EVALUATING RAIL PASSENGERS SECTOR IN TURKEY

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ABSTRACT

EVALUATING RAIL PASSENGERS SECTOR IN TURKEY

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With the rapid development of railways in Turkey, the research of railway passenger demand forecasting has gained much importance in the recent years. Passenger demand forecasting for transport services is essential for better management and better resource planning. In this study, a time-series-model was established using Auto Regressive Integrated Moving Average (ARIMA) forecasting method and then a regression model was formed to forecast the intercity railway passenger flow in Turkey. The daily passenger flow data from 2011 to 2015 was used to establish a model and 2016 daily passenger flow was predicted by the established model. To test the estimation power of the model, forecasting horizon was extended up to 2019. Analyzing forecasts from 2016 to 2019, reliability of the model was evaluated.

Additionally, a series of analyses was performed to understand the nature of Rail Passenger Survey (RPS) data, conducted at the train stations as a part of National Transport Master Plan (NTMP). The descriptive statistics based analyses included socio-demographic characteristics, geographical distribution, trip purposes, trip frequency, access/egress modes and rail passenger behavior difference between the High Speed Rail (HSR) and conventional services. A further attempt of modeling

using binary logistic regression enabled the detection of the passenger profile of a business trip traveler.

Keywords: Intercity Rail Travel, Passenger Demand Forecasting, Travel Behavior of Rail Passenger, Time Series Analysis of Rail Passenger Flow

ÖZ

TÜRKİYE’DE DEMİRYOLU YOLCU SEKTÖRÜNÜN DEĞERLENDİRİLMESİ

Ekici, Üsame
Doktora, İnşaat Mühendisliği
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Türkiye'de demiryollarının hızla gelişmesi ile birlikte son yıllarda demiryolu yolcu talep tahmini araştırmaları büyük önem kazanmıştır. Ulaşım hizmetleri için yolcu talebi tahmini, daha iyi yönetim ve daha iyi kaynak planlaması için esastır. Bu çalışmada, Oto Regresif Entegre Hareketli Ortalama (ARIMA) tahmin yöntemi kullanılarak bir zaman serisi modeli kurulmuş ve ardından Türkiye'deki şehirlerarası demiryolu yolcu akışını tahmin etmek için bir regresyon modeli oluşturulmuştur. Model oluşturmak için 2011-2015 yılları arasındaki günlük yolcu akışı verileri kullanılmış ve kurulan model ile 2016 günlük yolcu akışı tahmin edilmiştir. Modelin tahmin gücünü test etmek için tahminler 2019 yılına kadar uzatılmıştır. 2016'dan 2019'a kadar olan tahminler analiz edilerek modelin güvenilirliği ölçülmüştür.

Ayrıca, Ulusal Ulaştırma Ana Planı çalışmaları kapsamında tren istasyonlarında yapılan Demiryolu Yolcu Anketlerinin doğasını anlamak adına bir dizi analizler gerçekleştirilmiştir. Betimsel istatistik bazlı analizler, YHT ve konvansiyonel servisler arasındaki sosyo-demografik özellikleri, coğrafi dağılımı, seyahat amaçlarını, seyahat sıklığını, erişim/çıkış modlarını ve demiryolu yolcu davranış farkını içerir. Bunların yanında, ikili (binary) lojistik regresyon kullanarak bir başka

modelleme yapılması, bir iş seyahati yolcusunun yolcu profilinin tespit edilmesini sağlamıştır.

Anahtar Kelimeler: Şehirlerarası Demiryolu Yolculuğu, Yolculuk Talep Tahmini, Demiryolu Yolcusu Seyahat Davranışı, Demiryolu Yolcu Akışının Zaman Serileri Analizi

Dedicated to the memory of my mother…

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LIST OF ABBREVIATIONS

$\overline{dd}_{dow}$	: Average of daily passenger volume for each day of week
dd_i	: Total daily number of passengers
$\overline{ddJ}$	: Average daily number of passengers of each month
A	: Attraction
ACF	: Autocorrelation Function
ADF	: Augmented Dickey-Fuller
AIC	: Akaike Information Criterion
ARIMA	: Auto Regressive Integrated Moving Average
ATD	: Average Travel Distance
ConvRail	: Conventional Rail
dmj	: Total monthly number of passengers
EU	: European Union
F&F	: Friends and Family
FSM	: Four Step Model
GDP	: Gross Domestic Product
HSR	: High Speed Rail
IC	: Intracity
IPA	: Instrumentation for Pre-accession Assistance
MAE	: Mean Absolute Error
MAPE	: Mean Absolute Percentage Error
MoE	: Measures of Effectiveness
MoTMC	: Ministry of Transport, Maritime Affairs and Communications
NPax	: Number of Passenger
NTMP	: National Transport Master Plan
O-D	: Origin-Destination
P	: Production
PACF	: Partial Autocorrelation Function

Pax	: Passenger
RMSE	: Root Mean Square Error
RPF	: Rail Passenger Flow
RPS	: Rail Passenger Survey
RSI	: Roadside Interview
TCDD	: Turkish State Railways
TSI	: Technical Specification for Interoperability
UK	: United Kingdom
US	: United States
VoT	: Value of Time
WU	: Weekly Updated
XC	: Intercity
XSR	: Xiamen- Shenzhen Railway

CHAPTER 1

INTRODUCTION

The first railway line within the borders of Turkey was put into operation in 1856 between Aydın and İzmir. In 1923, length of rail lines in the Turkish Republic was 4,138 km, and increased to 7,153 km at the end of 1938 as the result of railway oriented transport policies during the first years of the Republic (MoTMC, 2017). This policy was pursued until 1950s and the share of railways increased to 42% for the passenger and 68% for freight. However, after 1950s the modal share of railways decreased to 3% and 5%, respectively, due to increased road-oriented policies. After almost 50 years neglecting, the railway network was in dilapidated condition around the beginning of 2000s.

By 2003, government decided that for a modern economy and a strong industry, a better performing rail system was needed with high speed rail (HSR) services, improved suburban systems around large cities, improved freight transport including multimodal terminals (MoTMC, 2017). This renaissance in the railway sector brought increased attention and development in the transport sector in Turkey. Current network (see Figure 1.1) connects most important cities in Turkey (i.e. Ankara, İstanbul, İzmir, Konya, etc.). A few cities are still not connected via railway (such as Bursa, Antalya), which were included in the development plans with proposed HSR lines projects. According to the statistics of Turkish State Railways (TCDD) almost 26 million passengers were carried in mainline trains in 2019, which was almost 10% of the total Rail Passenger Flow (RPF) of 246 million passengers, including the suburban train trips (TCDD, 2020). However, total share of railways in inland transportation is still below the shares in the EU countries, which are around 8% and 17.6% in passenger and freight, respectively (Eurostat, 2020a).

