some shops and various types of goods are bought and sold but in finance it has different description. In economics can be defined as where supply and demand on task, prices amended and regulated, beneficiary of some products are transferred, and physical exchanges happens (Cochrane, 1957:21-22). According to Houck (1984:353-356):

A market is where possible buyers and actual sellers are gathering to exchange specific goods or services. This gathering has two attributes: (1) buyers have no option to buy any good or service but from outside this market sellers and (2) sellers have no option to sell any good or service but from outside of this market buyers. Buyers and sellers are identifying the market spatially, temporally, and politically.

There are several markets for real estate, labour, capitals, or anything that has a price. Seller and buyer instead of meeting at marketplace may be connected to each other their office which might be any place in the world. Hence, negotiations and agreements may finalize over the telephone, fax, email, or letter. Also, agent of clients may be wholly or partly seller or buyer on behalf of their customers (Benham, 1943:20-21).

In addition to Benham, Jevons (1965:84) briefly explain "a market was a public place in a town where supplies and other necessities are provided for sale but now the hubs of market are public exchange, mart, or any other places, where the traders or their agent to meet and conduct business”.

In shipping we can discuss about four different shipping markets.

- Freight market where vessels chartered and FFA`s concluded,
- S&P market: For second hand vessels trade
- Shipbuilding market: For brand-new vessels trading
- Scrapping market: demolition/scrapping vessel trading

No formal structure of shipping market apart from above (Stopford, 2009:177).

Shipping market can be defined in several ways. Lun (2010:34) says shipping markets can be described in two ways such as real and auxiliary market. Real market includes “new-building” and “scrapping” market. Growth of new vessels indicates an expansion in total volume of tonnages, and growth of ship demolition signify a reduce in total volume of tonnages in shipping market. Alternatively, the secondary market relates to freight market which deals maritime transportation and S&P market for second-hand vessels sale. Since these business deals (freight agreements & S&P agreements) made between shipowners and shippers in auxiliary markets, there is no influence on the total volume of the vessel in dry bulk market (Lun and Quaddus, 2009:39).

1.3.2 The Freight Market

This is basically where the owners and shippers of shipping clients get together to reach a deal for cargo freight or vessel hire. This can be categorized in several ways Alderton and Rowlinson (2010:181-182) split freight market in to four major sections:

> *Voyage charter market is that owner provides vessel holds from one port to another against agreed freight rate per metric ton to charterers or shippers. The contract of affreightment Market (COA) is derived from voyage charterers market and aim is transport much cargo on a regular basis. Time charter market is different from voyage market. Charterers become a disponent owners and take more responsibility. Also, it can be divided in three: short, medium, and long term. Finally bareboat charter marker is charterers will be to ultimate responsible for the vessel (except capital cost) and operate the vessel their own account.*

1.3.3. The Sale and Purchase Market

Shipping is very different and active sector from other industries. The main assets of capital (the vessel themselves) are traded in this industry. S&P market (for second-hand vessels) plays very important part in this economic system. Shipowners or any investors have occasion to buy or sell the vessel immediately which permits them simple entrance or escape to maritime industry (Tsolakis et al., 2003:348).

Strandenes (2002:217-234) is mentioned that “Ships are changed hand at S&P market for further trading. These changes do not influence on world available transport capacity only shift ownership of the vessels among the companies. Hence S&P market described as auxiliary market”

The second-hand vessel price is not decided by cost of the building ship but buyers/seller’s expectation from the market, and profitability for now and future. After the agreement new building ships will be delivered within one to four years so this duration creates uncertainty risk. On the other hand, second-hand vessel might be delivered within one to three months. Hence these vessels deserve extra money for being available with short notice. this is called “second-hand ship time premium” (Goulielmos, 2009:76).

There are 5 stages in S & P market (Stopford, 2009:199-202):

- Putting the vessel in market
- Negotiating terms and conditions
- Recap of Agreement
- Inspection by investors

- Finishing the agreement

Trading ship to sell at deep of the shipping cycle can be tragedy for the seller and contrarily might be advantageous for the buyer. S&P values of the vessel might be affected for some reason such as vessel age, inflation, expectation, and current freight levels (Stopford, 2009:213).

1.3.4. The Newbuilding Market

Bruce (2021:4-5) says:

> *Where and when shipbuilding started is uncertain, but shipbuilding sector faced with major changes over the last 200 years. From past today changing the main structure from wood to steel, changing size and variety of vessels, changing propulsion from sail to electric, and increased qualified equipment fitted on board for safe of navigation are some developments to name but a few. Because of the cost of shipping per ton still better than other types of transportation shipowners can offer very competitive freight rates, accordingly, it makes seaborn trade to continue to expand. Due to globalization shipping industry will grow strongly, even if short term issues arise.*

Gradually growing need for seaborne transport influenced necessity of new vessels (Wright, 1991:47-54). This also increased need for oil, vessel hire rates, and putting much more money on new ships, therefore prices of new ships arise. But increased vessel price puts a barrier to support stabilization of the shipping market (Dikos, 2004:312-313).

It is very hard to estimate supply side of the ship building but some factors can be indicated what influence this market. After twenty-five years vessel is considered not profitable to operate generally. These vessels are sent to demolition market to replace with new one. Also, extra vessels are needed because of changes in world trade pattern, new trade routes and new types of cargoes (Bruce, 2021:2-8).

The key contributing factors of the brand-new vessel price are (Cullinane, 2005:70-71):

- Cost of building a new vessel
- Capacity of the shipyards
- How many vessel ordered for future
- Ship hires levels
- S&P prices

1.3.5. The Demolition Market

Freight is decided by impact of demand and supply. If demand exceeds supply, freight rates go up and players starts investing on new ships. Contrarily if supply exceeds demand, freight rates go down, and owners start to demolish unprofitable vessels. The speed of sending vessels to the demolition is always faster than receiving ships from newbuilding market. This will cause a new market balance at higher freight rate (Acık et al., 2017:96-112).

Several reasons influence demolition market which is also called scrapping the vessels. The sources for the demolition market are function of low vessel hire levels, age and type of vessels, and existing or expected rules/regulations. Also, price of steel and the costs affect market needs which is linked with scrapping activity (Knapp et al., 2007:7).

Decision of scrapping the vessel is depends on owner's anticipation of profit from the future freight market and their economical situations. Generally, sending vessel to demolition market depend on current value of scrap prices. Choice of scrapping is linked to Owners` hopes for the potential profit from the market. Vessel will be sent to demolition if the profit is low. When the scrap prices continue to arise, it encourages owner to send more vessel to demolition market. Consequently, it causes decries of fleet size of the shipowner. Demolition market helps ship operators to modify their capacity of fleet (Lun and Quaddus, 2009:41).

Developing countries are the key participant to scrapping market. Therefore, ship scrapping is one of the important sources of employment and income (Sarraf et al., 2010). Dedicated broker desks are offered in nearly every chartering companies. Leading countries of demolition market are Turkey, India, and Pakistan (UNCTAD, 2020).

1.4. FACTORS AFFECTING MARITIME SHIPPING MARKETS

Many economists accepted that shipping industry have cycles. Requirement for cargo transport identify demand side, and tonnage of vessels are representing supply side (Lemper and Tasto, 2015:3).

The Maritime industry is reacting according to today and future expectation of the world economy. When the today`s economy shows signs of recovery or expectation turns to positive, seaborne transportation is response to this and increases DWU (deadweight utilization). Contrarily, any negative sings of economy are influence freight rates, newbuilding, and second-hand prices (Karakitsos et al., 2014:294-295). Investors or Shipowners aim is to get benefit of the low market to buy and wait for right time to sell at the high market by using this shipping cycles.

Many factors may influence the shipping market. According to Stopford (Stopford, 2009:136) there are 5 reason impact on demand and supply individually

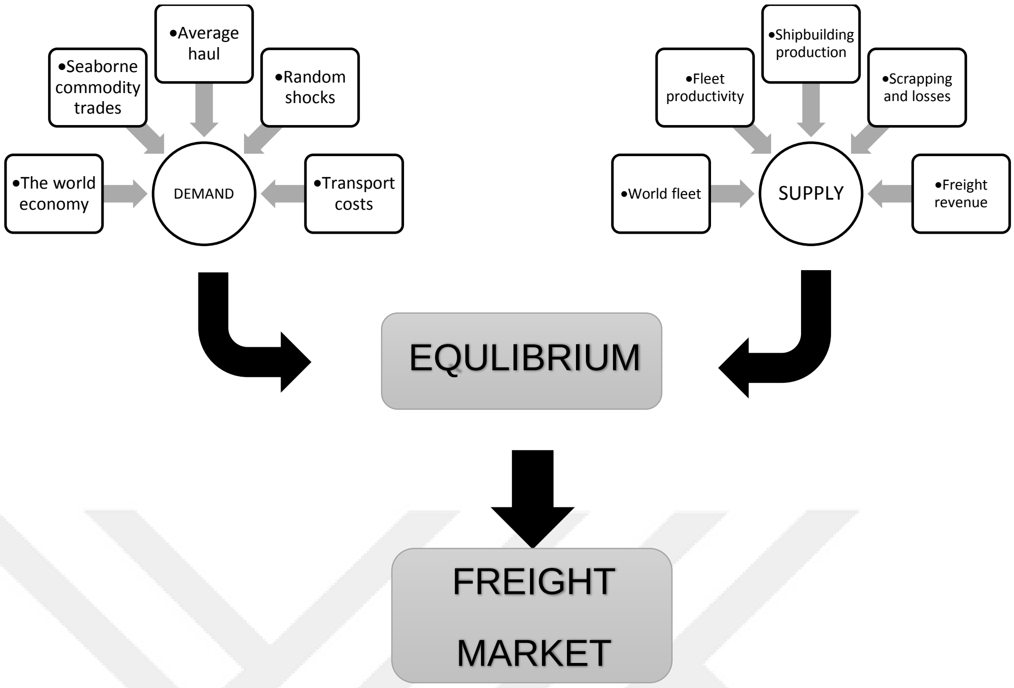
Factor effecting demand:

- The world economy
- Seaborne commodity trades
- Average Haul
- Random Shocks
- Transport Costs

Factors effecting supply:

- World Fleet
- Fleet Productivity
- Shipbuilding Production
- Scrapping and losses
- Freight Revenue

Figure 1 The shipping market model



Source: Stapford, 2009

1.4.1. Demand

1.4.1.1. The world economy

Maritime transport is one of the pillars of seaborne trade and world economy (UNCTAD RMT, 2018). It appears that economic expansion creates global business, which in turn generates need for ocean transportation (Lun et al., 2010:2). As per UNCTAD (2020) report “11.08-billion-tons of cargo shipped world widely. It makes world economy a key influencer on the necessity for ocean transportation”. Also, earlier findings (Alizadeh et al., 2014:445-461), (Baser et al.,2019:1-17), (Nektarios, 2020:7) support the idea that world economy have impact on demand in the maritime industry.

1.4.1.2. Seaborne commodity trades

Effects of seaborn commodity trades to demand can be discussed in short- and long-term run. A crucial reason of the short term volatility is the seasonal effect of some business (Stopford, 2009:143). Harvest of various commodities (grain, sugar, etc) are changes depend on seasonality in both Hemisphere. As an example, grain harvest is around September in Northern Hemisphere and around March in Southern Hemisphere. Same as grain the seasonal fluctuation in energy consumption changes oil demand. For liner trade important public holiday like Christmas and Chinese New Year changes demand for goods.

A longer-term strategy in commodity market can be ascertained changes in specific commodity demand (Changing primary energy source from coal to oil), source of supplier (for China getting iron ore from brasil instead of Australia and India), location of processing plant and transport policy (planning future transportation of product and building/chartering vessel for long term accordingly (Stopford, 2009:145).

1.4.1.3. Average haul

“Measures of shipping demand or freight work (tkm) combines both tonnages lifted (t) and distance hauled (km) and changes in both elements effect demand. Thus, risking global freight work may reflect either longer hauls as local material sources are exhausted or output increases” (Dinwoodie et al., 2014:65). Depends on place of the cargo shipped may increase or decrease demand for sea transport. Grain transportation from Argentina to Algeria creates much more demand for sea transport compared to grain shipment from France to Algeria. This distance impact is called “average haul” or “ton miles”. The effect of average haul can be explained with Suez Canal closure. It was increased regular steaming time from Persian Gulf to Turkey from 10 days to 40 days. Accordingly ship demand and freight/hire rates increased promptly.

1.4.1.4. Random shocks

Some of unique and unpredictable occasions can make quick and unforeseen need for sea transport. Wars, natural disasters, financial crises, political changes to name but a few.

1.4.1.5. Transport costs

The most crucial and essential element for the social and economic development of a particular region is transportation. Economic and effective transportation of the goods from giant factories to small corner shops increase ability of their competitiveness and reduce operating costs. Globalization of the world is increased the distance between buyer and seller, hence ocean transport become more critical for organizations (Novack et al., 2019:26).

The improvement of shipping techniques, larger vessels, and implementation of more efficient association of shipping operations have caused in a continuous decline in transportation prices (Lun et al., 2010:14). Influence of transport costs may not seem primarily, but its impact cannot be disregarded.

1.4.2. Supply

1.4.2.1. World fleet

Merchant fleet is primary source of sea transport which is defined by current fleet, new buildings, and scrapped vessels. The total world fleet 100 gross tons and above is 98,140 ships, equal to 2.061.944.484 dwt of volume. The distribution of across vessel types is 43% bulk carries, 29% oil tankers, 13% container and 15% others (gas carriers, chemical tankers, passenger vessels etc.). About 65 million gross ton new buildings delivered in 2019 and about 12 million gross ton vessel scrapped. In 2019 the world-wide fleet increased by 4.1% (RMT, 2020).

1.4.2.2. Fleet productivity

According to Jogovic (2015) 4 reason effect efficiency of fleet:

- Speed: affects time of ship movements
- Port time: Limits the physical performance of ships and terminals
- Deadweight utilization (DWU): preventing items to load the vessel completely such as bunkers.
- Spent time at seas divided into loaded steaming time and non-productive time (ballast time or port time)

The vessels designed for flexibility of goods transport can increase vessel loaded time at sea (Jugovic et al., 2015:26).

1.4.2.3. Shipbuilding production

The shipbuilding production is another important element for supply side of the shipping market. In 2019 92.5 per cent of the newbuilding was built by Republic of Korea, China, and Japan. China is leading builder of general cargo ships and bulk carriers, Japan leads for building chemical tankers and Korea is the leading builder of gas carriers, oil tankers (UNCTAD, 2020). Ship deliveries takes about 1 to 4 years after sinning agreement of course depends on current order book. So which type of ship built is important. Ups and downs in delivery have an influence on shipping market. (Stopford, 2009:156-157).

1.4.2.4. Scrapping and losses

One of the key elements for balancing supply and demand for ship demolition market but not too many articles published relatively. When owner`s profit is decreasing in existing markets, they have option to wait for to market (they can continue trading, laying up the vessel or modernize vessel), sell the vessel in second-hand market or send vessel to scrap (Buxton, 1991:109). When the vessel life cycle is completed, it will be scrapped. Ships basic materials, steels, and other parts will be demolished or sold (Anyanwu, 2013:29-41). Reason for sending ships to scrap depends on many different factors like vessel ages, technical obsolescence breaking prices, financial position (Stopford, 2009:158-159).

Total volumes of recycled tonnage about 12.218 thousand gross tons. 90.3 per cent of the ship demolished in Bangladesh, India and Turkey (RMT, 2020).

1.4.2.5. Freight revenue

The freight rate has a major impact in the shipping business. Finance sectors take the highest percentage of risk and contribute up to 75–80%, of the construction cost in a shipping deal (Goulielmos and Psifia, 2006:301). Also, Volk (1984) commented that “most of the ship investment activities are concurrent with the high freight rate. Consequently, it is crucial for the financer to follow the shipping cycle and give significant attention when making loan decisions” (Volk, 1984, as cited in Luo at al., 2009:508).

1.4.3 Freight

Supply and demand determine the equilibrium price of freight rates. If Supply is tight freight rates increase, oppositely if demand is tight freight rates decrease. Timescale is important is reaching and equilibrium price. As per Stopford (2009) there are three time period that need to be considered (Stopford, 2009:163-167):

- Momentary equilibrium: Prompt ships open for cargoes in certain area.
- Short-run Equilibrium: If vessels have time to steaming around the world, modify their speed or consume time in lay-up.
- Long term equilibrium: Volume of the world fleet can be balanced by ordering new vessel and send the old ones to the demolition.

CHAPTER TWO
SHIPPING ORGANIZATIONS, ROUTES AND CHARTER PARTIES

2.1. THE BALTIC EXCHANGE

The Baltic exchange (as a Virginia and Baltic Coffee House) was established in London in 1744. The Baltic exchange is a worldwide organization that unites about 3000 global members from shipping industry includes shipbrokers, freight derivative brokers, trading houses, shipowners, and cargo interests. The organisation also contains maritime lawyers and arbitrators, insurers, ship registries, financiers, ship classification societies. Represented in 60 countries and publishing indices more than 35 years. Their main goals are providing standardized benchmark of evaluations for the dry bulk, tanker, gas and container markets, assisting to resolve disputes, provide training and escrow services for their members (Baltic Exchange, 2021).

The indices that published by The Baltic Exchange are closely followed by freight derivatives industry, charterers, and shipowners. Some physical contracts (charter parties) are concluded based on fluctuating rates determined by the Baltic indices or route assessments. The Baltic indices are calculated evaluations of the cost of transporting various cargoes such as wet cargoes (e.g., crude oil and oil products), dry cargoes (e.g., coal and iron ore) and gas cargoes (LNG and LPG) provided by shipbroking houses located all around the world (Baltic Exchange, 2021).

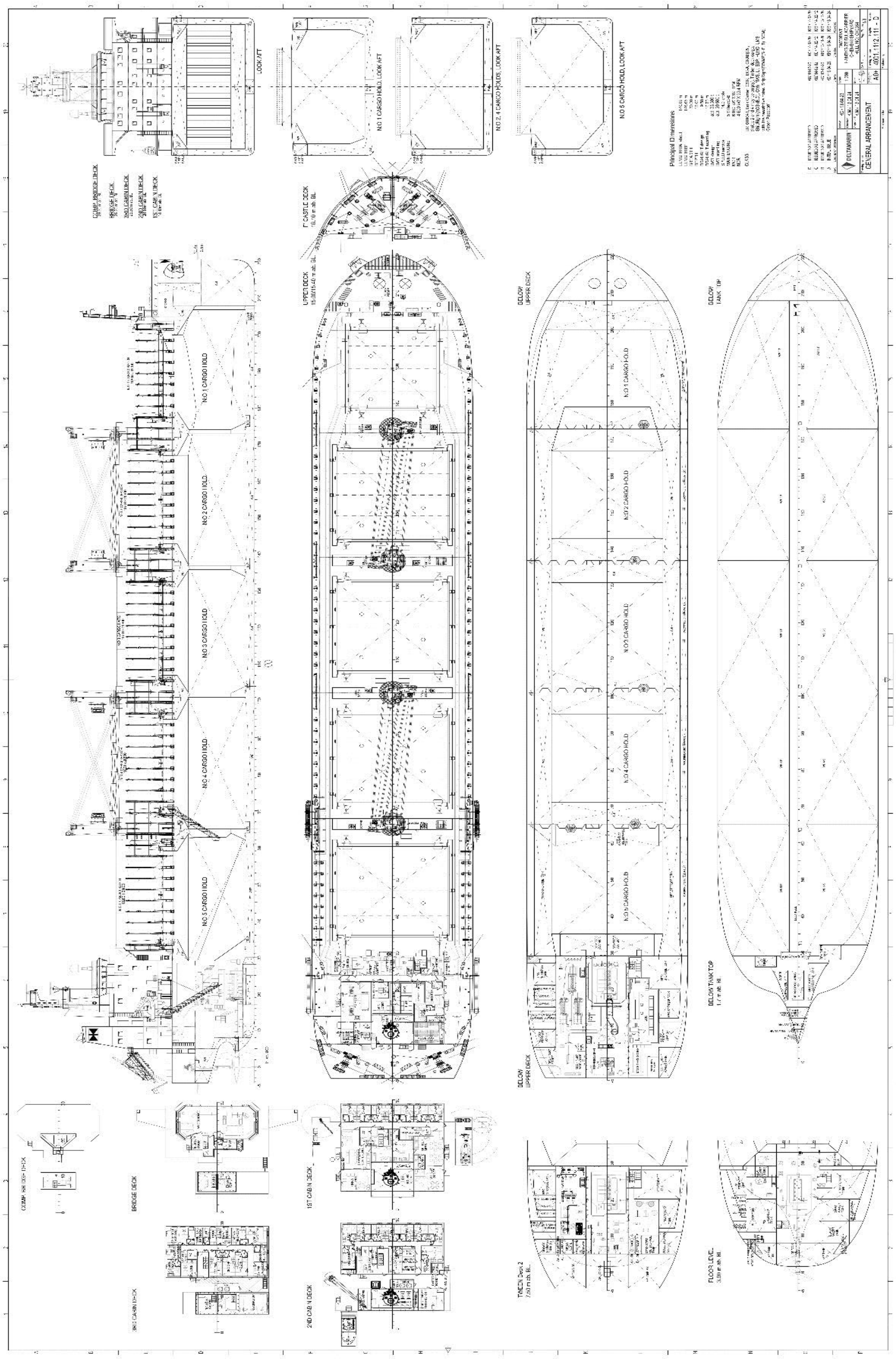
2.2. HANDYSIZE VESSEL DESCPRIPTION

Handysize are smaller bulk carriers with a deadweight from 25.000 up to 50.000 tonnes. Advantage of their size is to permits them to enter smaller ports to load and discharge cargoes. Most of them are geared fitted with cranes. Typical cargoes carried by handysize vessel are grains, cements, steels, fertiliser, forest products, ores, and other type of break bulk cargoes. Handysize vessel are most commons size of dry bulk marker.

Description for Handysize Ship:

SINGLE DECKER
SELF TRIMMING
BULK CARRIER
NON-SCRUBBER
DEADWEIGHT: 38,200MT
DRAFT: 10.538 Sea water density
MAX AGE: 15 YEARS
LOA: 180M
BEAM: 29.8M
TPC: 49MT
GRAIN CAPACITY: 47,125 CBM
BALE CAPACITY: 45,300CBM
HOLD/HATCHES: 5 HOLDS / 5 HATCHES
GEARS: 4 x 30MT
SPEED AND CONSUMPTION (INCLUDING MAIN ENGINE AND AUXILARY ENGINES)
LADEN: 14 KNOTS ON 26 MT IFO (380 CST) + 0.1 MT MDO
BALAST: 14 KNOTS ON 24 MT IFO (380 CST) + 0.1 MT MDO
ALTERNATIVE SPEED AND CONSUMPTION (INCLUDING MAIN ENGINE AND AUXILARY ENGINES)
LADEN: 12 KNOTS ON 18 MT IFO (380 CST) + 0.1 MT MDO
BALAST: 12 KNOTS ON 17 MT IFO (380 CST) + 0.1 MT MDO

Figure 2 General Arrangement Plan



Source: Author

2.3. HANDYSIZE TIME CHARTER ROUTES

The Baltic Exchange Handiysize Index (BHSI) was officially launched in 2017 to calculate spot earnings of a standard 28,000 dwt bulk carrier. Since 2 Jan 2020, this route computed based on a standard 38,000 dwt bulk carrier (Baltic Exchange, 2021:86-87). These routes are:

HS1

Vessel delivery at passing or dropping of pilot at 1 safe port at Skaw-Passero range with Laycan 5/10 days from the index date, redelivery of the vessel passing or dropping of pilot at 1 safe port Recalada-Rio de Janeiro range, voyage duration about 35/45 days and 5% total commission.

HS2

Vessel delivery at passing or dropping of pilot at 1 safe port at Skaw-Passero range with Laycan 5/10 days from the index date, redelivery of the vessel passing or dropping of pilot at 1 safe port Boston-Galveston range, voyage duration about 35/45 days and 5% total commission.

HS3

Vessel delivery at passing or dropping of pilot at 1 safe port at Recalada-Rio de Janeiro range with Laycan 5/10 days from the index date, redelivery of the vessel passing or dropping of pilot at 1 safe port Skaw-Passero range, voyage duration about 35/45 days and 5% total commission.

HS4

Vessel delivery at passing or dropping of pilot at 1 safe port at US Gulf range with Laycan 5/10 days from the index date, one trip charter via US gulf or north coast south America, redelivery of the vessel passing or dropping of pilot at 1 safe port Skaw-Passero range, voyage duration about 35/45 days and 5% total commission.

HS5

Vessel delivery at passing or dropping of pilot at 1 safe port at South East Asia range with Laycan 5/10 days from the index date, one trip charter via Australia, redelivery of the vessel passing or dropping of pilot at 1 safe port Singapore–Japan range including China, voyage duration about 25/30 days and 5% total commission.

HS6

Vessel delivery at passing or dropping of pilot at 1 safe port at South Korea-Japan range with Laycan 5/10 days from the index date, one trip charter via North Pacific, redelivery of the vessel passing or dropping of pilot at 1 safe port Singapore–Japan range including China, voyage duration about 40/45 days and 5% total commission.

HS7

Vessel delivery at passing or dropping of pilot at 1 safe port at North China-South Korea-Japan range with Laycan 5/10 days from the index date, redelivery of the vessel passing or dropping of pilot at 1 safe port Krabi-Campha range including Malaysia, Indonesia & Philippines, voyage duration about 25/30 days and 5% total commission.

AVERAGE OF 7 T/C ROUTE

Average of 7-time charter routes.

2.4. SEASONALITY

Starting with (Sims, 1974) and (Wallis, 1974) seasonality effect is a research area in economics. Then two conferences organized by (Zellner, 1978 and1983). In these meetings, the first steps were taken for economists to conduct proper research due to the growing interest in the seasonality effect in the economy (Brendstrup, 2004: 362-394).

Hylleberg (1992:4) defines seasonality:

> *As a systematic, although not necessarily regular, intra-year movement caused by the changes of the weather, the calendar, and timing of decision, directly or indirectly through the production and consumption decisions made by agents of the economy. These decisions are influenced by endowments, the expectations and preferences of the agents, and the production techniques available in the economy*.

Added to above as per OECD (1999: viii) seasonal effects impact another type of variations that is associated to the calendar. This is called “trading day effect”. Trading day impact rises because of the number of such days in the month. Other types of effects are not fixed celebrations like Korean full moon day, Easter, Chinese

New Year Day, Ramadan, and Pentecost, which do not occur in the same calendar month each year.

Time series of various financial data have a seasonality effect and financial investors need to consider this. Therefore, economical representative should always think of seasonality effect in these series before acting. They also need to take into account and react to exogenous elements like holidays, the weather, and etc (Hylleberg, 2018:12100).

2.5. CHARTER TYPES

When ship owner or ship operator provide the ship cargo capacity fully or partly in disposal of charterers, and charterers reimburse ship owners or ship operator with agreed freight this is called " a charter" (Gorton et al., 1995:78).

A charter party is a standardized written text between a shipowner/disponent owner of a vessel and cargo owner or trader or another person/company which known as charterer. Shipowner(s)/disponent owner(s) give the ship (full or part of it) at the disposal of a charterers under agreed conditions and terms in the charter party. This Carriage of commodities could be between port to port against paying freight or for duration of certain period against paying hire. Charter party forms are legally binding and internationally recognised document. Most of them have prepared and drafted by internationally recognized organizations like BIMCO and ASBA. These charter parties are more general in form but some of larger Maritime companies or shippers have made their own charter-parties for specific trade such ad BP, SHELL.

Using of a ship requires some expenses. There are capital investment costs, which must be paid firstly. Management, manning of ship, repairs, maintenance, bunkers, etc are other costs. Maritime industry is also associated with various risks, and these are not similar to each other, and it changes depends on whether vessel at sea or port. These costs and risks are shared by the contractual parties in various ways Current market condition, risks, and various factors are involved in shipping business are influence choice of the type of charter party (Gorton et al., 1995:95-96). Two essential categories of charter parties are voyage and time charters.

2.5.1. Voyage Charter

The voyage charter is the basic type of shipping contract (Ozer and Cetin, 2012: 206). Force (2013:44) mentioned for voyage charter that:

> *A shipowner promises to load, and discharge agreed goods to the agreed named ports for a voyage or voyages. Ship crews are provided by the ship owners. The charterers are only getting full or a part of vessel cargo capacity. Shipowners are still responsible for repairs, maintenance of the vessel, damages to third parties due to crew`s negligence, and bunkers.*

As voyage contract are generally negotiated shortly before the loading of the cargo, they are called spot charter parties, even though owners and shipper occasionally agree forward voyage contracts a month or more in advance for an agreed laycan (Ozer and Cetin, 2012: 206).

2.5.1.1. Consecutive voyage charter

Cooke (2014:3-4) briefly explains that consecutive voyage charters are where each voyage follows on directly from the previous one.

Gorton (1995) says "Consecutive voyage charters are where the vessel is contacted for several voyages which follow consecutively upon each other. Sometimes the charter-party states that the ship will make a certain number of consecutive voyages and may perform during a certain period of time" (Gorton et al., 1995:89-90).

All voyages are protected by the same simple conditions even though it may be decided that the freight levels rise and fall over the duration of the contract. Each One of the voyages is considered as a single agreement for reasons of demurrage and despatch (ICS, 2014:66).

A consecutive voyage charter contains both voyage and time charter elements, it is considered a hybrid charter form. In a typical consecutive voyage charter, a named ship is chartered usually on one charterparty, to proceed loaded from loading port to discharging port, to return in ballast and repeat the voyages consecutively until all the agreed cargo has been transported. The individual voyages are made on voyage charter terms and conditions, with the freight typically being paid per voyage in USD per ton of cargo carried, a laytime calculation is ports of loading and discharge respectively etc. This charter type is common where large volumes of cargo are concerned (Plomaritou, 2018:229).

2.5.1.2. Contract of affreightment

This kind of contracts occurs once an operator or a ship owner deals to transport a provided quantity of goods among the named ports on approved voyage chartering conditions over numerous voyages. The Owner can employ its own tonnages or alternatively charter in separate ships from the market in order to comply with contractual responsibilities (ICS, 2014:65).

A contract of affreightment (CoA) is also a hybrid charter borrowing characteristic from a voyage and a time charter (Plomaritou, 2018:230). "Under a CoA owner promises to satisfy the charterer`s need for transport capacity over a certain period of time, often one year or several years. It is not unusual that contracts of affreightment are also made up within the framework of liner operation" (Gorton et al., 1995:93). Under a quantity contract the individual vessel has less importance for the charterers (Plomaritou, 2018:230).

When shipowners predict that future freight rates will be low then today, these contracts give shipowners advantages of securing one or more of their vessels at higher level freight levels at the duration of the contract. Same situation can be talk about ship operator as well. After making a contract with higher level of freight, they hope to make profit from falling market fixing the vessel from low freight levels. On the other side If the freight market goes up, since charterers made the contract with a low freight level, charterers might be to get some advantage from this agreement (ICS, 2014:65).

2.5.2. Time Charter

A time charter contracts are another most common used agreement that a ship cargo capacity provided to use of charterers for a determined duration of time such as monthly, yearly or among the agreed dates. Unless otherwise mention in charter party, shipowners are responsible for technical management, manning and navigation of the vessel like case in voyage charter. In the agreed duration, charterers have right to unlimited time of voyages. Hence the ship is controlled by charterers for the matters such as voyage orders, ports of calls, goods carried and other related issues. Since only cargo capacity is employed to charterers, master and crew are remain under control of ship owners for navigation and maintenance of vessel. Accordingly cost for maintenance and damages to third parties will be owners responsibility but charterers will be responsible for operating the ship (Force, 2013: 44).

2.5.2.1 Trip time charter

This type of charter defines duration of the period and limits the services to be given to a voyage or a trip. This service is called " time charter trip". Even though hire will be paid to owners periodically, a time charter trip is much more similar to voyage charter than longer period trip which gives characters to load all kind of cargoes and visit many areas (Coghlin, 2014:4).

A trip time charter will take the ship among port to port same as under a voyage charter. However here charterers are paying hire per day, instead of freight per ton of cargo carried. Trip time charters are separate from the customary period time charter (Plomaritou, 2018:226).

2.5.2.2. Period Time charter

Period time charters where parties agree that a ship will be chartered for a particular period, the charter doesn’t automatically expire at the end of period. If the ship is still being employed in the charterers when the agreed period comes to an end, then, the charter continues, and the charterers must continue to pay hire” (Coghlin, 2014:4).

When the ship is engaged for a period, she will be employed within an agreed geographical area or on a worldwide basis but typically within internationally acceptable trading/navigating limits. Delivery/redelivery will be normally agreed to take place somewhere withing an agreed geographical area, e.g. It is not an easy task to set out precisely when the vessel shall be redelivered, and therefore, the partied may have to use different contractual methods to solve this particular problem. The types of cargo allowed for carriage will normally be agreed specifically in the time charterparty (Plomaritou, 2018:226).

2.5.3. Bareboat Charter

Bareboat charter is another type of charter which owners pays only the investment costs and propose the vessel at charterers service for a certain period of time and charterers takes nearly entire responsibility and all the costs and expenses that may occur. Generally, shipowners provide the vessel without any crew on board. This makes charterers both the commercial and the technical manager of the vessel therefore, characters become responsible for vessel maintenance, wages of crew, insurance of ship, finding future business for the vessel etc. Contrast to others this type of charter was not a common agreement but since world trading is changing, these charters become common. Several reasons like policies applied by international organizations might encourage companies to use bareboat charter but that may cause other problems like manning rules, nationality of the vessel, etc. (Gorton et al., 1995:92-93).

Table 3 Responsibilities in the main types of charter

Responsibilities & Duties	Voyage charter		Time charter	
	Shipowner	Charterer	Shipowner	Charterer
Description of the vessel	X		X	
Delivery of the vessel	N/A	N/A	X	
Redelivery of the vessel	N/A	N/A		X
Chartered & substituted vessel	N/A	N/A	X	
Seaworthiness	X		X	
Maintenance	X		X	
Cargo worthiness	X		X	
Preliminary voyage	X		X	
Despatch	X		N/A	N/A
Deviation	X		N/A	N/A
Arrived ship	X		N/A	N/A
Notice of readiness	X		N/A	N/A
Loading	X		X	X
Voyage	X			X
Discharging	X		X	X
Delivery of the cargo	X			X
Right for lien	X			X
Warehousing unclaimed goods	X			X
Claims against third parties	X		X	
Nomination of ports		X		X
Description of the cargo		X		X
Provision of cargo		X	N/A	N/A
Quantity & quality of cargo		X	N/A	N/A
Bringing the cargo alongside		X	N/A	N/A
Load port laytime		X	N/A	N/A
Discharge port laytime		X	N/A	N/A
Freight payment		X	N/A	N/A
Safe ports		X		X
Lawful merchandise		X		X
Not to ship dangerous goods		X		X
Trading limits	N/A	N/A		X
Employment and indemnity	X			X
Hire payment	N/A	N/A		X
Commercial operation	X		X	
Manning of vessel	X		X	

Equipment and provision	X		X	
Insurance	X		X	
Administration duties	X		X	
Navigation/salvage/towage	X		X	
Operating costs	X		X	
Capital costs	X		X	
Voyage costs	X			X
Inspection & dry-docking costs	X		X	
Cargo handling costs	X	X		X

Source: Adopted from (Plomaritou, 2014:319)

2.6. CALCULATION OF FREIGHT AND TIME CHARTER EQUIVALENT

The freight can be calculated in more than a few ways and can be paid basis per metric ton (i.e., USD 30 per metric ton) or basis lump sum (i.e., USD 300.000) An example calculation is shown in the case below:

<u>Cargo Details:</u>

Shipper/charterers: ABC limited.

Cargo: 25.000 metric ton Minerals in bulk 10 percent more or less in owners option

Stowage factor of cargo 38 cu/ft

Loading port: Gulluk/Turkey

Loading Rates: 4500 per metric ton per weather working day Sundays and holidays included

Discharging port: Rotterdam/The Netherlands

Loading Rates: 7000 per metric ton per weather working day Sundays and holidays included

Total commissions: 5 percent

Dates: 01/10 April 2021

Freight Idea: usd 22 per mt

Vessel Details:

Vessel Name: MV XYZ

Vessel Type: Single Decker Bulk Carrier

Built: 2012 BLT

LOA/LBP/BEAM: 179.9M / 171.5M / 28.4M

International gross ton: 22402

International net ton:12019

Class: BV

Summer deadweight: 35.207 dwt at 10,80M

Grain/Bale capacity: 44.294.3CBM / 42.586.84CBM

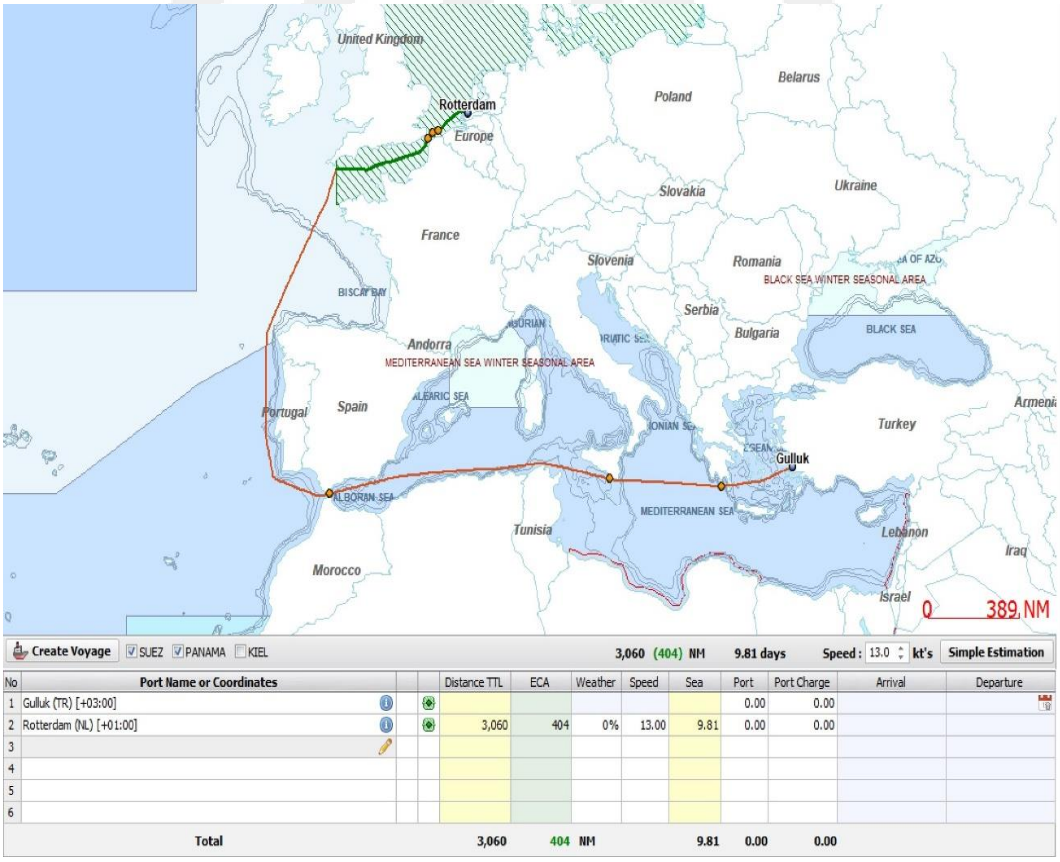
Speed and bunker consumption

At laden voyage about 13 knots on abt 25 mt ifo 380 cst

At port 5mt marine diesel oil

Vessel Daily Operation Cost: USD 7500

Figure 3 Voyage Distances for Calculation



Source: Author

Table 4 Voyage Costs

Ports	Loading Port USD 30.000	
	Discharging Port USD 50.000	
	Total Cost	USD 80.000
Running Cost	Total Sailing 3060 miles/ 13knots = 235 hours= 9.81 days 9.81 days + 5pct weather margin = 10.30 days Total Load Port time 27500 mt/ 4500 mt= 6.1 days Total Discharging port time 27500 mt/ 7000 mt= 3.92 days Total duration 20.32 days Total Cost 20.32 days x USD 7500	USD 152.400
Bunker	Gibraltar IFO price USD 450 per mt Gibraltar MDO price USD 500 per mt IFO Consumption 10.30 days x 25 mt IFO = 257.5 mt MDO Consumption 10.20 days x 5 mt MDO= 51 mt IFO cost 257.5 mt x USD 450= USD 115.875 MDO cost 51 mt x USD 500 = USD 25.500 Total Cost	USD141.375
Commission	Total Cost 27500mtxUSD 22X 5 PCT	USD 30.250
Total Cost		USD404.025

Source: Author

Table 5 Voyage Earnings

Freight	Total Earning 27500 mt x USD 22 pmt	USD605.000

Source: Author

Net Profit = Total Voyage Earnings - Total Voyage Costs

Net profit = USD 605.000 – USD 404.025 = USD 200.975

Gross Daily Time charter Equivalent = (lumpsum freight – commission – Voyage Costs) / Total days

GDTCE= (USD 605.000 – USD 30.250 – USD USD 221.375) / 20.3 Days

GDTCE= USD 17.407

CHAPTER THREE
FORECASTING OF TIME SERIES

3.1. TYPES OF FORECASTING METHODS

Forecasting methods are known for calculating forecast from current and previous information. For example, it might be an algorithmic model and not necessity to rely on an original likelihood model. Generally forecasting methods be described in three types (Chatfield, 2020:3-4):

- Judgemental forecast: Stand on the use of opinion, intuitive judgement, industrial expertise, and further admissible knowledge.
- Univariate Methods: The method deals with current and previous data of forecasted single series
- Multivariate Methods: In this method at best the given variable depend on values of one or more additional time series variables. Where they are named as predictor or explanatory variables. Multivariate forecasts mostly depend on a multivariate model which have more than one equation. The equation works if the variables depend jointly.

Chatfield in his study states that “A time series is a set of observations measured sequentially through time” (Chatfield, 2000:11).

Time series forecasting is an essential part of predicting future. Previous observations of the equivalent variable are gathered and investigated to create a model explaining the core correlation. Model is applied to generalize the time series into the future. This approach is especially effective when not enough information is available on the main documents creating procedure or if there are no reasonable descriptive approaches that relates the forecast variable to other descriptive variables (Zhang, 2003:159-160). There are various patterns that affect the characteristics of time series (Mills, 2019:6-7) These components are:

- Trend: A long-term increase or decrease in time series.
- Seasonal: Seasonal pattern in which changes are specific to a particular time range.
- Cyclic: Rise and fall in time series which are not of a fixed frequency.
- Irregular: Irregular or random unexpected influences affecting time series patterns.

Above approaches can be mixed for a forecasting method. Mathematical models need external information which are difficult to express formally, when univariate or multivariate forecasts are adjusted (Chatfield, 2000:13-14).

3.2. JUDGEMENTAL FORECAST

Webby and O'Connor (1996:91-92) reviewed "the literature on the importance of human-interaction factors in a comparison of judgemental and statistical approaches to time series forecasting and demonstrated the crucial role of the knowledge of the context of the time series to accuracy". One of the famous judgemental method is probably that called the "Delphi Technique" (Chatfield, 2000:4-5).

Even though lots of Delphi techniques available for several needs, practical outline of the model can be described in a way (Masini, 1993:91).

Beginning of the 1950`s, Rand Corporation studied use of expert judgment. This research was called "Project Delphi". The aim of this study was to get most dependable decisions of a consortium of specialists by a series of surveys with checked opinion response (Linstone at al., 2002:10).

According to Linstone (2002:5-6) Today the Delphi process exist in two distinct forms.

- Delphi Exercise: Questionnaires prepared by a small group which is called "monitor team" and sent to another bigger group to answer them. After examining the returned questionnaires, monitor group prepare another questionnaire to respondent group. At this stage, respondent group are requested to revise their answers if any hesitation according to result of analysis of the questionnaire. this type of Delphi can be said that it is hybrid method that combines pooling procedures and conference procedures. This form tries to replace larger answering groups which need considerable effort need to communicate, into a smaller monitor group.
- Delphi Conference: This is recently used form for Delphi. Instead of monitor group, a computer program tries to analyse result of the larger groups. This process helps to eliminate the delay of analysing the result each time and give opportunity to communicate real time based. However, it is required to determine feature of communication very well before starting this Delphi procedures.