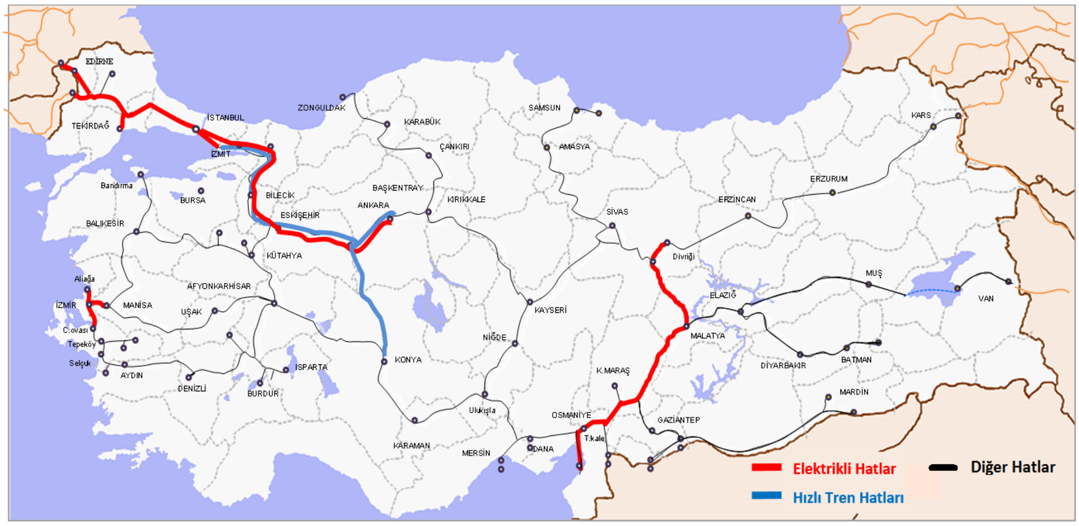


Figure 1.1 Current Situation of the Turkish Railway Network (MoTMC, 2017)

Despite high budget investments in the HSR lines, the desired modal shift from road to rail has not been achieved, yet. That further required development of tools and policies, as well as the National Transport Master Plan (NTMP) (NCCAP, 2011). The recent NTMP for Turkey was conducted by the MoTMC in 2016, as a project co-financed by the European Union (EU) in the scope of Instrumentation for Pre-accession Assistance (IPA) to prepare Turkey's new transportation strategy with reliance upon the 2023 targets and the 2035 vision. Its purpose was set to propose improvements in the transportation infrastructure, services and policies in the short, medium and long terms.

Especially with the upcoming changes in railways in Turkey, such as expected liberalization, it is more crucial to understand the RPF to better manage this big transformation. RPF is affected by many factors: While there are rapid increases in railway traffic during holidays, there can be high volumes due to summer vacation/tourism periods. Day of the week can be very influential, which leads to higher volumes before -or at the end- of the weekend.

1.1 Motivation

Without knowing people's preferences and a good planning, including academic research, railway project investment might not be efficient or beneficial. To shed light for future policies to increase railway share in intercity passenger transportation, it is important to understand who use railways and for what kind of trips in Turkey. Passenger demand forecasting for transport services is essential for better management and better resource planning. Accurate forecasting of passenger volume (also referred to as flow) is the basic task of capacity planning and revenue management (Luo et al., 2015). With the rapid development of railways in Turkey, the research of railway passenger demand forecasting has gained more importance in the recent years. Proper analyses have to be conducted on variations over time (day-to-day, seasonal, etc.) for the integration of railway management system. Developing demand forecasting models can lead to development of operating strategies with regard to destinations and routes, fleet planning and human resources, as in the case of air transportation sector (Çuhadar, 2014).

Simply stated, a forecasting model analyses the behavior of past data and finds a pattern in data and use this pattern for forecasting the future data (Prakaulya et al., 2017). If a good forecasting model can be established, it can help railway administration to improve its pricing policies, organization of the railway stations, optimize the allocation of railway vehicles resources, and improve the service capability of the passenger transport equipment, which is essential to improve the railway passenger transport (Xu et al. 2018). Xu et al. (2018) categorized passenger flow forecasting into two groups: i) related models (establishing the functional relationship between passenger flow and related factors via various regression models) and ii) time models (using time as an independent variable to establish a flow prediction).

1.2 Research Objectives

This study aims at analyzing rail passenger travel characteristics in Turkey in two major directions:

A main research goal is to create insights regarding the travel behavior of rail passengers. This step will address the questions such as

1. What does a rail passenger profile look like in Turkey in general?
2. Are there any differences in rail travelers' characteristics between regions?
3. Does HSR passenger profile differ from conventional rail (ConvRail) passenger profile?
4. What factors affect trip making of a business purpose rail traveler?

Business trips are analyzed in more detail as they are much lower than expected levels in intercity rail demand, but should be increased to improve economic sustainability of the rail passenger services.

The second goal is to develop forecasting models to estimate/analyze daily RPF. For this purpose, regression and time series models were developed

- to find factors effecting intercity rail passenger demand
- to evaluate estimation power of different forecasting models

Finally, there are policy recommendations as an output of this study not only for the demand side, but also for the supply side. Building new tracks, renovation of the existing tracks and stations, fleet allocation, human and other resource management can be planned based on a methodology. The decision makers can make their decisions on new investment projects according to outputs of the study. Also in the long term, findings of this study can be a basis for new standardization works in this field.

1.3 Scope of the Study

As a part of the NTMP, to gain insights, a comprehensive Rail Passenger Survey (RPS) was conducted at the train stations focused on rail passenger behavior and trends, which are analyzed in this study. The analyses include socio-demographic characteristics, geographical distribution, trip purposes, trip frequency, access/egress modes and rail passenger behavior difference between the HSR and conventional services. A further attempt of modeling using Binary logit enabled the detection of the passenger profile of a business trip traveler.

It is important to find a way of combining both types of forecasting models to predict the RPFs in the future. This requires testing of prediction power of these models, thus, first, time-series models using ARIMA forecasting method were developed for the prediction of intercity railway passenger flow in Turkey, which are later compared to regression models using seasonal and regional characteristics. Daily RPF (DRPF) data from 2011 to 2015 was used to establish the models and tested to predict the ridership for 2016-2019.

On the other hand, there were some research limitations that limit the scope of the study. Although the data obtained was very generic, it was lack of prices, daily number of trains running and fullness of the services. Therefore efficiency of the services cannot be identified and capacity management cannot be performed with the existing data. Due to the lack of price information, policy recommendation on pricing could not be achieved.

Another limitation is about the survey data. Firstly, the existing survey data belongs to the year 2016. Secondly, although there are more than 330000 surveys in total in the NTMP, only 7028 of them were conducted with rail passengers. Due to low number of surveys, it does not cover all the country and cannot represent the nature of the rail travels throughout the country very well. Therefore desire lines were limited and it is very difficult to be able to scale. It is not very useful to expand the data and four step model could not be performed.

1.4 Layout of the Thesis

After a brief introduction is given in Chapter 1, Chapter 2 presents an overview on intercity rail passenger transportation and chapter 3 reviews travel demand modeling studies. Methodology of this study is described in Chapter 4, analyses on RPF data of Turkey is performed in Chapter 5. While travel behavior for intercity rail passengers in Turkey was evaluated in Chapter 6, forecasting studies for RPF is covered in Chapter 7. Finally, conclusions of the study are given in Chapter 8.

CHAPTER 2

INTERCITY RAIL PASSENGER TRANSPORTATION AND LITERATURE

A study by Jones and Nichols (1983) show that intercity rail travel demand in the UK is highly price-inelastic. Also, it is indicated that the behavior described by the set of relationships used in the study would generate a sample of price-quantity observations. It is found that demand is significantly affected by the level of average fare paid, deflated by the retail price index, by rail journey time, by the level of service offered on competing modes, by the level of cyclical economic activity, and by seasonal factors. There is a very limited evidence of a positive relationship between the demand for travel and population at the provincial end of the rail journey. There is no evidence found that demand is significantly responsive to the changes in train departure frequency within the range of experiments observed in the sample of the study. Also, no consistent evidence found that demand for rail travel is related to variations in real GDP (Jones and Nichols, 1983).

A case study was conducted in 1999 and examined the vehicle trip generation at the intercity rail station in Providence, Rhode Island. It is indicated that the results can be used to make general predictions regarding trip generation trends at other rail transit stations that have similar service and environmental characteristics However, they did not specifically examine the mode split of the overall trip generation (vehicles plus other modes), and recommended such for future research (Young et al, 1999).

Another study showed that the growth in intercity RPF across the U.S. has caused the need for a better understanding of how train passengers make decisions about travel. The study examined the rail station access patterns of passengers on four of

Amtrak intercity rail passenger routes in Michigan and Wisconsin, U.S. Passenger survey data from 2011 and two previous surveys in Wisconsin (2005) and Michigan (2007) were analyzed for trends and patterns in station access and egress trips (Sperry and Warner, 2012).

A different paper analyzes the potential competition of the high speed rail with the main competing modes on the Madrid-Barcelona corridor, where a new HSR infrastructure was recently built at the time the study was performed. The analysis is based upon the estimation of disaggregated Nested Logit models using the information supplied by travelers on the main routes: Madrid-Zaragoza and Madrid-Barcelona. The utility specification considers the influence of the main level-of-service attributes as well as some latent variables on modal choice. The results indicate that the low level of competition that the HSR could exert over air transport services in Madrid-Barcelona corridor, demonstrating that policy makers might have been very optimistic about the figures of traffic diversion from air that could be attained (Roman et al, 2010).

While attitudes of passengers in urban transportation in terms of travel behavior has been reviewed in detail by many studies e.g. (Beck and Rose, 2016; Harvey et al., 2014; Kroesen et al., 2017) intercity rail passenger transportation literature is relatively less focused by scientists. (Losada-Rojas et al., 2019)

Regarding intercity travel, it is stated by Limtanakool et al. (2006) that the relative importance of each of the factors involved in choosing the use of car or rail for medium and long distance trips, such as socioeconomic characteristics, land use, and travel time considerations, depends also on the purpose of the trip. The most engaging factors for rail passengers in the US are comfort, speed, and cost (Drea and Hanna, 2000). Rietveld (2000) also found that access is another important factor for passengers in determining whether to choose rail as a mode alternative.

Long-distance trip is defined as 50 miles from a traveler's home to the farthest destination in the US (Losada-Rojas et al., 2019) and it is in doubt that whether HSR can compete with private cars in the US because 58% of long distance trips are less than 250 miles (or 400 km) in round trip distance and private car trips correspond to 90% of trips longer than 50 miles. However previous studies in Europe and Asia indicate that HSR can have strong potential at a one-way service range between 250 mile and 500 mile (Cho, 2013).

On the other hand, the share of long distance in the total clearly depends on the definition of "long distance", which usually ranges from 50 km to 100 km. Petersen et al. (2009) estimate a 55% share for trips over 100 km (all modes) in Europe; this percentage is decreased to 20% by Emisia (2013), considering only travels more than 300 km. Estimation of Grimal (2010) is 40% for journeys above 80 km, according to the French 2008 National Transport Survey (NTS). Dargay and Clark (2010) described long-distance travel patterns in the UK and estimated that 31% of all distance traveled and 29% of all distance traveled by car correspond to trips over 80 km. Despite the different numbers, it can be concluded that long-distance travel accounts for a significant share of the total passenger-km for cars and for all modes taken together (Aparicio, 2016).

A study conducted in Taiwan was performed to measure willingness to take HSR. The data with 300 subjects was collected from a university in northern Taiwan. Results of analyses show that attitude, perceived behavioral control and subjective norm have positive impacts on behavioral intention of taking HSR. (Hsiao and Yang, 2010)

2.1 Intercity Rail Passenger Characteristics in Turkey

Intercity passenger transportation is a transportation subsector served by different alternatives (air, rail, etc.) with different modal characteristics (cost, travel time, comfort, etc.). However, to understand the relation between the network, modal characteristics and traveler behaviour, it is important to conduct surveys and collect demand data emerging as a result of socio-economic and cultural structure (Akgüngör and Demirel, 2004).

A transport system is desired to be fast, economic, safe, with minimum damage to the environment and suitable with the conditions of the country. The flexibility and the comfort of the road transportation coupled with the economic development over the last 50 years have overturned the balanced market share between the road and rail transportation, creating a dominancy of the former with almost 90% current market share in Turkey (see Table 2.1). Also, establishment of good quality highway networks coupled with lack of investments in network growth and modernization of railways was very critical in this process (Ministry of Transport, Maritime and Communications- MoTMC and ITU, 2005; MoTMC, 2017). Almost negligible share of railways (1.1%) has been criticised in the national policy documents since late 1970s, and led to policy shift in favour of rail investments, more specifically development of high-speed rail (HSR) projects in pursuit of developing more sustainable transportation as well as connection to European rail network (Babalik-Sutcliffe, 2007).

While policy documents and declared goals aimed 10% rail share in passenger transportation by 2023 (MoTMC, 2013), these investments have not resulted in a marked modal shift, yet. Thus, the 2023 target was revised as 3.8% in the 11th Development Plan in 2019 (SBB, 2019). Despite the substantial coverage of rail network through 55 provincial borders, the real accessibility is rather limited when approximately a 30 km-radius capture zone is drawn as shown in Figure 2.1. The rail density differs between the cities as well; some cities have limited rail access in one side of the city, while other may have longer rail corridors with multiple stations. In 2016, rail passenger volumes reached up to 4.32 million passenger-km (pax-km), while 75.6% of this took place on mainline trains, more than half of which (1.87 million pax-km) was on HSR trains (TCDD, 2016). The total ridership of the suburban lines in Istanbul, Ankara and Izmir (155.7 million passengers) is almost 7.5 times of national RPF (20.8 million passengers), showing the limited rail passenger market in Turkey.

Table 2.1 Evolution of Intercity Passenger Transportation Sector in Turkey (MoTMC-ITU, 2005, TCDD Transport, 2017)

Year	Modal Shares (%)				Total Pax-Km (x 10^9)	Rail Statistics		
	Road	**Rail**	**Maritime**	**Air**		**Pax-Km (x 10^6)**	**XC Ridership (x 10^6)**	**Suburban Ridership (x 10^6)**
1950	49.9	42.0	7.5	0.6	5.8	N/A		
1960	72.9	24.0	2.0	0.8	14.9			
1970	91.4	7.6	0.3	0.7	54.2			
1980	94.0	4.1	1.2	0.7	86.2			
1989	94.2	4.9	0.1	0.8	139.1			
2000	95.2	3.1	0.0	1.7	195.1			
2010	97.8	1.6	0.7	-	232.1	3606	24.01	59.90
2011	97.8	1.6	0.6	-	247.8	4002	26.14	59.43
2012	91.5	1.1	0.5	7.0	283.1	3006	19.80	50.36
2013	90.5	1.0	0.6	7.9	296.2	3020	20.89	25.45
2014	89.8	1.1	0.6	8.5	307.5	3458	22.85	55.40
2015	89.2	1.1	0.6	9.1	326.1	3708	23.28	72.04
2016	89.3	1.0	0.3	9.4	337.0	3323	20.96	68.08
2017	88.8	1.0	0.6	9.6	354.5	3683	22.25	63.09
2023 [1]	N/A	**3.8**	N/A					
2035 [2]		**15.0**						

*Civil aviation data could not be obtained for 2010-2011.
[1]Targets for 2023 declared in the 11th Development Plan
[2]Targets for 2035 declared in the 11th Transportation Maritime Affairs and Communications Forum