3.3. UNIVARIATE METHODS

"Univariate time-series models are a class of specifications where one attempts to model and to predict financial variables using only information contained in their own past values and possibly current and past values of an error term" (Brooks, 2019:330).

3.3.1 Autoregressive integrated moving average (ARIMA) Model

Univariate time-series prediction is important in several scientific domains. A forecasting procedure may be needed for predicting a single time-depended variable or predicting several independent variables individually to forecast a dependent variable as in multivariate analysis (Singh, 2000:49-65). Chatfield (2000:35) stated that:

> *The ARIMA class of models is an important forecasting tool and is the basis of many fundamental ideas in time-series analysis. The acronym ARIMA stands for "autoregressive integrated moving average", and the different components of this general class of model will be introduced in turn. The original components of this general class od models will be introduced in turn. The original key reference is Box and Jenkins (1970), and ARIMA models are sometime called Box-Jerkins models.*

Autoregressive integrated moving average (ARIMA) modelling is a standard technique for modelling time series and has been extensively used in literature.

ARIMA method is divided into stages and these stages explained by (Box et al., 2015:16-17). These stages:

- From the interaction of theory and practice, a useful class of models for the purpose at hand in considered.
- Because this class is too extensive to be conveniently fitted directly to data, rough methods for identifying subclassed of these models are developed. Such methods of model identification employ data and knowledge of the system to suggest an appropriate parsimonious subclass of models that may be tentatively entertained. In addition, the identification process can be used to yield rough preliminary estimates of the parameters in the model.
- The tentatively entertained model is fitted to data and its parameters estimated. The rough estimates obtained during the identification stage can now be used as starting values in more refined iterative methods for estimating the parameters, such as the nonlinear least squares and maximum likelihood methods.

- Diagnostic checks are applied with the goal of uncovering possible lack of fit and diagnosing the cause. If no lack of fit is indicated, the model is ready to use. If any inadequacy is found, the iterative cycle of identification, estimation, and diagnostic checking is repeated until a suitable representation is found.

3.3.2. State space model

According to Durbin and Koopman (2012:1):

> *State space modelling provides a unified methodology for a treating a wide range of problems in time series analysis. In this approach it is assumed that the development over time of the system under study is determined by an unobserved series of vectors α1,...,αn, with which are associated a series of observations y1,...,yn; the relation between the αt's and the yt's is specified by the state space model. The main purpose of state space analysis is to infer the relevant properties of the αt's from a knowledge of the observations y1,...,yn. Other purposes include forecasting, signal extraction and estimation of parameters.*

3.3.3. Growth curve model

The Growth Curve Model introduced by (Potthoff and Roy, 1964:313-326). The term growth curve was originally used to describe a graphic display of the physical statute (e.g., the height or weight) of an individual over consecutive ages. Growth curves have unique features:

- The same entities are repeatedly observed.
- The same procedures of measurement and scaling of observation are used.
- The timing of the observations is known.

The term growth curve analysis denotes the processes of describing, testing hypotheses, and making scientific inferences about the growth and change patterns in a wide range of time-related phenomena. In this sense, growth curve analyses are a specific form of the larger set of developmental and longitudinal research methods, but unique features of growth data permit unique kinds of analyses (McArdle and Nesselroade, 2003:447-480).

3.3.4 Non Lineer Models

In the literature scholars were generally focused on linear models and methods for time series, but it has been noticed that there are time series show some characteristic which cannot be described by linear models. Occasionally, time series rises with faster rate than it declines. This kind of trends can be seen in economic series. Such as series may tend to behave differently as the world economy enter and exit recessions. In addition to above some series may act unusual period with high fluctuation after stable period. Nonlinear methods work well with economical series but compared to linear models, it complicated to fit the series to procedure. Therefore, the problem is it is very hard to find suitable type of nonlinear model to apply. Although forecast accuracy may small amount of difference from simple models, searching for suitable model can be advantageous to understand the nonlinear modes (Chatfield, 2000:54-55).

3.4. MULTIVARIATE FORECASTING MODELS

Most of the time economic data are taken from two or more time series at the same time. Evaluation of economic situation of a particular country can be conducted regularly. When evaluating the economy some variables are used such as inflation, unemployment rate, GDP, or retail price indexes. Multivariate models are there to explain relation between these kinds of series and make forecast by using different models. When modelling it need to be considered that both interdependence among the series and the serial dependence within the component series (Chatfield, 2000:109-110).

3.4.1. Single-equation models

Single-equation models are used to study the pattern of changes in aggregate productivity over time in conjunction with the time pattern of other aggregate variables that might be expected to relate to, or explain, productivity This approach, which is described by (Haveman and Christainsen, 1981: 381-390) as “less ad hoc than the approach used by Denison” involves the estimation of regression equations in which productivity is the dependent variable and the explanatory variables are the hypothesized determinants of productivity (such as regulatory intensity and cyclical factors) (Moosa, 2016:265–292).

3.4.1.1. Regression models

According to Kelley and Bolin (2013:71):

> *Multiple regression is a commonly used analytic method in the behavioural, educational, and social sciences because it provides a way to model a quantitative outcome variable from regressor variables. Multiple regressions is an especially important statistical model to understand because special cases and generalizations of multiple regression are many of the most commonly used models in empirical research. Correspondingly, multiple regression occupies a core position in the analytic architecture of behavioural, educational, and social science research.*

3.4.1.2. Transfer function models

Transfer function models have found extensive practical application. These models naturally arise in areas where either correlative or causal structure exists between variables that are temporarily or spatially related. For example, sales in period t (the output series) are related to advertising expenditures in previous periods (the input series); daily peak electricity generation (output) is related to certain weather variables such as daily maximum temperature, relative humidity, and cloud cover (inputs); and peak flood discharge from a stream (output) is related to rainfall intensity at various upstream locations (inputs). These models are also useful in many types of process and quality control problems where the value of a quality characteristic at time t is related to the adjustment to the controllable process variables at previous time periods (Montgomery and Weatherby, 1980:289-307).

3.4.2. Vector Autoregressive (AR) and Autoregressive Moving Average (ARMA) models

When the “outputs” affect the “inputs” there is a closed-loop system. It no longer makes much sense to talk about an “input” and an “output”, and a single-equation model will no longer be adequate to describe the data. As a simple example of such a system in economics, it is known that a rise in prices will generally lead to a rise in wages which will in turn lead to a further rise in prices. A model with more than one equation will be needed to satisfactorily model the system. Modelling a set of interrelated variables in often called multiple time-series modelling. An exogenous variable is one which affects the system but is no affected by it, whereas an endogenous variables is affected by the system and is therefore typically correlated with the series of observation errors (Chatfield, 2000:130).

3.4.2.1. Multivariate white noise

"Multivariate white noise processes arise in a variety of contexts, for example, as error terms in multivariate regression models, as innovations in multiple time series models, or simply as random samples from multivariate normal distribution" (Chitturi, 1976:223).

3.4.2.2. Vector Autoregressive Moving Average (VARMA) models

According to Ghysels and Marcellino (2018:253-254):

> *The vector (multivariate) ARMA is a natural extension of the univariate time series models. In these models, each variable depends on its own lags, on the lags of all the other variables, on its own current and lagged errors, and on the lagged errors for all the other variables. Hence, they provide a very general representation for the joint dynamics of the variables under analysis. The main advantage of these models is their generality and that they do not impose any strong a priori restrictions on the cross-variable relationships. The cost is that they can be very heavily parameterized, which makes estimation challenging, in short samples, and can reduce forecast efficiency. These pros and cons should be evaluated in the context of the specific application of interest particularly for the purpose of macroeconomic modelling.*

3.4.2.3. Vector Autoregressive (VAR) models

Multivariate simultaneous equations models were used extensively for macro econometric analysis. In the past longer and more frequently observed macroeconomic time series called for models which described the dynamic structure of variables. VAR models lend themselves to this purpose. They typically treat all variables as a priori endogenous. Restrictions, including exogeneity of some of the variables, may be imposed on VAR models based on statistical procedures. VAR models are natural tools for forecasting. Their set-up us such that current values of a set of variables are partly explained by past values of the variables involved. They can also be used for economic analysis, however, because they describe the joint generation mechanism of the variables involved. Impulse response analysis, forecast error variance decompositions, historical decompositions and the analysis of forecast scenarios are the tools which have been proposed for disentangling the relations between the variables in a VAR model (Lütkepohl, 2013:139).

3.4.2.4. Vector Moving Average (VMA), Vector Autoregressive Integrated Moving Average (VARIMA) and Vector Autoregressive Moving Average eXogenous (VARMAX) model

It is rather unusual to use VMA models in practice, but they have some theoretical interest arising from the multivariate generalization of Wold`s theorem which effectively says that any purely non-deterministic process can be represented as a VMA process of infinite order. A VARMA process can then be seen as a rational approximation to this infinite VMA. Various further generalizations of VARMA models can readily be made. VARMA models can be further generalized of by adding terms involving additional exogenous variables and such a model is sometimes abbreviated as VARMAX model (X stands for exogenous).

3.5. TIME SERIES FORECASTING MODELS IN SHIPPING

According to Zhang (2014), “seasonality, cyclicality, high volatility, and capital intensiveness are one of the ways to describe shipping market. Main players of maritime business such as ship owners’ charterers, shippers, financial investor and shipyards have growing interested in fluctuations of ship hire levels" (Zhang et al., 2014:1-10).

According to Stopford (2009:703) to create the ground rules for producing useful information and analysis for decision-maker, there are three principles of forecasting: Relevance, Rationale and Research. Also, Successful modelling depends on applying variables (tangible, technological, behavioural, and wild card) to suitable analytical techniques.

Forecasting models can be separated in to two different groups. these groups can be named as traditional methods and artificial intelligence methods. AI techniques (i.e., artificial neural network (ANN)) seen very adequate in time series forecasting, but these methods have weaknesses which are inherent. These weaknesses are named as parameter sensitiveness and potential problems of local minima and overfitting. Over the past findings it is found that forecasting methods have traditional approaches. These approaches include statistical an economical model. Linear regression analysis generalized autoregressive conditional heteroskedasticity (GARCH), univariate and multivariate statistical models, autoregressive integrated moving average (ARIMA) and the nonparametric statistical methods are the statistical and economical models. Historical findings says that the usage of these techniques is very trendy in time series forecasting (Yu et al., 2016:122-138).

Conditions such as volume of trade, structure and government policies in maritime industry can create high risk, volatility, and uncertainty in this market. The dry bulk freight market is important for maritime trade and contributes to the global economy (Chen et al., 2012:498–537).

Political events always have great influence on freight market and creates fluctuation in hire levels. However, handysize market have limited unpredictability compared to other size for tonnage in dry bulk market (Yang et al., 2019:390-414).

Compare to other size of tonnages the reasons for lower volatility levels in handy size vessel are smaller ships serves more different types of trade and able to load more wide-range cargoes. Also, these tonnages have shallow draft which increase option to call many ports. Contrarily larger vessels serve major commodities and specific port options (Kavussanos, 1996:67–82).

In this market, forecasting is a subject which has a much attraction, and it draws consideration of academic and business communities (Chen et al., 2012:498–537). Some research and their models are Artificial neural network used by (Li and Parson, 1997), (Lyridis et al., 2004), (Lyridis et al., 2013), (Leonov and Nikolov, 2012), (Santos et al., 2014), ARCH used by (Kavussanos, 1996), (Kavussanos, 2003), (Adland and Cullonane, 2005), Co-integration analysis used by (Tsioumas and Papadimitriou, 2016), VECM used by (Kavussanos and Nomikos, 2003), (Zhang et al., 2014), (Kavussanos and Visvikis, 2004), (Kasimati and Veraros, 2017), (Kavussanos et al., 2010), (Munim and Schramm, 2017), (Kavussanos and Alizadeh, 2001), ARIMA used by (Munim and Schramm, 2017), (Kavussanos and Alizadeh, 2001), (Chen et al., 2012), (Batchelor et al., 2007), GARCH used by (Batchelor et al., 2005), (Gavriilidis et al., 2018), (Kavussanos et al., 2004), VAR used by (Tsioumas and Papadimitriou 2015), (Veenstra and Franses, 1997), (Tsioumas et al., 2017), trigonometric regression used by (Papailias et al., 2017), Augmented EGARCH used by (Alizadeh and Nomikos, 2011), EMD and ANN used by (Zeng et al., 2016), FILF used by (Duru, 2010), fuzzy neural network (GA-based RFNN) used by (Uyar et al., 2016), Fuzzy-DELPHI (FD) used by (Duru et al., 2012), Judgmental forecasting used by (Duru and Yoshida, 2009), long-term fuzzy inference system used by (Duru et al., 2010), MGARCH used by (Li et al., 2014), Multivariate autoregressive time-series used by (Veenstra and Haralambides, 2001), SR-based FNN approach used by (Yu et al., 2016), SVM/CFS used by (Bao et al., 2016), and VEC used by (Bessler et al., 2008).

CHAPTER FOUR
FORECASTING DRY CARGO HIRE RATES AND SEASONALITY EFFECT

4.1. AIM OF STUDY

The aim of this study, understand the seasonality effect in the handysize dry cargo ship market and to make future forecasts by examining the daily hire rate in the handysize dry cargo ship market between 2017-2021. In this research, it is aimed to assist companies such as shipowners, charterers, operators, operating in the field of ship chartering etc. to determining the right time to charter in or out their vessels.

4.2 METHODOLOGY OF STUDY

In this study, first it was researched if there is any seasonality effect then Seasonal ARIMA Method is used to explain the seasonality relationship. In this study also time series analysis was applied. Different types of method such as trend analysis, ARIMA (autoregressive moving averages-also called Box-Jenkins method) and exponential smoothing, which explains the time series with its historical values and possible error terms, was used.

4.3 FINDINGS

To perform the analysis, seven Baltic Exchange Handysize routes and Baltic Exchange seven route average was used. The data set consisted of a database of 890 daily observations for each route between November 1, 2017, and May 28, 2021.

4.3.1 Baltic Handysize Route 1

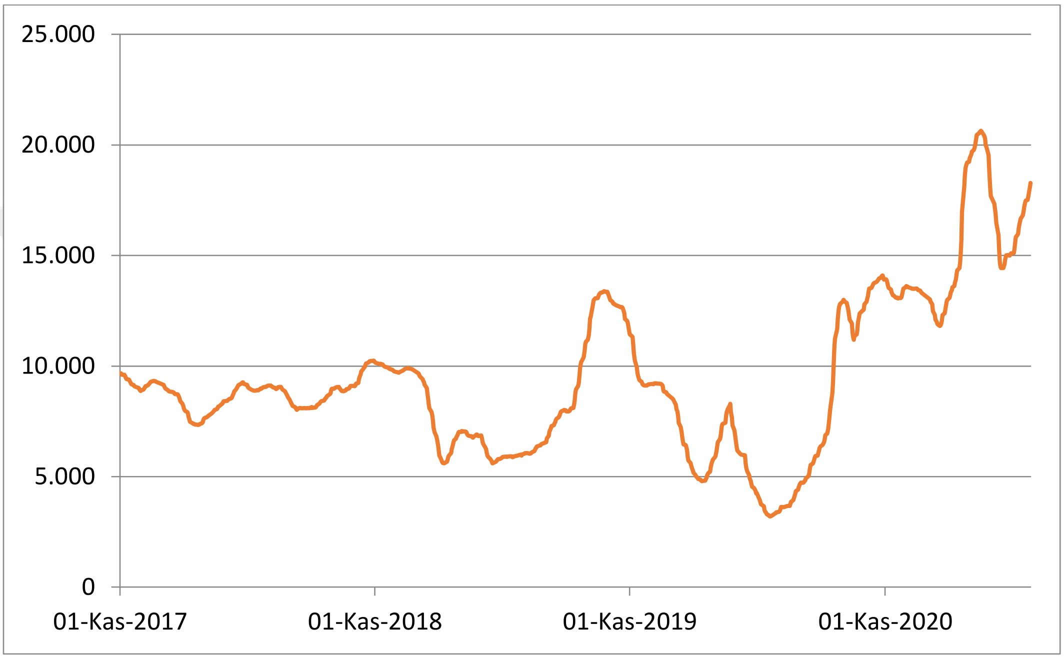
4.3.1.1 Modelling

First BHS 1 examined whether has a seasonal component from the data set then it was analysed with different time series approaches to get appropriate evaluation results. Main ones of these methods are Box – Jenkins (ARIMA), trend analysis, Exponential smoothing methods.

In time series analysis first step is the assumption which the series have a stationary structure on the time axis. According to this assumption, the data should exhibit a certain mean and variance, and should be free from other components (trend, seasonality, etc.).

The natural logarithm of the data was taken and made stationary by performing the necessary operations, then the most suitable model for the series was determined with different modelling methods and the values that it could take in the future were estimated. Statistical package programs such as Minitab and SPSS were used in the analysis of the data.

Figure 4 BHS 1 Route Time Series Graph



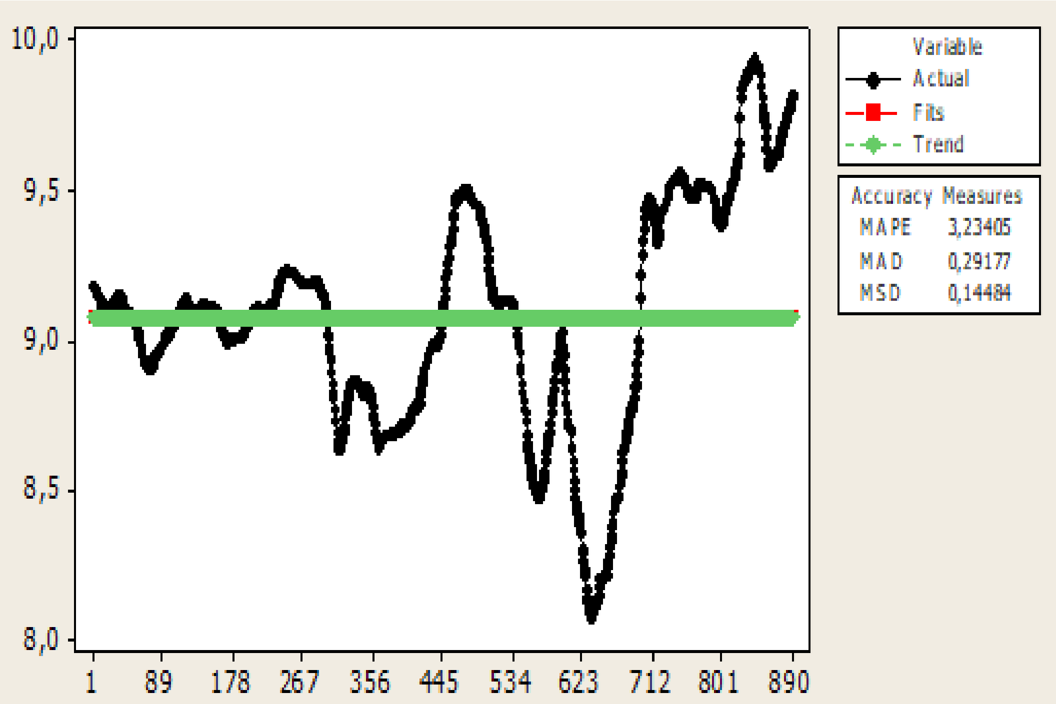
Source: Author

When the Figure 4 is examined; It has been observed that there is no generalizable linear trend but after May 2020 there is a strong linear trend. In terms of seasonality, both the limited data on a yearly basis and the fact that the changes on a monthly basis do not show a pattern indicate that this effect does not exist. The following analyses show whether there are any effects by modelling both components.

4.3.1.2 Seasonality analysis

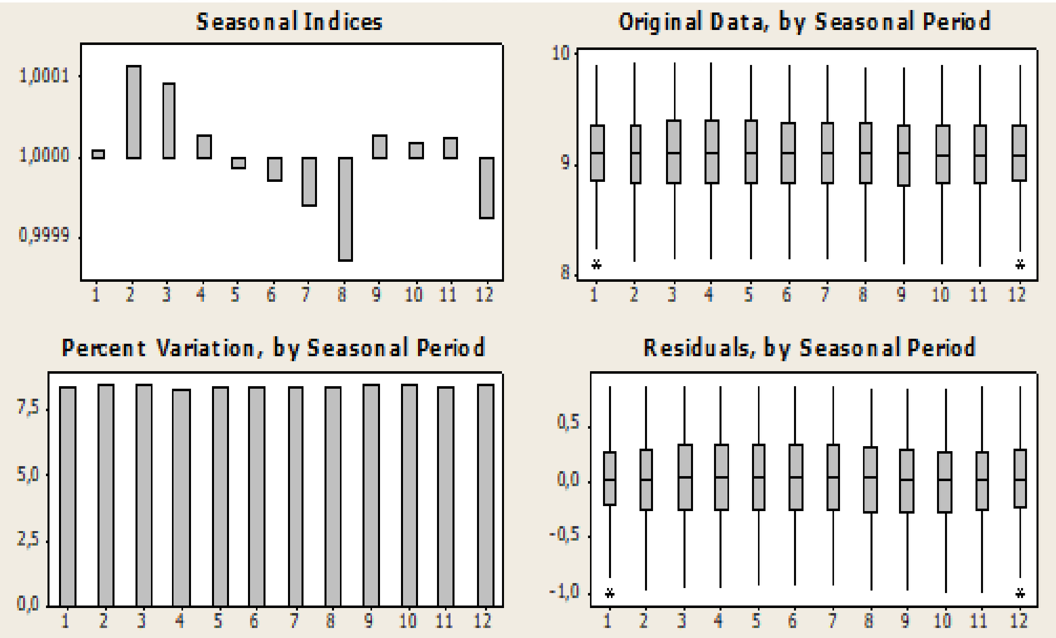
After analysis BHS 1 data, results for seasonality effect to BHS 1 series are shown Figure 5 and Figure 6.

Figure 5 BHS 1 Time series decomposition plot



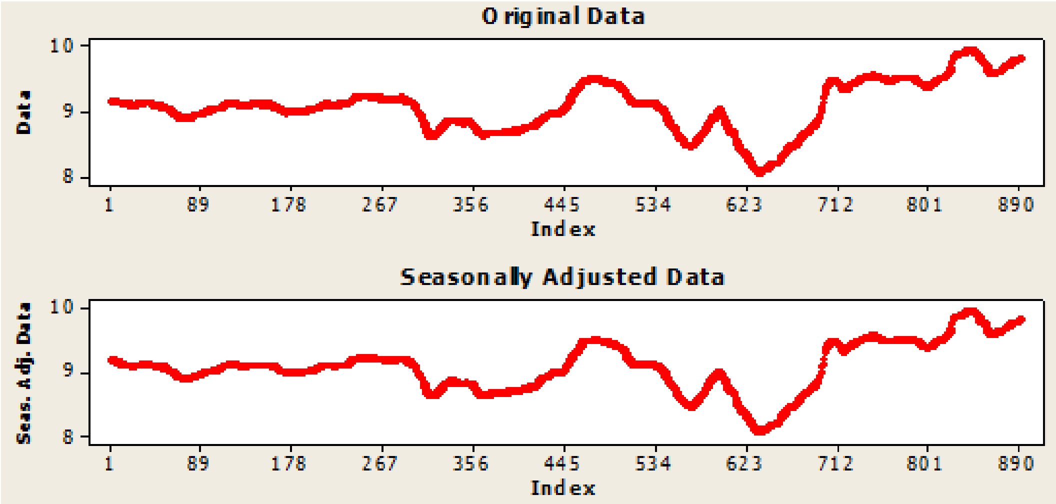
Source: Author

Figure 6 BHS 1 Seasonal analysis



Source: Author

Figure 7 BHS 1 Component Analysis and Seasonally adjusted data



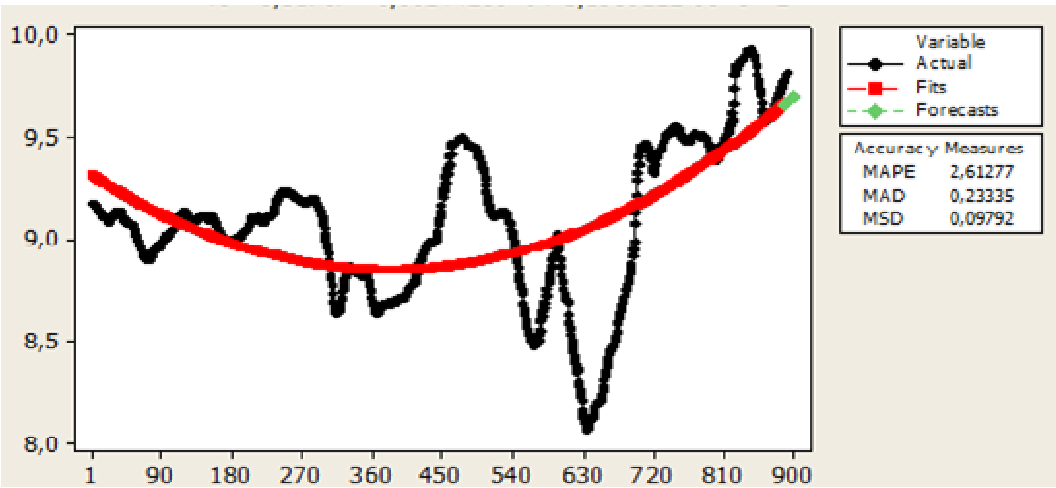
Source: Author

The fact that the seasonal indexes are very close to 1 in the data indicates that there is no seasonal effect. In addition, graphically, it can be seen at Figure 7 that the seasonally adjusted graph does not differ significantly from the original graph. The criteria to be used to evaluate the model with other models were MAPE:3,234, MAD:0,291 and MSD:0,144.

4.3.1.3 Trend Analysis

It has been observed that the trend structure in the data has a quadratic rather than linear structure and modelling has been done.

Figure 8 BHS 1Trens Analysis Plot



Source: Author

When the model was examined, it was observed that the MAPE, MAD, MSD criteria had lower values compared to the seasonal model. The fact that these criteria are low indicates that the established model is more compatible with the data. The red in the Figure 8 shows the regression curve, while the green part shows the predictions of the model.

The model is as follows. Although the "t" in the model represents the time, the necessary conversion must be made to reach the real estimate since it is obtained using logarithmic data.

Fitted Trend Equation: Yt = 9.31767 - 0.00244280*t + 3.198012E-06*t**2

4.3.1.3.1 Forecasting

While estimating, the last 8 observations of the series were estimated to see control and deviation. A total of 15 observation estimates were made and findings listed at Table 6.

Table 6 BHS 1Forecasting Results for Trend Analysis

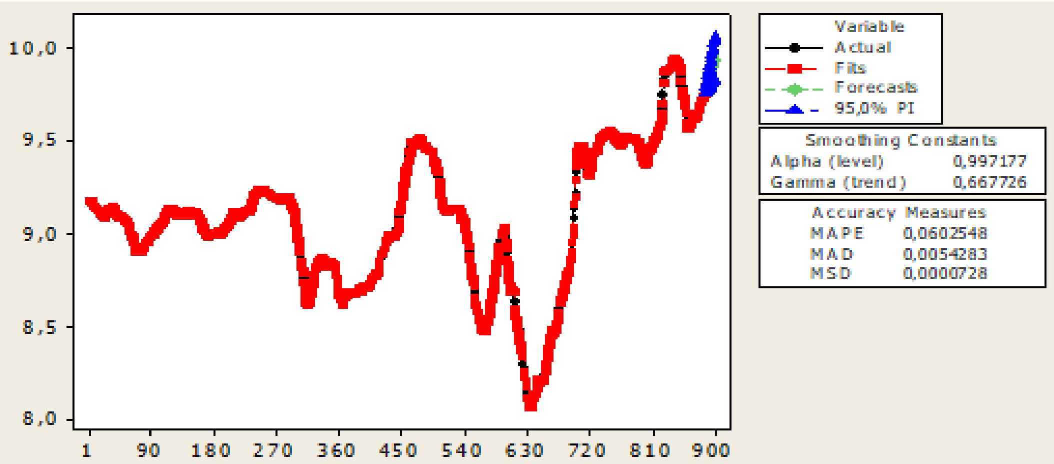
Date	Period	Actual	Forecast
19-May-21	886	17.164	15624
20-May-21	887	17.379	15674
21-May-21	888	17.479	15724
24-May-21	889	17.507	15774
25-May-21	890	17.664	15825
26-May-21	891	17.921	15876
27-May-21	892	18.079	15927
28-May-21	893	18.279	15979
	894		16031
	895		16083
	896		16135
	897		16188
	898		16241
	899		16294
	900		16348

Source: Author

4.3.1.4. Exponential Smoothing Analysis

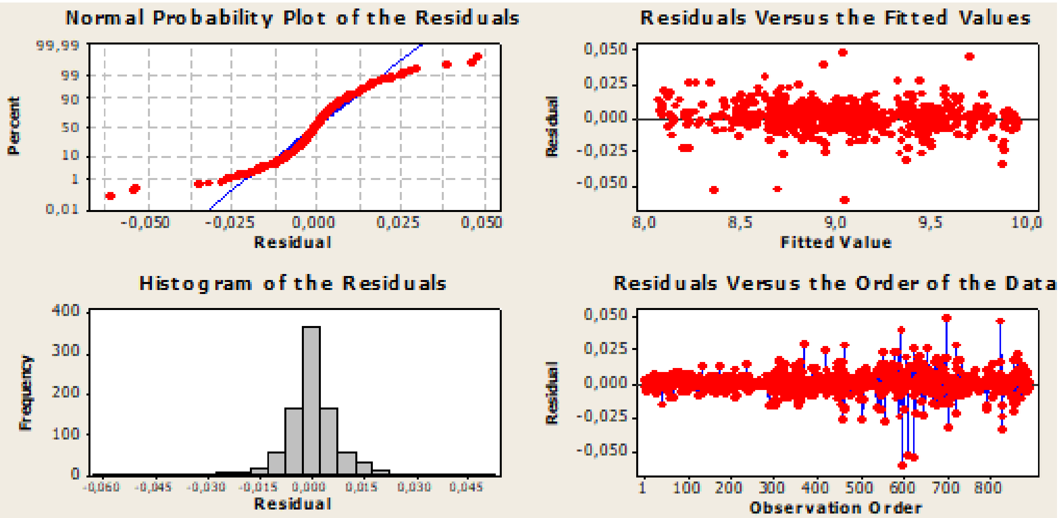
The exponential smoothing is a approaches which starts from the current values of the data with a certain correction coefficient and models the series according to the older data. Since it is a dynamic model, the past and future predictions for each data are determined iteratively. The following Figure 9 includes predictive values, exponential smoothing coefficients (Alpha, Gamma), error term assumptions and model criteria.

Figure 9 BHS 1 Double exponential smoothing plot



Source: Author

Figure 10 BHS 1 Residual plots



Source: Author

When Figure 9 and Figure 10 are examined, it is seen that the assumptions of the error terms produced by the model are provided. It can be noticed that the residuals (error) are generally distributed with a mean of 0, and homogeneously distributed rather than concentrated in certain regions. However, it can be stated that some values are observed as extreme values, thus negatively affecting the model.

4.3.1.4.1. Forecasting

Model estimation, actual values, and the lowest and highest limits at 95% confidence level is listed at Table 7 below. When the estimations are examined, it can be said that it has less errors than the previously established Trend model estimations.

Table 7 BHS 1 Forecasting Results for exponential smoothing

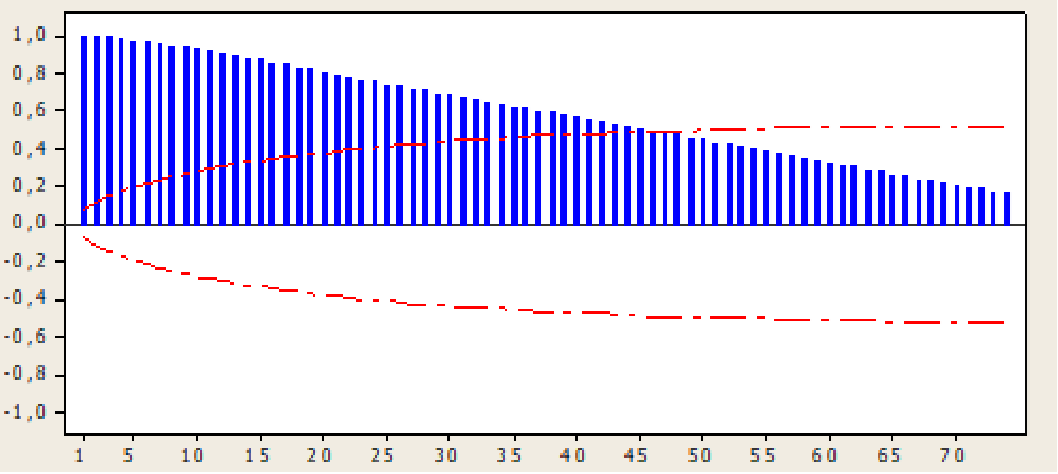
Date	Period	Actual	Forecast	Lower	Upper
19-May-21	886	17.164	17583	17350	17818
20-May-21	887	17.379	17789	17432	18153
21-May-21	888	17.479	17998	17508	18501
24-May-21	889	17.507	18210	17583	18858
25-May-21	890	17.664	18424	17656	19223
26-May-21	891	17.921	18640	17730	19596
27-May-21	892	18.079	18859	17803	19978
28-May-21	893	18.279	19081	17876	20365
	894		19305	17950	20762
	895		19532	18023	21164
	896		19761	18097	21577
	897		19993	18171	21997
	898		20228	18245	22426
	899		20466	18320	22863
	900		20706	18394	23309

Source: Author

4.3.1.5. Box – Jenkins Modelling

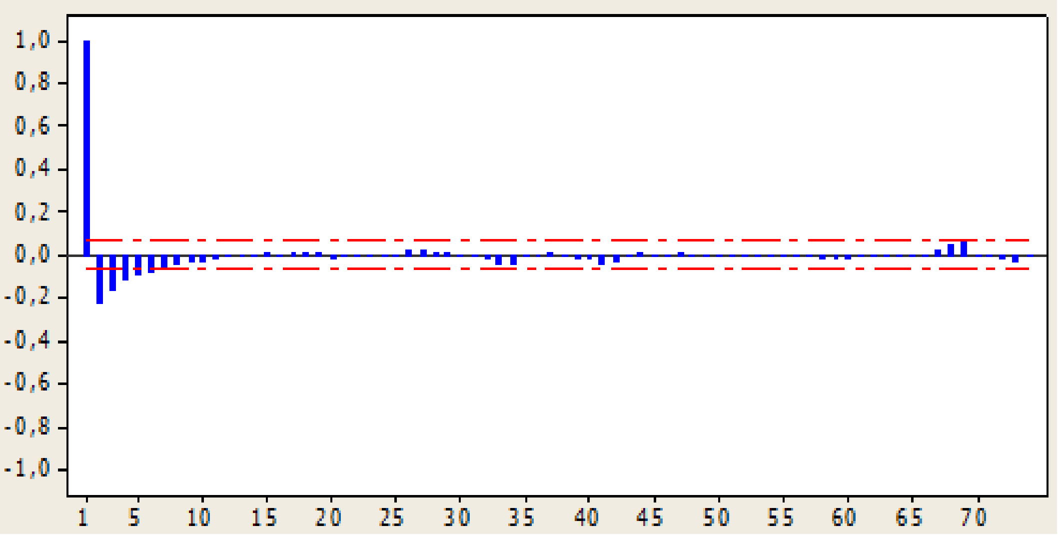
For widely applied ARIMA method, the statistics should show a constant distribution around a constant mean. To provide this assumption, which is expressed as stationarity, the difference operator is used (Wei, 1990). The correlation of each value of the series with its historical values is expressed as autocorrelation. A high value indicates that the values are highly influenced by each other. In order to eliminate this negative effect, the difference processor (d) is used. Since there is no significant seasonality in the series, the normal difference processor was used.

Figure 11 BHS 1 Autocorrelation function



Source: Author

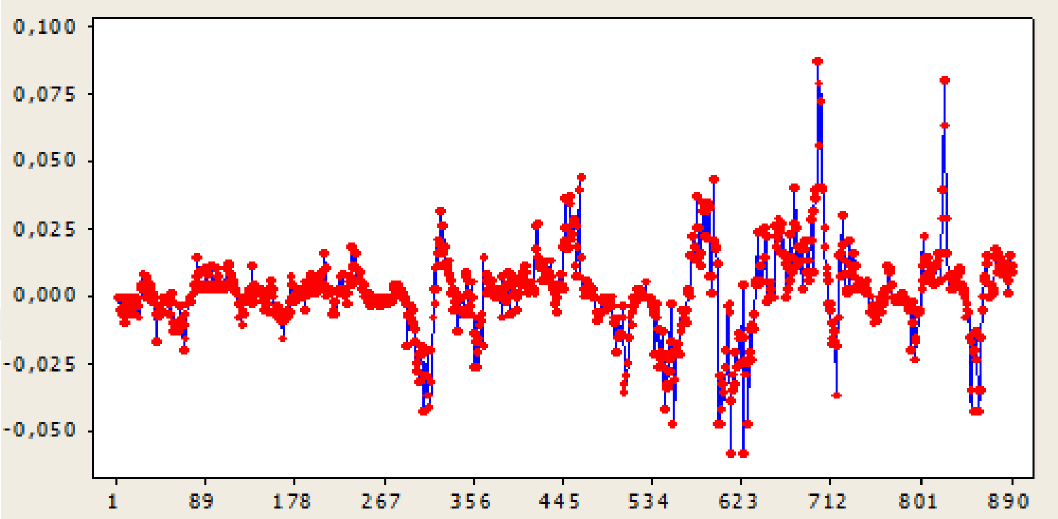
Figure 12 BHS 1 Partial Autocorrelation on function



Source: Author

When the Figure 11 and Figure 12 are examined, lag at different times slowly approaches zero, which shows that the stationarity assumption is not met. The BHS1 series and autocorrelation graphs after the difference process are as follows.

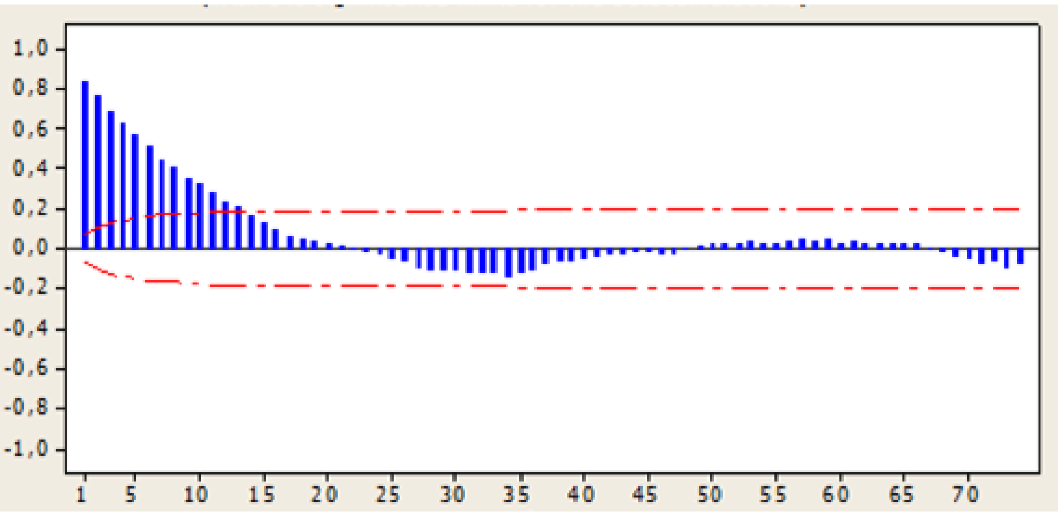
Figure 13 BHS 1 Plot of differences



Source: Author

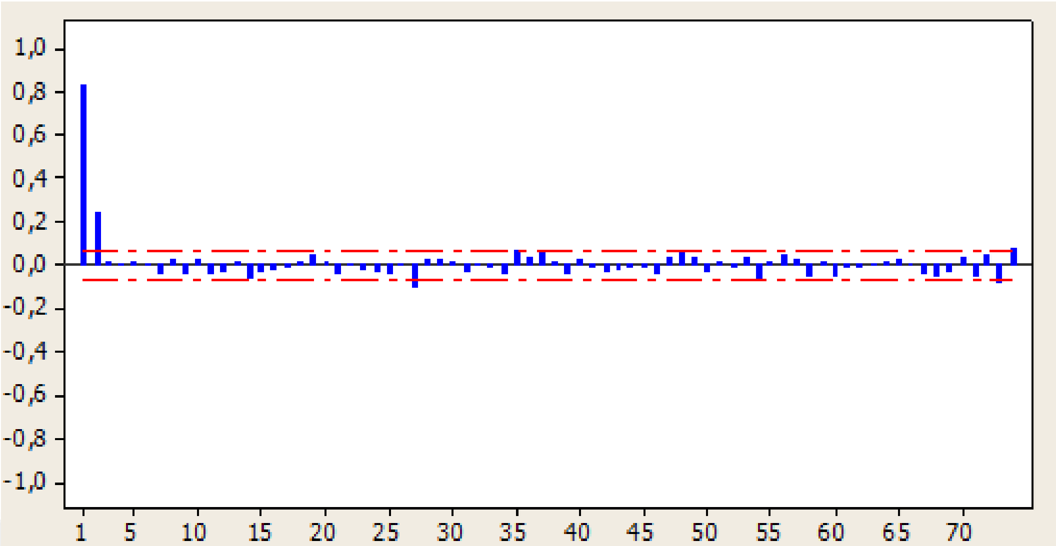
At Figure 13 it can be stated that the series oscillates around a certain average, but there are some openings towards the end of the series. These opening and outlier observations have the potential to affect the margin of error of the model. The series become stationary as per Figure 14 and Figure 15.

Figure 14 BHS 1 Autocorrelation Function for differences



Source: Author

Figure 15 BHS 1 Partial Autocorrelation Function for differences



Source: Author

The most appropriate model was attempted to be defined for data set that provided stationarity assumption. For this purpose, it was decided which model would be more suitable by examining SAC and SPAC of series. While there is no obvious cut-off status (rapidly approaching zero) in the SAC graph, it is observed that the SPAC graph approaches zero after the 2nd delay. Considering that once the difference is taken (d=1), our model is determined as ARIMA(2,1,0).

A general "ARIMA model" can be stated as follows.

"$z_t = \delta + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \cdots + \varphi_p z_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q}$"

To show the Zt two-difference series, our time series model can be shown below.

"$z_t = \delta + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + a_t$"

The model parameters and hypotheses for the constant term can be expressed as follows:

H_0: $\theta_1 = 0$ H_0: $\phi_i = 0$ H_0: $\delta = 0$

H_1: $\theta_1 \neq 0$ H_1: $\phi_i \neq 0$ H_1: $\delta \neq 0$

Model

Type	Coef	SE Coef	T	P
AR 1	0.6254	0.0326	19.21	0.000
AR 2	0.2444	0.0326	7.50	0.000
Constant	0.0001024	0.0002804	0.37	0.715

Differencing: 1 regular difference

Number of observations: Original series 891, after differencing 890

Residuals: SS = 0,0620592 (backforecasts excluded)

MS = 0,0000700 DF = 887

When the significance of the model parameters was examined, the P value of AR 1 and AR2 parameters were 0. Since "P" below 0.05 the assumption stating "model was insignificant" was rejected. These parameters must include in model. However, the "P" value of constant term was meaningless with a value of 0.715.

As a result of the analysis, as seen above, the constant term was found to be meaningless and therefore it was not necessary to include it in the model. In addition, the model parameters were found to be highly significant.

The hypotheses and results for the model adequacy analysis (Ljung-Box) are as follows. In order for the model to be sufficient, the model should be sufficient for each lag in below.