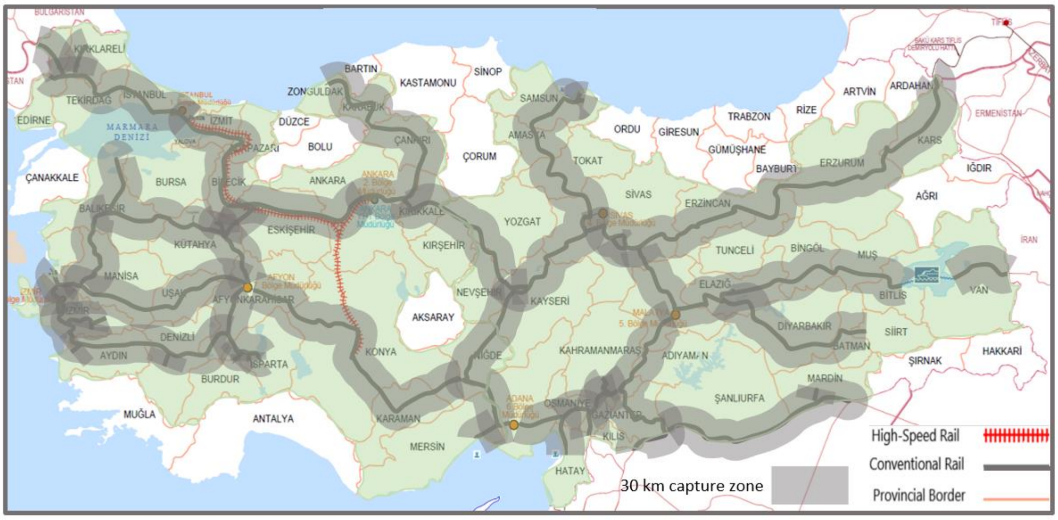


Figure 2.1 Existing Intercity Rail Network Coverage in Turkey Showing Rail Existing Provincial Borders and Rail Passenger Capture Zone

According to TCDD statistics, about 22.5 million passengers were carried annually in average between 2011 and 2018. Statistics also show that high speed usage is increasing every year. Table 2.2 summarizes total rail passenger transport in Turkey between 2011 and 2018. Turkey's rail passenger statistics showed that there are few cities generating/attracting rail passenger demand (see Figure 2.2) such as Ankara and Mersin with more than 3 million travelers annually. It is clear that there is a strong HSR effect in the rail passenger, such as in the case of Konya, which had HSR services in 2011. It is also seen that while the total rail passenger volume in 2018 has reached up to the levels in 2010, the HSR share has been rising constantly since 2010, suggesting that there has been major loses in other conventional lines. According to 2018 data, the rail passenger demand in the listed 20 cities made up to the 91.5% of the total rail passengers. When compared with the city population in Table 2.3, it is clearly seen that there is no direct relationship between population and number of rail passengers: Although İstanbul is the most populated city, it is on the 7th rank in terms of passengers.

Table 2.2 Rail Passenger Transport between 2011 and 2018 in Turkey

	Number of Passengers Carried in the Mainline Railways							
Year	2011	2012	2013	2014	2015	2016	2017	2018
Pax (Million)	26.1	19.8	20.9	22.8	23.1	20.8	22.1	24.1
HSR Share (%)	9	17	20	22	25	28	32	33

Table 2.3 RPF Data for Intercity Rail Travels (TCDD, 2014, 2018)

City	Boarding Passengers (Production-P) (x10^6)						2018 Pop. (10^6)	Trip per 10^6 People
	2010	**2012**	**2014**	**2016**	**2018**	**Change** (2018-2010)		
Ankara	**1.8**	**2.33**	**3.05**	**2.87**	**3.33**	1.53	5.5	0.61
İçel/Mersin	2.93	2.6	2.9	2.76	3.05	0.12	1.81	1.69
İzmir	1.6	2.13	2.8	2.52	2.63	1.03	4.32	0.61
Eskişehir	**1.88**	**1.3**	**1.49**	**1.55**	**1.96**	0.08	0.87	2.25
Adana	1.8	1.68	1.82	1.6	1.91	0.11	2.22	0.86
Konya[1]	0.25	**0.94**	**1.49**	**1.27**	**1.78**	1.53	2.21	0.81
İstanbul[2]	2.93	0.23	0.28	**0.87**	**1.66**	-1.27	15.07	0.11
Manisa	1	0.99	1.64	1.39	1.53	0.53	1.43	1.07
Aydın	0.53	1.03	1.62	1.34	1.43	0.9	1.1	1.3
Zonguldak	0.35	0.15	0.1	0.42	0.79	0.44	0.6	1.32
Denizli	-	0.08	0.22	0.27	0.33	-	1.03	0.32
Sakarya	1.14	0.1	0.01	0.14	0.27	-0.87	1.01	0.27
Kütahya	0.33	0.25	0.11	0.15	0.24	-0.09	0.58	0.41
Karaman	0.09	0.14	0.25	0.12	0.21	0.12	0.25	0.84
Sivas	0.14	0.2	0.35	0.21	0.2	0.06	0.65	0.31
Diyarbakır	0.15	0.09	0.15	0.13	0.18	0.03	1.73	0.1
Erzincan	0.08	0.12	0.13	0.12	0.14	0.06	0.24	0.58
Kayseri	0.12	0.16	0.19	0.11	0.13	0.01	1.39	0.09
Malatya	0.07	0.09	0.16	0.12	0.12	0.05	0.8	0.15
Osmaniye	0.03	0.07	0.09	0.09	0.12	0.09	0.53	0.23
Other	3.75	4.86	4	2.73	2.08	-1.67	38.66	0.05
Total	20.97	19.54	22.85	20.79	24.09	3.12	82	0.29
Total pax-km	3493	2949	3388	3268	4313			
ATD km/pass	167	151	148	157	179			
HSR Ratio	8%	17%	22%	28%	34%			

[1] Konya HSR Line was opened in August, 2011.
[2] Rail services to/from Istanbul was closed during 2012-July, 2014 due to HSR line construction.
Note: Figures in bold shows the number of passengers when HSR line is open in the corresponding city.

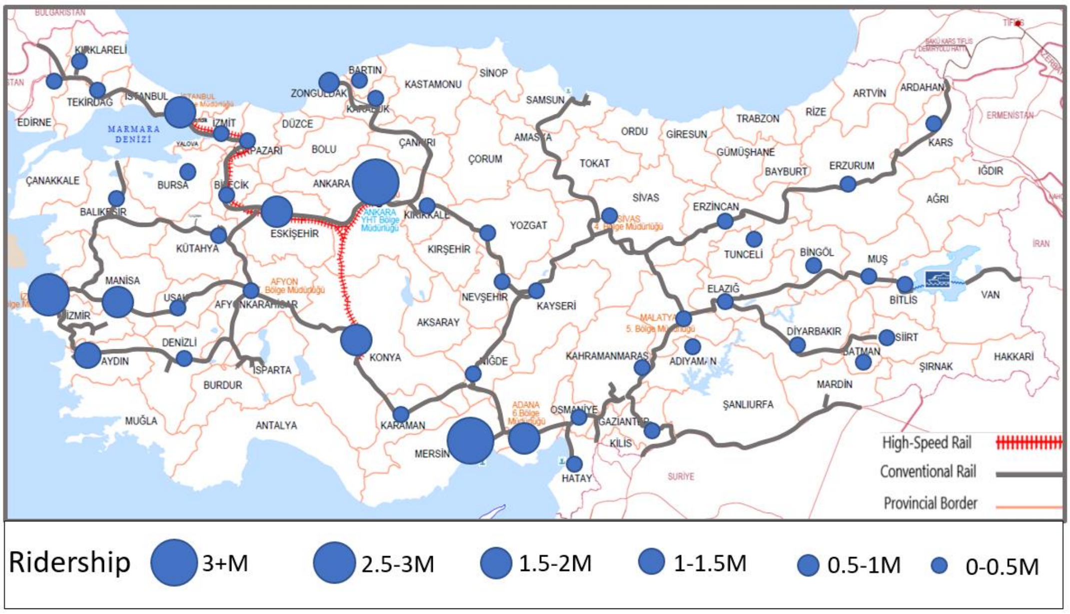


Figure 2.2 Spatial Distribution of Rail Passenger Demand in Turkey in 2018

After long years of duration, Turkey has re-opened its rail age as a developing country but still there's a long way to reach the average condition of European rail network. Also as a candidate member of the European Union (EU), Turkey adapts the mandatory requirements of EU in rail services such as European Norm (EN) standards and Technical Specification for Interoperability (TSI). Table 2.4 shows a comparison between Turkey and other countries in terms of length of highway and railway, density of railway (railway per 1000 km^2), and railway/population ratio with the data of year 2018.