H0: Model significant

H1: Model not significant

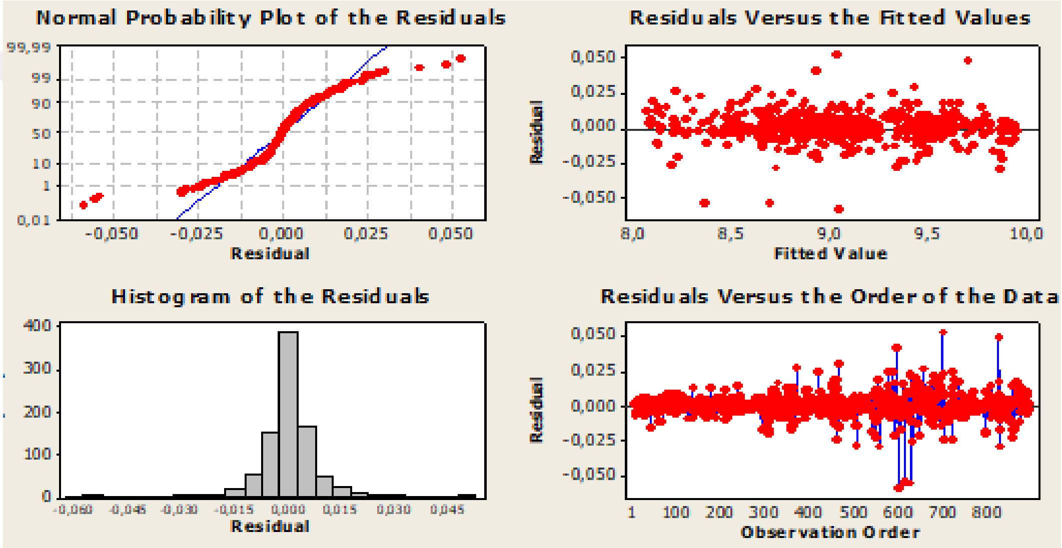
Statistics:

Lag	12	24	36	48
Chi-Square	5.4	12.1	34	43
DF	9	21	33	45
P-Value	0.799	0.936	0.418	0.559

According to results from the Minitab package program, the hypothesis established for the adequacy of the model could not be rejected for any lag. This shows that the model is sufficient.

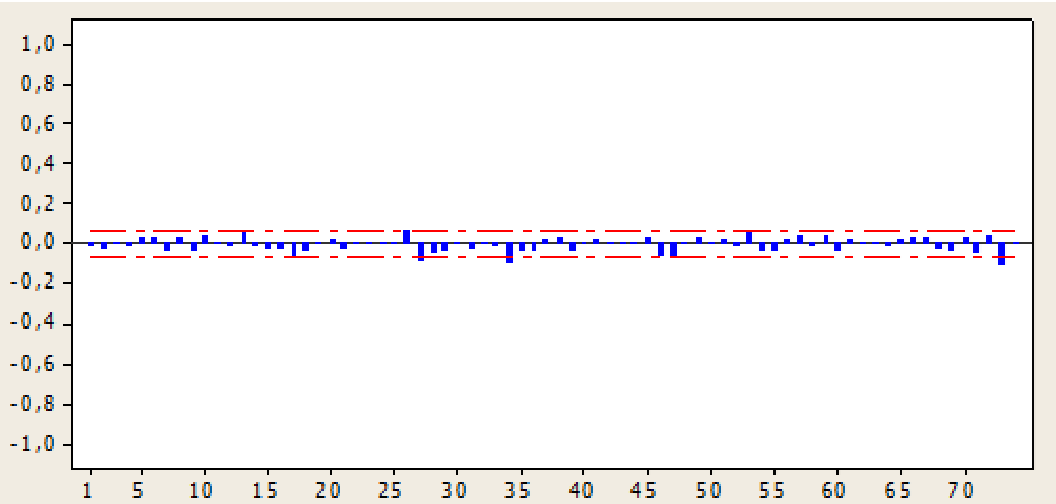
With the Ljung-Box statistics, the assumptions of the random error term of the model should be provided. Figure 16 show that the assumptions of the errors are provided. It can be stated that the distributions of the residuals do not go beyond the confidence limits and conform to the homogeneous and normal distribution. Figure 17 and Figure 18 are shown autocorrelation and Partial autocorrelation of the BHS 1 series.

Figure 16 BHS 1 Residual Plots



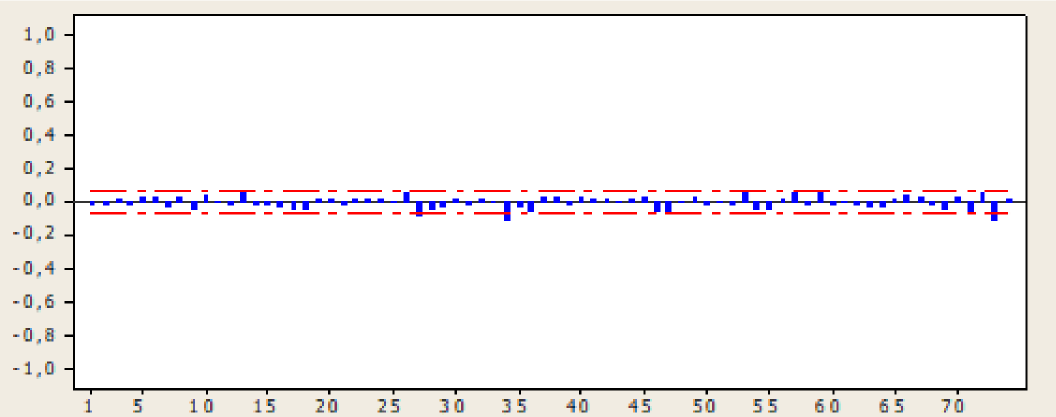
Source: Author

Figure 17 BHS 1 Autocorrelation Function



Source: Author

Figure 18 BHS 1 Partial Autocorrelation Function



Source: Author

4.3.1.5.1 Forecasting

The estimation of the series was made with the help of the model's parameters and historical values. For the reliability of the model, 15 realized values were estimated, and error rates were obtained. The predictions of the proposed model make accurate predictions with an error of up to 3 percent. In addition, 7 predictions at 95 confidence scale for future data is listed at Table 8.

Table 8 BHS1 Forecasting Result for ARIMA

Period	Actual	Forecast	Lower	Upper	Error
886	17.164	17560	17276	17851	2,31
887	17.379	17728	17182	18292	2,01
888	17.479	17879	17033	18768	2,29
889	17.507	18016	16850	19262	2,91
890	17.664	18139	16642	19772	2,69
891	17.921	18251	16416	20290	1,84
892	18.079	18352	16179	20816	1,51
893	18.279	18442	15934	21346	0,89
894		18525	15686	21877	
895		18600	15435	22411	
896		18665	15184	22944	
897		18725	14936	23478	
898		18779	14691	24007	
899		18828	14449	24536	
900		18873	14213	25059	

Source: Author

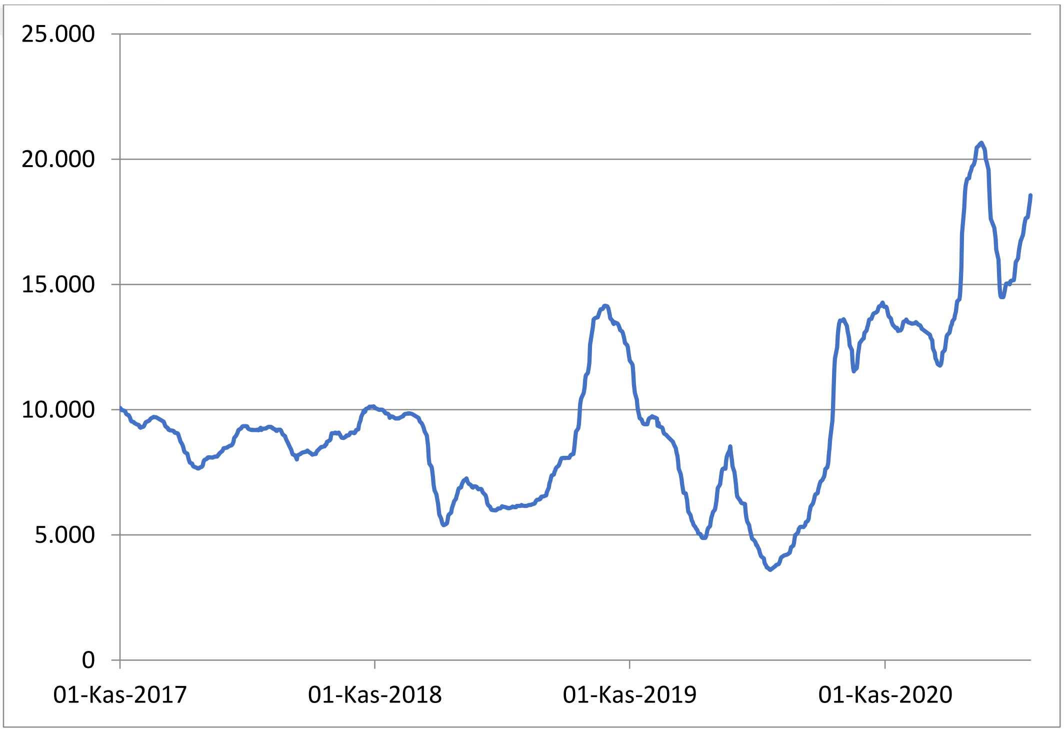
When all models were evaluated, it was seen that the most suitable method was the ARIMA(2,1,0) model.

4.3.2 Baltic Handysize Route 2

4.3.2.1 Modelling

For analysis of BHS 2 the natural logarithm of the data was taken and made stationary by performing the necessary operations, then the most suitable model (Box – Jenkins (ARIMA), trend analysis, Exponential smoothing methods) for the series was determined with different modelling methods and the values that it could take in the future were estimated. Statistical package programs such as Minitab and SPSS were used in the analysis of the data.

Figure 19 BHS 2 Route Time Series Graph



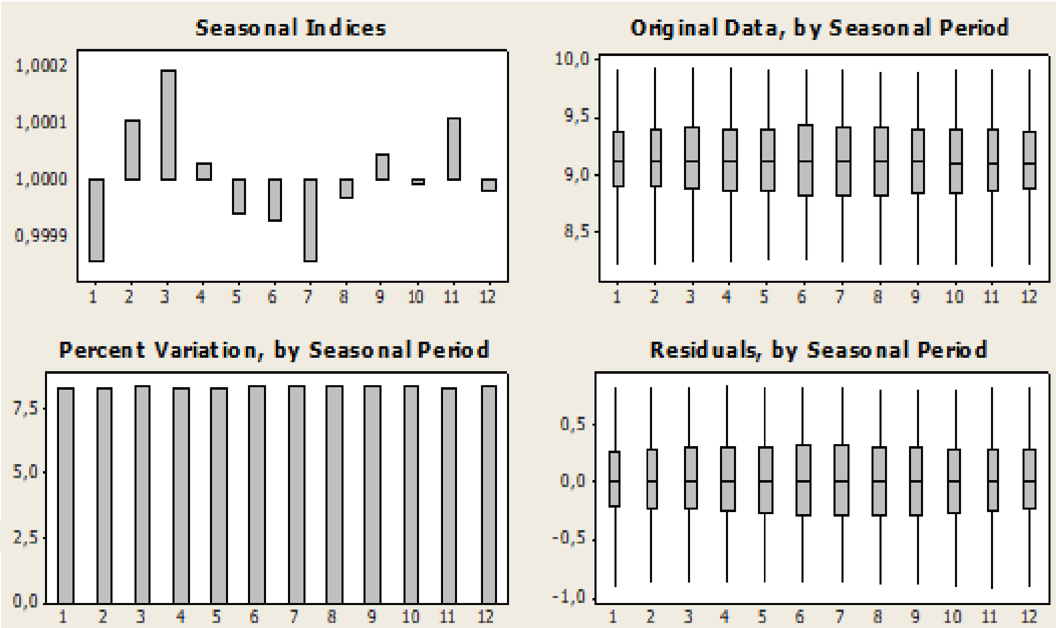
Source: Author

When the Figure 19 is examined; It was observed that there was a strong linear trend after May 2020 but there is no generalizable linear trend. In terms of seasonality, it can be said that there is no certain pattern. The following analyses show if there are any effects by modelling both components.

4.3.2.2 Seasonality analysis

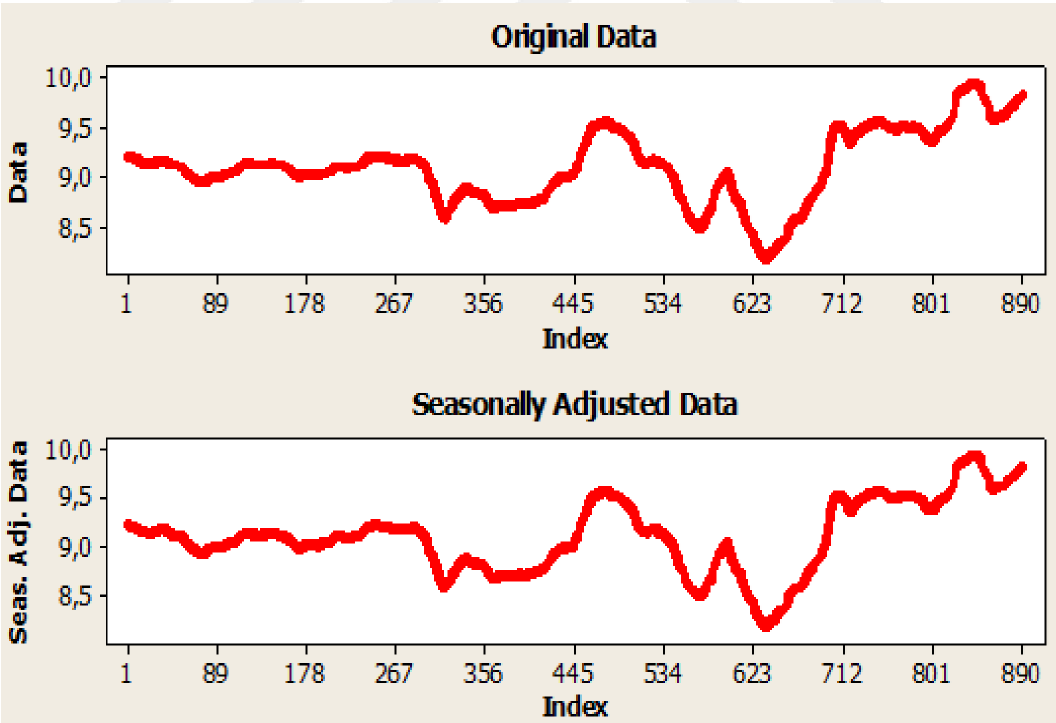
After analysis BHS 2 data, results for seasonality effect to BHS 2 series are shown Figure 20 and Figure 22.

Figure 20 BHS 2 Seasonal Analysis



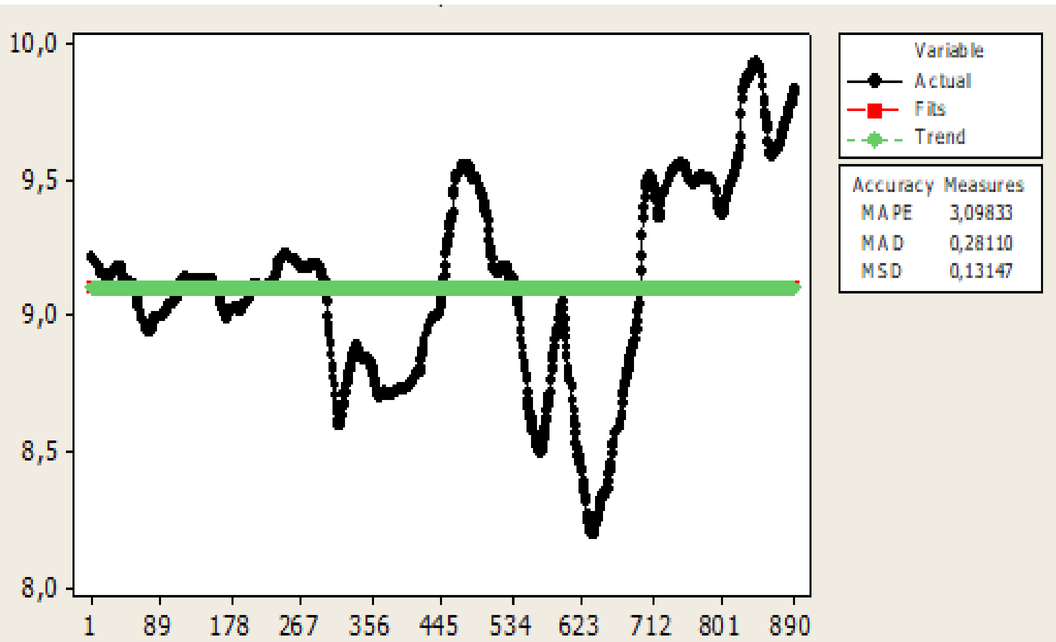
Source: Author

Figure 21 BHS 2 Component Analysis and Seasonally adjusted data



Source: Author

Figure 22 BHS 2 Time series decomposition plot



Source: Author

The fact that the seasonal indexes are very close to 1 in the data indicates that there is no seasonal effect. In addition, graphically, it can be seen at Figure 21 that the seasonally adjusted graph does not differ significantly from the original graph. The criteria to be used to evaluate the model with other models were MAPE:3.098, MAD:0.281 and MSD:0.1315.

4.3.2.3 Trend Analysis

It has been observed that the trend structure in the data has a quadratic rather than linear structure and modelling has been done.

Equation: Yt = 9,32618 - 0,00235504*t + 3,121750E-06*t**2

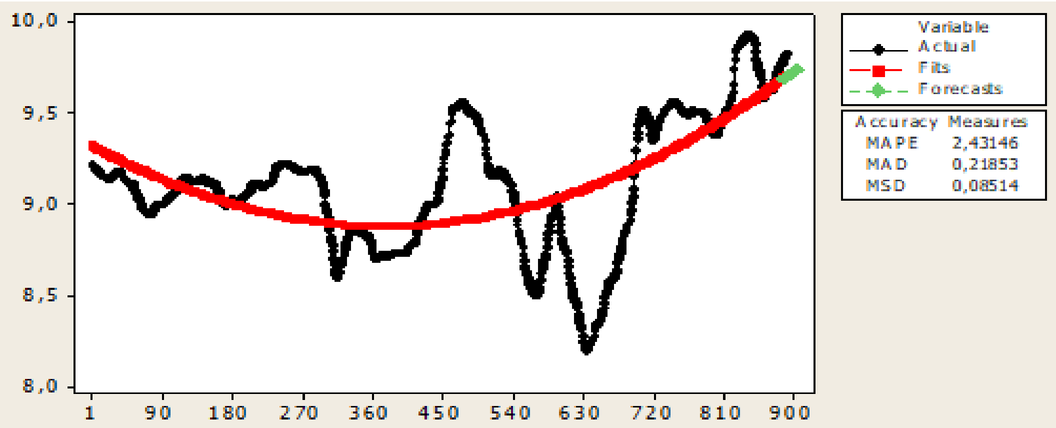
Accuracy Measures

MAPE: 2.43146

MAD: 0.21853

MSD: 0.08514

Figure 23 BHS 2 Trend Analysis Plot



Source: Author

MAPE, MAD and MSD error criteria used in the comparison criteria are lower than the model established for seasonal analysis at Figure 23. It can be said that this model gives better results.

4.3.2.3.1 Forecasting

While estimating, the last 7 observations of the series were estimated to see control and deviation. A total of 20 observation estimates were made and output listed at Table 9.

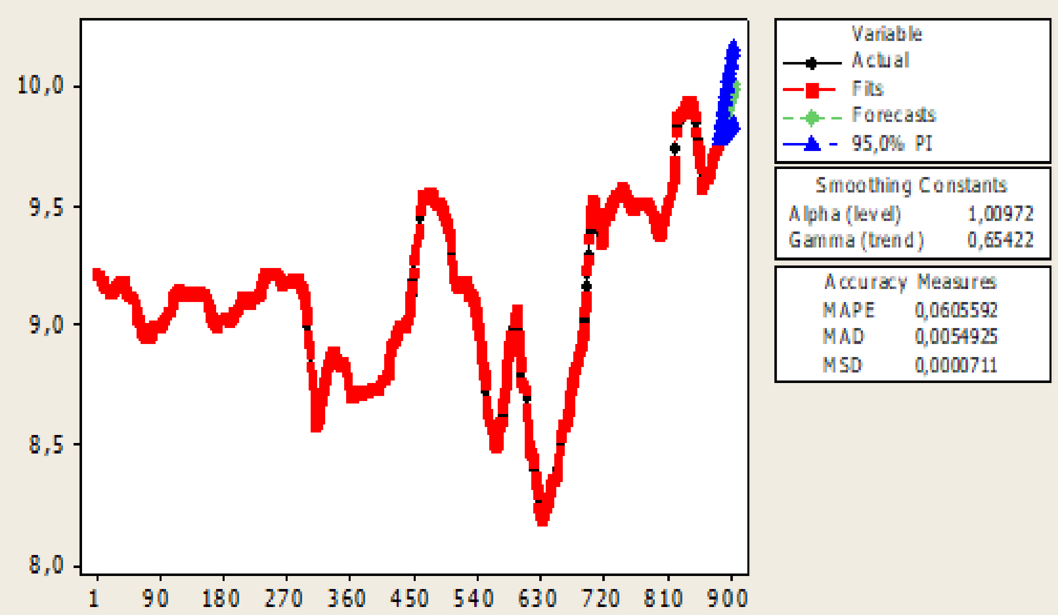
Table 9 BHS 2 Forecasting Results for Trend Analysis

date	Period	Actual	Forecast
20-May-21	886	17.543	16057
21-May-21	887	17.650	16108
24-May-21	888	17.679	16159
25-May-21	889	17.829	16210
26-May-21	890	18.129	16261
27-May-21	891	18.293	16313
28-May-21	892	18.571	16365
	893		16417
	894		16470
	895		16523
	896		16576
	897		16629
	898		16683
	899		16737
	900		16791
	901		16845
	902		16900
	903		16955
	904		17010
	905		17066

Source: Author

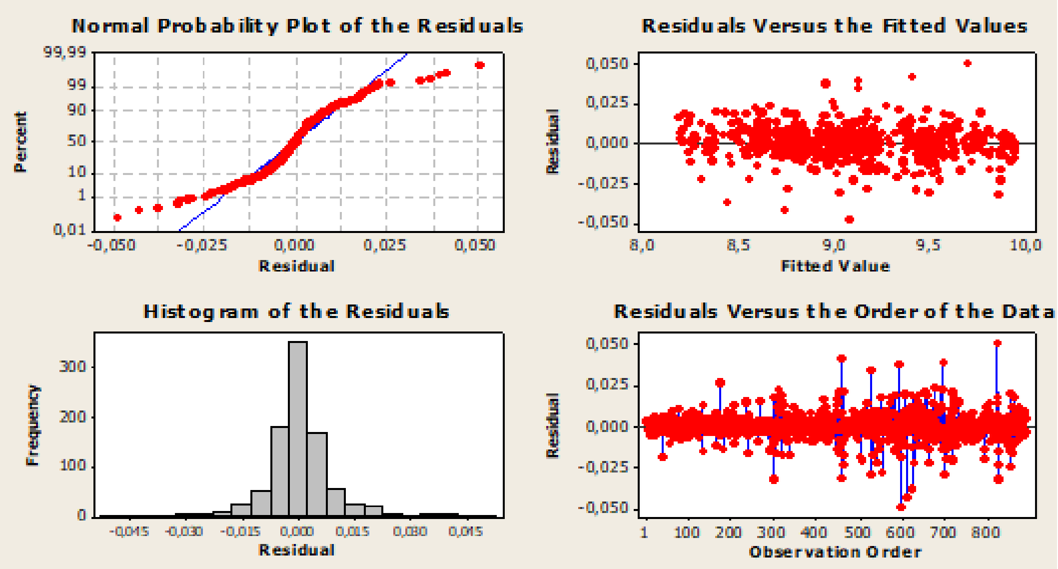
4.3.2.4. Exponential Smoothing Analysis

Figure 24 BHS 2 Double exponential smoothing plot



Source: Author

Figure 25 BHS 2 Residual plots



Source: Author

Above Figure 24 and Figure 25 of the error terms produced by the model are shows that the expectation is met. It can be notice residual (error) is generally distributed with a mean of 0, and homogeneously distributed rather than concentrated in certain regions. But it can be stated that some values are observed as extreme values, thus negatively affecting the model.

4.3.2.4.1. Forecasting

Model estimation, actual values, and the lowest and highest limits at 95% confidence level is listed at Table 10. When the estimations are examined, it can be said that it has less errors than the previously established Trend model estimations.

Table 10 BHS 2 Forecasting Results for exponential smoothing

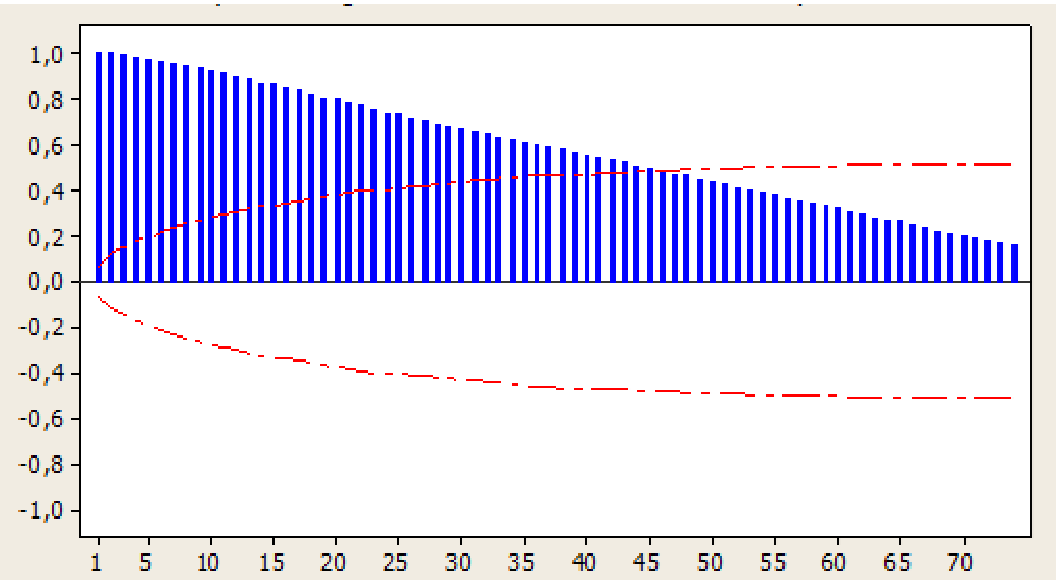
date	Period	Actual	Forecast	Lower	Upper
20-May-21	886	17.543	17744	17506	17983
21-May-21	887	17.650	17953	17586	18328
24-May-21	888	17.679	18166	17660	18687
25-May-21	889	17.829	18381	17732	19053
26-May-21	890	18.129	18600	17803	19431
27-May-21	891	18.293	18819	17874	19813
28-May-21	892	18.571	19042	17945	20205
	893		19268	18016	20605
	894		19495	18087	21013
	895		19726	18158	21431
	896		19960	18229	21855
	897		20195	18300	22288
	898		20435	18372	22729
	899		20677	18444	23181
	900		20923	18516	23640
	901		21169	18588	24108
	902		21420	18661	24588
	903		21675	18734	25074
	904		21930	18807	25573
	905		22190	18881	26079

Source: Author

4.3.2.5. Box – Jenkins Modelling

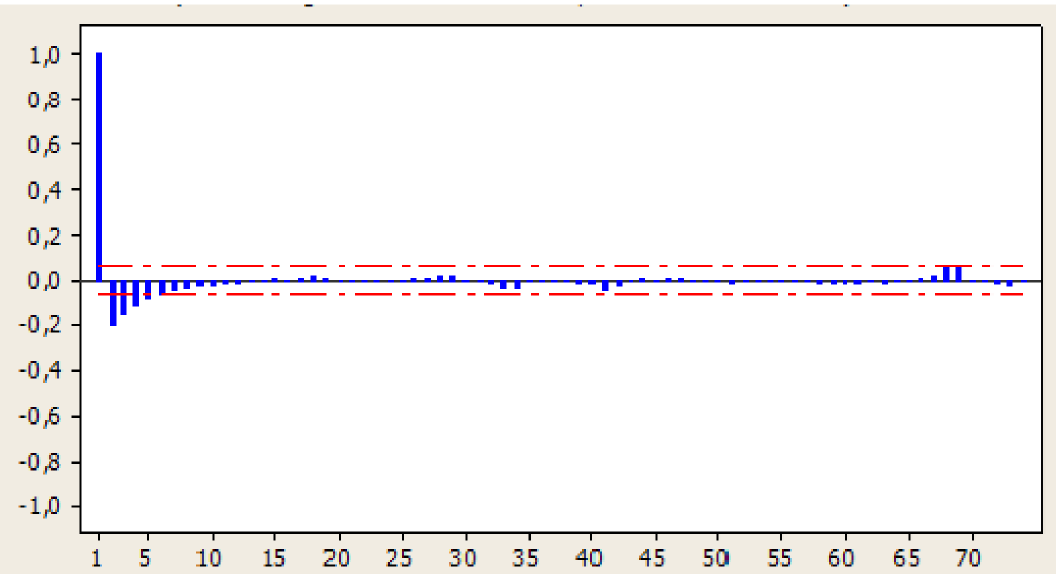
As can be seen from Figure 26 and Figure 27, there is a high-level dependence among the values of data.

Figure 26 BHS 2 Autocorrelation function



Source: Author

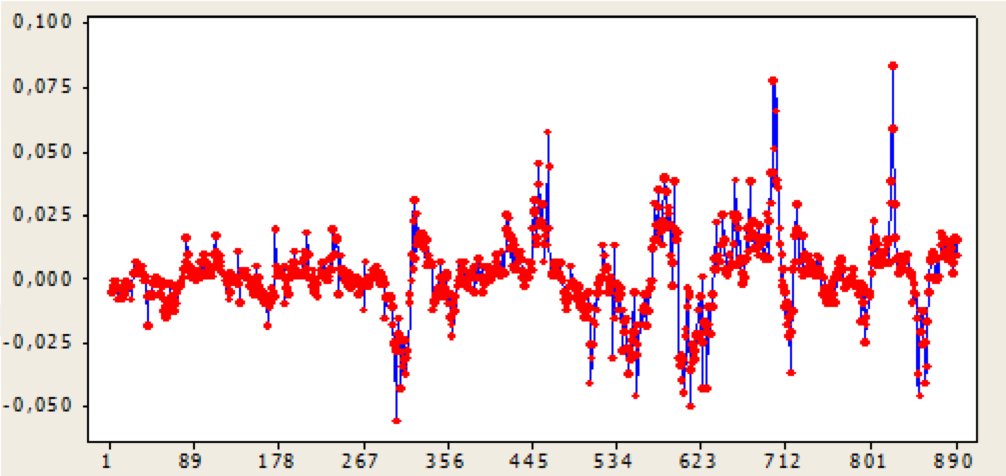
Figure 27 BHS 2 Partial Autocorrelation function



Source: Author

In order to eliminate this negative effect, the difference processor (d) is used. Since there is no significant seasonality in the series, the normal difference processor was used.

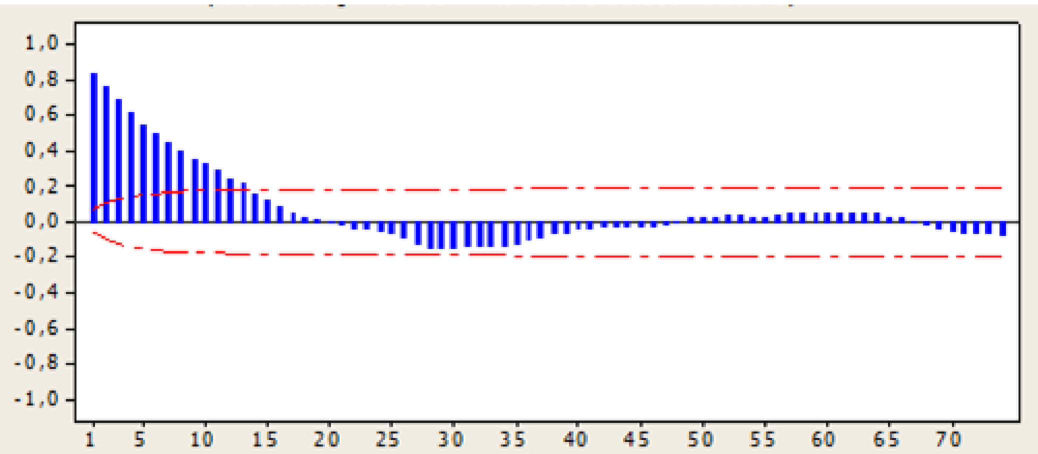
Figure 28 BHS 2 Plot of differences



Source: Author

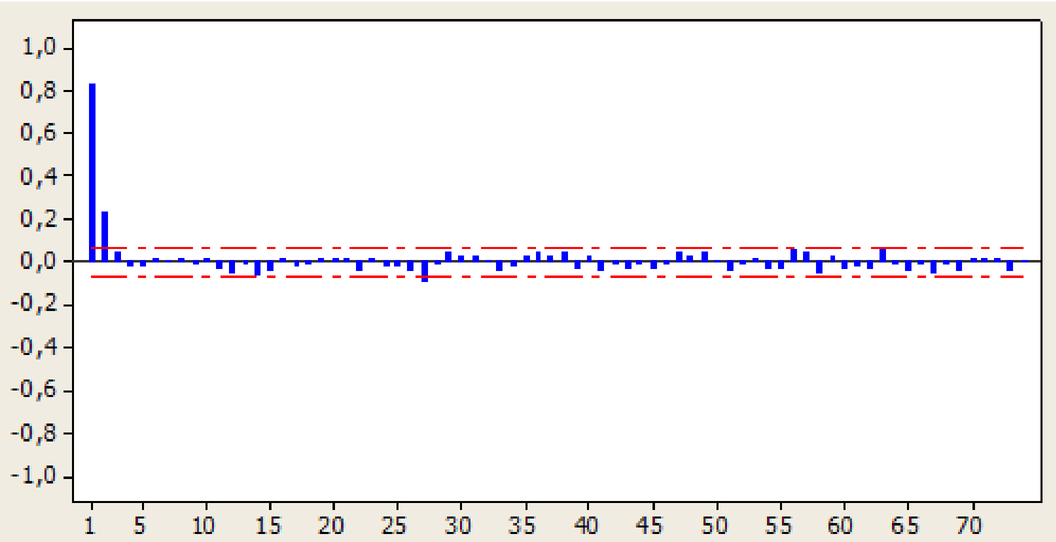
At Figure 28, It can be stated that the series oscillates around a certain average, but there are some openings towards the end of the series. These opening and outlier observations have the potential to affect the margin of error of the model. However, it can be seen from the graphs below that autocorrelation structures have become more suitable for modelling. The series become stationary as per Figure 29 and Figure 30.

Figure 29 BHS 2 Autocorrelation Function for differences



Source: Author

Figure 30 BHS 2 Partial Autocorrelation Function for differences



Source: Author

The most appropriate model was attempted to be defined for data set that provided stationarity assumption. For this purpose, it was decided which model would be more suitable by examining SAC and SPAC of series. While there is no obvious cut-off status (rapidly approaching zero) in the SAC graph, it is observed that the SPAC graph approaches zero after the 2nd delay. Considering that the difference is taken once (d=1), our model is determined as ARIMA(2,1,0) or (ARI(2,1)).

A general ARIMA model can be stated as follows.

"$z_t = \delta + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \cdots + \varphi_p z_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q}$"

In order to show Z_t two-difference series, our model suitable for time series can be shown in below.

"$z_t = \delta + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + a_t$"

The model parameters and hypotheses for the constant term can be expressed as follows;

H_0: $\theta_1 = 0$	H_0: $\phi_i = 0$	H_0: $\delta = 0$
H_1: $\theta_1 \neq 0$	H_1: $\phi_i \neq 0$	H_1: $\delta \neq 0$

Model

Type	Coef	SE Coef	T	P
AR 1	0.6362	0.0327	19.46	0.000
AR 2	0.2306	0.0327	7.05	0.000
Constant	0.0001013	0.0002773	0.37	0.715

Differencing: 1 regular difference

Number of observations: Original series 891, after differencing 890

Residuals: SS = 0,0607192 (backforecasts excluded)

MS = 0,0000685 DF = 887

When the significance of the model parameters was examined, the P value of AR 1 and AR2 parameters were 0. Since "P" below 0.05 the assumption stating "model was insignificant" was rejected. These parameters must include in model. However, the "P" value of constant term was meaningless with a value of 0.715.

As a result of the analysis, as seen above, the constant term was found to be meaningless and therefore it was not necessary to include it in the model. In addition, the model parameters were found to be highly significant.

The hypotheses and results for the model adequacy analysis (Ljung-Box) are as follows. In order for the model to be sufficient, the model should be sufficient for each lag in below.

H0: Model significant

H1: Model not significant

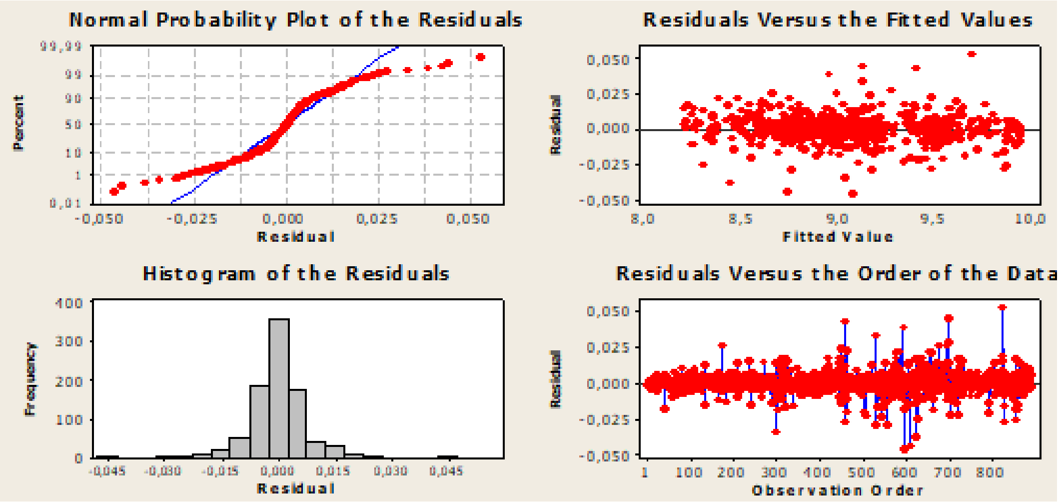
Statistic

Lag	12	24	36	48
Chi-Square	4.2	11.1	28.4	33.5
DF	9	21	33	45
P-Value	0.895	0.960	0.697	0.898

According to results of the Minitab package program, the hypothesis established for the adequacy of the model could not be rejected for any lag. This shows that the model is sufficient.

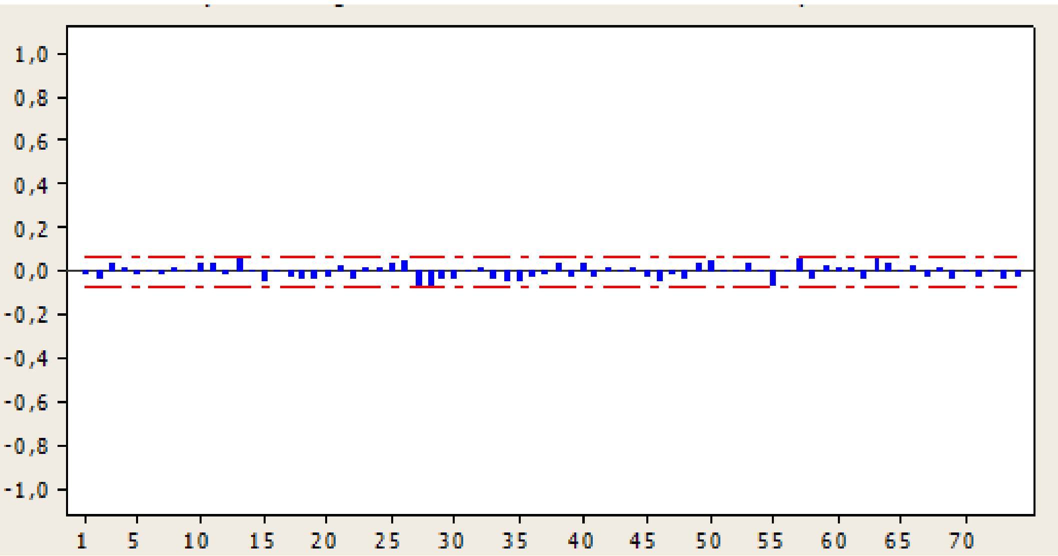
With the Ljung-Box statistics, the assumptions of the random error term of the model should be provided. Figure 31 show that the assumptions of the errors are provided. It can be stated that the distributions of the residuals do not go beyond the confidence limits and conform to the homogeneous and normal distribution. Figure 32 and Figure 33 are showing autocorrelation and Partial autocorrelation of the BHS 2 series.

Figure 31 BHS 2 Residual Plots



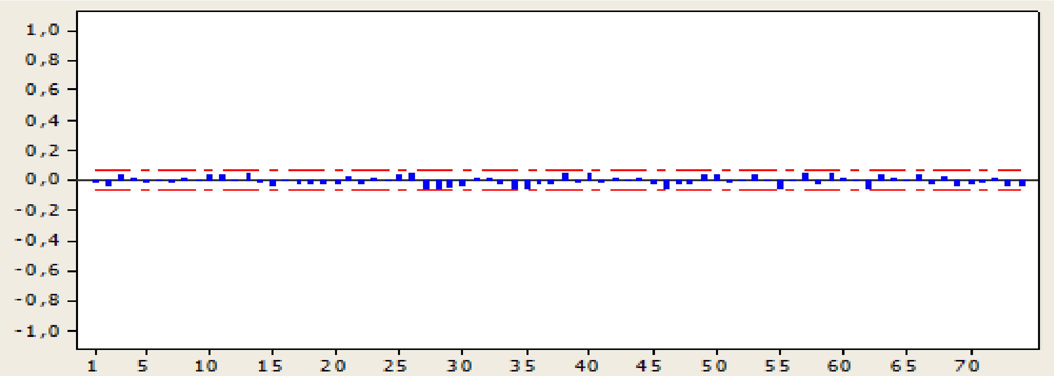
Source: Author

Figure 32 BHS 2 Autocorrelation Function



Source: Author

Figure 33 BHS 2 Partial Autocorrelation Function



Source: Author

4.3.2.5.1 Forecasting

The estimation of the series was made with the help of the model's parameters and historical values. For the reliability of the model, 20 realized values were estimated, and error rates were obtained. The predictions of the proposed model make accurate predictions with an error of up to 2 percent. In addition, 13 predictions at 95% confidence level for future data is listed at Table 11.