Table 2.4 Comparison of Land Transportation Modes between EU Countries (2018) (TCDD, 2019)

Country	Area (10^3 km^2)	Population (10^6)	Length (x10^3 km)		Railway Density	
			Road	Rail	per 10^3 Km^2	per 10^6 people
EU28	**4460**	**511**	**1975**	**216.9**	**49**	**4.2**
Germany	357	83	230	38.4	108	4.6
France	633	67	399	28.1	44	4.2
Poland	313	38	175	19.2	61	5.1
Italy	301	60	183	16.8	56	2.8
UK	244	66	86	16.3	67	2.5
Spain	506	47	166	15.4	31	3.3
Sweden	450	10	173	10.9	24	10.7
Romania	238	19	53	10.8	45	5.5
Turkey	**785**	**82**	**68**	**10.3**	**13**	**1.3**
Czechia	79	11	56	9.6	121	9
Hungary	93	10	32	7.7	83	7.9
Finland	338	6	78	5.9	18	10.7
Austria	84	9	38	5.5	66	6.5
Bulgaria	111	7	20	4	36	5.7
Slovakia	49	5	8	3.6	74	6.7
Belgium	31	11	16	3.6	118	3.2
Netherlands	42	17	13	3.1	74	1.8
Croatia	57	4	18	2.6	46	7
Portugal	92	10	14	2.5	28	2.5
Greece	132	11	42	2.2	17	2.1
Ireland	70	5	18	2	29	4.2
Denmark	43	6	73	2	46	3.4
Lithuania	65	3	21	1.9	29	6.8
Latvia	65	2	7	1.9	29	9.7
Slovenia	20	2	12	1.2	60	5.8
Estonia	45	1	41	1.2	26	8.8
Luxemburg	3	1	3	0.3	104	4.5

2.2 Intercity Rail Passenger Characteristics in the European Union

Regarding rail transport, the number (N) of passengers (pax) traveled on national railway networks in the EU in 2018 is 8 billion (Table 2.5). It is important to note that international transport figures represented less than 8% of the total rail passenger transport for almost all countries. Only exception is Luxembourg where it represented 26%. The total number of passengers transported in 2018 increased in 19 of the EU-27 Member States ─ and decreased in three countries comparing to 2017.─ in (Cyprus and Malta have no railways, and the data is confidential for Belgium, Hungary and the Netherlands). The highest increases are seen in Lithuania (+11.7%), Greece (+9.4%), Sweden (+7.3%) and Austria (+7.1%). The candidate country Turkey also rose substantially (+17.8%). On the other hand, the number of passengers decreased by 3.9% in Romania and 2.4% in France. While France is the highest at average travel distance (ATD), Turkey ranges in the middle. (Eurostat, 2020b).

An empirical study of modal choice routines was carried out for Barcelona, Spain (Garcia-Sierra et. al., 2018). They analyzed the passengers of different modes in 7 behavioral segments. The segments obtained later have profiles on where they reside, socioeconomic features, access to a car, and other factors related to routines becoming habits - (low) use of travel information and the disproportionate use of preferred means of transportation. The results give a clue about how to design environmental policy for transport. The results also suggest exploring formation of driving habits for Barcelona in depth.

Also, some studies focus on traveler behavior of passengers with a specific purpose. Delaplace et al. (2014a) investigated interactions between HSR systems and tourism market. They proposed that HSR routes may contribute to the development of tourism since tourism is based on mobility behavior naturally. To support this, a further study was performed analyzing results of revealed preference survey conducted with tourists in Rome (152 participants) and Paris (226 participants). It was found out that HSR system effect on destination choice showed difference between Rome and Paris. Almost half of the respondents (49%) were positively affected by the existence of HSR in the destination choice in Paris while only 26% of the Rome respondents were influenced positively. The study was concluded with stating reason of the difference might be the difference of history of HSR in the countries where the sample cities were located (Delaplace et al., 2014b).

Table 2.5 Rail passenger transport statistics in EU (Eurostat, UIC)

Country	All[1]			HSR[2]		
	Pax-km ($x10^6$)	Pax ($x10^3$)	ATD (km)	Pax-km ($x10^6$)	Pax ($x10^3$)	ATD (km)
EU-27	380154	8003672	47.5	-	-	-
Bulgaria	1457	20534	71.0	-	-	-
Czechia	8515	182513	46.7	795	2974.0	267.2
Denmark	5764	192211	30.0	-	-	-
Germany	93112	2865171	32.5	31067	93303.0	333.0
Estonia	396	7652	51.8	-	-	-
Ireland	2210	47546	46.5	-	-	-
Greece	1102	16778	65.7	-	-	-
Spain	27660	595114	46.5	16126	42002.0	383.9
France	83840	1206606	69.5	56808	106329.0	534.3
Crotia	726	19942	36.4	-	-	-
Italy	54385	863992	62.9	-	-	-
Latvia	584	18075	32.3	-	-	-
Lithuania	339	4300	78.8	-	-	-
Luxembourg	313	17155	18.2	-	-	-
Austria	12226	262719	46.5	-	-	-
Poland	20512	297230	69.0	1550	4346.0	356.8
Portugal	4487	147408	30.4	661	2207.0	299.6
Romania	5392	64539	83.5	-	-	-
Slovenia	524	12677	41.3	2	14	128.5
Slovakia	3684	73380	50.2	-	-	-
Finland	4392	86951	50.5	795	3198.0	248.6
Sweden	13058	235330	55.5	3523	9733.0	362.0
United Kingdom	67736	1762710	38.4	-	-	-
Norway	3684	77298	47.7	-	-	-
Switzerland	18157	482376	37.6	-	-	-
North Macedonia	63	534	118.0	-	-	-
Turkey (all)	5499	100368	54.8	2551	8104.0	314.8
Turkey[3] (intercity)	4313	24089	179.0	-	-	-

(-) not available

[1] Values are taken from Eurostat

[2] Values are taken from UIC Statistics

[3] Values are taken from TCDD Statistics

Note: Passsenger and Passenger-km figures in "All" include suburban transport.