Table 11 BHS 2 Forecasting Result for ARIMA

date	Period	Actual	Forecast	Lower	Upper	Error
20-May-21	886	17.543	17721	17436	18010	1,01
21-May-21	887	17.650	17892	17342	18457	1,37
24-May-21	888	17.679	18046	17195	18938	2,08
25-May-21	889	17.829	18186	17016	19436	2,00
26-May-21	890	18.129	18315	16813	19950	1,03
27-May-21	891	18.293	18431	16592	20474	0,76
28-May-21	892	18.571	18538	16362	21005	-0,18
	893		18635	16125	21539	
	894		18725	15883	22075	
	895		18805	15640	22613	
	896		18881	15400	23149	
	897		18949	15160	23685	
	898		19012	14924	24222	
	899		19071	14693	24753	
	900		19124	14465	25283	
	901		19174	14244	25810	
	902		19220	14028	26334	
	903		19262	13818	26852	
	904		19303	13613	27370	
	905		19339	13415	27881	

Source: Author

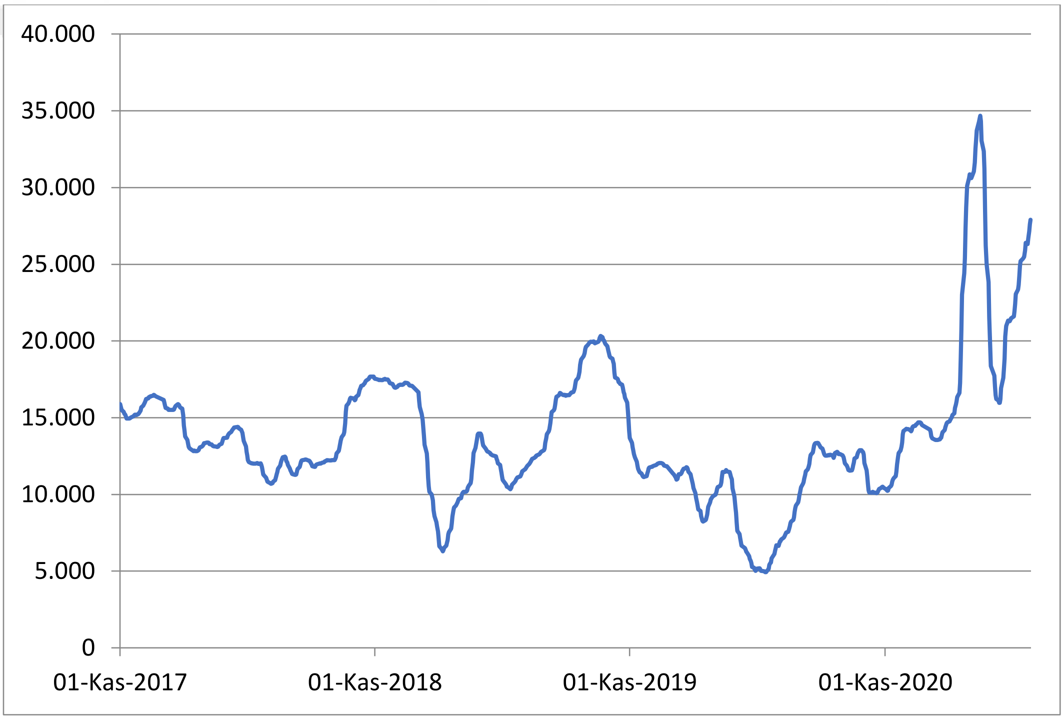
All models were evaluated, it was seen that the most suitable method was the ARI(2,1).

4.3.3 Baltic Handysize Route 3

4.3.3.1 Modelling

For analysis of BHS 3 the natural logarithm of the data was taken and made stationary by performing the necessary operations, then the most suitable model (Box – Jenkins (ARIMA), trend analysis, Exponential smoothing methods) for the series was determined with different modelling methods and the values that it could take in the future were estimated. Statistical package programs such as Minitab and SPSS were used in the analysis of the data.

Figure 34 BHS 3 Route Time Series Graph



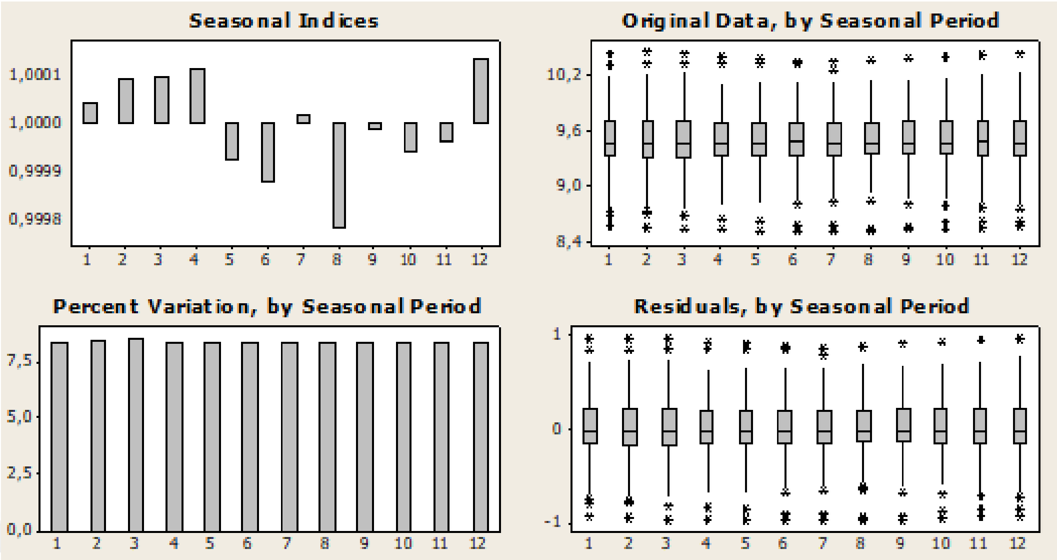
Source: Author

When Figure 34 is examined; It was observed that there was a strong linear trend after February 2021 but there is no generalizable linear trend. In terms of seasonality, it can be said that there is no certain pattern. The following analyses show whether there are any effects by modelling both components.

4.3.3.2 Seasonality analysis

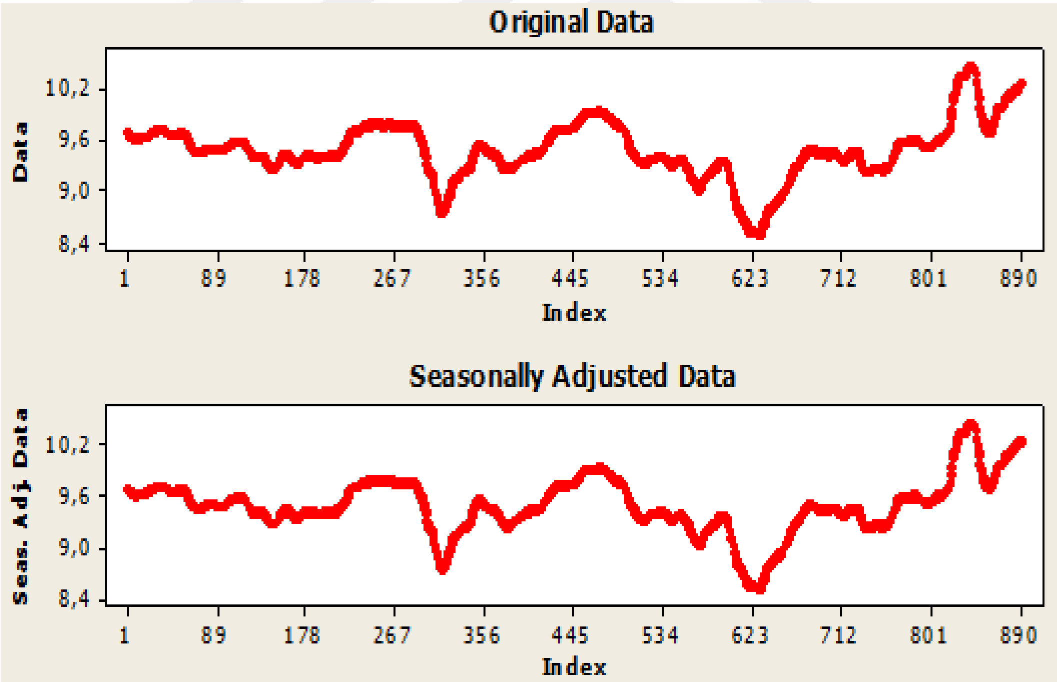
After analysis BHS 3 data, results for seasonality effect to BHS 3 series are shown at Figure 35 and Figure 37.

Figure 35 BHS 3 Seasonal Analysis



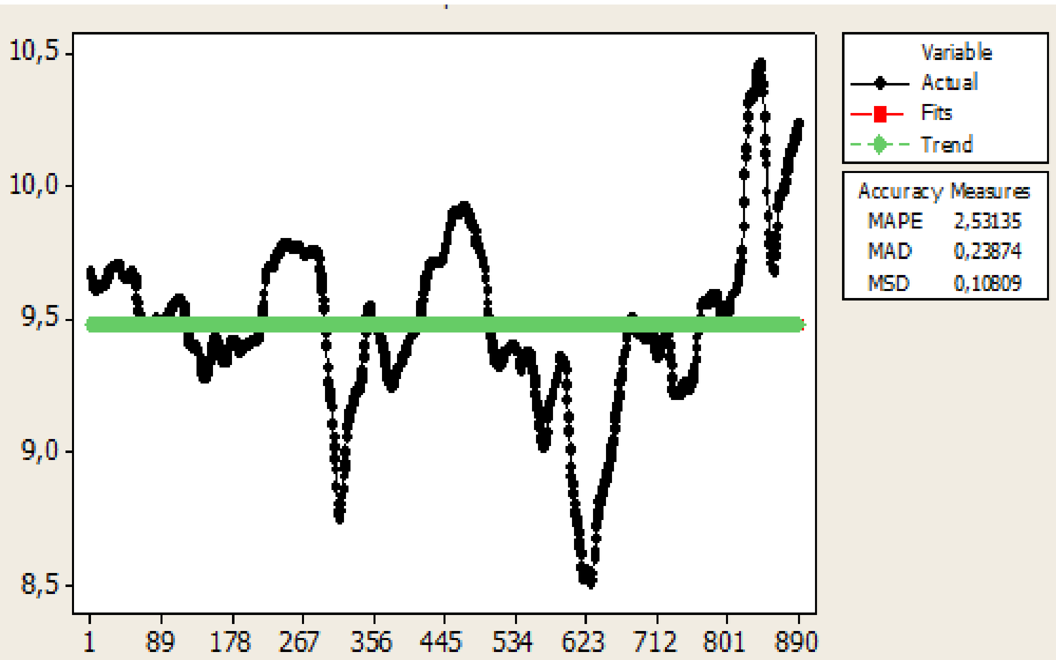
Source: Author

Figure 36 BHS 3 Component Analysis and Seasonally Adjusted data



Source: Author

Figure 37 BHS3 Time series decomposition plot



Source: Author

Results show that the data indications have no seasonal effect since the indexes are so close to 1. In addition, graphically, it can be seen at Figure 36 that the seasonally adjusted graph does not differ significantly from the original graph. The criteria to be used to evaluate the model with other models were MAPE:2.531, MAD:0.238 and MSD:0.108.

4.3.3.3 Trend Analysis

It has been observed that the trend structure in the data has a quadratic rather than linear structure and modelling has been done.

Equation Yt= 9,75163 – 0,00194486*t + 2,240832E-06*t**2

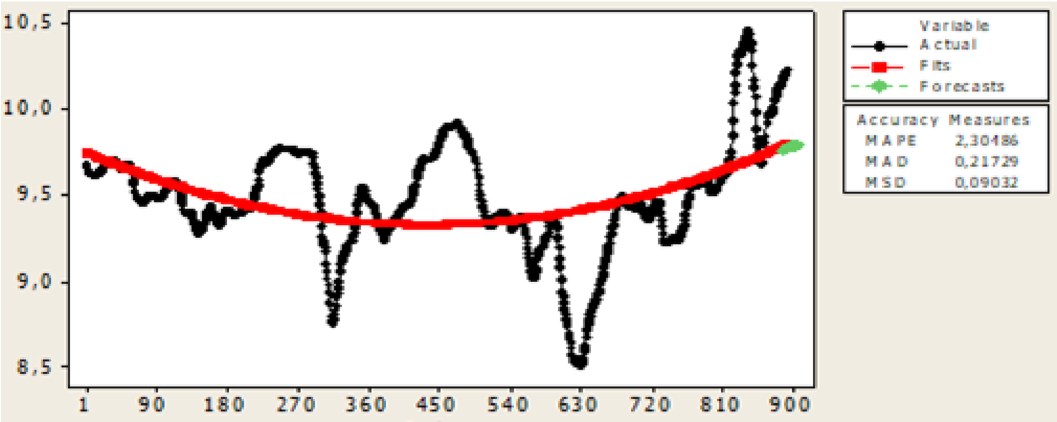
Accuracy Measures

MAPE: 2.30486

MAD: 0.21729

MSD: 0.09032

Figure 38 BHS 3 Trend Analysis Plot



Source: Author

MAPE, MAD and MSD error criteria used in the comparison criteria are lower than the model established for seasonal analysis at Figure 38. It can be said that this model gives better results.

4.3.3.3.1 Forecasting

While estimating, the last 7 observations of the series were estimated to see control and deviation. There were 20 observation estimates in total and Table 12 shows the forecasting results for trend analysis.

Table 12 BHS 3 Forecasting Results for Trend analysis

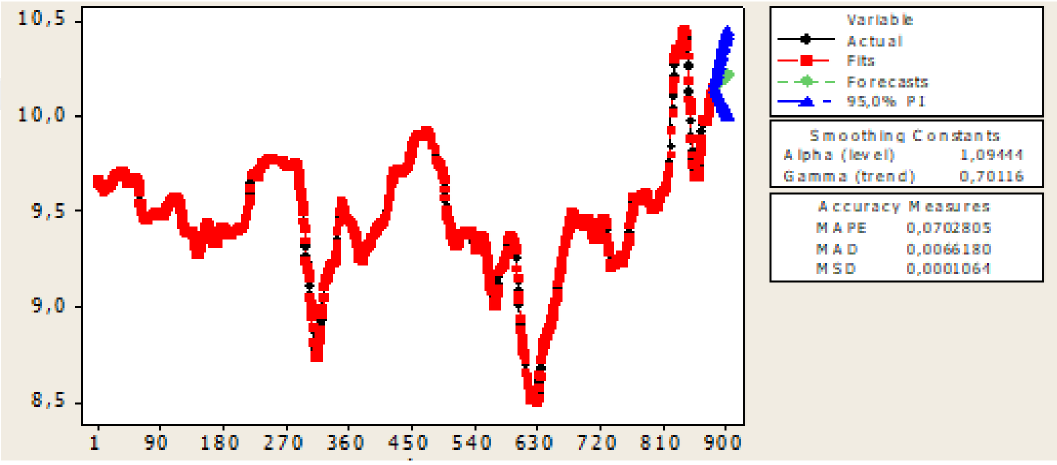
date	Period	Actual	Forecast
20-May-21	885	25.900	17258
21-May-21	886	26.389	17290
24-May-21	887	26.325	17323
25-May-21	888	26.694	17356
26-May-21	889	27.150	17389
27-May-21	890	27.606	17422
28-May-21	891	27.894	17456
	892		17489
	893		17523
	894		17557
	895		17590
	896		17624
	897		17658
	898		17693
	899		17727
	900		17762
	901		17797
	902		17831
	903		17866
	904		17902

Source: Author

4.3.3.4. Exponential Smoothing Analysis

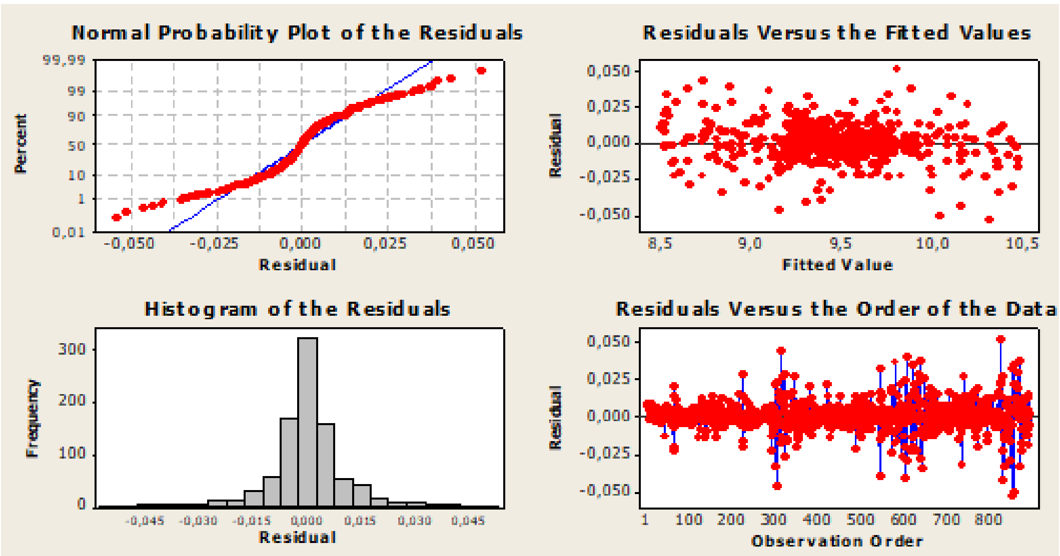
The exponential smoothing approach is one of the methods that starts from the current values of the data with a certain correction coefficient and models the series according to the older data. Since it is a dynamic model, the past and future predictions for each data are determined iteratively. The following table includes predictive values, exponential smoothing coefficients (Alpha, Gamma), error term assumptions and model criteria.

Figure 39 BHS 3 Double exponential smoothing plot



Source: Author

Figure 40 BHS 3 Residual plots



Source: Author

Above Figure 39 and Figure 40 of the error terms produced by the model are shows that the expectation is met. The residual (error) is generally distributed with a mean of 0, and homogeneously distributed rather than concentrated in certain regions. But it can be stated that some values are observed as extreme values, thus negatively affecting the model.

4.3.3.4.1. Forecasting

At Table 13, it shows that the model estimation, actual values, and the lowest and highest limits at 95% confidence level. When the estimations are examined, it can be said that it has less errors than the previously established Trend model estimations.

Table 13 BHS 3 Forecasting Results for Exponential Smoothing

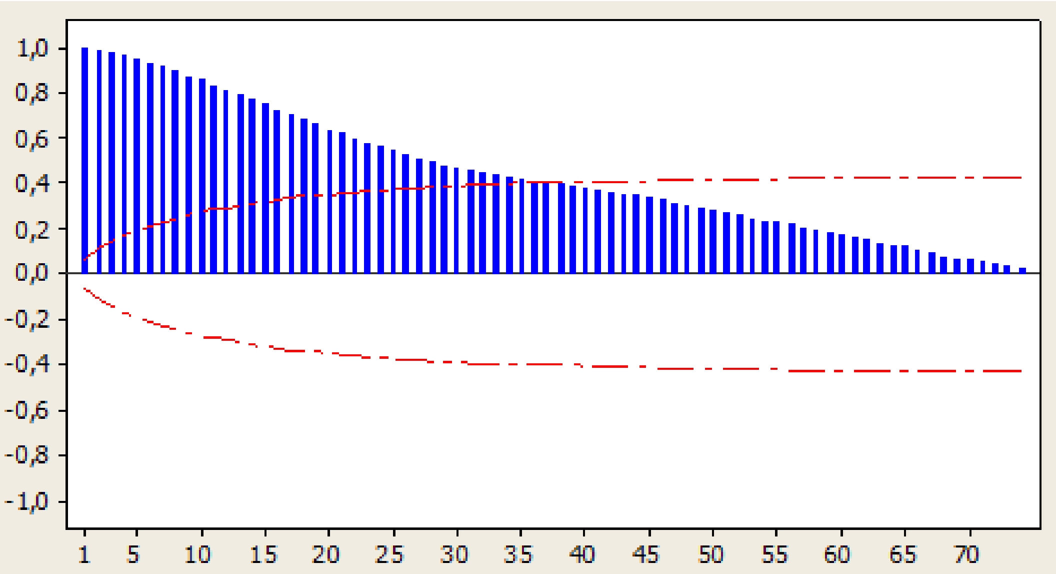
Date	Period	Actual	Forecast	Lower	Upper	error %
20.May.21	885	25.900	25583	25172	25999	1,22
21.May.21	886	26.389	25678	25012	26360	2,69
24.May.21	887	26.325	25773	24842	26740	2,10
25.May.21	888	26.694	25869	24671	27125	3,09
26.May.21	889	27.150	25965	24499	27518	4,36
27.May.21	890	27.606	26061	24328	27920	5,60
28.May.21	891	27.894	26158	24156	28328	6,22
	892		26257	23988	28739	
	893		26355	23818	29158	
	894		26452	23650	29584	
	895		26550	23485	30019	
	896		26649	23318	30458	
	897		26748	23153	30903	
	898		26847	22990	31354	
	899		26949	22827	31812	
	900		27049	22666	32277	
	901		27149	22505	32748	
	902		27250	22346	33230	
	903		27351	22188	33715	
	904		27452	22033	34207	

Source: Author

4.3.3.5 Box – Jenkins Modelling

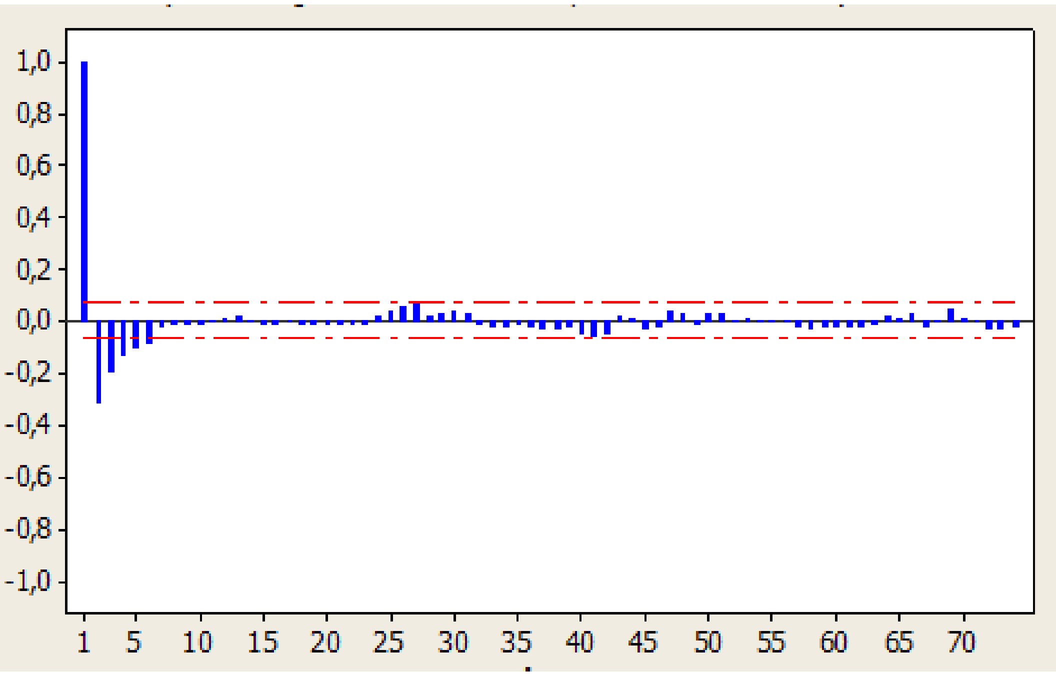
As can be seen from Figure 41 and Figure 42, there is a high-level grade of dependence among the data.

Figure 41 BHS 3 Autocorrelation function



Source: Author

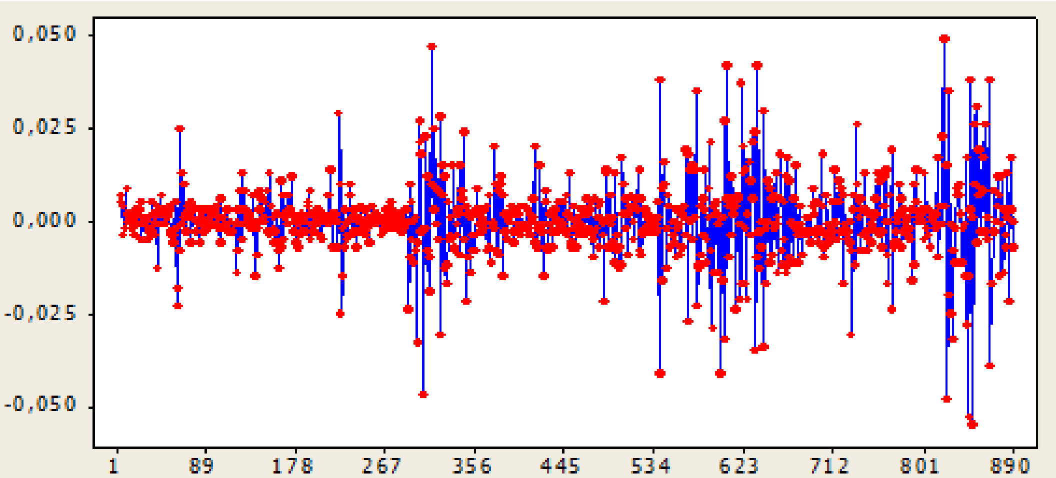
Figure 42 BHS 3 Partial Autocorrelation on function



Source: Author

In order to eliminate this negative effect, the difference processor (d) is used. Since there is no significant seasonality in the series, the normal difference processor was used. Differentiation processor was taken twice to find the appropriate model.

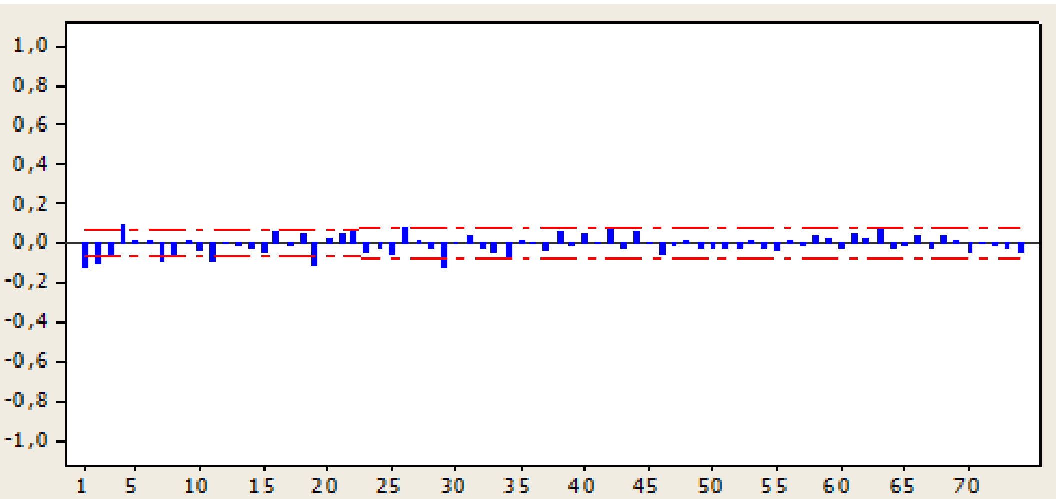
Figure 43 BHS 3 Plot difference



Source: Author

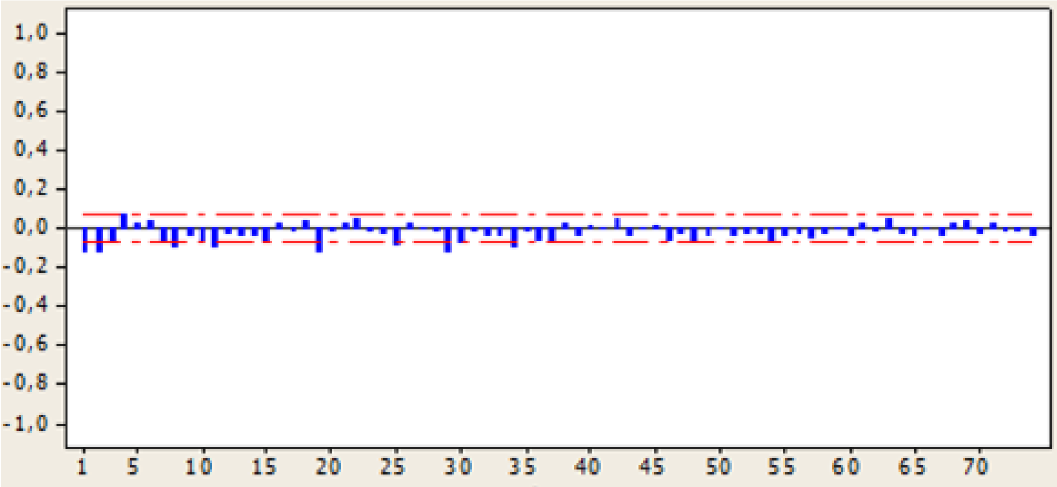
At Figure 43, it can be stated that the series oscillates around a certain average, but there are some openings towards the end of the series. When the autocorrelation and partial autocorrelation graphs are examined, it is seen that there is no significant structure. Possible ARIMA model The ARIMA(2,2,2) model has been tried and the results are shown in the outputs at Figure 44 and Figure 45.

Figure 44 BHS 3 Autocorrelation Function for differences



Source: Author

Figure 45 BHS 3 Partial Autocorrelation Function for differences



Source: Author

A general "ARIMA (p,d,q) model" can be expressed as follows.

"$z_t = \delta + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \cdots + \varphi_p z_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q}$"

In order to show Z_t two-difference series, our model suitable for time series can be shown in below.

"$z_t = \delta + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2}$"

The hypotheses for the model parameters and constant term can be expressed as follows;

H_0: $\theta_1 = 0$ H_0: $\phi_i = 0$ H_0: $\delta = 0$

H_1: $\theta_1 \neq 0$ H_1: $\phi_i \neq 0$ H_1: $\delta \neq 0$

Model

Type	Coef	SE Coef	T	P
AR 1	0.668	0.1644	4.06	0.000
AR 2	-0.6365	0.1067	-5.69	0.000
MA 1	0.7974	0.1699	4.69	0.000
MA 2	-0.6099	0.1255	-4.86	0.000

Differencing: 2 regular differences

Number of observations: Original series 891, after differencing 889

Residuals: SS = 0.0935100 (back forecasts excluded)

MS = 0.0001057 DF = 885

When the significance of the model parameters was examined, the P value of AR 1, AR 2, MA 1 AND MA 2 parameters were 0. Since “P” below 0.05 the assumption stating “model was insignificant” was rejected.

The hypotheses and results for the model adequacy analysis (Ljung-Box) are as follows. In order for the model to be sufficient, the model should be sufficient for each lag in below.

H0 : The model is significant.

H1 : The model is not significant.

Statistics

Lag	12	24	36	48
Chi-Square	26.3	45.9	71.7	94.4
DF	8	20	32	44
P-Value	0.001	0.001	0	0

According to results from Minitab package program, hypothesis for the adequacy of the model was rejected for all lags. This shows that the model is not sufficient. Apart from the ARIMA(2,2,2) model, different models were also tried, but model significance could not be achieved for any of the ARIMA models.

Within the framework of these results, modelling of BHS3 series could not be done by ARIMA methods. There may be different reasons why the assumptions, which are the main reason for this situation, cannot be met. The excess of extreme and effective observations in the series, the trend structure changing the direction of the series significantly at the end of the series, etc. can be sorted.

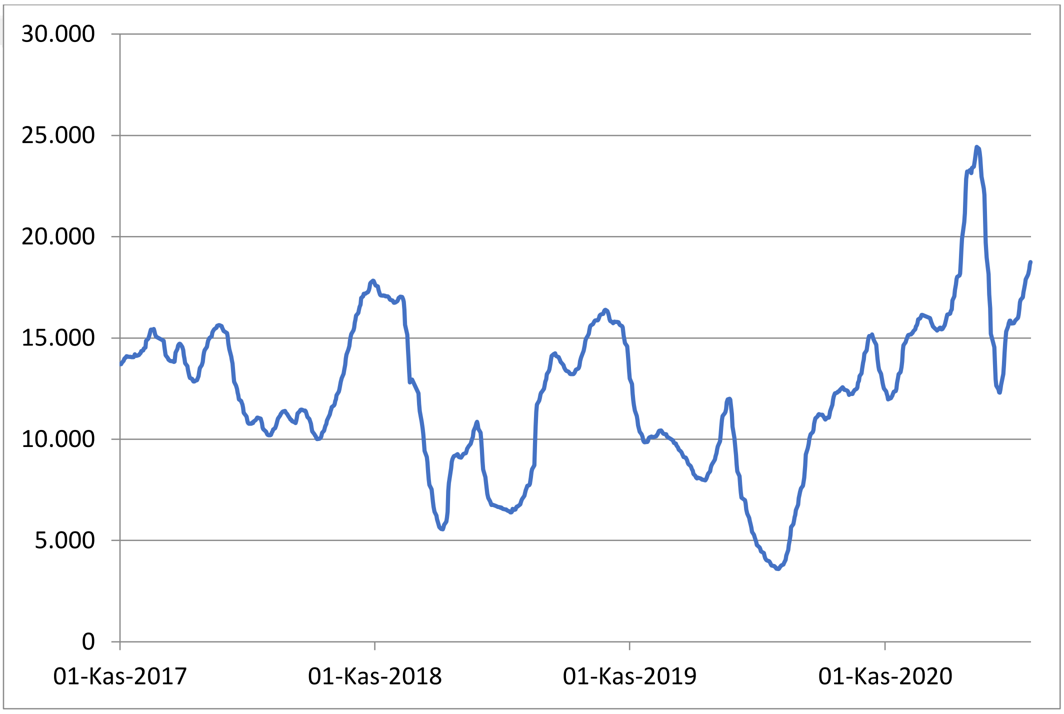
When all models were evaluated, it was found appropriate to model the series with the exponential smoothing method and use its estimations.

4.3.4 Baltic Handysize Route 4

4.3.4.1 Modelling

For analysis of BHS 4 the natural logarithm of the data was taken and made stationary by performing the necessary operations, then the most suitable model (Box – Jenkins (ARIMA), trend analysis, Exponential smoothing methods) for the series was determined with different modelling methods and the values that it could take in the future were estimated. Statistical package programs such as Minitab and SPSS were used in the analysis of the data.

Figure 46 BHS 4 Route Time Series Graph



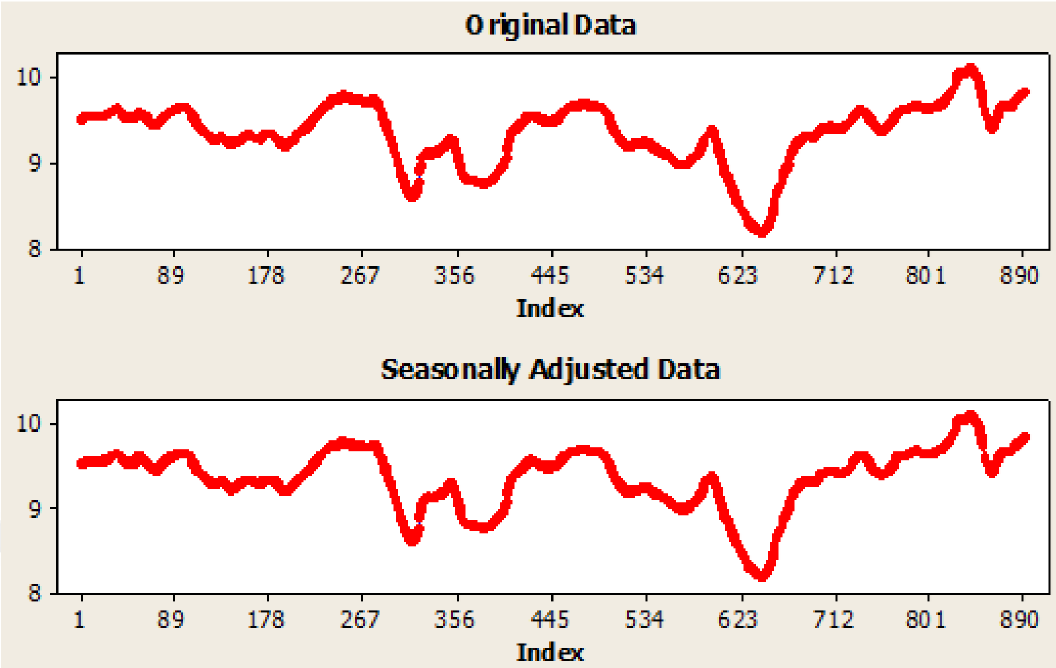
Source: Author

When Figure 46 is examined; It was observed that there was a strong linear trend after May 2020 but there is no generalizable linear trend. In terms of seasonality, it can be said that there is no certain pattern. The following analyses show whether there are any effects by modelling both components.

4.3.4.2 Seasonality analysis

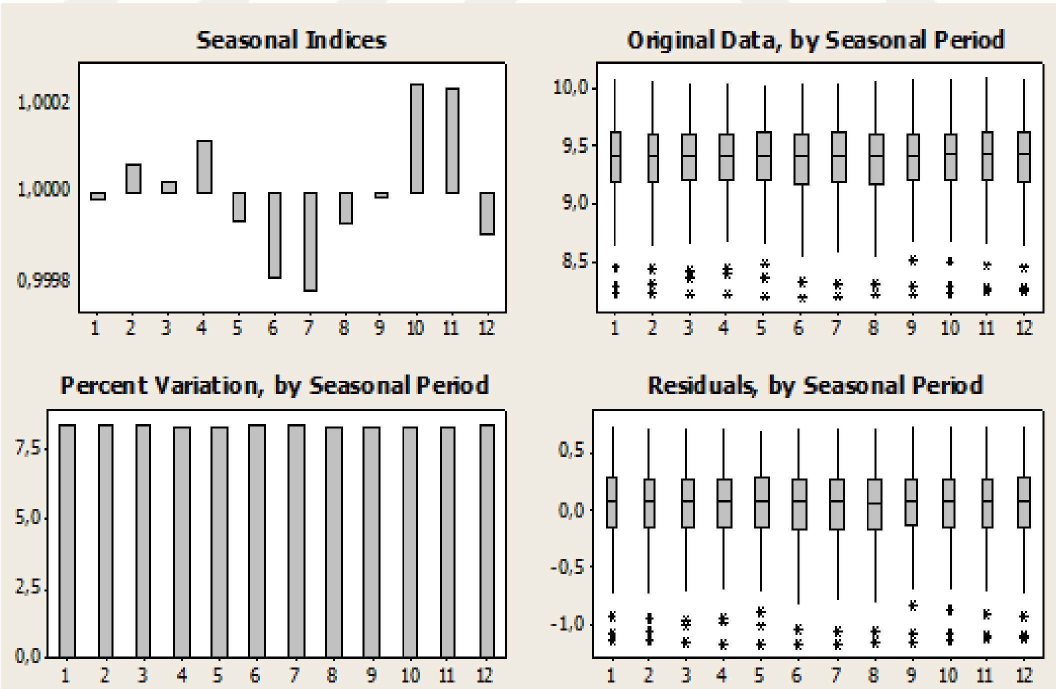
After analysis BHS 4 data, results for seasonality effect to BHS 4 series are shown below Figure 47 and Figure 49.

Figure 47 BHS 4 Component Analysis and Seasonally Adjusted data



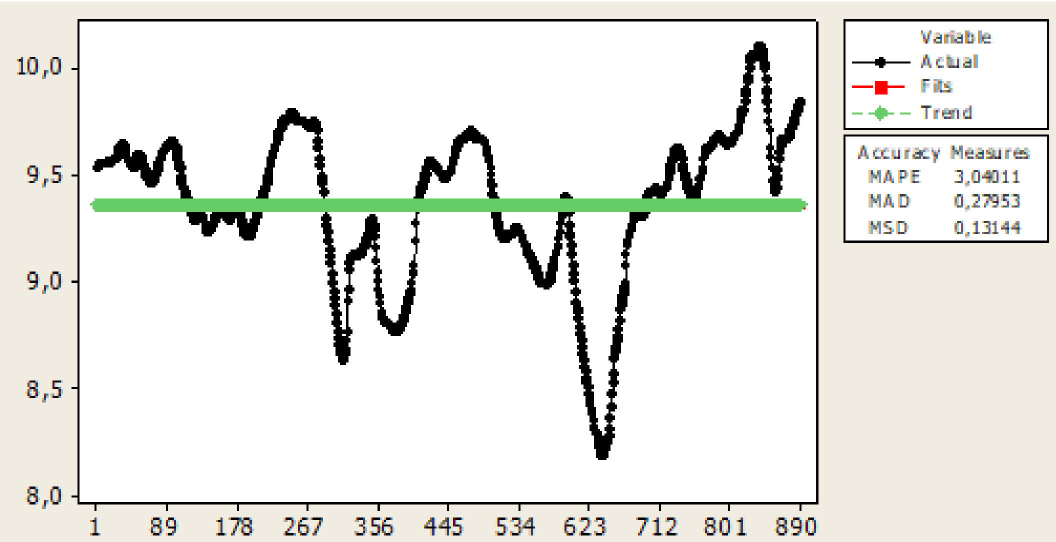
Source: Author

Figure 48 BHS 4 Seasonal Analysis



Source: Author

Figure 49 BHS 4 Time series decomposition plot



Source: Author

Results show that the data indications have no seasonal effect since the indexes are so close to 1. In addition, graphically, it can be seen Figure 48 that the seasonally adjusted graph does not differ significantly from the original graph. The criteria to be used to evaluate the model with other models were MAPE:3.04, MAD:0.279 and MSD:0.131

4.3.4.3 Trend Analysis

It has been observed that the trend structure in the data has a quadratic rather than linear structure and modelling has been done.

Equation: Yt = 9,74065 - 0,00258893*t + 2,910512E-06*t**2

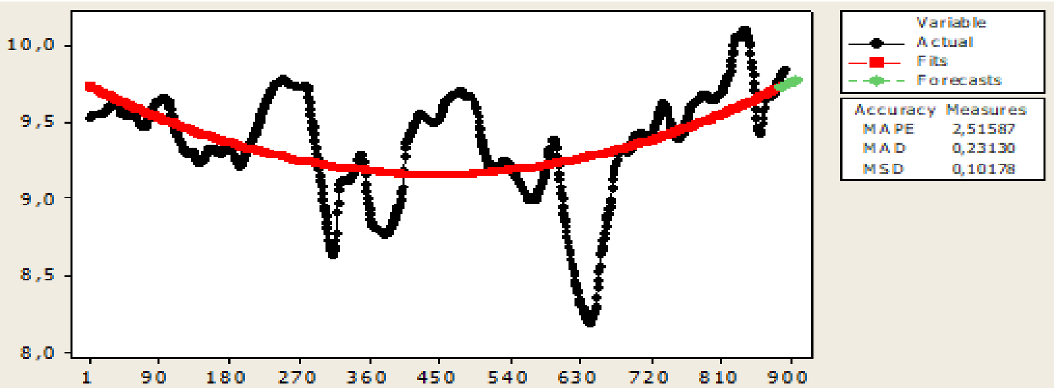
Measures

MAPE: 2.51587

MAD: 0.23130

MSD: 0.10178

Figure 50 BHS 4 Trend Analysis Plot



Source: Author

At Figure 50, MAPE, MAD and MSD error criteria used in the comparison criteria are lower than the model established for seasonal analysis. It can be said that this model gives better results.

4.3.4.3.1 Forecasting

While estimating, the last 7 observations of the series were estimated to see control and deviation. There were 20 observation estimates in total and at Table 14 shows the forecasting results for trend analysis

Table 14 BHS 4 Forecasting Results for Trend analysis

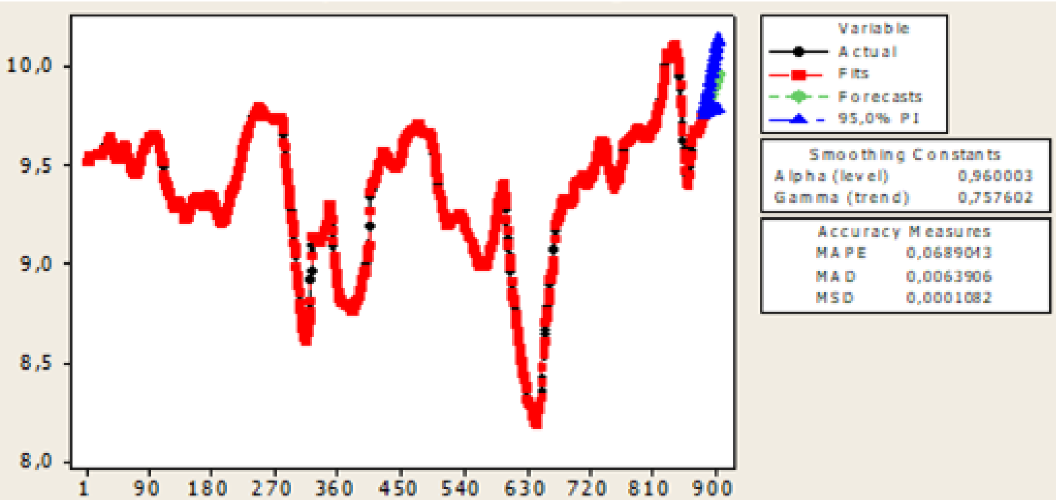
date	Period	Actual	Forecast
20-May-21	885	17.679	16709
21-May-21	886	17.893	16751
24-May-21	887	18.080	16794
25-May-21	888	18.157	16837
26-May-21	889	18.379	16880
27-May-21	890	18.643	16923
28-May-21	891	18.743	16967
	892		17011
	893		17055
	894		17099
	895		17143
	896		17188
	897		17232
	898		17277
	899		17323
	900		17368
	901		17414
	902		17460
	903		17506
	904		17552

Source: Author

4.3.4.4. Exponential Smoothing Analysis

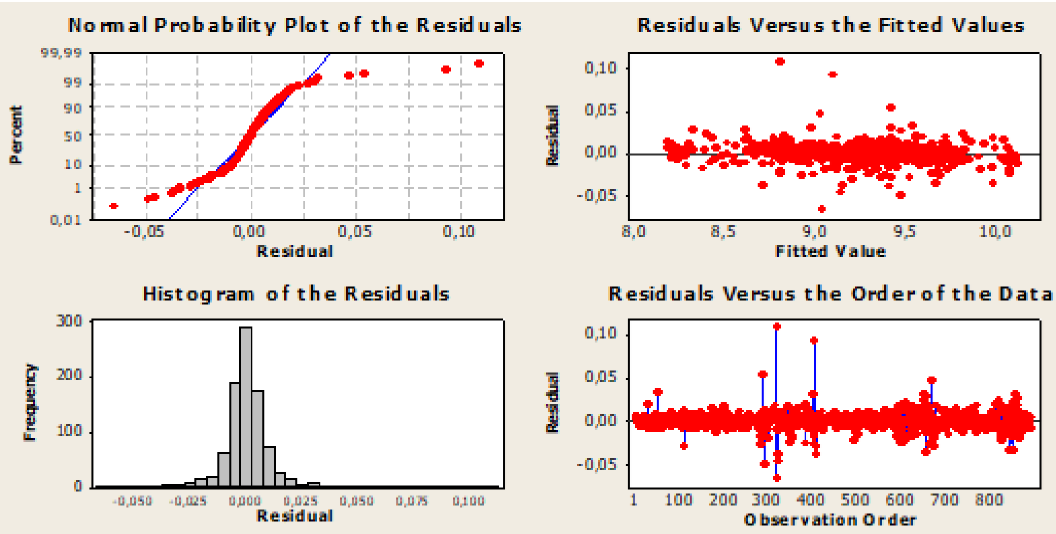
The exponential smoothing approach is one of the methods that starts from the current values of the data with a certain correction coefficient and models the series according to the older data. Since it is a dynamic model, the past and future predictions for each data are determined iteratively. The following table includes predictive values, exponential smoothing coefficients (Alpha, Gamma), error term assumptions and model criteria.

Figure 51 BHS 4 Double exponential smoothing plot



Source: Author

Figure 52 BHS 4 Residual plots



Source: Author

Above Figure 51 and Figure 52 of the error terms produced by the model are shows that the expectation is met. The residuals (error) are normally distributed with a mean of 0, and homogeneously distributed rather than concentrated in certain regions.

4.3.4.4.1. Forecasting

At Table 15, it shows Model estimation, actual values, and the lowest and highest limits at 95% confidence level. When the estimations are examined, it can be said that it has less errors than the previously established Trend model estimations.

Table 15 BHS 4 Forecasting Results for Exponential Smoothing

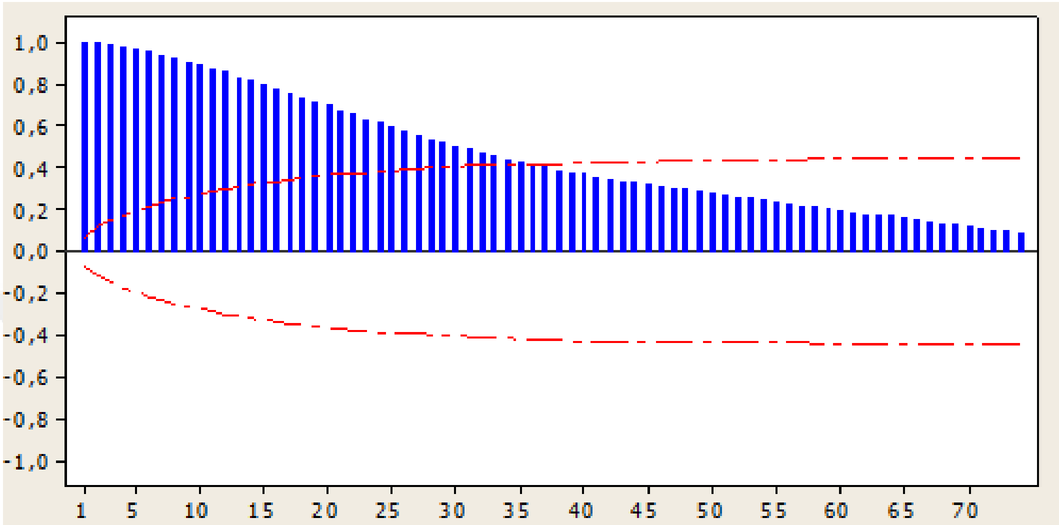
Date	Period	Actual	Forecast	Lower	Upper	error %
20.May.21	885	17.679	17592	17318	17870	0,49
21.May.21	886	17.893	17771	17361	18190	0,68
24.May.21	887	18.080	17951	17396	18524	0,71
25.May.21	888	18.157	18132	17428	18866	0,14
26.May.21	889	18.379	18316	17459	19216	0,34
27.May.21	890	18.643	18502	17489	19573	0,76
28.May.21	891	18.743	18689	17519	19938	0,29
	892		18879	17548	20311	
	893		19070	17578	20690	
	894		19263	17607	21076	
	895		19459	17636	21470	
	896		19656	17665	21871	
	897		19855	17695	22279	
	898		20056	17724	22695	
	899		20260	17753	23121	
	900		20465	17782	23553	
	901		20672	17811	23993	
	902		20882	17840	24443	
	903		21093	17869	24899	
	904		21307	17898	25364	

Source: Author

4.3.4.5 Box – Jenkins Modelling

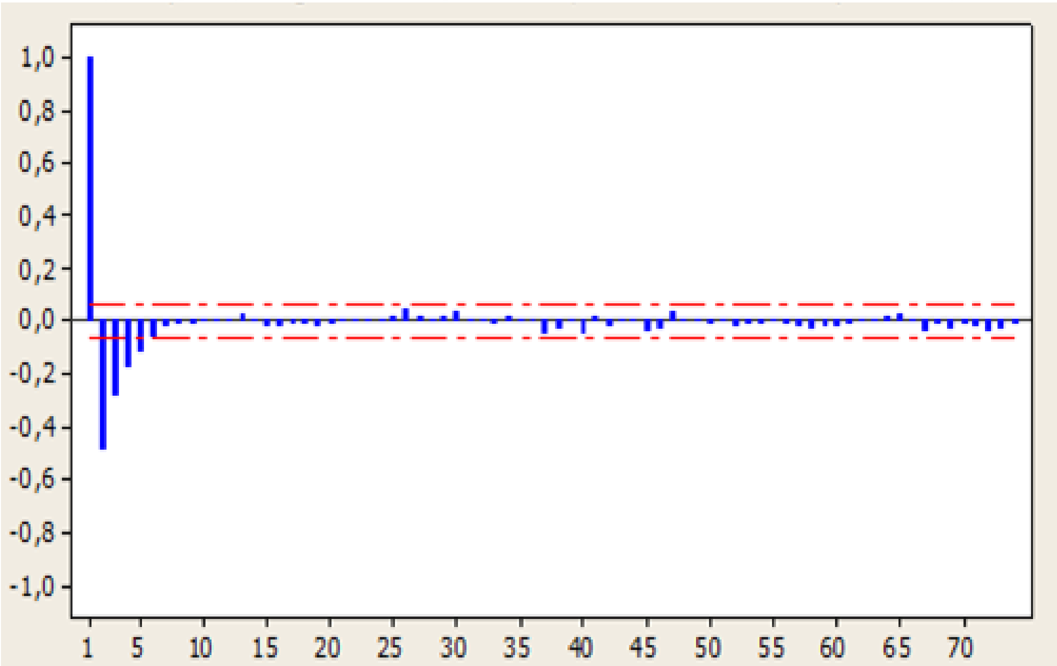
As can be seen from Figure 53 and Figure 54, there is a high-level grade of dependence among the data.

Figure 53 BHS 4 Autocorrelation function



Source: Author

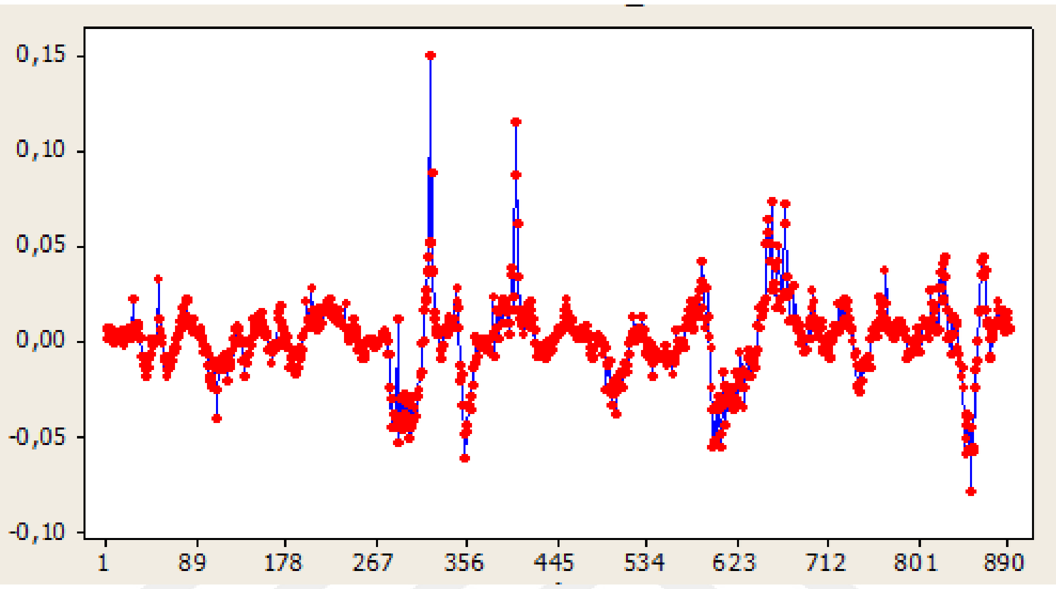
Figure 54 BHS 4 Partial Autocorrelation on function



Source: Author

In order to eliminate this negative effect, the difference processor (d) is used. Since there is no significant seasonality in the series, the normal difference processor was used.

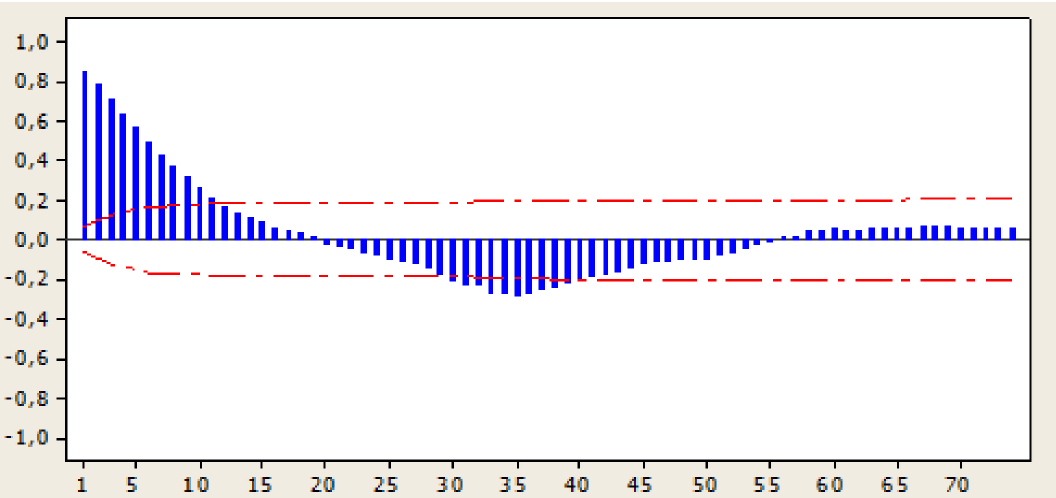
Figure 55 BHS 4 Plot difference



Source: Author

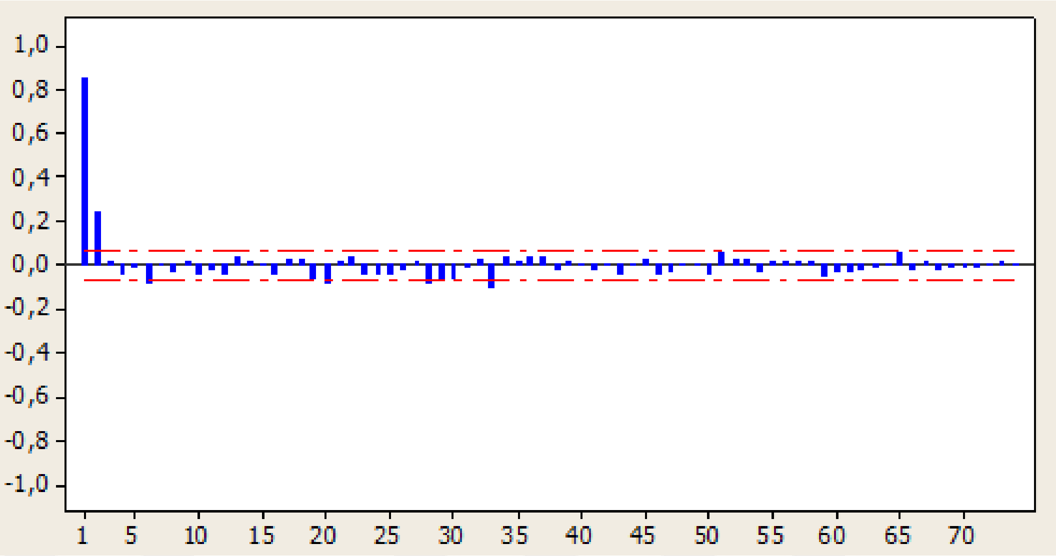
At Figure 55, it can be stated that the series oscillates around a certain mean. However, it can be seen from the graphs below that autocorrelation structures have become more suitable for modelling. Model has been tried and the results are shown in the outputs at Figure 56 and Figure 57.

Figure 56 BHS 4 Autocorrelation Function for differences



Source: Author

Figure 57 BHS 4 Partial Autocorrelation Function for differences



Source: Author

The most appropriate model was attempted to be defined for data set that provided stationarity assumption. For this purpose, it was decided which model would be more suitable by examining SAC and SPAC of series. While there is no obvious cut-off status (rapidly approaching zero) in the SAC graph, it is observed that the SPAC graph approaches zero after the 2nd delay. Considering that once the difference is taken (d=1), our model is ARIMA(2,1,0) or (ARI(2,1)).

A general "ARIMA model" can be expressed as follows.

"$z_t = \delta + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \cdots + \varphi_p z_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q}$"

In order to show Z_t a differenced series, our model suitable for time series can be shown in below

"$z_t = \delta + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + a_t$"

The hypotheses for the model parameters and constant term can be expressed as follows;

H_0: $\theta_1 = 0$	H_0: $\phi_i = 0$	H_0: $\delta = 0$
H_1: $\theta_1 \neq 0$	H_1: $\phi_i \neq 0$	H_1: $\delta \neq 0$

Model

Type	Coef	SE Coef	T	P
AR 1	0.6441	0.0326	19.75	0.000
AR 2	0.2398	0.0326	7.35	0.000
Constant	0.0000573	0.0003419	0.17	0.867

Differencing: 1 regular difference

Number of observations: Original series 891, after differencing 890

Residuals: SS = 0.0922775 (back forecasts excluded)

MS = 0.0001040 DF = 887

When the significance of the model parameters was examined, the P value of AR 1 AR2 parameters were 0. Since "P" below 0.05 the assumption stating "model was insignificant" was rejected. These parameters must include in model. However, the "P" value of constant term was meaningless with a value of 0.867.

As a result of the analysis, as seen above, the constant term was found to be meaningless and therefore it was not necessary to include it in the model. In addition, the model parameters were found to be highly significant.

The hypotheses and results for the model adequacy analysis (Ljung-Box) are as follows. In order for the model to be sufficient, the model should be sufficient for each lag in below.

H0 : The model is significant.

H1 : The model is not significant.

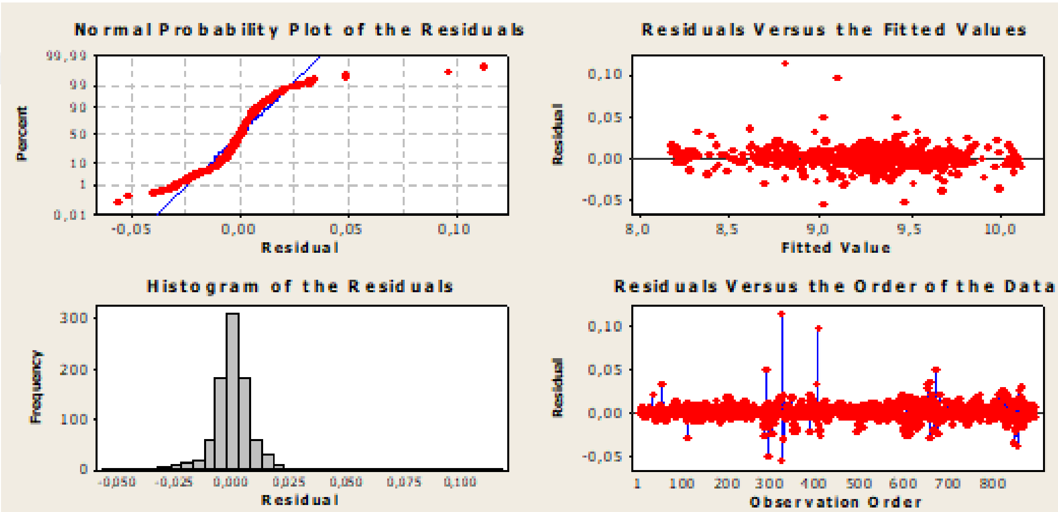
Statistic

Lag	12	24	36	48
Chi-Square	10.3	24.1	56.2	65
DF	9	21	33	45
P-Value	0.325	0.288	0.107	0.127

According to the results of the Minitab package program; the hypothesis established for the adequacy of the model could not be rejected for any lag. This shows that the model is sufficient.

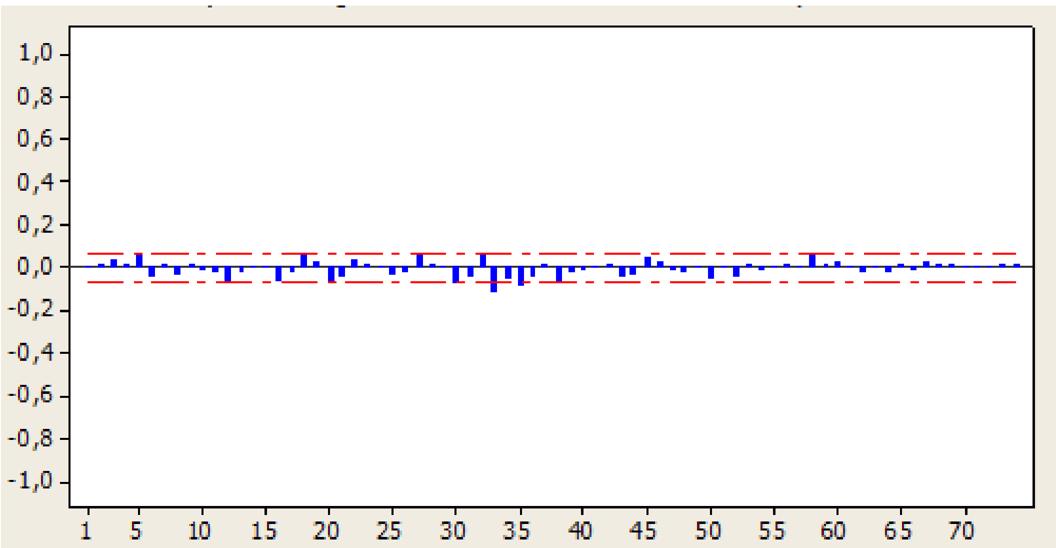
With the Ljung-Box statistics, the assumptions of the random error term of the model should be provided. Figure 58 show that the assumptions of the errors are provided. It can be stated that the distributions of the residuals do not go beyond the confidence limits and conform to the homogeneous and normal distribution. Figure 59 and Figure 60 are showing autocorrelation and Partial autocorrelation of the BHS 4 series.

Figure 58 BHS 4 Residual Plots



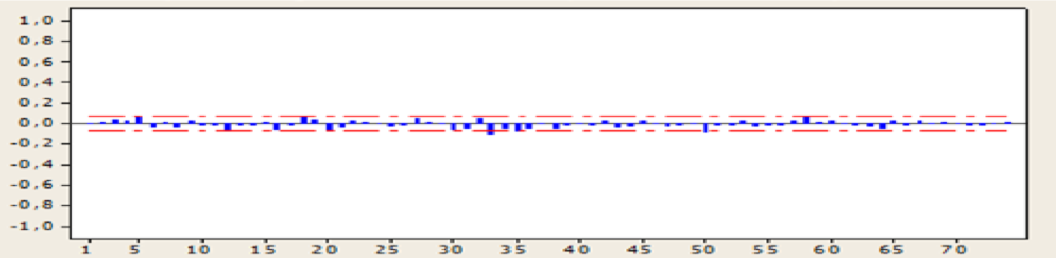
Source: Author

Figure 59 BHS 4 Autocorrelation Function



Source: Author

Figure 60 BHS 4 Partial Autocorrelation Function



Source: Author

4.3.4.5.1 Forecasting

The estimation of the series was made with the help of the model's parameters and historical values. For the reliability of the model, 20 realized values were estimated, and error rates were obtained. The predictions of the proposed model make accurate predictions with an error of up to 2 percent. Table 16 shows 13 predictions at 95% confidence level for future data.

Table 16 BHS 4 Forecasting Result for ARIMA

date	Period	Actual	Forecast	Lower	Upper	Error
20-May-21	885	17.679	17574	17226	17929	0,60
21-May-21	886	17.893	17719	17050	18413	0,98
24-May-21	887	18.080	17853	16813	18955	1,27
25-May-21	888	18.157	17974	16543	19532	1,02
26-May-21	889	18.379	18088	16246	20139	1,61
27-May-21	890	18.643	18191	15935	20769	2,48
28-May-21	891	18.743	18288	15614	21420	2,49
	892		18376	15288	22090	
	893		18457	14959	22772	
	894		18533	14634	23471	
	895		18602	14313	24178	
	896		18667	13996	24894	
	897		18725	13686	25622	
	898		18781	13382	26355	
	899		18832	13089	27095	
	900		18879	12801	27839	
	901		18922	12524	28590	
	902		18962	12254	29343	
	903		19000	11993	30101	
	904		19036	11742	30863	

Source: Author

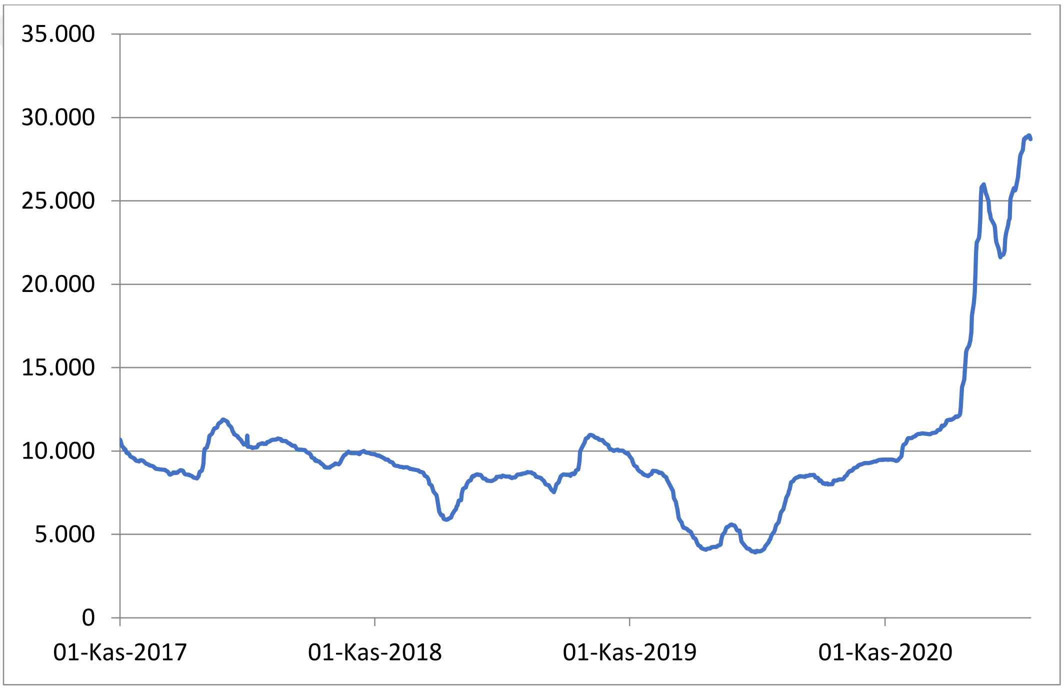
When all models were evaluated, it was seen that the most suitable method was the ARI(2,1).

4.3.5 Baltic Handysize Route 5

4.3.5.1 Modelling

For analysis of BHS 5 the natural logarithm of the data was taken and made stationary by performing the necessary operations, then the most suitable model (Box – Jenkins (ARIMA), trend analysis, Exponential smoothing methods) for the series was determined with different modelling methods and the values that it could take in the future were estimated. Statistical package programs such as Minitab and SPSS were used in the analysis of the data.

Figure 61 BHS 5 Route Time Series Graph



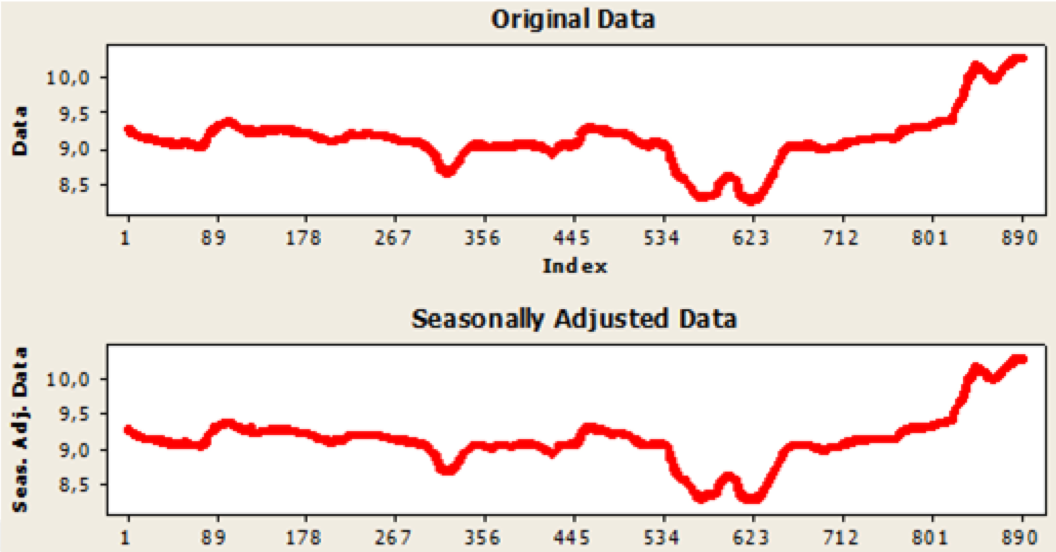
Source: Author

When the Figure 61 is examined; It was observed that there was a strong linear trend after February 2021, where there was no generalizable linear trend. However, it can be said that this trend is not sufficient in terms of modelling. In terms of seasonality, it can be said that there is no certain pattern. The following analyses show whether there are any effects by modelling both components.

4.3.5.2 Seasonality analysis

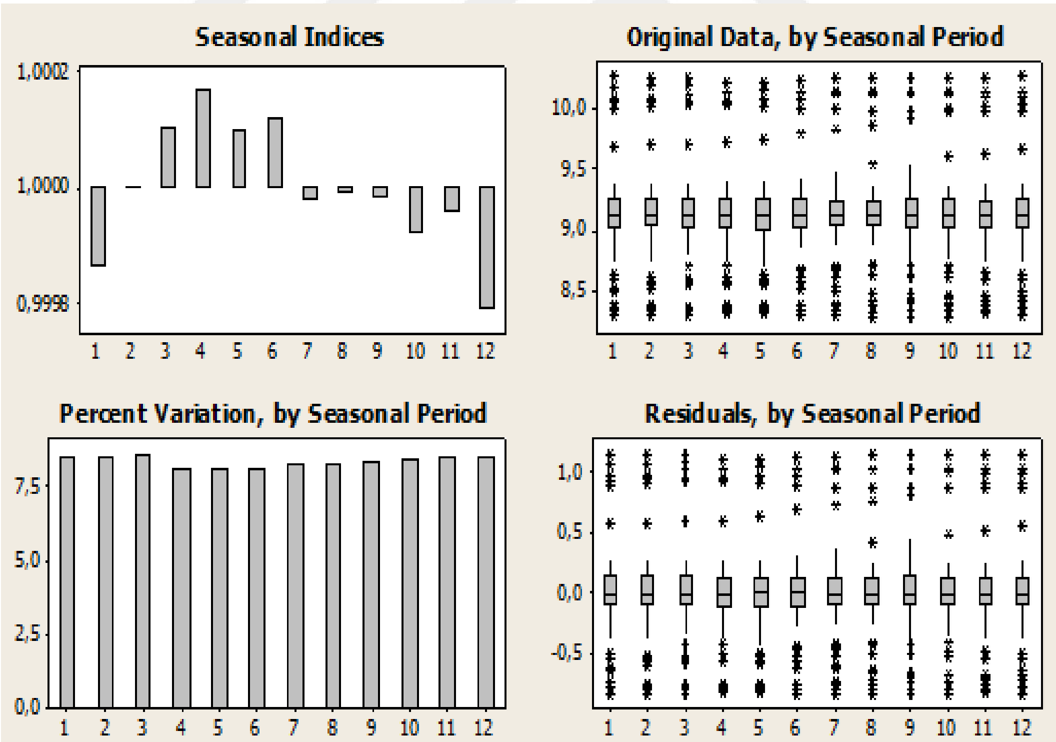
After analysis BHS 5 data, results for seasonality effect to BHS 5 series are shown at Figure 62 and Figure 64.

Figure 62 BHS 5 Component Analysis and Seasonally Adjusted data



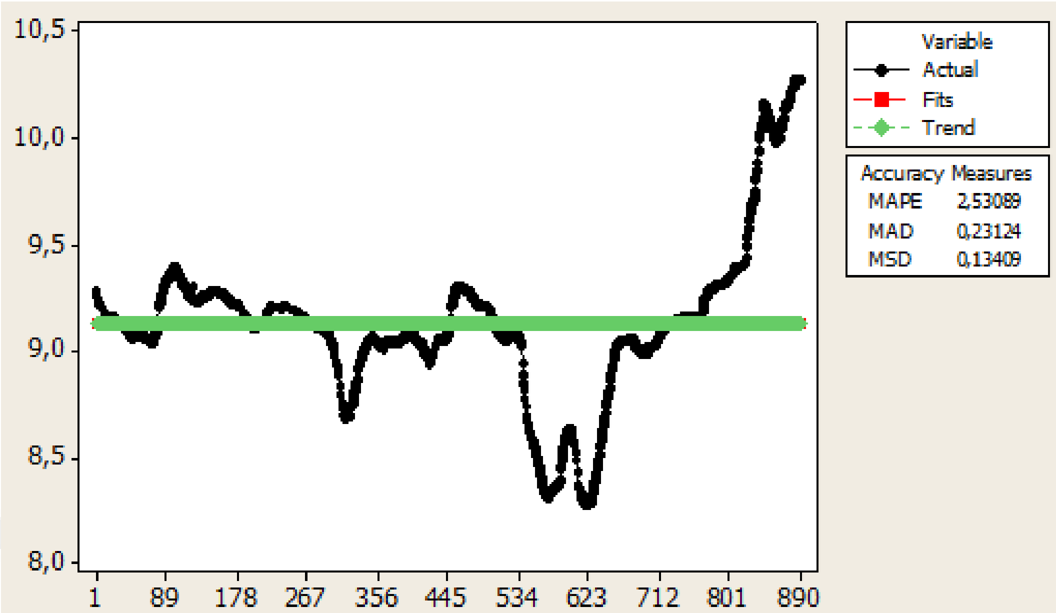
Source: Author

Figure 63 BHS 5 Seasonal Analysis



Source: Author

Figure 64 BHS 5 Time series decomposition plot



Source: Author

Results show that the data indications have no seasonal effect since the indexes are so close to 1. In addition, graphically, it can be seen at Figure 62 that the seasonally adjusted graph does not differ significantly from the original graph. The criteria to be used to evaluate the model with other models were MAPE:2.53, MAD:0.230 and MSD:0.134.

4.3.5.3 Trend Analysis

It has been observed that the trend structure in the data has a quadratic rather than linear structure and modelling has been done.

“Equation Yt = 9,51379 - 0,00313734*t + 3,799127E-06*t**2”

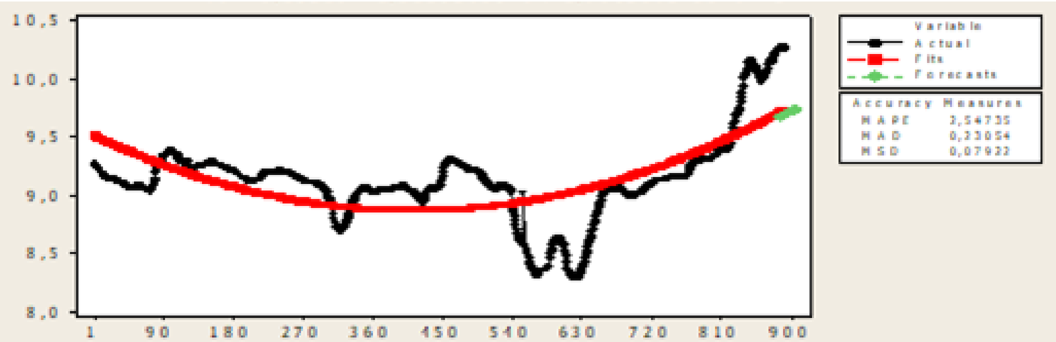
Measures

MAPE: 2.55227

MAD: 0.23097

MSD: 0.07937

Figure 65 BHS 5 Trend Analysis Plot



Source: Author

At Figure 65, MAPE, MAD and MSD error criteria used in the comparison criteria are not significantly different from the model established for seasonal analysis. It can be said that both models give the same results.

4.3.5.3.1 Forecasting

While estimating, the last 7 observations of the series were estimated to see control and deviation. A total of 20 observation estimates were made and the results are shown at Table 17. It is observed that there are significant differences between the estimates and the actual values. It can be said that these models are not suitable.

Table 17 BHS 5 Forecasting Results for Trend analysis

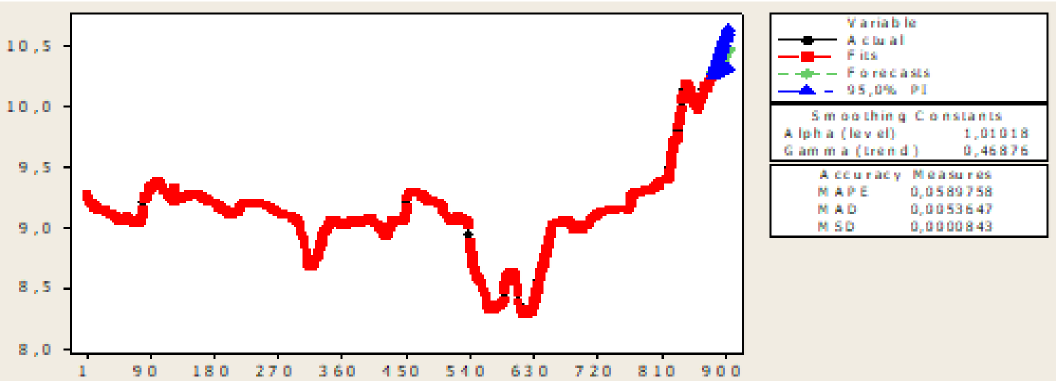
date	Period	Actual	Forecast
20-May-21	885	28.719	15885
21-May-21	886	28.813	15939
24-May-21	887	28.819	15993
25-May-21	888	28.906	16048
26-May-21	889	28.925	16103
27-May-21	890	28.844	16159
28-May-21	891	28.706	16214
	892		16270
	893		16327
	894		16383
	895		16440
	896		16498
	897		16555
	898		16613
	899		16671
	900		16730
	901		16789
	902		16848
	903		16907
	904		16967

Source: Author

4.3.5.4. Exponential Smoothing Analysis

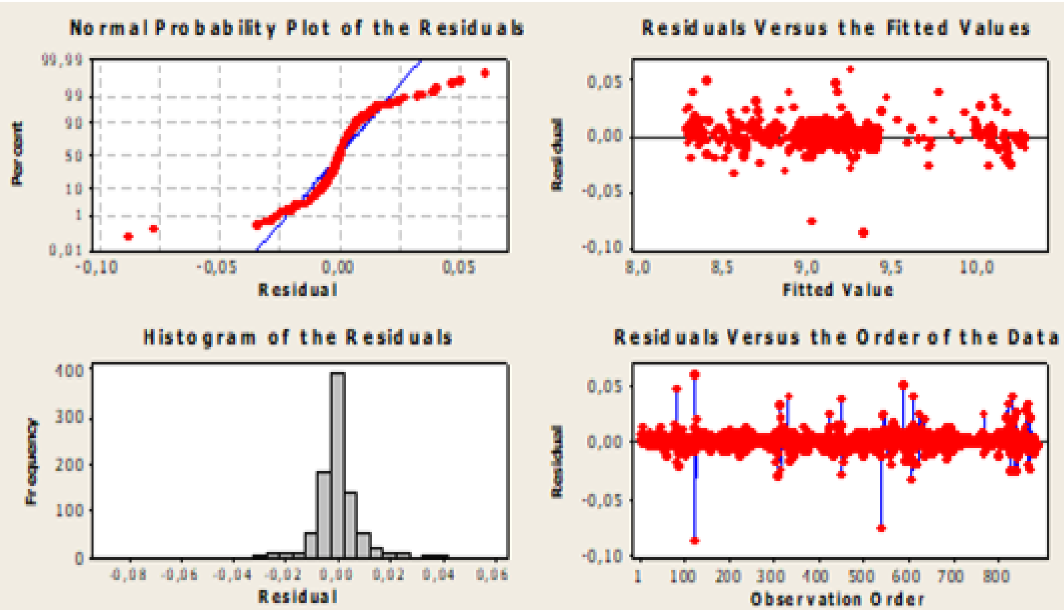
The exponential smoothing approach is one of the methods that starts from the current values of the data with a certain correction coefficient and models the series according to the older data. Since it is a dynamic model, the past and future predictions for each data are determined iteratively. The following table includes predictive values, exponential smoothing coefficients (Alpha, Gamma), error term assumptions and model criteria.

Figure 66 BHS 5 Double exponential smoothing plot



Source: Author

Figure 67 BHS 5 Residual plots



Source: Author

When Figure 66 and Figure 67 of the error terms produced by the model, shown above, are examined, it is seen that the assumptions are met. It can be seen residuals (error) are generally distributed with a mean of 0 and are homogeneously distributed rather than concentrated in certain regions. Very few extreme values caused the other data in the series to be consolidated. This can be considered as a small disruptive effect for modelling.

4.3.5.4.1. Forecasting

At Table 18, it shows model estimation, actual values, and the lowest and highest limits at 95% confidence level. When the estimations are examined, it can be said that it has less errors than the previously established Trend model estimations.

Table 18 BHS 5 Forecasting Results for Exponential Smoothing

date	Period	Actual	Forecast	Lower	Upper	error
20-May-21	885	28.719	29,015	28,635	29,398	1,02
21-May-21	886	28.813	29,325	28,735	29,923	1,75
24-May-21	887	28.819	29,637	28,827	30,470	2,76
25-May-21	888	28.906	29,953	28,914	31,029	3,50
26-May-21	889	28.925	30,272	29,001	31,599	4,45
27-May-21	890	28.844	30,595	29,088	32,183	5,72
28-May-21	891	28.706	30,921	29,173	32,777	7,16
	892		31,250	29,257	33,382	
	893		31,586	29,342	33,999	
	894		31,923	29,427	34,627	
	895		32,263	29,513	35,270	
	896		32,607	29,599	35,921	
	897		32,955	29,685	36,585	
	898		33,306	29,768	37,264	
	899		33,661	29,854	37,952	
	900		34,019	29,941	38,653	
	901		34,382	30,028	39,371	
	902		34,748	30,115	40,098	
	903		35,122	30,200	40,843	
	904		35,496	30,287	41,597	

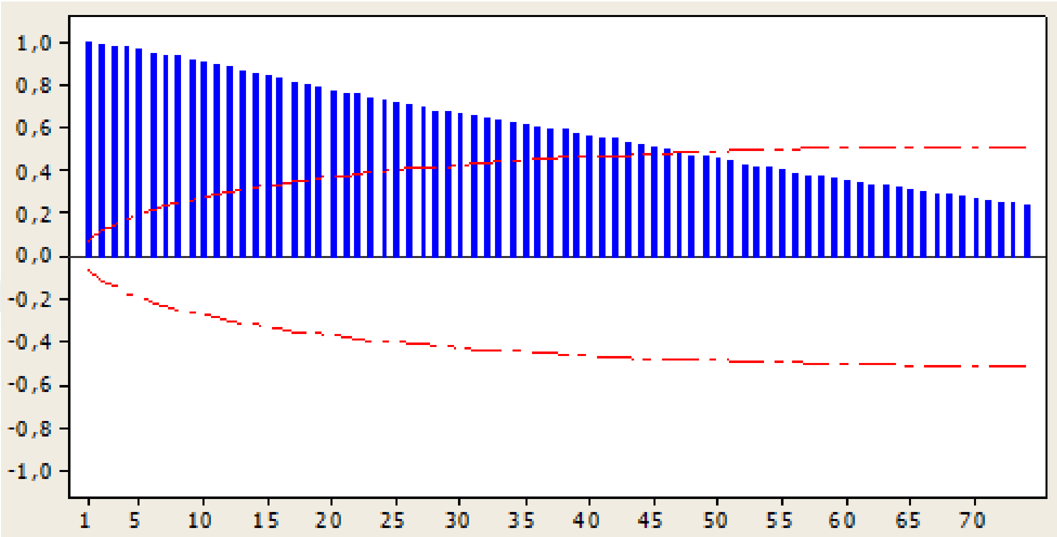
Source: Author

The increase in the error percentage between the predictions and the real rates shows that success of model to represent the series will decrease in the future.

4.3.5.5 Box – Jenkins Modelling

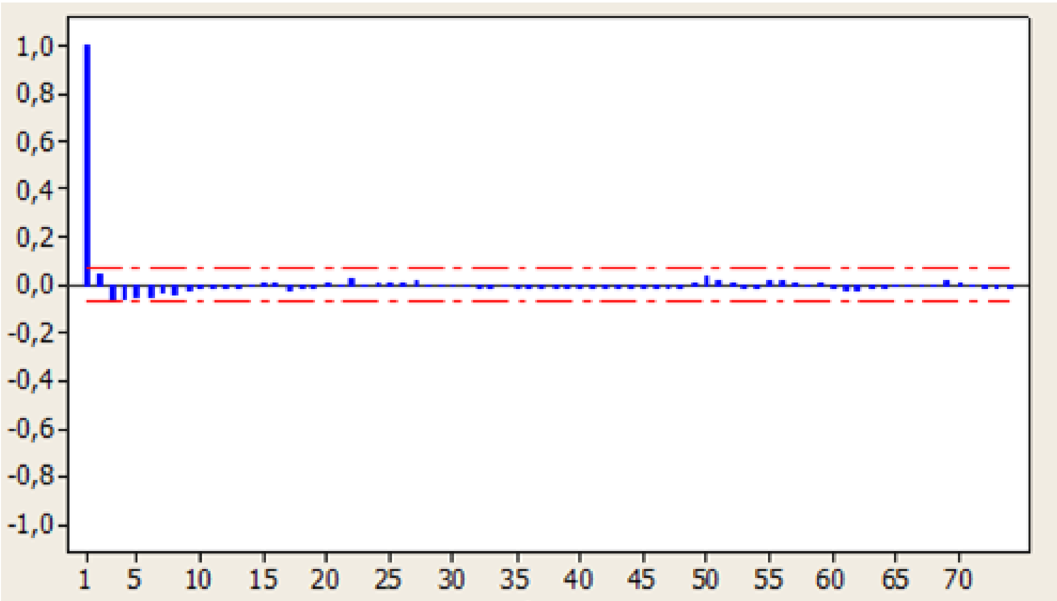
As can be seen from Figure 68 and Figure 69, there is a high-level grade of dependence among data.