CHAPTER 3

REVIEW OF TRAVEL DEMAND MODELING STUDIES

3.1 Rail Passenger Demand Modeling Studies

The history of demand modeling for person travel has been dominated by the modeling approach that has come to be referred to as the four-step model (FSM). Travel, always viewed in theory as derived from the demand for activity participation, in practice has been modeled with trip-based rather than activity-based methods. Trip origin-destination (O-D) rather than activity surveys form the principle database. The influence of activity characteristics decreases, and that of trip characteristics increases, as the conventional forecasting sequence proceeds. The application of this modeling approach is almost universal, as in large measure are its criticisms. The current FSM can be analyzed in 2 phases. In the first phase, different characteristics of the traveler and the land use - activity system (and to a varying degree, the transportation system) are "evaluated, calibrated, and validated" to produce a non-equilibrated measure of travel demand (or trip tables). In the second phase, this demand is loaded onto the transport network in a process more than just the formal balancing of route selection and not other choice dimensions such as destination, mode, time of day, or whether to travel (feedback to previous phases was often introduced, but not in a consistent and convergent way). Although this approach has been moderately successful in the aggregate, it has failed to perform in most relevant policy tests, whether on the demand or supply side (McNally, 2007). The classical 4-step model is simply represented by a sketch by Ortuzar and Willumsen (2011) as in Figure 3.1:

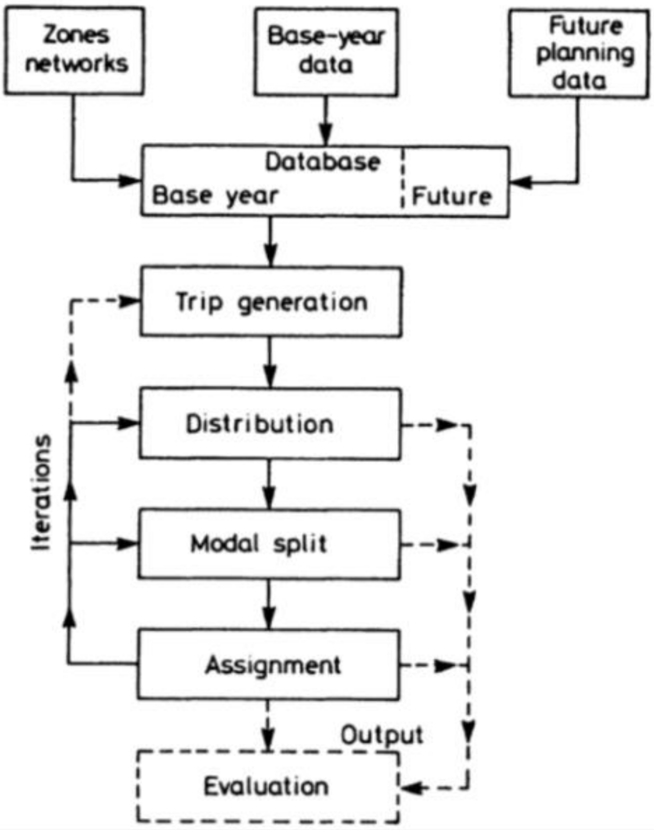


Figure 3.1 The classical 4-step transportation model (Ortuzar and Willumsen, 2011)

3.1.1 Intercity Passenger Travel Studies in General

A study in the UK by Wardman et. al. (2007) tells that the direct demand modeling approach so-called because it deals directly with variations in total rail demand rather than its separate components of trip generation, distribution, and mode choice, has allowed the estimation of a large number of influences on rail demand. These include: factors external to the rail industry, such as GDP, car ownership, employment levels, and competition from other modes as well as various aspects of rail service quality, such as journey time, service frequency, interchange and rolling stock. Methodological developments have been made in this study to allow station access and egress time elasticities to be estimated when the ticket sales data upon which the models are calibrated relate only to station-to-station movements and without the need for any supplementary data. Further enhancements relate to the functional relationship between rail demand and access and egress time and modeling competition between stations.

Dogan et.al. (2006) investigated the intercity transport demand of university students who are forming part of the society which has one of the highest mobility. In this scope, passenger transport demand of Ataturk University students from Erzurum to the other cities in Turkey was analyzed. According to the results of 556 interviews conducted with students of Ataturk University, it was found out that the most preferred mode is bus with 90% and then air with 9%. The rail and private car usage is at very low level (1%) as expected. When the intercity trips of students in all modes were considered, it is observed that as the number of studying family members is increasing, tendency to intercity trip making decreases. Beside this, application of discounted tariffs and increase in the income of student are variables that affect students' trip making positively.

3.1.2 Rail Passenger Studies in the World

Most of the rail passenger studies are in corridor level or based on a specific location and focused on modal split or captive ridership between different modes, rather than national scale e.g. Hsiao and Yang (2010), Danapour et al (2018). Surveys were generally conducted with passengers at a certain location or along specific routes.

A recent study by Chan and Yuan (2017) analyzed the effect of HSR on traveler behavior in China through the survey with a sample of 328 passengers from the Xiamen- Shenzhen Railway (XSR). The results showed railway partly caused modal shifts by diverting passengers from other transport modes to the study corridor. Among the expected effect of age, occupation and income, only significant factor found was income as XSR preference was increasing with monthly personal income. However contextual analysis is required to allow a model workable and conditions comparable in specific regions or connection of destinations.

Socio-demographic parameters are quite important in travel behavior patterns. A study in Japan’s Keihanshin (Kyoto-Osaka-Kobe) metropolitan area analyzed the composition of urban activities and travel characteristics among intracity rail passengers. It showed that there is a high level of correlation between facility development around railway station and railway usage patterns for leisure. Furthermore, it was suggested that travel behavior of each age group should carefully be analyzed in future development projects for railway stations and urban planning (Akiyama and Okushima, 2009).

Analyzing responses of 320 interviews (with 88% return rate success after validation) at 16 main stations in China, Chen et al. (2016) stated that there was a change in travel behaviour of residents and the households with the construction of Beijing-Shanghai HSR line. It was found out that main purposes of HSR passengers were work (66.3%), tourism (28.7%) and visits to friends and relatives (26.2%). The survey results also showed that 50.7% of the respondents traveled by HSR more than once a month. This study supported that HSR enabled intercity family migration to some extent; as popularity of HSR grows, it is expected that families would settle in developed cities more, while urban household migration would occur between these developed cities (Chen et al., 2016).

HSR projects played a significant role in Iran’s investments. Danapour et al. (2018) analyzed the competition between the proposed HSR service and air transport on Tehran-Isfahan route. A survey was conducted in the Mehrabad Airport of Tehran between January and April 2015 in the scope of the study. Analyses of the 437 questionnaires collected in the survey were performed, after identifying the variables of ticket price, travel time, hospitality and convenience by reviewing past studies. Having developed the binary logit model for choice of the two modes, they concluded the study with the finding that travel time is the most important variable in determining the share of each mode, given that all these variables above-mentioned compete to influence decisions.

In a study by Gutierrez and Ortuno (2017) on passenger profiles and travel behavior of the HSR passengers near touristic destinations on the Mediterranean Coast, a logistic regression model was developed showing the effect of passenger profile (i.e. gender, age, education level), trip characteristics (i.e. trip purpose, egress mode choice, traveling in a group or alone) and stay conditions (i.e. type of accommodation, length of stay) on the use of HSR services to coastal destinations.

As indicated by Cheng (2009), the introduction of HSR is considered to have spatial and socio-economic impacts on regional development. However, the socio-economic benefit of HSR needs substantial investments. The impacts from HSR on the existing transportation modes of the intercity transportation market seem significant. In terms of market scope in the intercity transportation market, there are typical time thresholds relating to the lower and upper bounds in which HSR has a clear advantage based on previous experiences in Japan, France and Germany. These thresholds are between 1-3 hours by riding on the HSR, representing distances between 200-600 km, and based on an average operating speed of 200 km/h. This distance can increase along with improved HSR technology, as the operating speed can reach up to 300 km/h and the high-speed threshold can be upgraded to at least 700 km (Paris-Marseille and Madrid-Barcelona are both more than 600 km long).