Figure 68 BHS 5 Autocorrelation function



Source: Author

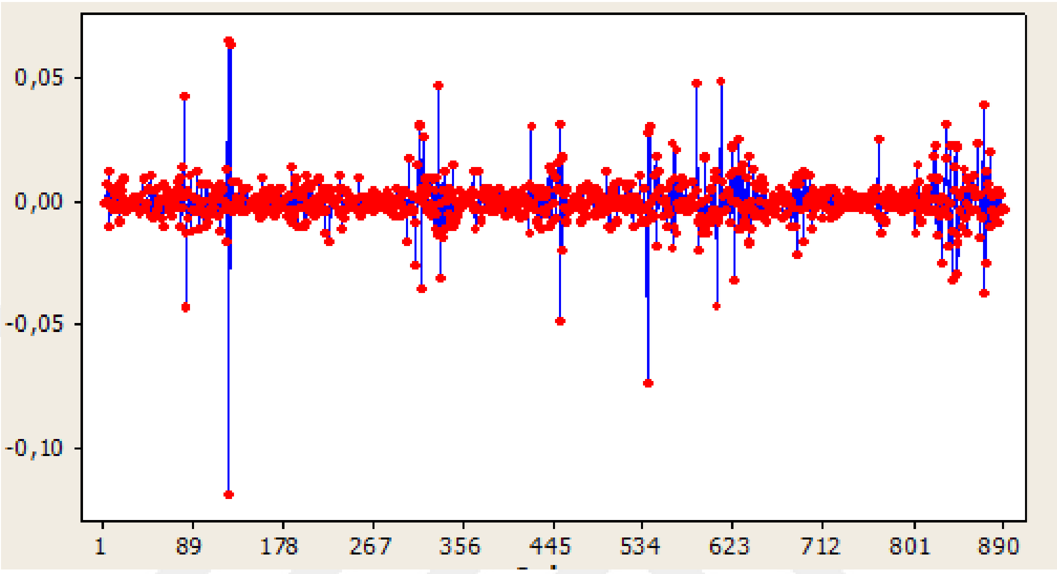
Figure 69 BHS 5 Partial Autocorrelation on function



Source: Author

In order to eliminate this negative effect, the difference processor (d) is used. Since there is no significant seasonality in the series, the normal difference processor was used twice.

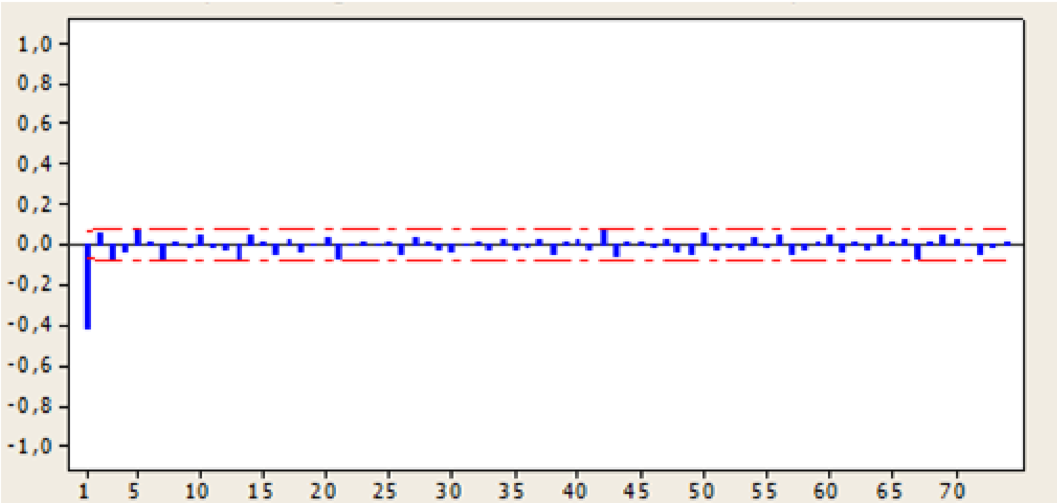
Figure 70 BHS 5 Plot difference



Source: Author

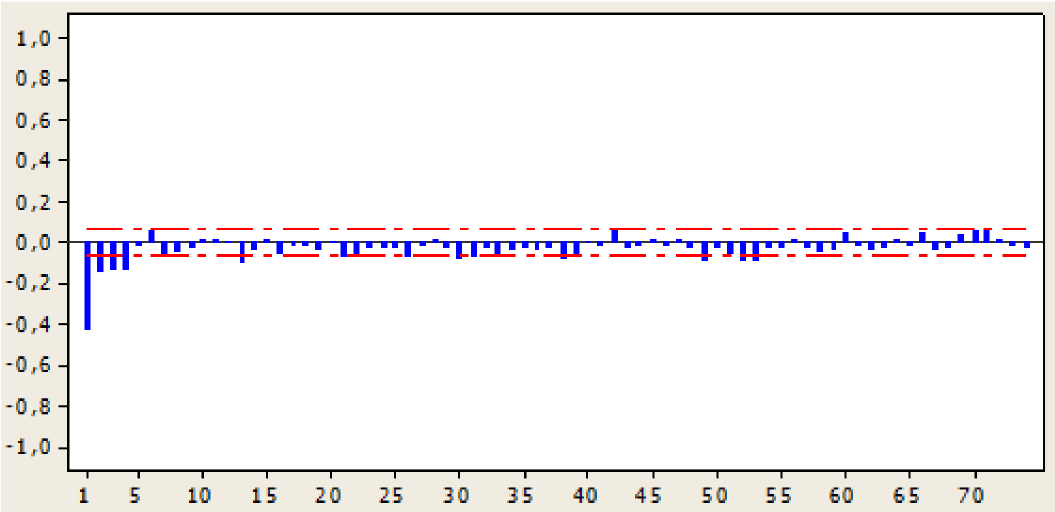
At Figure 70, it can be stated that the series oscillates around a certain mean. However, it can be seen from the graphs below that autocorrelation structures have become more suitable for modelling. Model has been tried and the results are shown in the outputs at Figure 71 and Figure 72.

Figure 71 BHS 5 Autocorrelation Function for differences



Source: Author

Figure 72 BHS 5 Partial Autocorrelation Function for differences



Source: Author

The most appropriate model was attempted to be defined for data set that provided stationarity assumption. For this purpose, it was decided which model would be more suitable by examining SAC and SPAC of series. It's observed that the cut off status (rapidly approaching zero) is seen in the SAC graph after the 1st delay, while the SPAC graph approaches zero after the 4th delay. Considering that once the difference is taken into account (d=2), our model was determined as ARIMA(4,2,1), in other words (ARI(2,1)).

A general "ARIMA model" can be expressed as follows.

"$z_t = \delta + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \cdots + \varphi_p z_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q}$"

To show Z_t two-difference series, model shown in below

"$z_t = \delta + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \varphi_3 z_{t-3} + \varphi_4 z_{t-4} + a_t + \theta_1 a_{t-1}$"

The hypotheses for the model parameters and constant term can be expressed as follows;

H_0: $\theta_1 = 0$	H_0: $\phi_i = 0$	H_0: $\delta = 0$
H_1: $\theta_1 \neq 0$	H_1: $\phi_i \neq 0$	H_1: $\delta \neq 0$

Model

Type	Coef	SE Coef	T	P
AR 1	-0.4844	0.2452	-1.98	0.049
AR 2	-0.2185	0.126	-1.73	0.083
AR 3	-0.1863	0.0621	-3.00	0.003
AR 4	-0.1323	0.0457	-2.90	0.004
MA 1	0.0290	0.2474	0.12	0.907
Constant	0.0000279	0.0002985	0.09	0.926

Differencing: 2 regular differences

Number of observations: Original series 891, after differencing 889

Residuals: SS = 0.0742102 (backforecasts excluded)

MS = 0.0000840 DF = 883

Statistics

Lag	12	24	36	48
Chi-Square	9.4	27.1	35.6	49.2
DF	6	18	30	42
P-Value	0.152	0.076	0.220	0.207

When the significance of the model parameters was examined, the P value of AR parameters were 0 and the moving average (MA) and constant term (Constant) parameters were meaningless. The meaningless parameters were removed from the model and the model was rearranged, and the following “ARIMA (4,2,0), ARI (4,2)” model was determined as the best suitable model.

To show the Z_t two-difference series, our time series model can be shown in below.

“$z_t = \delta + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \varphi_3 z_{t-3} + \varphi_4 z_{t-4} + a_t$”

Model

Type	Coef	SE Coef	T	P
AR 1	-0.5129	0.0333	-15.40	0.000
AR 2	-0.2327	0.0369	-6.30	0.000
AR 3	-0.1921	0.037	-5.20	0.000
AR 4	-0.1359	0.0333	-4.08	0.000

Differencing: 2 regular differences

Number of observations: Original series 891, after differencing 889

Residuals: SS = 0.0742128 (backforecasts excluded)

MS = 0.0000839 DF = 885

As per above outcome, model parameters were found to be highly significant.

The hypotheses and results for the model adequacy analysis (Ljung-Box) are as follows. In order for the model to be sufficient, the model should be sufficient for each lag in below.

H0 : The model is significant.

H1 : The model is not significant.

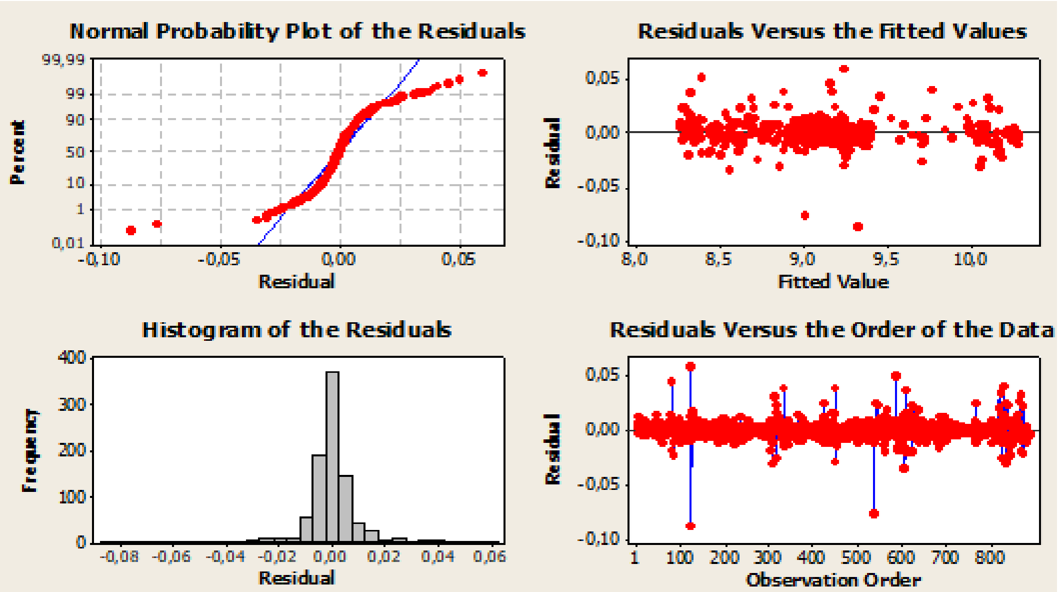
Statistics

Lag	12	24	36	48
Chi-Square	9.4	27.0	35.5	48.9
DF	8	20	32	44
P-Value	0.311	0.134	0.308	0.281

According to the results of the Minitab package program; The hypothesis established for the adequacy of the model could not be rejected for any lag. This shows that the model is sufficient.

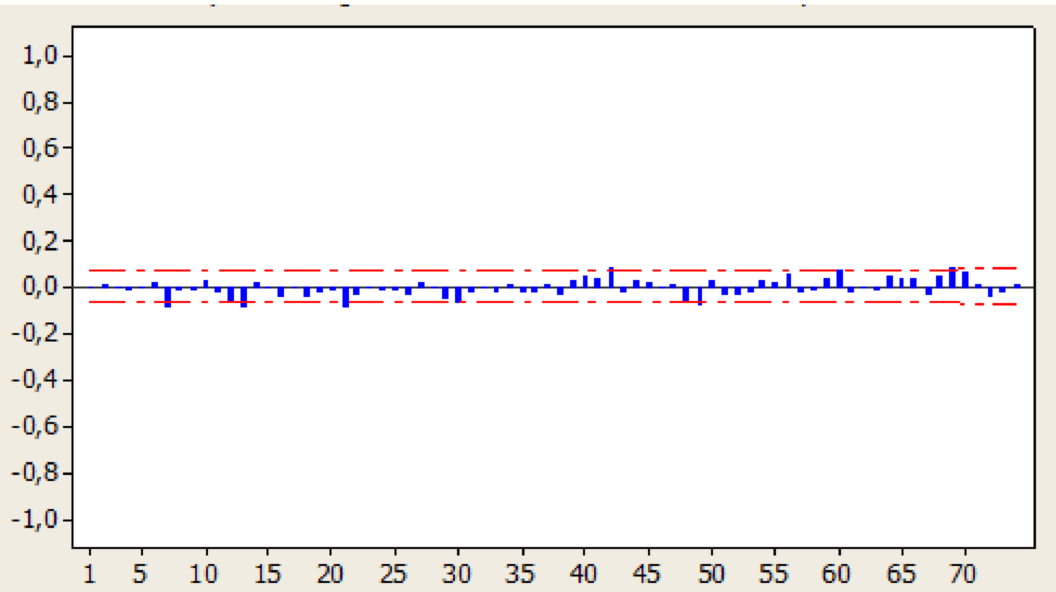
With the Ljung-Box statistics, the assumptions of the random error term of the model should be provided. Figure 73 show that the assumptions of the errors are provided. It can be stated that the distributions of the residuals do not go beyond the confidence limits and conform to the homogeneous and normal distribution. Although outliers and clusters in some observations reduced the quality of the model, they did not adversely affect its usability. Figure 74 and Figure 75 are showing autocorrelation and Partial autocorrelation of the BHS 1 series.

Figure 73 BHS 5 Residual Plots



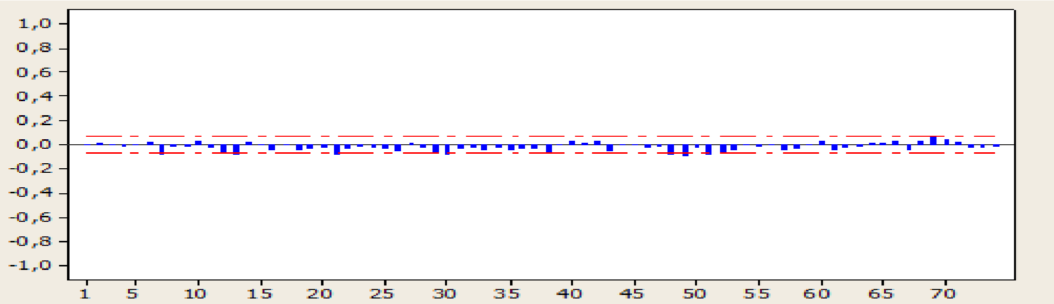
Source: Author

Figure 74 BHS 5 Autocorrelation Function



Source: Author

Figure 75 BHS 5 Partial Autocorrelation Function



Source: Author

4.3.5.5.1 Forecasting

The estimation of the series was made with the help of the model's parameters and historical values. For the reliability of the model, 20 realized values were estimated, and error rates were obtained. The predictions of the proposed model make accurate predictions with an error of up to 4 percent. Table 19 shows 13 predictions at 95% confidence level for future data

Table 19 BHS 5 Forecasting Result for ARIMA

Date	Period	Actual	Forecast	Lower	Upper	Error
20-May-21	885	28.719	29028	28513	29555	1,06
21-May-21	886	28.813	29319	28390	30276	1,73
24-May-21	887	28.819	29626	28232	31092	2,72
25-May-21	888	28.906	29947	28060	31962	3,48
26-May-21	889	28.925	30261	27850	32876	4,41
27-May-21	890	28.844	30580	27595	33891	5,68
28-May-21	891	28.706	30903	27299	34979	7,11
	892		31226	26971	36156	
	893		31559	26617	37414	
	894		31888	26236	38762	
	895		32225	25833	40199	
	896		32565	25410	41739	
	897		32909	24967	43378	
	898		33256	24507	45130	
	899		33607	24033	46995	
	900		33962	23548	48982	
	901		34321	23052	51098	
	902		34683	22546	53354	
	903		35049	22031	55754	
	904		35419	21511	58314	

Source: Author

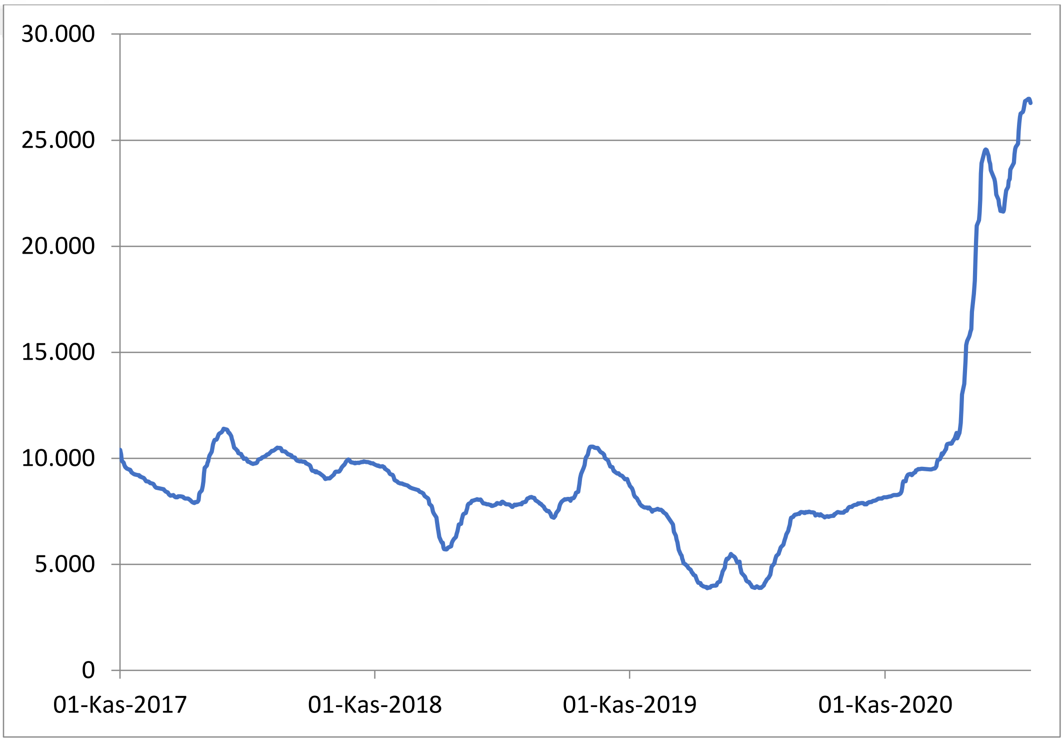
When all models were evaluated, it was seen that the most suitable method was the ARI(4,2) model and the exponential smoothing methods.

4.3.6 Baltic Handysize Route 6

4.3.6.1 Modelling

For analysis of BHS 6 the natural logarithm of the data was taken and made stationary by performing the necessary operations, then the most suitable model (Box – Jenkins (ARIMA), trend analysis, Exponential smoothing methods) for the series was determined with different modelling methods and the values that it could take in the future were estimated. Statistical package programs such as Minitab and SPSS were used in the analysis of the data.

Figure 76 BHS 6 Route Time Series Graph



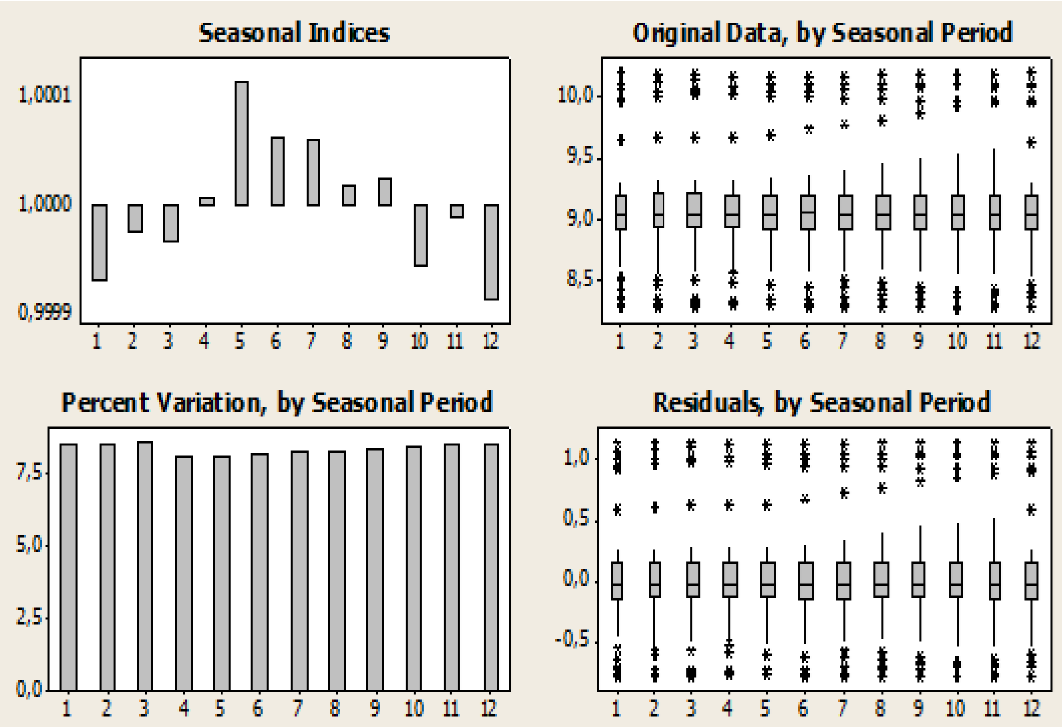
Source: Author

When Figure 76 is examined; It was observed that there was a strong linear trend after February 2021, where there was no generalizable linear trend. In terms of seasonality, it can be said that there is no certain pattern. The following analysis show whether there are any effects by modelling both components.

4.3.6.2 Seasonality Analysis

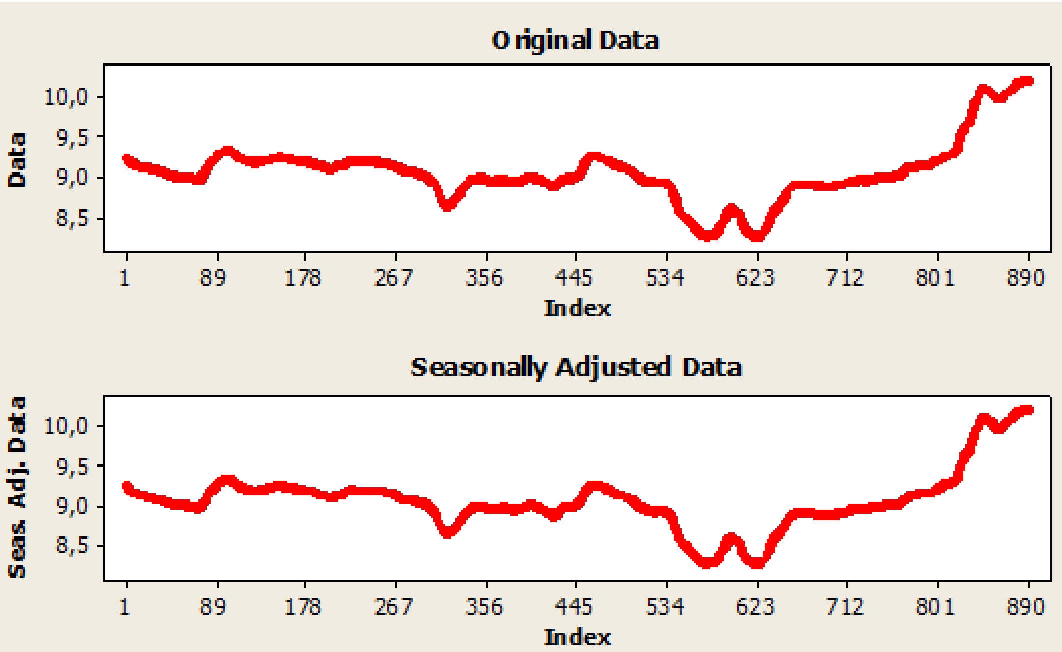
After analysis BHS 6 data, results for seasonality effect to BHS 6 series are shown at Figure 77 and Figure 79

Figure 77 BHS 6 Seasonal Analysis



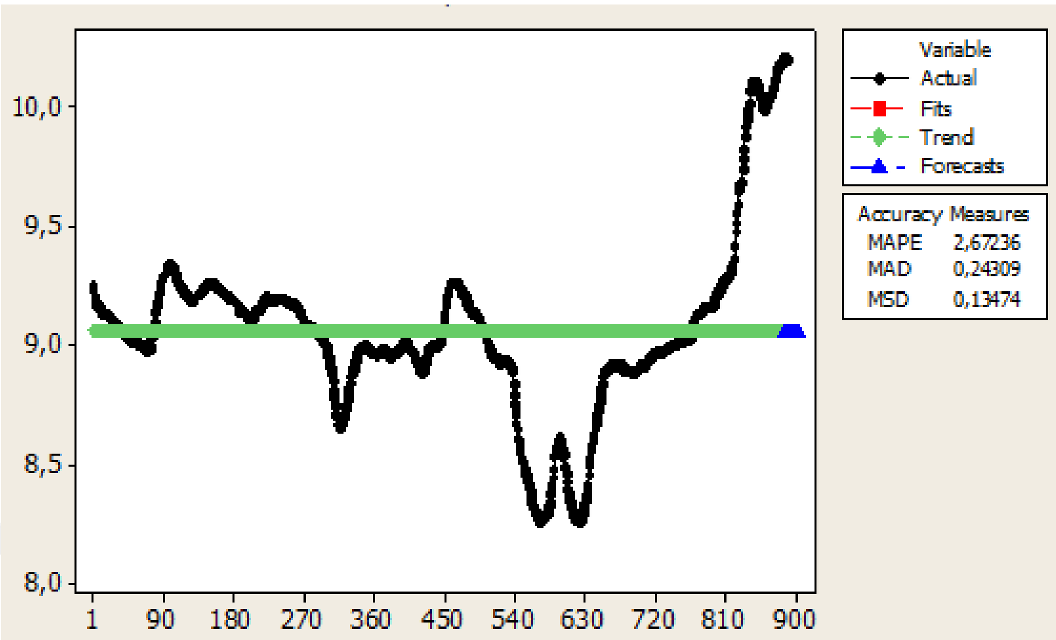
Source: Author

Figure 78 BHS 6 Component Analysis and Seasonally Adjusted data



Source: Author

Figure 79 BHS 6 Decomposition plot



Source: Author

The fact that the seasonal indexes are very close to 1 in the data indicates that there is no seasonal effect. In addition, graphically, it can be seen at Figure 78 that the seasonally adjusted graph does not differ significantly from the original graph. The criteria to be used to evaluate the model with other models were MAPE:2.67, MAD:0.243 and MSD:0.134.

4.3.6.3 Trend Analysis

It has been observed that the trend structure in the data has a quadratic rather than linear structure and modelling has been done.

“Equation Yt = 9,49255 - 0,00322753*t + 3,793119E-06*t**2”

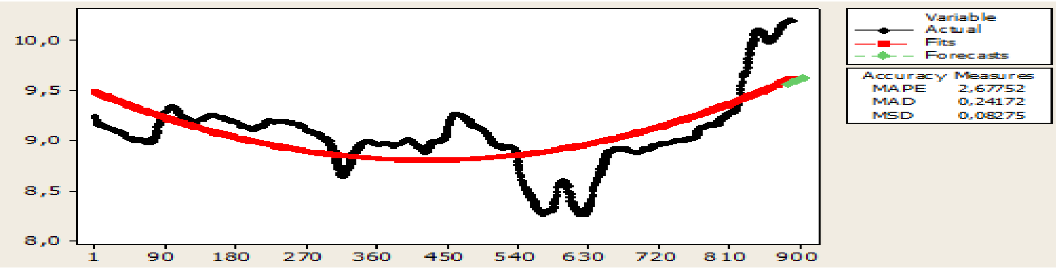
Measures

MAPE: 2.67752

MAD: 0.24172

MSD: 0.08275

Figure 80 BHS 6 Trend Analysis Plot



Source: Author

MAPE, MAD and MSD error criteria used in the comparison criteria are not significantly different from the model established for seasonal analysis at Figure 80. It can be said that both models give the same results.

4.3.6.3.1 Forecasting

While estimating, the last 7 observations of the series were estimated to see control and deviation. Table 20 shows total 20 observation estimate results.

Table 20 BHS 6 Forecasting Results for Trend analysis

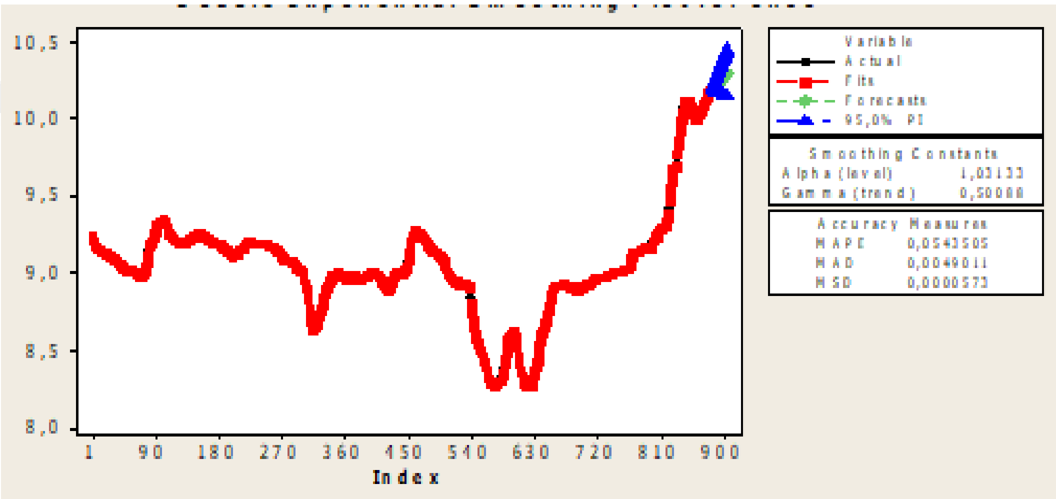
date	Period	Actual	Forecast
20-May-21	885	26.850	14255
21-May-21	886	26.856	14302
24-May-21	887	26.919	14349
25-May-21	888	26.950	14397
26-May-21	889	26.944	14445
27-May-21	890	26.875	14493
28-May-21	891	26.750	14541
	892		14590
	893		14639
	894		14688
	895		14738
	896		14787
	897		14837
	898		14888
	899		14938
	900		14989
	901		15040
	902		15092
	903		15144
	904		15196

Source: Author

4.3.6.4. Exponential Smoothing Analysis

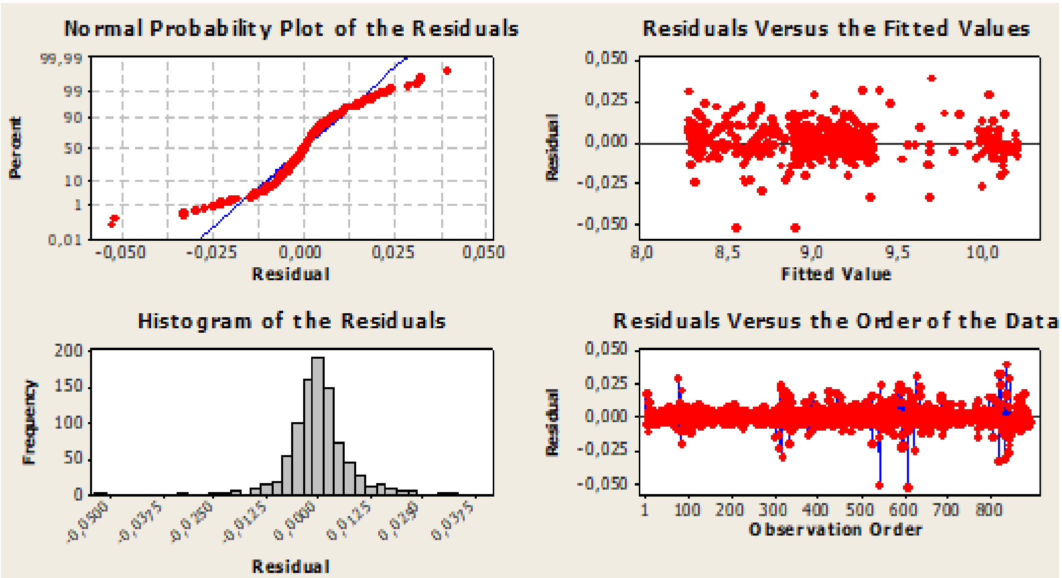
The exponential smoothing approach is one of the methods that starts from the current values of the data with a certain correction coefficient and models the series according to the older data. Since it is a dynamic model, the past and future predictions for each data are determined iteratively. The following table includes predictive values, exponential smoothing coefficients (Alpha, Gamma), error term assumptions and model criteria.

Figure 81 BHS 6 Double exponential smoothing plot



Source: Author

Figure 82 BHS 6 Residual plots



Source: Author

When Figure 81 and Figure 82 of the error terms produced by the model, shown above, are examined, it is seen that the assumptions are met. It can be seen that residual (error) is generally distributed with a mean of 0, and homogeneously distributed rather than concentrated in certain regions. Although there were partial clusters, it was seen that it did not have a great effect on the results.

4.3.6.4.1. Forecasting

At Table 21, it shows model estimation, actual values, and the lowest and highest limits at 95% confidence level. When the forecasts are examined, it can be said that it has less errors than the previously established Trend model forecasts.

Table 21 BHS 6 Forecasting Results for Exponential Smoothing

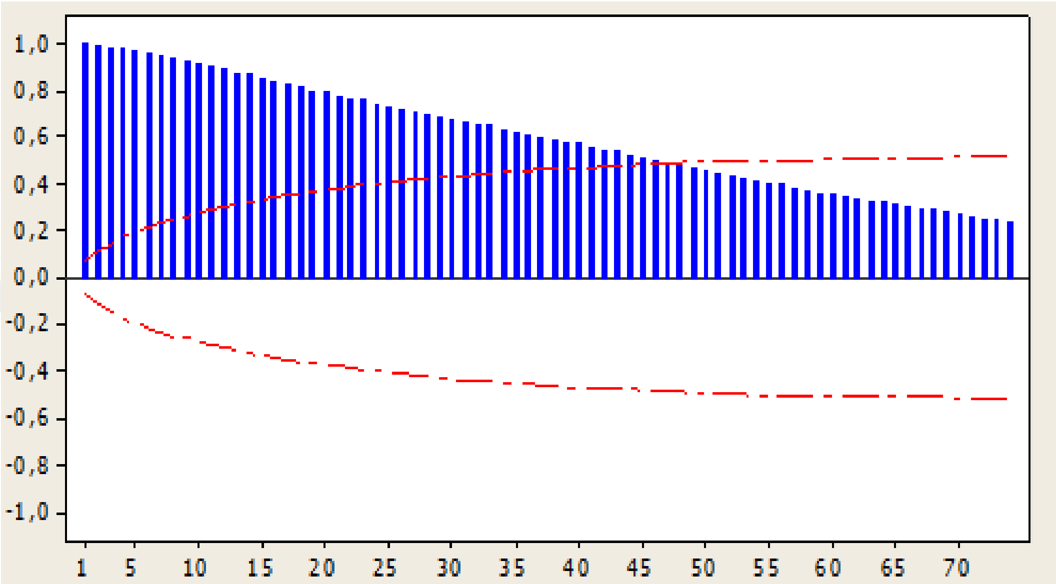
date	Period	Actual	Forecast	Lower	Upper	Error %
20.May.21	885	26.850	26729	26410	27054	0,45
21.May.21	886	26.856	26876	26378	27386	-0,07
24.May.21	887	26.919	27025	26336	27734	0,39
25.May.21	888	26.950	27174	26291	28085	0,83
26.May.21	889	26.944	27323	26247	28447	1,41
27.May.21	890	26.875	27474	26200	28811	2,23
28.May.21	891	26.750	27626	26152	29182	3,27
	892		27778	26108	29558	
	893		27931	26061	29938	
	894		28085	26014	30321	
	895		28240	25967	30712	
	896		28396	25918	31107	
	897		28553	25872	31511	
	898		28710	25825	31917	
	899		28868	25779	32328	
	900		29028	25732	32745	
	901		29188	25686	33167	
	902		29349	25640	33594	
	903		29510	25591	34027	
	904		29673	25545	34465	

Source: Author

4.3.6.5 Box – Jenkins Modelling

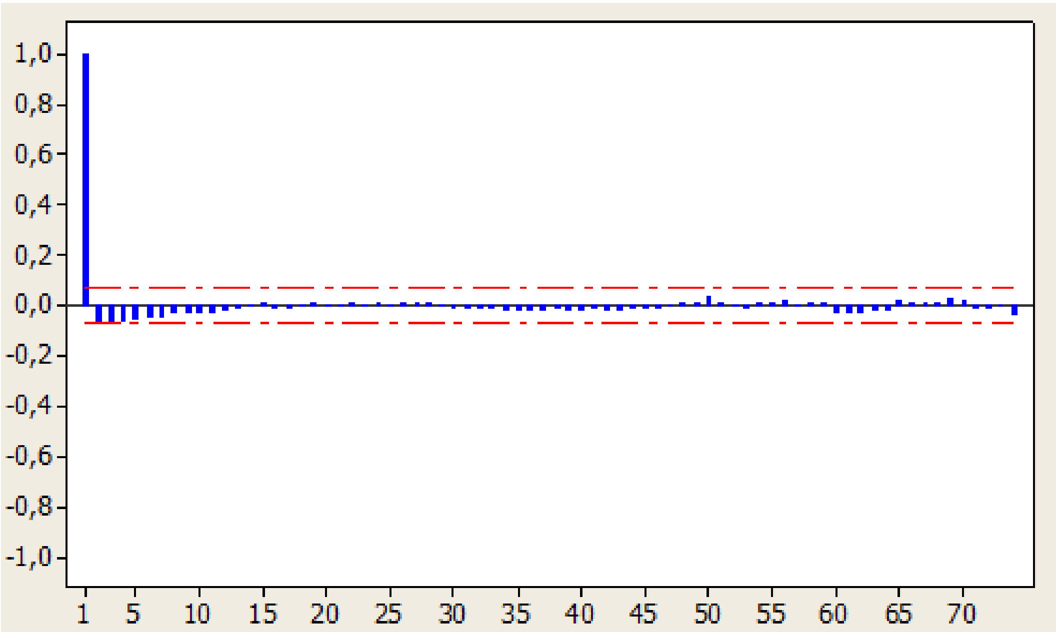
As can be seen from Figure 83 and Figure 84, there is a high-level grade of dependence among data.

Figure 83 BHS 6 Autocorrelation function



Source: Author

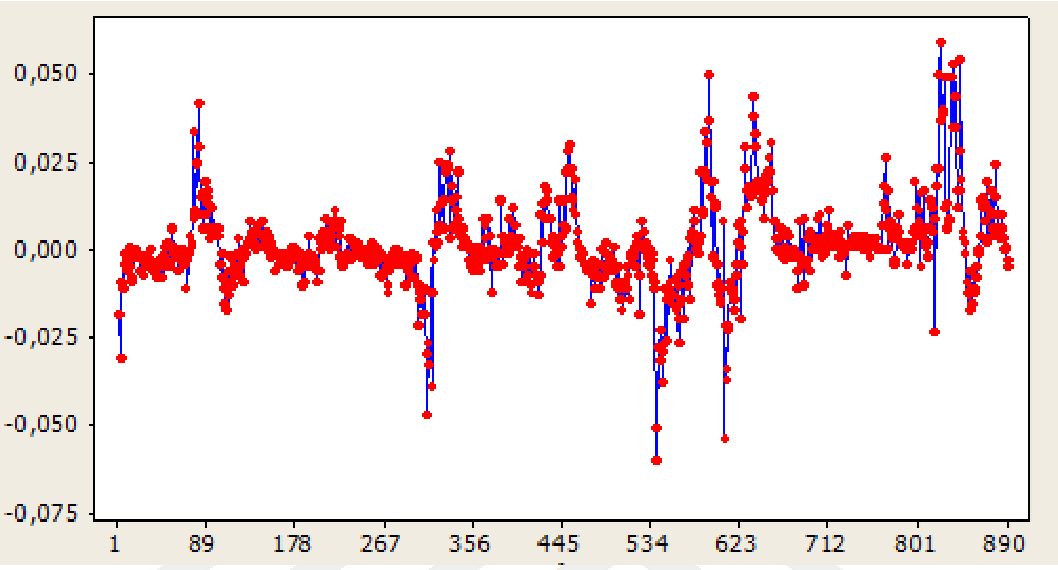
Figure 84 BHS 6 Partial Autocorrelation on function



Source: Author

In order to eliminate this negative effect, the difference processor (d) is used. Since there is no significant seasonality in the series, the normal difference processor was used.

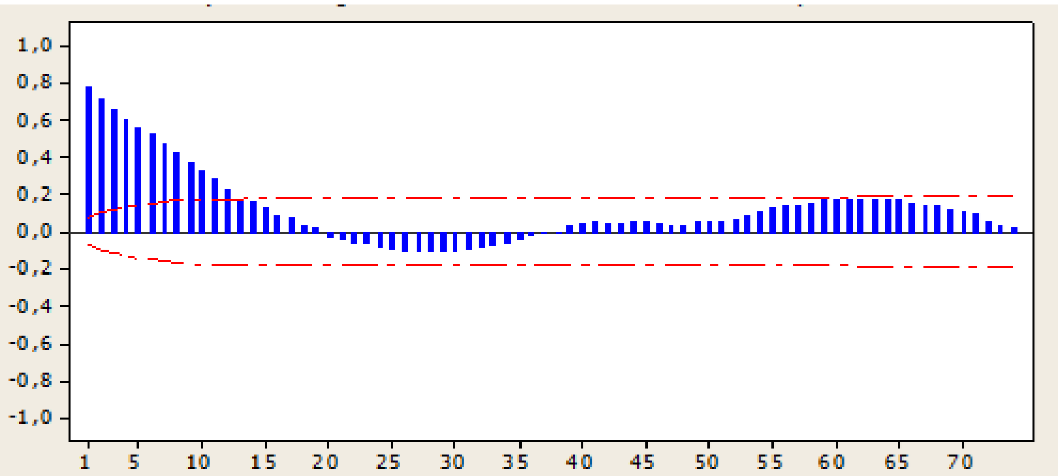
Figure 85 BHS 6 Plot difference



Source: Author

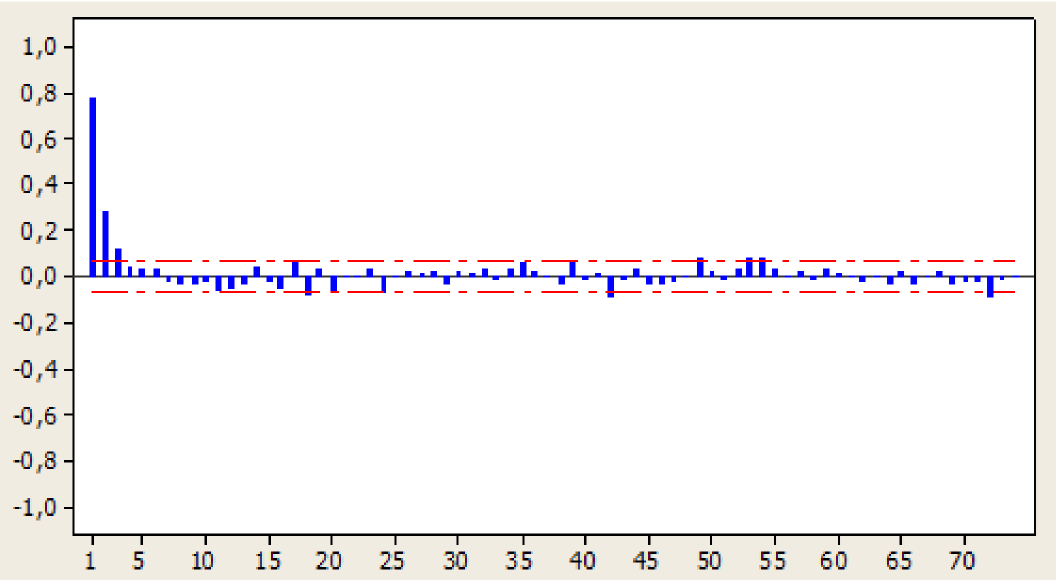
At Figure 85, it can be stated that the series oscillates around a certain mean. However, it can be seen from the graphs below that autocorrelation structures have become more suitable for modelling. Model has been tried and the results are shown in the outputs at Figure 86 and Figure 87.