3.1.3 Rail Passenger Studies in Turkey

Rail transportation studies in Turkey are mostly on material and system design, environment and sustainability and with a focus on freight transport, where rail passenger behavior has not been much studied. Since the start of HSR services in Turkey, different HSR studies were conducted on areas including a) customer satisfaction and service quality evaluations, b) HSR preference and Value of Time (VoT) studies and c) environmental impact evaluations (emission reduction, life cycle assessment etc.). Customer satisfaction studies showed that in-train services and service personnel attitudes were very important for HSR users (Sarı et al., 2011; Ayyildiz-Alçura et al., 2016). In terms of HSR preference in Turkey, travel time saving was the most important factor followed by cost, comfort and safety (Kılıçlar et al., 2010). A study on potential users of HSR emphasized that a passenger shift was possible from road to railways as a result of these HSR investments particularly when connections were made to remote parts of the country, such as south-eastern Turkey while intercity travels are often long-distance (Dalkic, 2014). In a study by Celikkol-Kocak (2017), importance of the effects of city socio-economics in terms of potential ridership was investigated, based on a rail passenger survey conducted at 4 HSR stations in Turkey. Purpose of the survey was to collect data on i) intercity mode choice of HSR users for different trip purposes, ii) alternative modes preferred in HSR corridors and iii) user perspectives on modal service attributes (i.e. travel time, cost, safety, etc.). Growing demand of HSR was seen mostly among those who were experiencing HSR for the first time. It is stated in the paper that main trip purpose of the sample was business and education. Also, many of the respondents stated their important factor in their HSR trip was travel time, safety and punctuality. Another study (Tuydes-Yaman and Dalkic, 2018) showed that passengers use bus ticket prices as a basis when determining HSR usage. Also, the study demonstrated that preferability of HSR is high as long as ticket prices are lower than air tickets. The statements were supported with figures from results of the survey conducted in the scope of this study. 421 HSR passengers were interviewed in November and December months of 2014. Almost all (more than 90%) of the respondents stated that they would choose HSR if the ticket prices are lower than bus and air tickets. However, only 18.7% told they could choose HSR if it's more expensive than air service.

3.2 Demand Forecasting for Passenger Transportation

A review of the available literature reveals that even though there have been many previous studies on modeling and forecasting passenger demand applied to monthly and annual data sets, little research is available on a daily basis. Although daily passenger data can be collected by institutions, most researchers appear to use annual or monthly data to model and predict passenger flows. Çuhadar (2014) modeled daily air passenger demand at Antalya Airport using the Autoregressive Integrated Moving Average (ARIMA), which is also known as Box-Jenkins methodology. It is also observed that there is no study published in academic journals on modeling and forecasting rail passenger demand in Turkey. All this led the author to focus on modeling and predicting rail passenger demand in Turkey to fill this gap.

In traditional parametric techniques, the historical average (Smith, Demetsky 1997; Stephanedes et al. 1981), smoothing techniques (Williams et al. 1998) and ARIMA (Hansen et al. 1999; Williams et al. 1998; Lee, Fambro 1999; Williams 2001; Kamarianakis, Prastacos 2005) are applied to estimate transport demand.

The most popular short-term traffic flow estimation method was reported by Wang et al. (2018) as a time series model. The general features of such a model are to set up the data series model using only historical traffic situation measurements and simplify the traffic flow as a linear system. The uncertainty of the traffic flow is assumed to be due to external random input factors, and the statistical assumption about these factors is made to establish the corresponding mathematical model, usually a linear equation plus random terms. ARIMA-family models are the most widely analyzed and used time series models (Mascha et al., 1996).

In the parametric methods class, ARIMA has become one of the common parametric estimation approaches since the 1970s (Wei, Chen 2012). The ARIMA model, presented by George Box and Gwilym Jenkins, has been one of the most popular approaches to prediction. ARIMA models have been successfully applied for modeling in the transportation literature but mostly for air transportation (i.e. Postorino & Russo, 2001; Lee et al. 2005; Lai & Lu 2005; Andreoni & Postorino, 2006; Pitfield, 2008; Samagaio & Wolters, 2010; Min et al. 2010; Xie et al. 2014). These models are based on a statistical modeling theory known as the Box - Jenkins methodology. The ARIMA modeling approach expresses the current time series value as a linear function of the past time series values (AR) and the current delayed values of a white noise process (MA) (Çuhadar, 2014).

Ahmaed and Cook (1979) first used the ARIMA model for highway flow estimation in the field of transportation. Williams et al. (1998) applied the seasonal ARIMA model for urban traffic flow estimation and the model has been reported to produce good performance. Luo and others (2015) proposed a non-linear regression model to forecast the aggregated passenger volume of Beijing–Shanghai high-speed railway (HSR) line in China. They stated that with a definite formation, their proposed model can be further used to forecast the effects of train planning policies. Woroniuk et al. (2013) investigated rail freight services by the private sector through Europe and evaluated the corridor using time series analysis.

3.2.1 ARIMA Models

A time series is a series of observations taken sequentially over time. Many datasets emerge as time series: a monthly series of the quantity of goods shipped from a factory, a weekly series of the number of road accidents, daily precipitation amounts, hourly observations on the yield of a chemical process, etc. There are many examples of time series in fields such as economics, business, engineering, natural sciences (especially geophysics and meteorology), and social sciences (Box et al, 2016). ARIMA models presents an approach to time series analysis. Exponential smoothing and ARIMA models are the two most commonly used approaches to time series analysis and present complementary approaches to the problem. Exponential smoothing models rely on an explanation of trend and seasonality in the data, while ARIMA models aim to explain autocorrelations in the data (Hyndman & Athanasopoulos, 2018).

ARIMA models are based on Auto Regressive Model (**AR**), Moving Average Model (**MA**) and combination of **AR** and **MA**, **ARMA** models. The **AR** model contains lagged terms in the time series itself, and the **MA** model contains lagged terms related to noise or residuals. The first requirement for **ARIMA** modeling is that the time series data to be modeled are stationary or can be converted to stationary. Therefore, the letter "**I** (Integrated)" means that the first order difference is applied to stabilize the given time series (Suhartono 2011).

AR polynomial term of degree p,

$$\emptyset_p(B) = 1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p \qquad \text{Eq. 3.1}$$

MA portion of degrees q,

$$\theta_p(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_p B^p \qquad \text{Eq. 3.2}$$

The differentiation operator, $(1\text{-B})^d$, is the degree d used to eliminate polynomial trends.

The Box-Jenkins method essentially includes three steps to align the **ARIMA** model. These are the determination, prediction and verification of the model (Box et al. 2016; Prista et al. 2011). The first step is generally based on Autocorrelation Function (**ACF**) and partial **ACF** (**PACF**) analysis and comparison with theoretical profiles of these functions in **AR**, **MA** and **ARMA** processes. The appropriate $(p,d,q)\text{x}(P,D,Q)_S$ model structure is determined as the output of the identification step. The model structure selected in the previous step must be matched to the time series and parameters to be estimated. This is the essence of the second step and is done using the conditional sum of squares or maximum likelihood method (Milenković et al., 2015). The verification of the selected model is carried out within the scope of diagnostic control by analysis of the presence of stationarity, invertibility and redundancy in the model parameters. If a selected model fails the diagnostic check, it is necessary to repeat the entire procedure. Once a suitable model is found, it can be used for prediction (Box et al. 2016; Prista et al. 2011).

3.2.2 Regression Models

Regression analysis is a method used to measure the relationship between many variables. If the dependent variable is studied based on a single independent variable, it is called univariate regression; whereas it is called a multivariate regression analysis, when two or more independent variables are used to explain the dependent one. A typical multi-variate regression equation is as follows:

$$Y = a_0 + a_1 x_1 + a_2 x_2 + \cdots + a_n x_n \qquad \text{Eq. 3.3}$$

Where **Y** is the dependent variable and $\boldsymbol{X_i}$ are the independent variables, n corresponding to number of variables.