Figure 86 BHS 6 Autocorrelation Function for differences



Source: Author

Figure 87 BHS 6 Partial Autocorrelation Function for differences



Source: Author

The most appropriate model was attempted to be defined for data set that provided stationarity assumption. For this purpose, it was decided which model would be more suitable by examining SAC and SPAC of series. While there is no obvious cut off status (rapidly approaching zero) in the SAC graph, it is observed that the SPAC graph approaches zero after the 3rd delay. Considering that once the difference is taken (d=1), our model is determined as ARIMA(3,1,0), in other words (ARI(3,1)).

A general "ARIMA model" can be expressed as follows.

"$z_t = \delta + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \cdots + \varphi_p z_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q}$"

In order to show a Z_t differenced series, our time series model can be shown as follows

"$z_t = \delta + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \varphi_3 z_{t-3} + a_t$"

The hypotheses for the model parameters and constant term can be expressed as follows;

H_0: $\theta_1 = 0$ H_0: $\phi_i = 0$ H_0: $\delta = 0$

H_1: $\theta_1 \neq 0$ H_1: $\phi_i \neq 0$ H_1: $\delta \neq 0$

Model

Type	Coef	SE Coef	T	P
AR 1	0.5216	0.0334	15.62	0
AR 2	0.2254	0.0369	6.11	0
AR 3	0.1121	0.0333	3.36	0.001
Constant	0.00011	0.00025	0.45	0.655

Differencing: 1 regular difference

Number of observations: Original series 891, after differencing 890

Residuals: SS = 0.0490358 (backforecasts excluded)

MS = 0.0000553 DF = 886

When the significance of the model parameters was examined, the P value of AR 1, AR 2, AR 3 parameters were 0. Since "P" below 0.05 the assumption stating "model was insignificant" was rejected. These parameters must include in model. However, the "P" value of constant term was meaningless with a value of 0.655.

As a result of the analysis, as seen above, the constant term was found meaningless and therefore it was not necessary to include it in the model. In addition, the model parameters were found to be highly significant.

The hypotheses and results for the model adequacy analysis (Ljung-Box) are as follows. In order for the model to be sufficient, the model should be sufficient for each lag in below.

H0 : The model is significant.

H1 : The model is not significant.

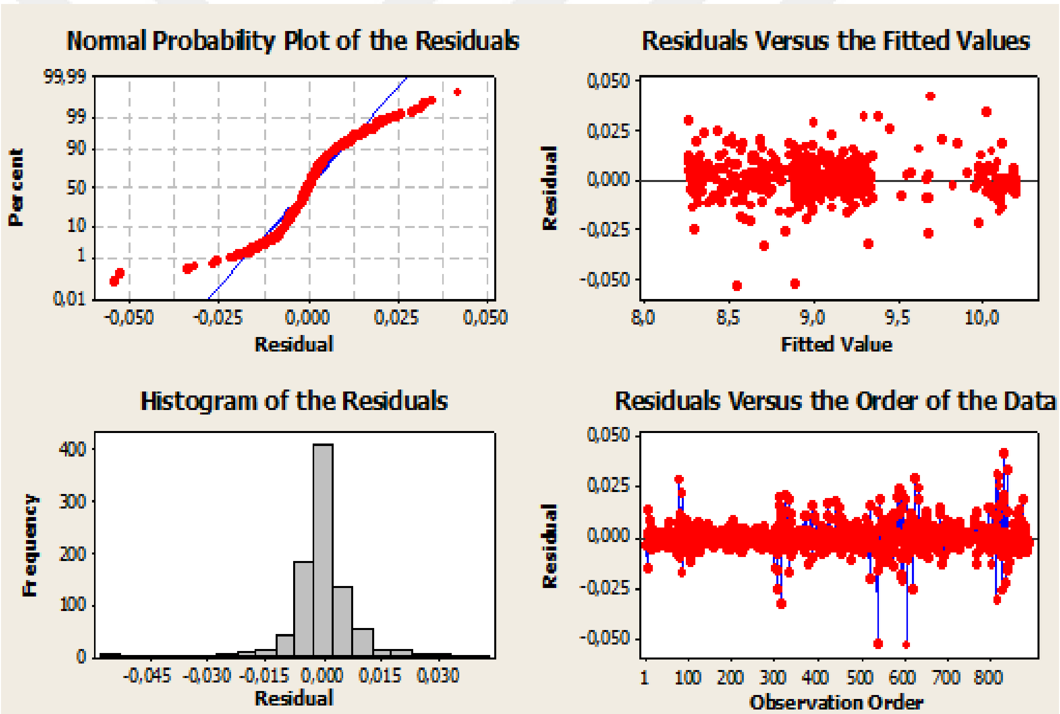
Statistics

Lag	12	24	36	48
Chi-Square	7.9	29.7	36.7	50.5
DF	8	20	32	44
P-Value	0.442	0.075	0.260	0.231

According to the results of the Minitab package program; The hypothesis established for the adequacy of the model could not be rejected for any lag. This shows that the model is sufficient.

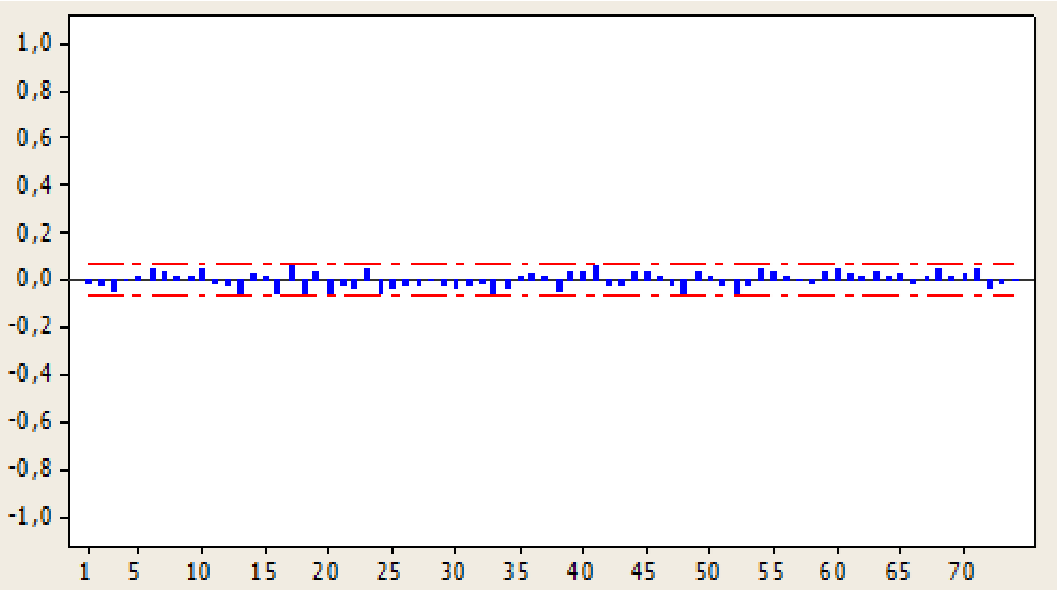
With the Ljung-Box statistics, the assumptions of the random error term of the model should be provided. Figure 88 show that the assumptions of the errors are provided. It can be stated that the distributions of the residuals do not go beyond the confidence limits and conform to the homogeneous and normal distribution. Although extreme values in some observations reduced the quality of the model, it did not adversely affect its usability. Figure 89 and Figure 90 are showing autocorrelation and Partial autocorrelation of the BHS 6 series.

Figure 88 BHS 6 Residual Plots



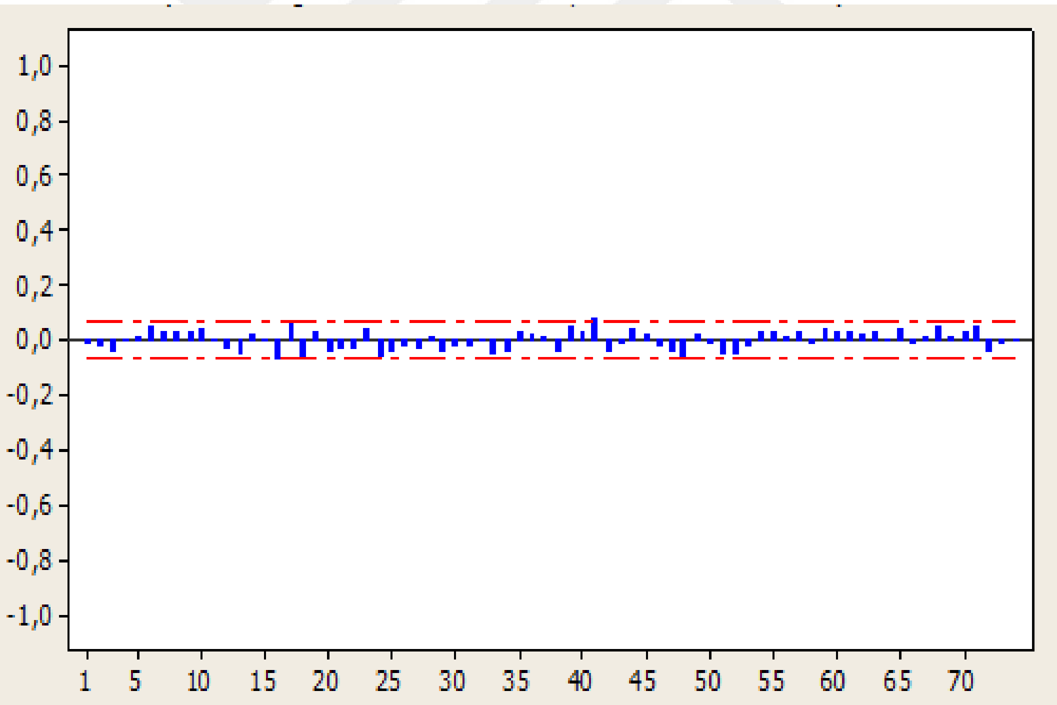
Source: Author

Figure 89 BHS 6 Autocorrelation Function



Source: Author

Figure 90 BHS 6 Partial Autocorrelation Function



Source: Author

4.3.6.5.1 Forecasting

The estimation of the series was made with the help of the model's parameters and historical values. For the reliability of the model, 20 realized values were estimated, and error rates were obtained. The predictions of the proposed model make accurate predictions with an error of up to 2 percent. Table 22 shows 13 predictions at 95% confidence level for future data.

Table 22 BHS 6 Forecasting Result for ARIMA

date	Period	Actual	Forecast	Lower	Upper	error %
20.May.21	885	26.850	26699	26313	27089	0,56
21.May.21	886	26.856	26807	26105	27529	0,18
24.May.21	887	26.919	26911	25866	28001	0,03
25.May.21	888	26.950	27008	25589	28504	0,22
26.May.21	889	26.944	27098	25293	29028	0,57
27.May.21	890	26.875	27182	24987	29570	1,14
28.May.21	891	26.750	27258	24669	30119	1,90
	892		27332	24348	30678	
	893		27400	24026	31245	
	894		27463	23704	31818	
	895		27524	23386	32393	
	896		27579	23073	32968	
	897		27634	22763	33547	
	898		27684	22460	34122	
	899		27731	22163	34700	
	900		27778	21873	35277	
	901		27820	21590	35850	
	902		27861	21314	36425	
	903		27903	21045	36994	
	904		27940	20783	37564	

Source: Author

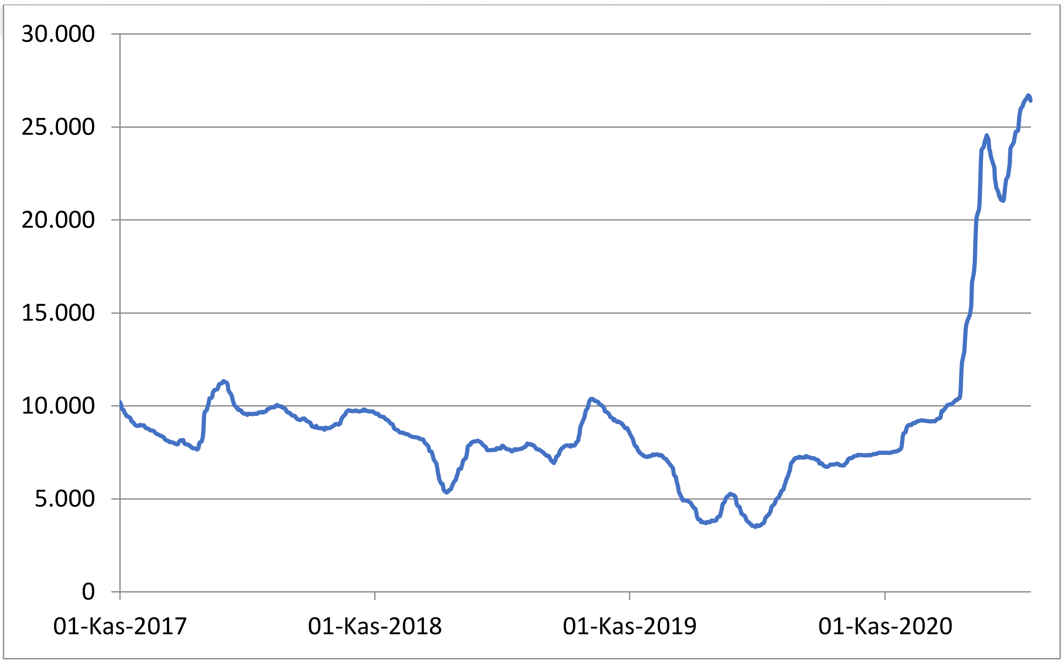
When all models were evaluated, it was seen that the most suitable model was the ARI(3,1) model.

4.3.7 Baltic Handysize Route 7

4.3.7.1 Modelling

For analysis of BHS 7 the natural logarithm of the data was taken and made stationary by performing the necessary operations, then the most suitable model Box – Jenkins (ARIMA), trend analysis, Exponential smoothing methods) for the series was determined with different modelling methods and the values that it could take in the future were estimated. Statistical package programs such as Minitab and SPSS were used in the analysis of the data.

Figure 91 BHS 7 Route Time Series Graph



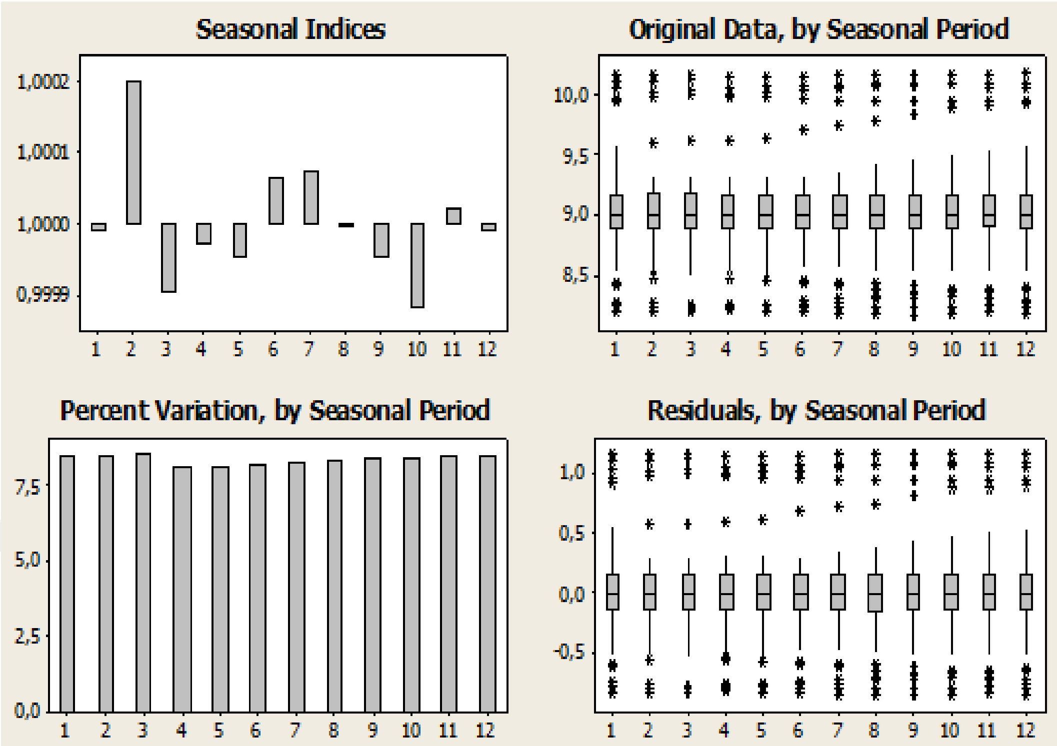
Source: Author

When Figure 91 is examined, and it was observed that there was a strong linear trend after February 2021, where there was no generalizable linear trend. In terms of seasonality, it can be said that there is no certain pattern. The following analysis show whether there are any effects by modelling both components.

4.3.7.2 Seasonality Analysis

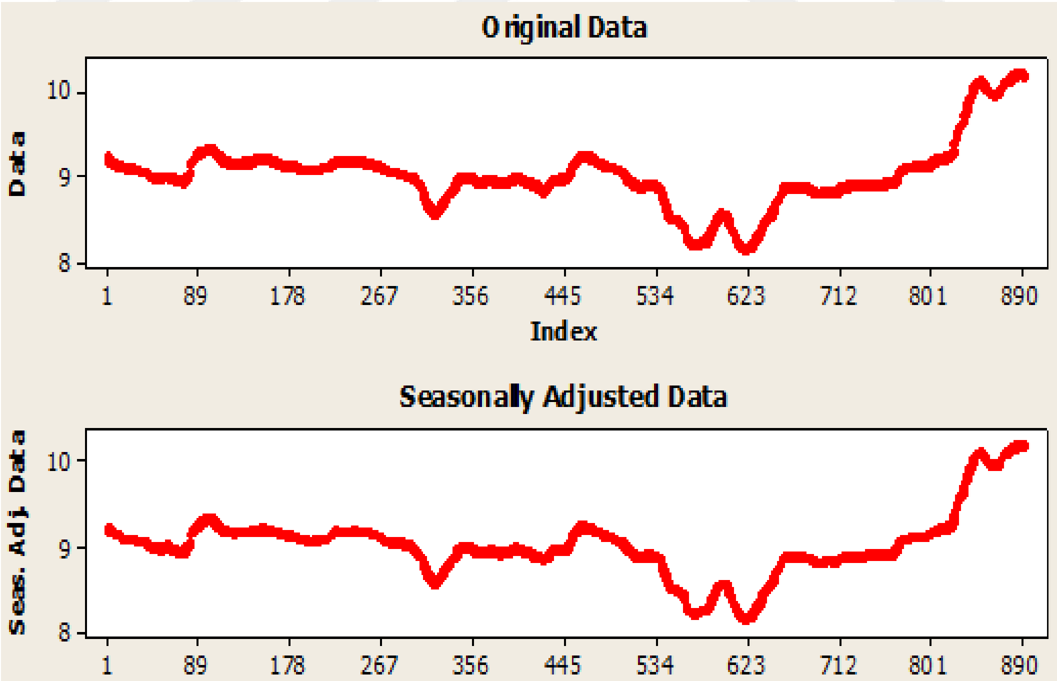
After analysis BHS 7 data, results for seasonality effect to BHS 7 series are shown at Figure 92 and Figure 94.

Figure 92 BHS 7 Seasonal Analysis



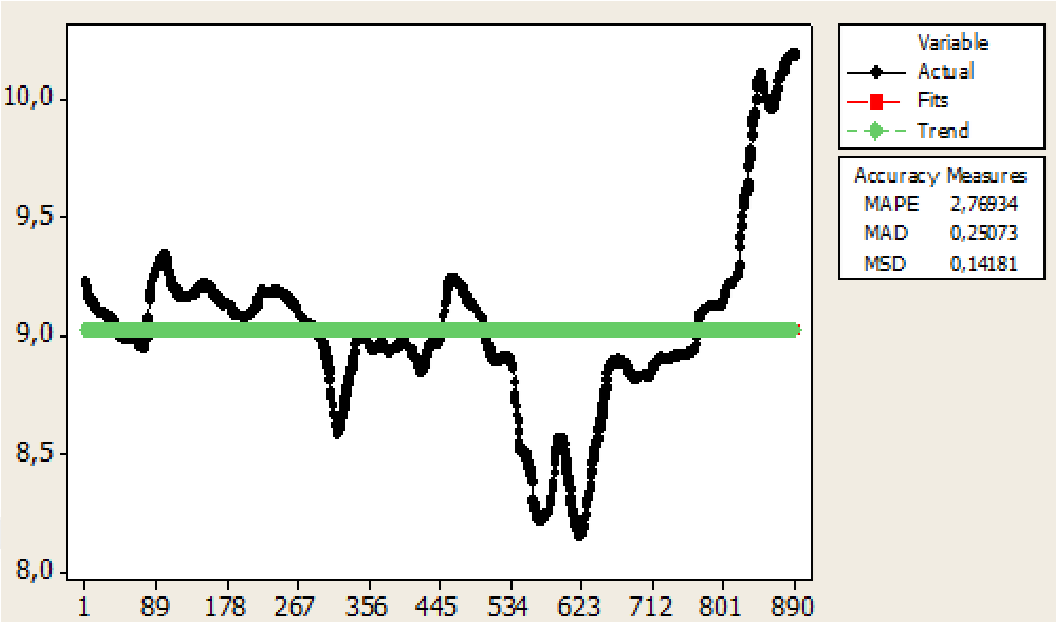
Source: Author

Figure 93 BHS 7 Component Analysis and Seasonally Adjusted data



Source: Author

Figure 94 BHS 7 Decomposition plot



Source: Author

The fact that the seasonal indexes are very close to 1 in the data indicates that there is no seasonal effect. In addition, graphically, it can be seen at Figure 93 that the seasonally adjusted graph does not differ significantly from the original graph. The criteria to be used to evaluate the model with other models were MAPE:2.77, MAD:0.250 and MSD:0.142.

4.3.7.3 Trend Analysis

It has been observed that the trend structure in the data has a quadratic rather than linear structure and modelling has been done.

Equation: “Yt = 9,47653 - 0,00329115*t + 3,826306E-06*t**2”

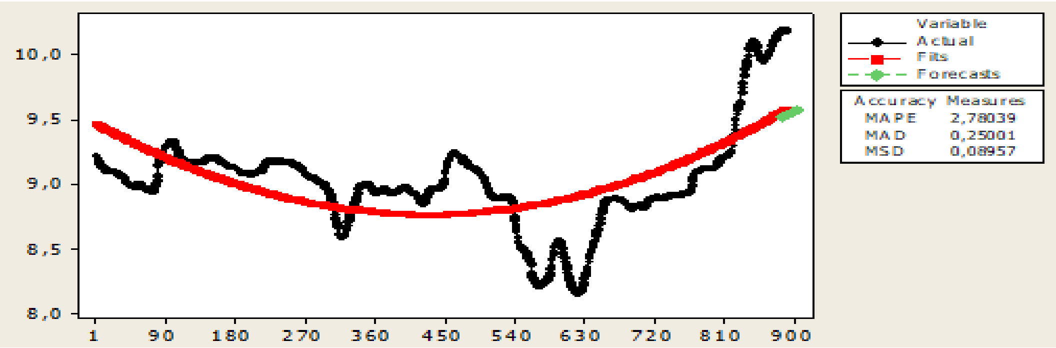
Measures

MAPE: 2.78039

MAD: 0.25001

MSD: 0.08957

Figure 95 BHS 7 Trend Analysis Plot



Source: Author

MAPE, MAD and MSD error criteria used in the comparison criteria are not significantly different from the model established for seasonal analysis at Figure 95. It can be said that both models give the same results.

4.3.7.3.1 Forecasting

While estimating, the last 7 observations of the series were estimated to see control and deviation. Table 23 shows output 20 observations estimate at below.

Table 23 BHS 7 Forecasting Results for Trend analysis

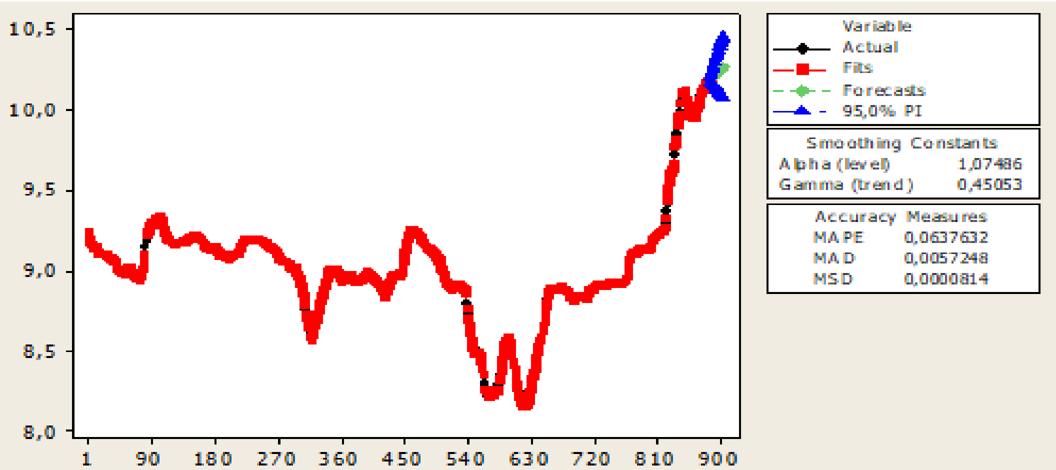
date	Period	Actual	Forecast
20-May-21	885	26.456	13575
21-May-21	886	26.463	13620
24-May-21	887	26.650	13665
25-May-21	888	26.706	13710
26-May-21	889	26.656	13755
27-May-21	890	26.613	13801
28-May-21	891	26.425	13847
	892		13893
	893		13939
	894		13986
	895		14033
	896		14080
	897		14127
	898		14175
	899		14223
	900		14271
	901		14320
	902		14368
	903		14417
	904		14467

Source: Author

4.3.7.4. Exponential Smoothing Analysis

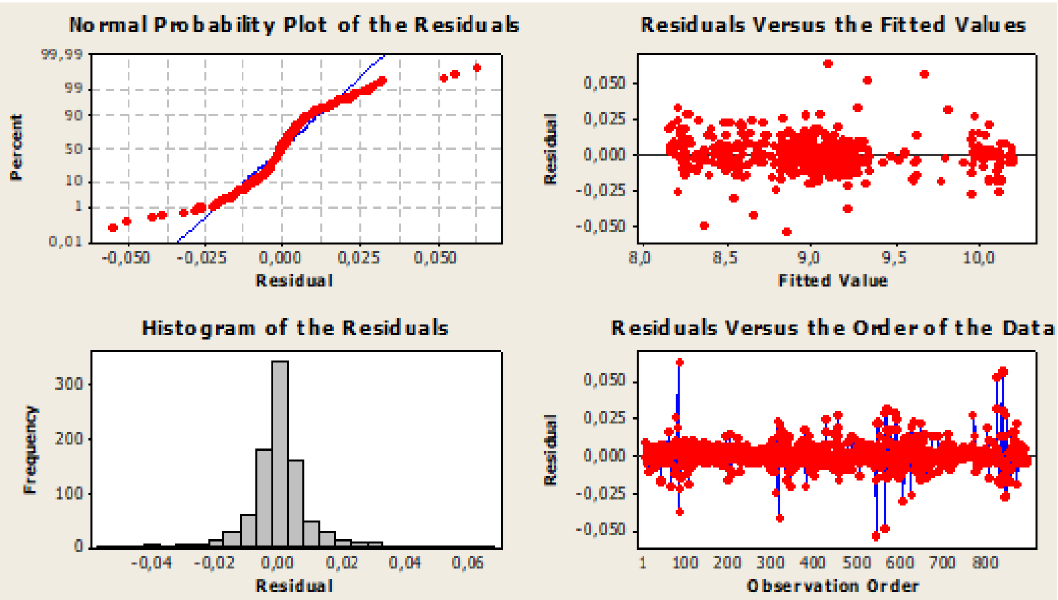
The exponential smoothing approach is one of the methods that starts from the current values of the data with a certain correction coefficient and models the series according to the older data. Since it is a dynamic model, the past and future predictions for each data are determined iteratively. The following table includes predictive values, exponential smoothing coefficients (Alpha, Gamma), error term assumptions and model criteria.

Figure 96 BHS 7 Double exponential smoothing plot



Source: Author

Figure 97 BHS 7 Residual plots



Source: Author

When Figure 96 and Figure 97, the error terms produced by the model are examined, it is seen that the assumptions are met. It can be seen residuals (error) are generally distributed with a mean of 0, and homogeneously distributed rather than concentrated in certain regions. Although there were partial clusters, it was seen that it did not have a great effect on the results.

4.3.7.4.1. Forecasting

At Table 24, it shows model estimation, actual values, and the lowest and highest limits at 95% confidence level. When the forecasts are examined, it can be said that it has less errors than the previously established Trend model forecasts.

Table 24 BHS 7 Forecasting Results for Exponential Smoothing

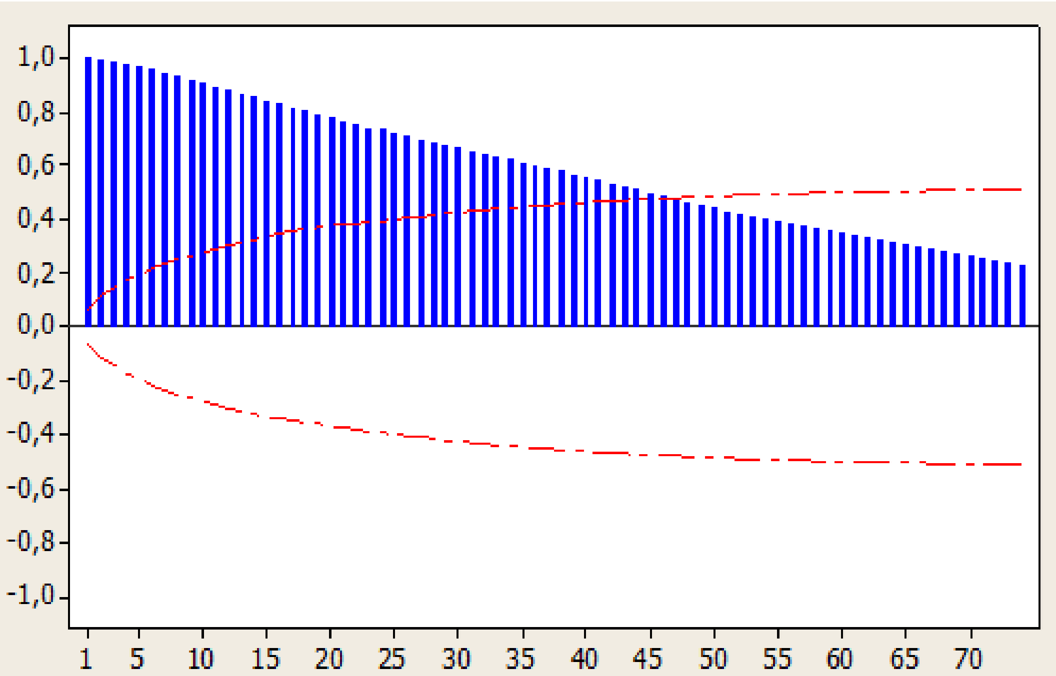
date	Period	Actual	Forecast	Lower	Upper	error %
20-May-21	885	26.456	26444	26077	26820	0
21-May-21	886	26.463	26558	25965	27165	0
24-May-21	887	26.650	26673	25846	27526	0
25-May-21	888	26.706	26788	25725	27898	0
26-May-21	889	26.656	26906	25604	28271	-1
27-May-21	890	26.613	27022	25481	28655	-2
28-May-21	891	26.425	27138	25357	29042	-3
	892		27255	25235	29434	
	893		27373	25114	29834	
	894		27491	24992	30236	
	895		27609	24872	30647	
	896		27728	24750	31061	
	897		27848	24629	31483	
	898		27968	24512	31911	
	899		28088	24392	32341	
	900		28209	24275	32781	
	901		28331	24156	33226	
	902		28453	24038	33675	
	903		28575	23923	34132	
	904		28698	23806	34596	

Source: Author

4.3.7.5 Box – Jenkins Modelling

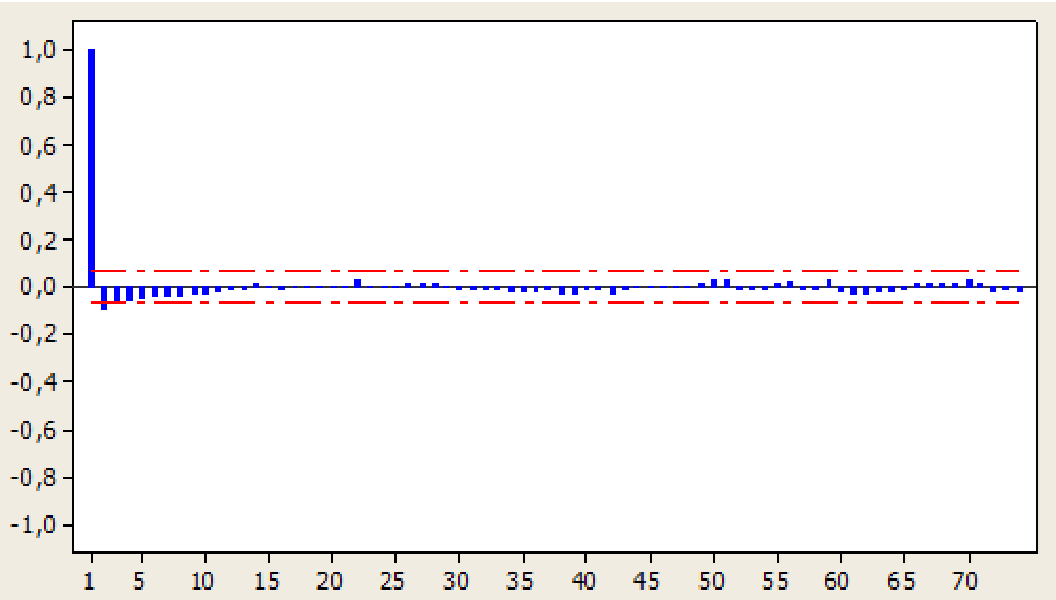
As can be seen from Figure 98 and Figure 99, there is a high-level grade of dependence among data.

Figure 98 BHS 7 Autocorrelation function



Source: Author

Figure 99 BHS 7 Partial Autocorrelation on function

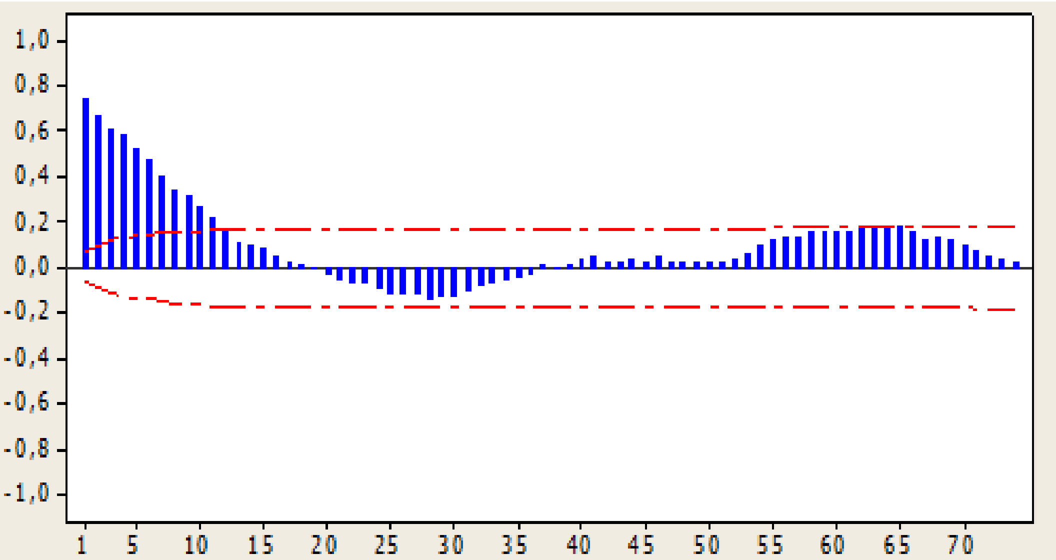


Source: Author

In order to eliminate this negative effect, the difference processor (d) is used. Since there is no significant seasonality in the series, the normal difference processor was used.

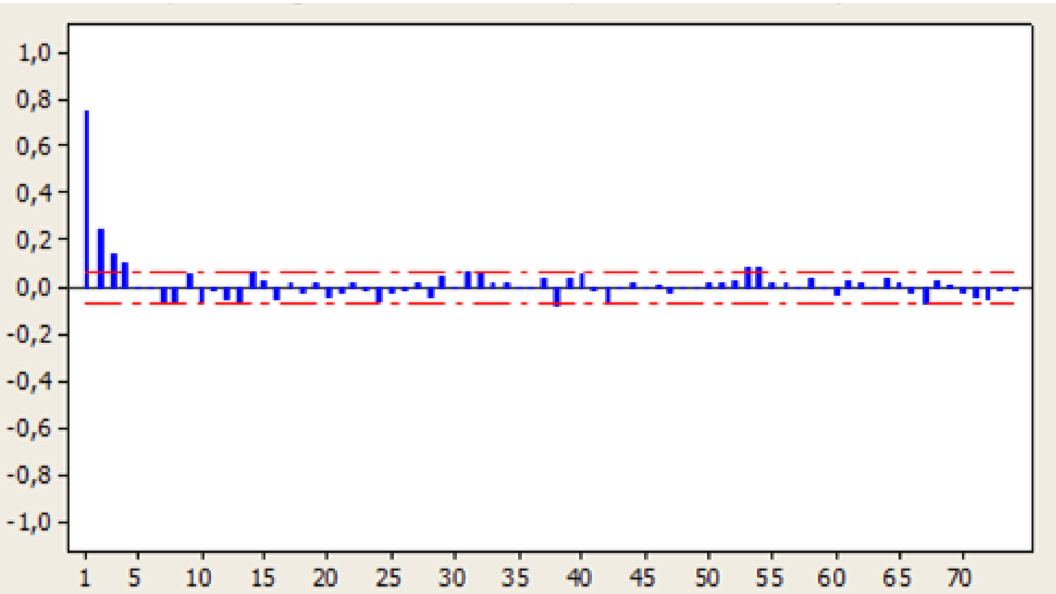
It can be stated that the series oscillates around a certain mean. However, it can be seen at Figure 100 and Figure 101 that autocorrelation structures have become more suitable for modelling.

Figure 100 BHS 7 Autocorrelation Function for differences



Source: Author

Figure 101 BHS 7 Partial Autocorrelation Function for differences



Source: Author

The most appropriate model was attempted to be defined for data set that provided stationarity assumption. For this purpose, it was decided which model would be more suitable by examining SAC and SPAC of series.. While there is no obvious cut-off status (rapidly approaching zero) in the SAC graph, it is observed that the SPAC graph approaches zero after the 4th delay. Considering that ARIMA(4,1,0), which is suggested by this approach, is taken once difference (d=1), our model is determined as ARIMA(4,1,0), in other words (ARI(4,1)).

A general "ARIMA model" can be expressed as follows.

"$z_t = \delta + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \cdots + \varphi_p z_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q}$"

In order to show a Z_t differenced series, our time series model can be shown as follows

"$z_t = \delta + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \varphi_3 z_{t-3} + \varphi_4 z_{t-4} + a_t$"

The hypotheses for the model parameters and constant term can be expressed as follows;

H_0: $\theta_1 = 0$ H_0: $\phi_i = 0$ H_0: $\delta = 0$

H_1: $\theta_1 \neq 0$ H_1: $\phi_i \neq 0$ H_1: $\delta \neq 0$

Model

Type	Coef	SE Coef	T	P
AR 1	0.5213	0.0334	15.59	0.000
AR 2	0.1494	0.0376	3.97	0.000
AR 3	0.0826	0.0376	2.20	0.028
AR 4	0.0990	0.0334	2.96	0.003

Differencing: 1 regular difference

Number of observations: Original series 891, after differencing 890

Residuals: SS = 0,0695261 (backforecasts excluded)

MS = 0,0000785 DF = 886

When the significance of the model parameters was examined, the P value of AR 1, AR 2, AR 3, and AR 4 parameters were 0. Since “P” below 0.05 the assumption stating “model was insignificant” was rejected. These parameters must include in model.

Hypotheses and outcomes for the model adequacy analysis (Ljung-Box) are as follows. In order for the model to be sufficient, the model should be sufficient for each lag in below.

H0: Model significant

H1: Model not significant

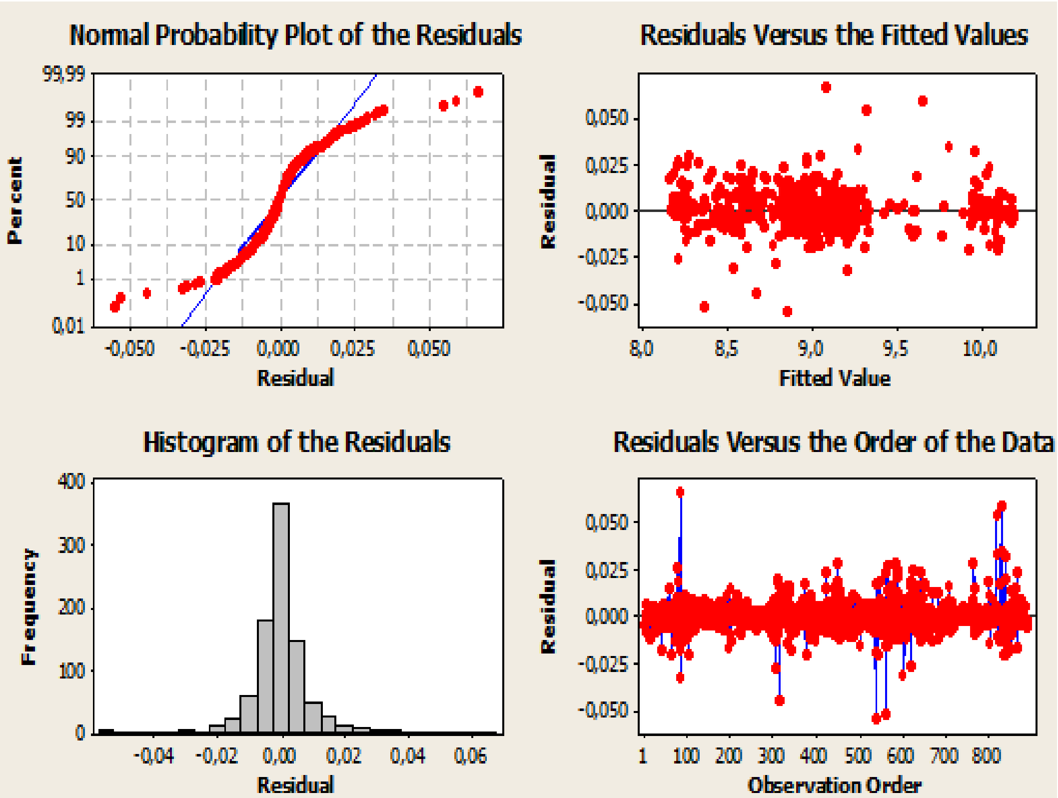
Statistics

Lag	12	24	36	48
Chi-Square	13.5	28.5	43.4	59.0
DF	8	20	32	44
P-Value	0.095	0.097	0.086	0.065

According to the results of the Minitab package program; The hypothesis established for the adequacy of the model could not be rejected for any lag. This shows that the model is sufficient.

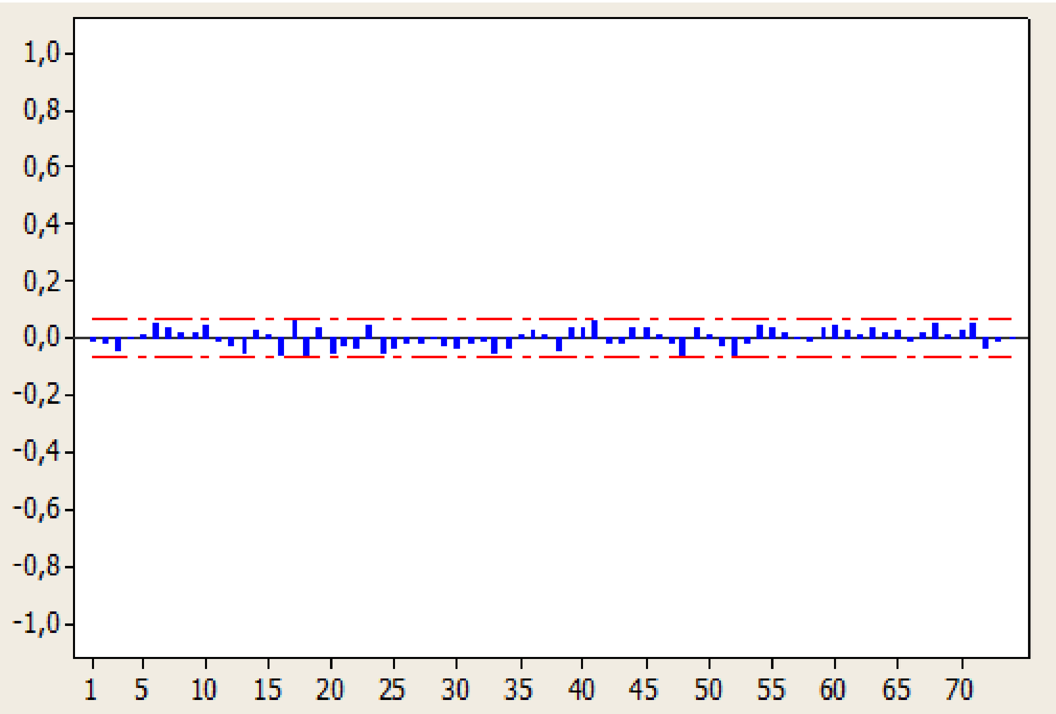
With the Ljung-Box statistics, the assumptions of the random error term of the model should be provided. Figure 102 show that the assumptions of the errors are provided. It can be stated that the distributions of the residuals do not go beyond the confidence limits and conform to the homogeneous and normal distribution. Although extreme values in some observations reduced the quality of the model, it did not adversely affect its usability. Figure 103 and Figure 104 are showing autocorrelation and Partial autocorrelation of the BHS 7 series.

Figure 102 BHS 7 Residual Plots



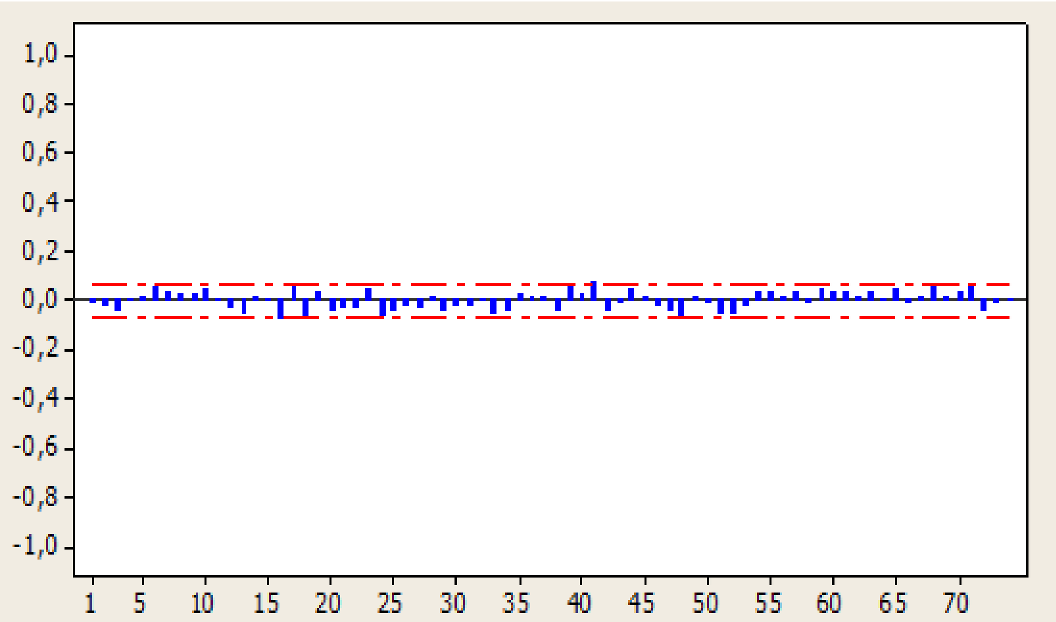
Source: Author

Figure 103 BHS 7 Autocorrelation Function



Source: Author

Figure 104 BHS 7 Partial Autocorrelation Function



Source: Author

4.3.7.5.1 Forecasting

The estimation of the series was made with the help of the model's parameters and historical values. For the reliability of the model, 20 realized values were estimated, and error rates were obtained. The predictions of the proposed model make accurate predictions with an error of up to 2 percent. Table 25 shows 13 predictions at 95% confidence level for future data.

Table 25 BHS 7 Forecasting Result for ARIMA

date	Period	Actual	Forecast	Lower	Upper	error %
20-May-21	885	26.456	26418	25962	26882	0
21-May-21	886	26.463	26492	25668	27343	0
24-May-21	887	26.650	26558	25359	27817	0
25-May-21	888	26.706	26614	25032	28300	0
26-May-21	889	26.656	26667	24679	28816	0
27-May-21	890	26.613	26716	24316	29352	0
28-May-21	891	26.425	26761	23947	29906	-1
	892		26801	23576	30467	
	893		26839	23204	31039	
	894		26871	22836	31619	
	895		26903	22474	32206	

	896		26930	22117	32794	
	897		26957	21766	33386	
	898		26981	21420	33982	
	899		27003	21085	34579	
	900		27022	20756	35179	
	901		27041	20437	35778	
	902		27057	20127	36374	
	903		27073	19823	36971	
	904		27087	19528	37568	

Source: Author

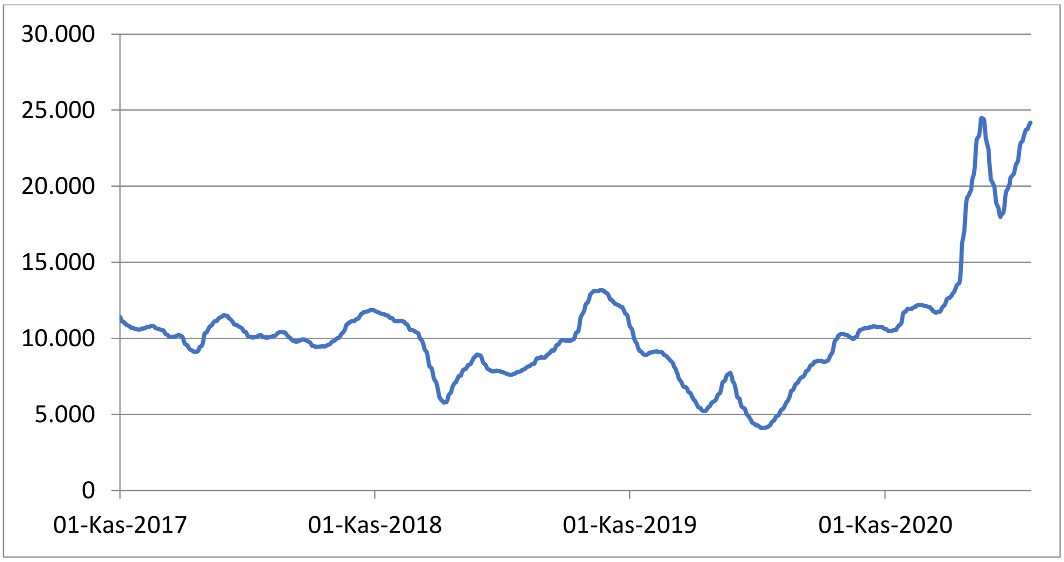
When all models were evaluated, it was seen that the most suitable model was the ARI(4,1) model.

4.3.8 Baltic Handysize Route 7 TC AVERAGE

4.3.8.1 Modelling

For analysis of 7 TC AVERAGE the natural logarithm of the data was taken and made stationary by performing the necessary operations, then the most suitable model (Box – Jenkins (ARIMA), trend analysis, Exponential smoothing methods) for the series was determined with different modelling methods and the values that it could take in the future were estimated. Statistical package programs such as Minitab and SPSS were used in the analysis of the data.

Figure 105 BHS 7 TC AVERAGE Time Series Graph



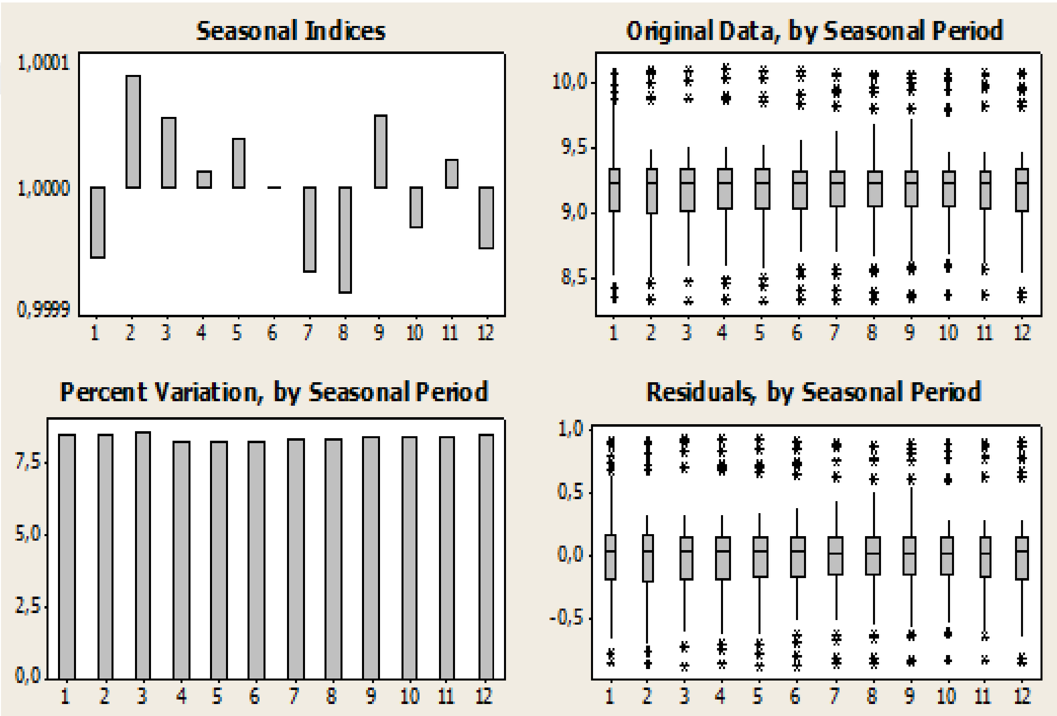
Source: Author

When Figure 105 is examined, and it was observed that there was a strong linear trend after February 2021, where there was no generalizable linear trend. In terms of seasonality, it can be said that there is no certain pattern. The following analysis show whether there are any effects by modelling both components.

4.3.8.2 Seasonality Analysis

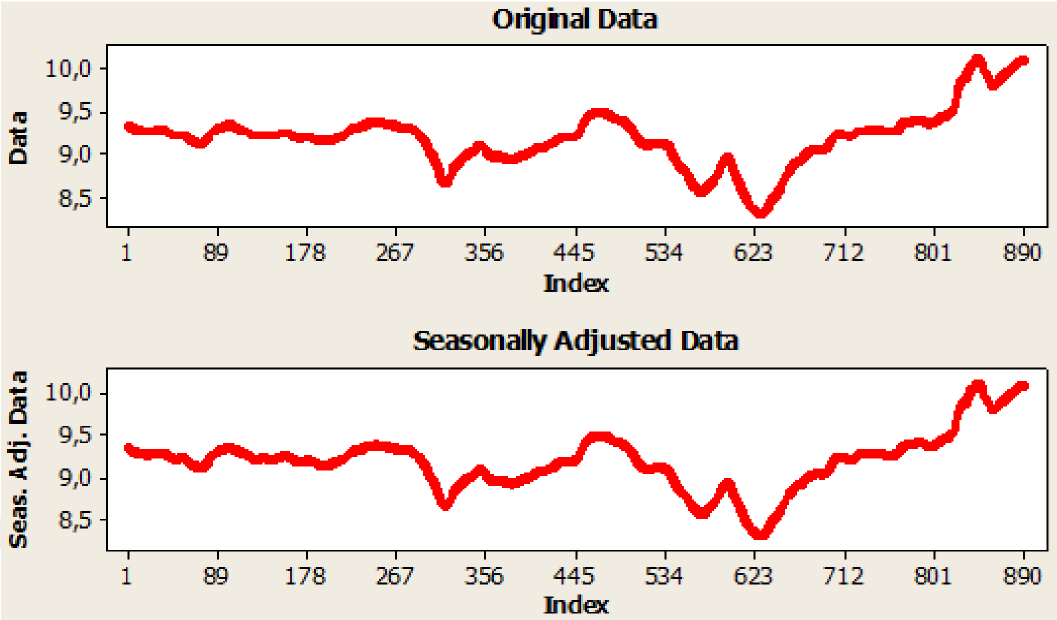
After analysis BHS 7 TC average data, results for seasonality effect to BHS 7 TC average series are shown at Figure 106 and Figure 108.

Figure 106 BHS 7 TC AVERAGE Seasonal analysis



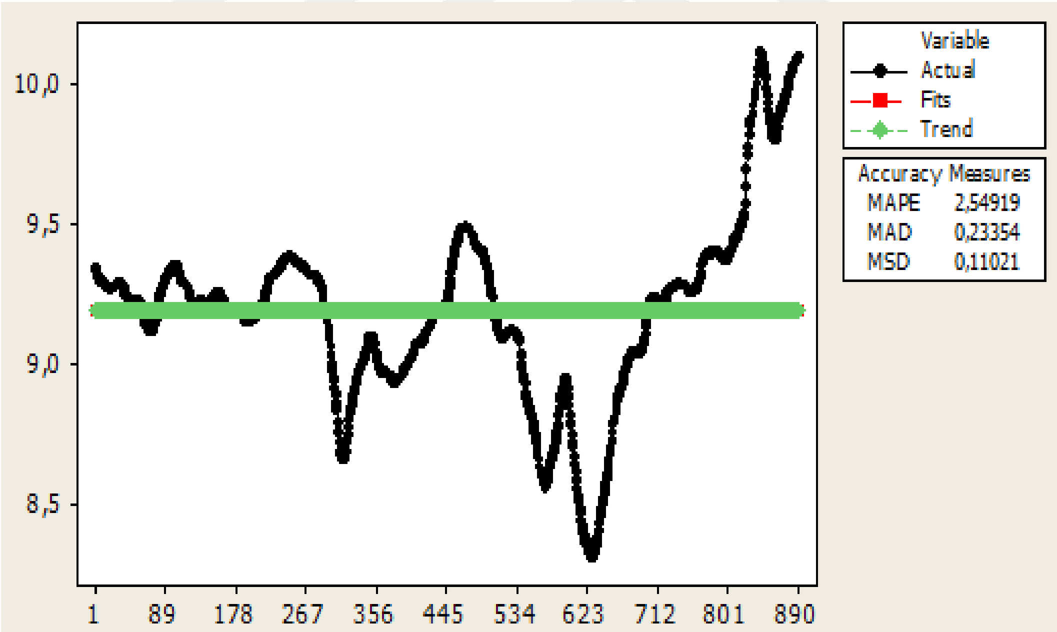
Source: Author

Figure 107 BHS7 TC AVERAGE Component Analysis and Seasonally Adjusted data



Source: Author

Figure 108 BHS 7 TC AVERAGE Time series decomposition plot



Source: Author

The fact that the seasonal indexes are very close to 1 in the data indicates that there is no seasonal effect. In addition, graphically, it can be seen at Figure 107 that the seasonally adjusted graph does not differ significantly from the original graph. The criteria to be used to evaluate the model with other models were MAPE:2.54, MAD:0.23 and MSD:0.11

4.3.8.3 Trend Analysis

It has been observed that the trend structure in the data has a quadratic rather than linear structure and modelling has been done.

Equation Yt = “9,52915 - 0,00271832*t + 3,286966E-06*t**2”

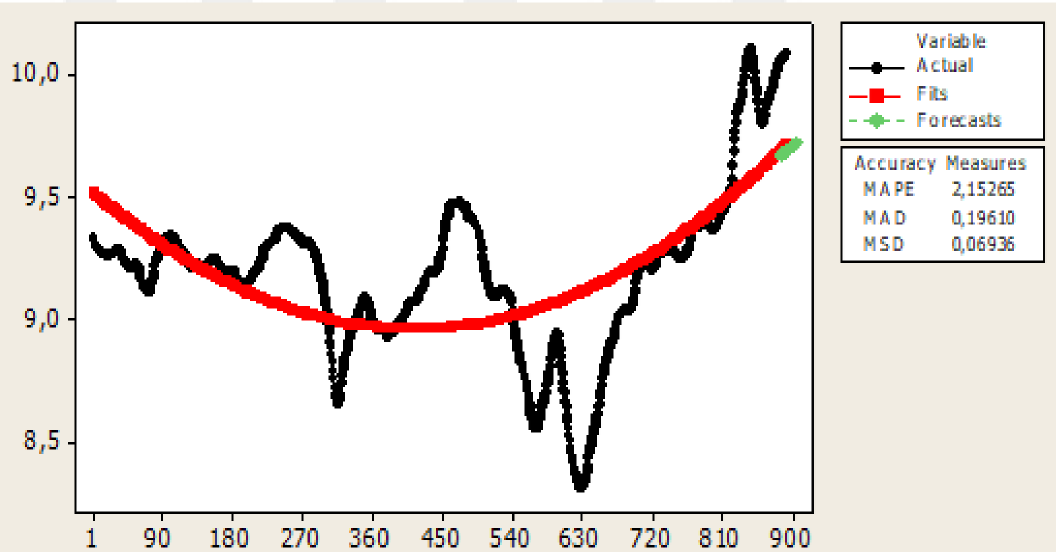
Measure

MAPE: 2.15265

MAD: 0.19610

MSD: 0.06936

Figure 109 BHS 7 TC AVERAGE Trend Analysis Plot



Source: Author

MAPE, MAD and MSD error criteria used in the comparison criteria are not significantly different from the model established for seasonal analysis at Figure 109. It can be said that both models give the same results.

4.3.8.3.1 Forecasting

While estimating, the last 7 observations of the series were estimated to see control and deviation. Table 26 shows a total of 20 observation estimates were made and outputs.

Table 26 BHS 7 TC AVERAGE Forecasting Results for Trend analysis

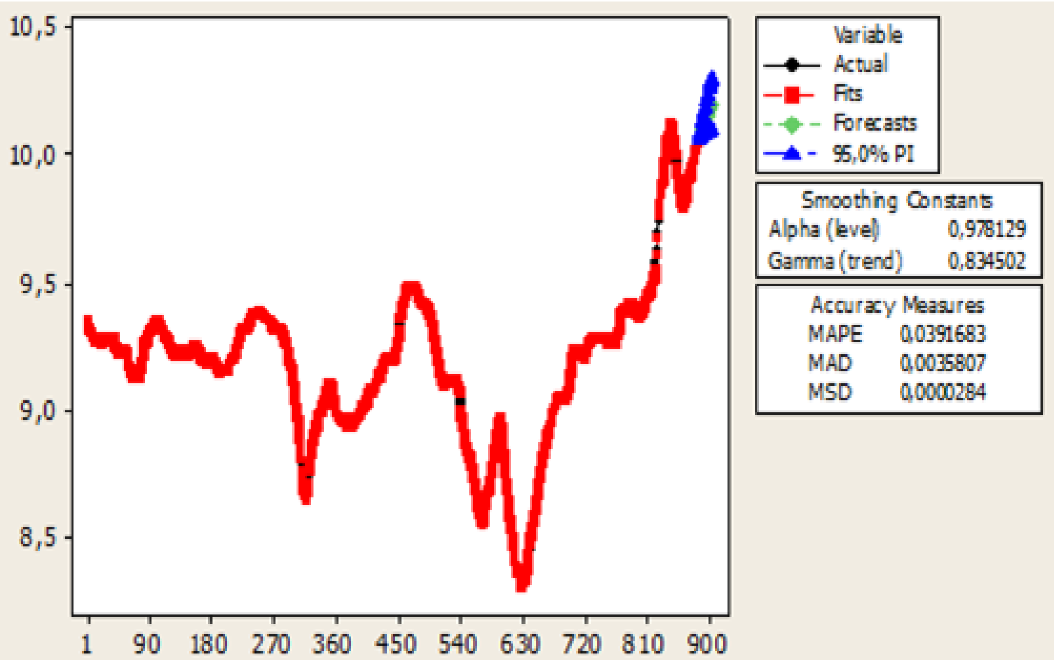
Date	Period	Actual	Forecast
20-May-21	885	23.572	15847
21-May-21	886	23.706	15894
24-May-21	887	23.761	15942
25-May-21	888	23.885	15989
26-May-21	889	24.037	16037
27-May-21	890	24.133	16086
28-May-21	891	24.170	16134
	892		16183
	893		16232
	894		16281
	895		16331
	896		16381
	897		16431
	898		16481
	899		16531
	900		16582
	901		16633
	902		16685
	903		16736
	904		16788

Source: Author

4.3.8.4. Exponential Smoothing Analysis

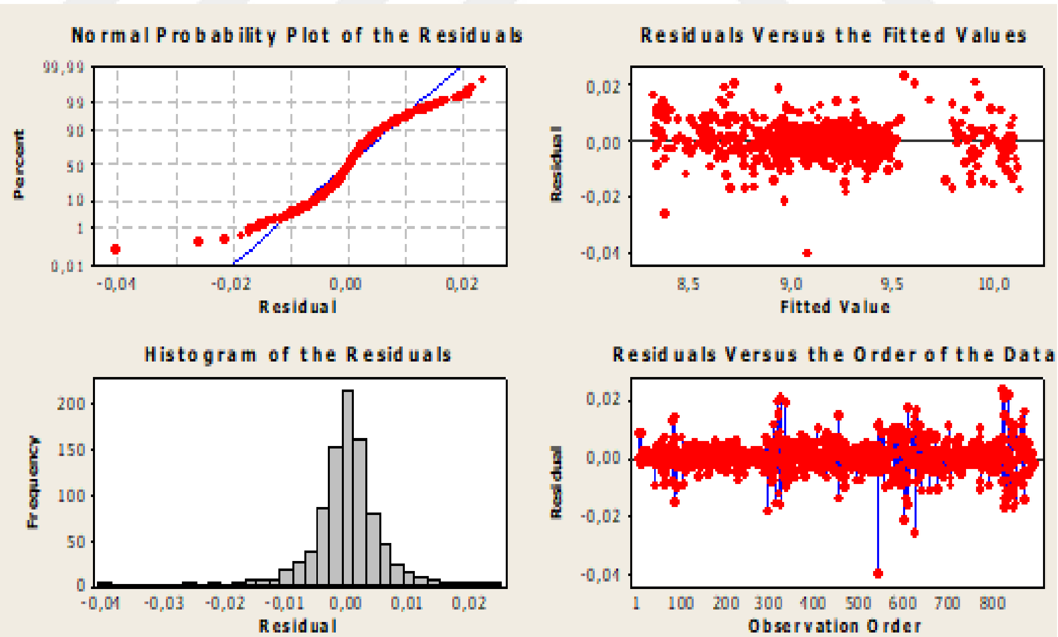
The exponential smoothing approach is one of the methods that starts from the current values of the data with a certain correction coefficient and models the series according to the older data. Since it is a dynamic model, the past and future predictions for each data are determined iteratively. The following table includes predictive values, exponential smoothing coefficients (Alpha, Gamma), error term assumptions and model criteria.

Figure 110 BHS 7 TC AVERAGE Double exponential smoothing plot



Source: Author

Figure 111 BHS 7 TC AVERAGE Residual plots



Source: Author

Figure 110 and Figure 111 of the error terms produced by the model, shown above, are examined, it is seen that the assumptions are met. It can be seen residuals (error) are generally distributed with a mean of 0, and homogeneously distributed rather than concentrated in certain regions. Although there were partial clusters, it was seen that it did not have a great effect on the results.

4.3.8.4.1. Forecasting

At Table 27, it shows model estimation, actual values, and the lowest and highest limits at 95% confidence level in below. When the forecasts are examined, it can be said that it has less errors than the previously established Trend model forecasts.

Table 27 BHS 7 TC AVERAGE Forecasting Results for Exponential Smoothing

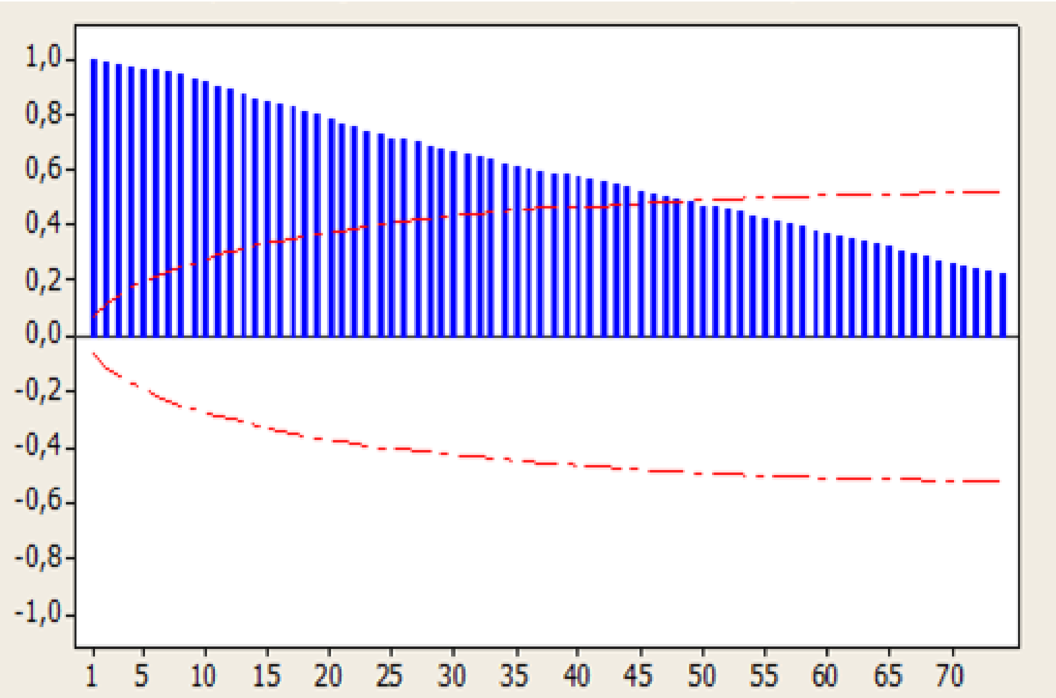
date	Period	Actual	Forecast	Lower	Upper	error %
20-May-21	885	23.572	23534	23328	23742	0,16
21-May-21	886	23.706	23704	23391	24019	0,01
24-May-21	887	23.761	23875	23449	24307	-0,48
25-May-21	888	23.885	24045	23508	24597	-0,67
26-May-21	889	24.037	24219	23562	24894	-0,76
27-May-21	890	24.133	24394	23619	25195	-1,08
28-May-21	891	24.170	24570	23673	25502	-1,66
	892		24748	23728	25810	
	893		24924	23782	26124	
	894		25104	23837	26439	
	895		25286	23892	26761	
	896		25469	23947	27084	
	897		25653	24002	27414	
	898		25835	24057	27745	
	899		26022	24113	28082	
	900		26210	24168	28424	
	901		26399	24224	28767	
	902		26590	24280	29118	
	903		26780	24336	29472	
	904		26973	24392	29828	

Source: Author

4.3.8.5 Box – Jenkins Modelling

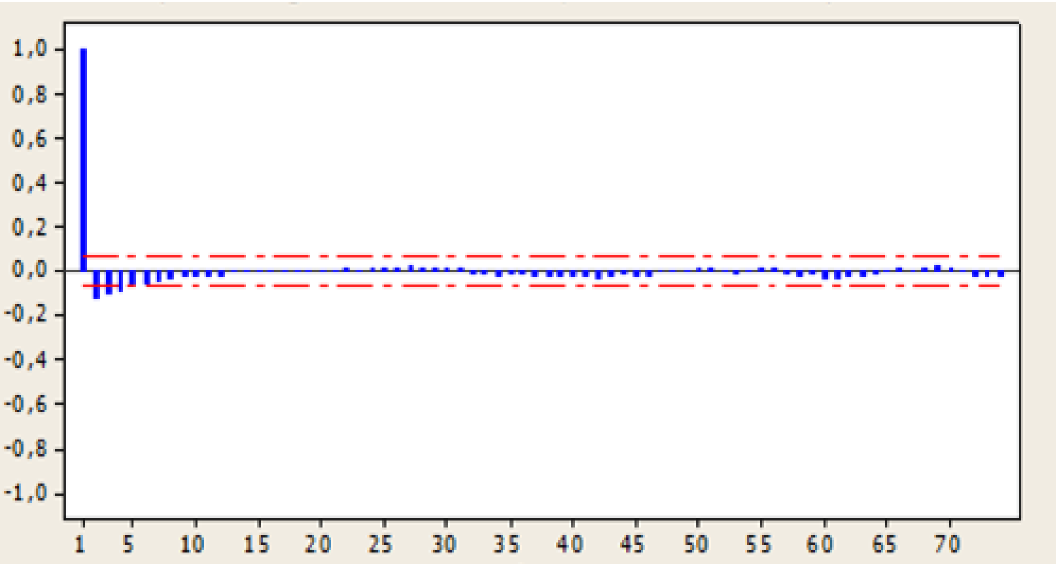
As can be seen from the autocorrelation and partial autocorrelation graphs, there is a high-level grade of dependence among data.

Figure 112 BHS 7 TC AVERAGE Autocorrelation function



Source: Author

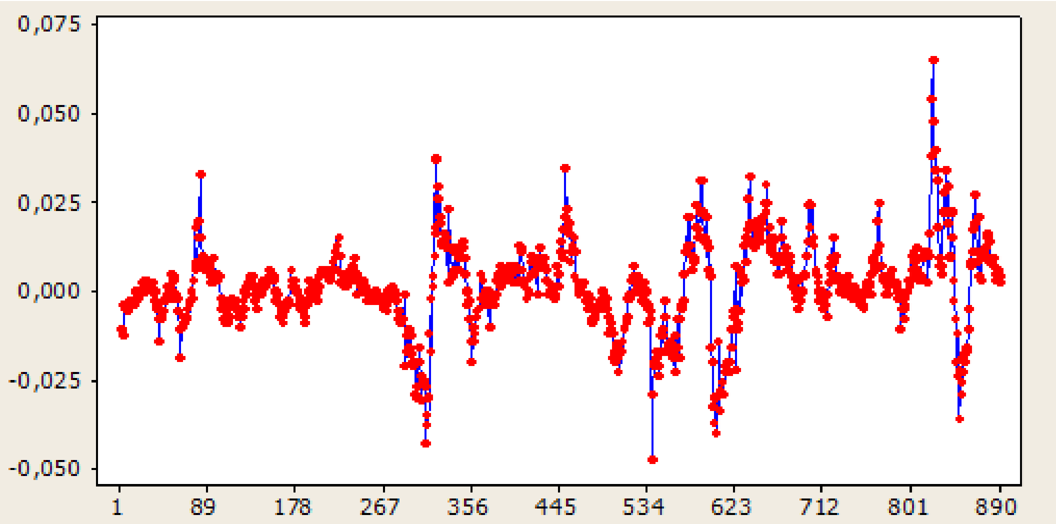
Figure 113 BHS 7 TC AVERAGE Partial Autocorrelation on function



Source: Author

In order to eliminate this negative effect, the difference processor (d) is used. Since there is no significant seasonality in the series, the normal difference processor was used.

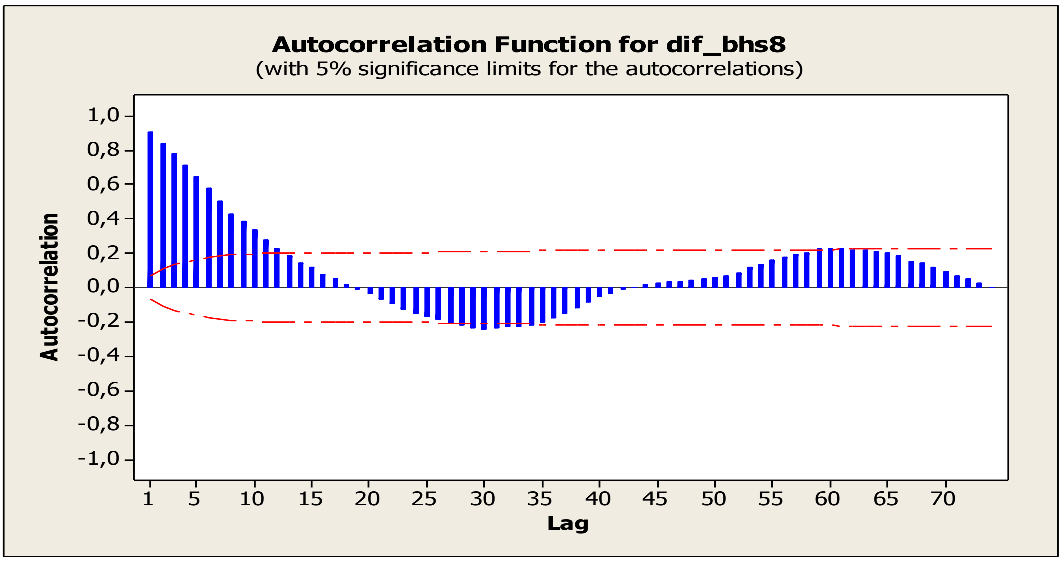
Figure 114 BHS 7 TC AVERAGE Time series plot of difference



Source: Author

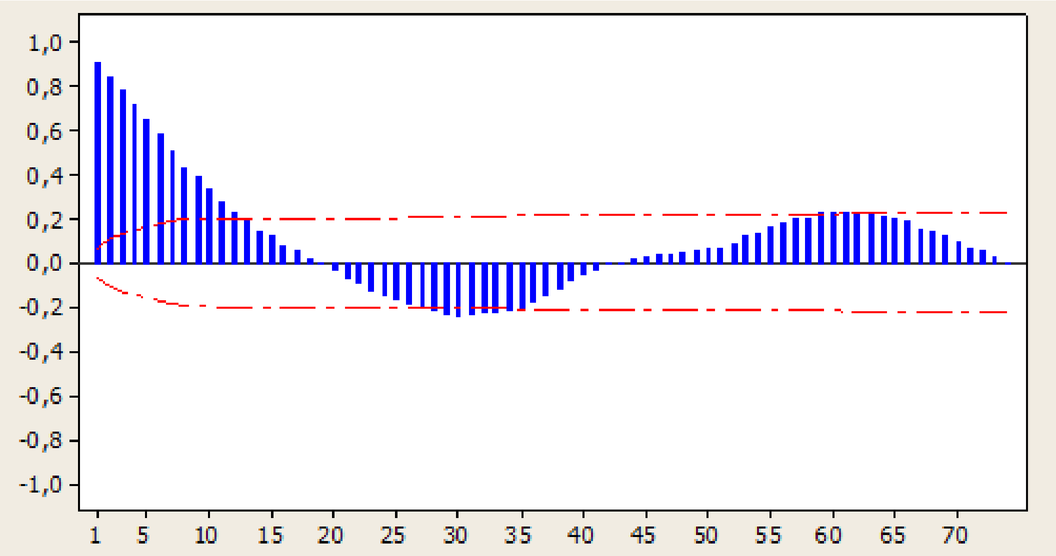
At Figure 114 it can be stated that the series oscillates around a certain mean. However, it can be seen at Figure 115 and Figure 116 that autocorrelation structures have become more suitable for modelling.

Figure 115 BHS 7 TC AVERAGE Autocorrelation Function for differences



Source: Author

Figure 116 BHS 7 TC AVERAGE Partial Autocorrelation Function for differences



Source: Author

The most appropriate model was attempted to be defined for data set that provided stationarity assumption. For this purpose, it was decided which model would be more suitable by examining SAC and SPAC of series. While there is no obvious cut off status (rapidly approaching zero) in the SAC graph, it is observed that the SPAC graph approaches zero after the 2nd delay. ARIMA(2,1,0) suggested by this approach. Considering that once the difference is taken (d=1), our model is determined as ARIMA(2,1,0), in other words (ARI(4,1)).

A general “ARIMA model” can be expressed as follows.

“$z_t = \delta + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \cdots + \varphi_p z_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q}$”

The hypotheses for the model parameters and constant term can be expressed as follows;

H_0: $\theta_1 = 0$ H_0: $\phi_i = 0$ H_0: $\delta = 0$

H_1: $\theta_1 \neq 0$ H_1: $\phi_i \neq 0$ H_1: $\delta \neq 0$

Model

Type	Coef	SE Coef	T	P
AR 1	0.7574	0.0331	22.86	0.000
AR 2	0.1595	0.0331	4.82	0.000

Differencing: 1 regular difference
Number of observations: Original series 891, after differencing 890
Residuals: SS = 0.0243969 (backforecasts excluded)
MS = 0.0000275 DF = 888

The significance of the model parameters was examined, the P value of AR 1, and AR 2 parameters were 0. Since “P” below 0.05 the assumption stating “model was insignificant” was rejected. These parameters must include in model.

Hypotheses and outputs for the model adequacy analysis (Ljung-Box) are as follows. In order for the model to be sufficient, the model should be sufficient for each lag in below.

H0: Model significant
H1: Model not significant
Statistics

Lag	12	24	36	48
Chi-Square	21.1	34.4	58.2	68.7
DF	10	22	34	46
P-Value	0.021	0.044	0.006	0.017

According to results of the Minitab package program; The hypothesis for the adequacy of the model was rejected for all lags. This shows that the model is not sufficient.

Apart from the ARIMA(2,1,0) model, different models were also tried, but model significance could not be achieved for any of the ARIMA models.

Within the framework of these results, modelling of 7 TC AVERAGE route series could not be done by ARIMA methods. There may be different reasons why the assumptions, which are the main reason for this situation, cannot be met. The excess of extreme and effective observations in the series, the trend structure changing the direction of the series significantly at the end of the series, etc. can be sorted.

When all models were evaluated, it was found appropriate to model the series with the exponential smoothing method and use its estimations.

CONCULUSION

This thesis deals with the Dry Bulk Market of Shipping. Specifically, Handysize vessels analysed. 7 Baltic Exchange Handysize Routes and Baltic Exchange 7 Time Charter Routes averages were researched, and different time series forecasting models are applied per category. The most suitable models were established from scholastic research that gives suitable variables for forecasting models.

In this study data was taken from the Baltic Exchange from November 1, 2017, to May 28, 2021, and the data set consists of a database of 890 daily observations. In this study, first all routes were examined whether has a seasonal component from the data. Then all Handysize Routes published by Baltic Exchange have been forecasted using time series analysis including ARIMA, Trend analysis, and Exponential Smoothing approached in order to obtain the best estimation results.

First, in terms of seasonality, it can be said that there is no certain pattern for any route, as seen in the graphics. It has been shown in the modelling results that the indices are very close to 1 which means there is no seasonal effect. In addition to above, it is seen that the seasonally adjusted graph does not differ from the original graph.

As a result of the tests, it was seen that the most suitable method for BHS 1 was the ARIMA (2,1,0) model. The predictions of the proposed model are correct with a maximum error of about 3 percent. 7 predictions at a 95% confidence level for future data are given above.

As a result of the tests, it was seen that the most suitable method for BHS 2 was the ARI (2,1) model. The predictions of the proposed model are correct with a maximum error of about 2 percent. 13 predictions at a 95% confidence level for future data are given above.

The hypothesis established for the adequacy of the BHS 3 model was rejected for all lag and it was seen that the model was not sufficient. Apart from the ARIMA (2,2,2) model, different models were also tried, but model significance could not be achieved for any of the ARIMA models. Accordingly, modelling of BHS3 series could not be done by ARIMA methods. Therefore, the exponential smoothing method found appropriate to model for forecasting the series.

According to tests, it was observed that the most suitable method for BHS 4 was the ARI (2,1) model. The predictions of the proposed model are correct with a maximum error of about 2 percent. 13 predictions at a 95% confidence level for future data are given above.

According to tests, it was observed that the most suitable method for BHS 5 was the ARI (4,2) model. The predictions of the proposed model are correct with a maximum error of about 4 percent. 13 predictions at a 95% confidence level for future data are given above.

As a result of the tests, it was seen that the most suitable method for BHS 6 was the ARI (3,1) model. The predictions of the proposed model are correct with a maximum error of about 2 percent. 13 predictions at a 95% confidence level for future data are given above.

As a result of the tests, it was seen that the most suitable method for BHS 7 was the ARI (4,1) model. The predictions of the proposed model are correct with a maximum error of about 2 percent. 13 predictions at a 95% confidence level for future data are given above.

The hypothesis established for the adequacy of the BHS 7-time charter averages model was rejected for all lag and it was seen that the model was not sufficient. Apart from the ARIMA (2,1,0) model, different models were also tried, but model significance could not be achieved for any of the ARIMA models. Accordingly, modelling of BHS 7-time charter averages series could not be done by ARIMA methods. Therefore, the exponential smoothing method found appropriate to model for forecasting the series.

Eventually the forecasting of Baltic Exchange Handysize Route Hire Rates by using Box-Jenkins (ARIMA) model confirmed to be successful in the short term. The only BHS 3 and BHS 7 TC averages models could not be forecasted by ARIMA.

Even though these models show its significance in forecasting of the Hire Rates, these models only take into consideration of the past figures published by Baltic Exchange. The factors affecting shipping market which explained in previous chapters should not be ignored and must be considered for forecasting hire rates.

Since Baltic Exchange was discontinued publishing hire rates for six different time charter routes for 28.000 dwt Handysize, in this study hire rates for seven different time charter routes for 38.000 dwt Handysize was used. As 38.000 dwt indexes was started to publish since 2017, only last 4 years data was analysed and hire rates were forecasted accordingly. Also, this thesis was prepared during pandemic period which affected all over the world due to COVID 19 virus. Hence there might be extreme positive or negative effect to shipping market. For example, Bulk carrier earnings averaged reached USD 21,039 per day. This is the highest half yearly average since first half of 2010, with earnings in Jun-21 the highest for any individual month since September 08. As this thesis conducted using data from November 2017 to June 2021, these results might be considered to have limitations to reflect real market behaviour.

As a further research, other traditional methods or hybrid approach can be performed on these Handysize routes. Especially for seasonality effect on Handysize routes, these studies could be carried out after a certain time receiving more data from Baltic Exchange for seven time charter routes for 38.000 DWT. Also, these models can be used to forecast Supramax, Panamax or Capsize vessel routes in another study.

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