Armstrong (2001) categorized methodology for demand forecasting as qualitative and quantitative methods. In the quantitative forecasting group, with different data sources, methods can be further divided into time series analysis and causal methods. Time series methods use only the time series history of the variable being estimated in order to predict future values, and popular model prototypes have exponential smoothing methods, moving average methods and later advocated ARIMA method (Luo et al, 2015). In order to compare these methods, Makridakis et. al. (1982) performed a competition in forecasting accuracy of these time series methods on their time series data. Time series model is appropriate when there is not much information about the factors influencing a variable to be forecast. However, as Wickham (1995) discussed, this methodology is based on the premise that the pattern in the past is very relevant with the future, but has the weakness that it fails to include the determinant of demand.

The impact is difficult to measure when there are changes in factors such as population and the nature of transport variables. As a comparison, estimation methods based on causal factors may make up for the shortcomings of the time series methods mentioned above. This methodology can form the relationship between a dependent variable and one or more casual variables. With the formed relationship, factor-based methods for the transportation problem can be used to examine the elasticity of various determinants on demand or to estimate the effects of different policies. (Luo et al, 2015)

Varagouli et al. (2005) developed multiple linear regression models for the travel demand of Xanthi in northern Greece using variables such as number of cars, GDP, population. Similarly, multiple linear regression models by Anderson et al. (2006) were developed to estimate travel demand for a small urban area, Anniston, Alabama, using socioeconomic effects and roadway characteristics (such as functional classification and number of lanes). Blainey and Mulley (2013) used a geographically weighted regression to estimate rail demand in New South Wales, Australia using variables such as population and employment of the catchment area, income and age profile, household size, car ownership rates, to get the most accurate estimate. Sivrikaya and Tunç (2013) applied a semi-logarithmic regression model to forecast the air transportation demand in Turkey, estimating passenger flow between 42 cities using variables such as population, GDP, bed capacity, etc.

CHAPTER 4

METHODOLOGY

As a first step of the methodology, extensive research was performed on transportation modeling, especially with a focus on rail passenger transportation. This research is mainly based on railway transportation sector and passenger oriented. There are 2 major data sources for this study: Rail passenger flow data which is on daily basis from station to station and the data of rail passenger survey which was conducted by the Ministry of Transport, Maritime Affairs and Communications in 2016 (see framework in Figure 4.1).

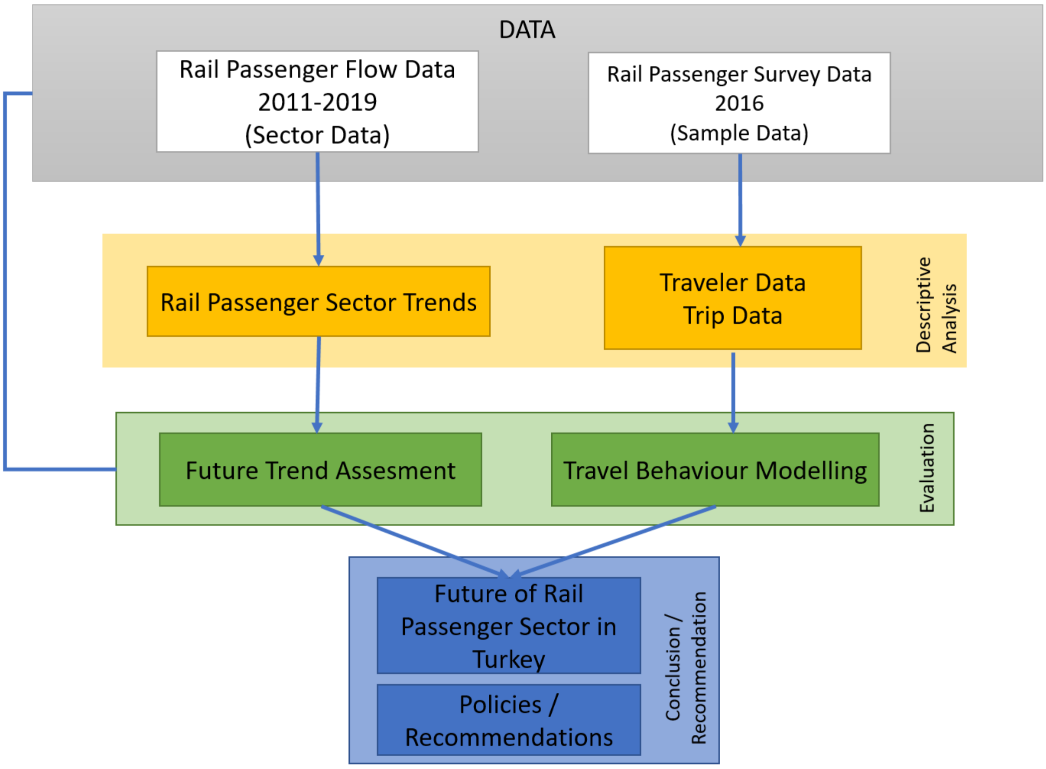


Figure 4.1 Framework of the Methodology

Rail passenger flow data for all intercity railway passengers on a daily basis has been obtained for the years between 2011 and 2020. However, as 2020 data is so different from other years due to pandemic, analyzes were performed on 2011-2019 data. This data is important to understand the seasonal variability in trips. Also, this data shows which stations are used mostly and how much volume the rail services have in terms of O-D pairs. These analyses were performed to figure out if there are any specific trends in intercity rail passenger flow in timely manner. Also, ARIMA and regressive forecasting methods were applied on this data and estimation power of the forecasting methods were measured.

Beside this, there are 332142 passenger interviews, 7028 of which were conducted at train stations in 2016 as part of National Transport Master Plan study for Turkish Republic. Results of this survey were evaluated in this thesis and a general overview was performed on these results. First, some inconsistency checks have been done as part of data cleaning process to remove illogical results in order to prevent any bias in the analyses. After that, evaluation have been made on the answers of questions such as trip frequency, trip purpose, car availability, reason of choosing that mode, income level, etc. These results have been investigated deeply in order to understand the characteristics of passengers in each category and show rail passenger profile in Turkey in general. Also, for certain regions results were investigated and compared in order to find out if there are any differences in rail travelers' characteristics between regions. Additionally, high-speed effect on passenger characteristics was analyzed considering several criteria to see if the characteristics of HSR passengers differ from ConvRail passengers.

Based on the data abovementioned, it is discussed in this thesis what triggers trip making and what rail passengers pay attention to in their trips for business purpose trips. A binary logistic regression model was formed in order to analyze the factors affecting the likelihood of trip making for business purpose travelers.

4.1 Travel Behaviour of Rail Passengers in Turkey

To understand travel behavior and travel characteristics, survey results were analyzed. A binary logistic regression was performed in order to identify passenger profile of a business purpose rail traveler. Different variables such as gender, age, trip purpose, trip frequency, car ownership and service type (HSR or Conventional) were used in the model. It is aimed to find out what is a business trip passenger profile. The data was classified in order to conduct a binary logistic regression model according to the criteria in Table 4.1:

Predicted logit

$$l = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 \mathrm{D}_{\mathrm{male}} + \beta_2 \mathrm{D}_{\mathrm{young}} + \cdots. \quad \text{Eq. 4.1.}$$

where p stands for probability of being a business traveler at a rail station.

4.2 Rail Passenger Forecasts for Turkey

Rail demand forecasting methodology used in this study takes into both modeling approaches: on one side, a multivariate regression model was developed using the daily RPF data between 2011-2015 and used to forecast a full-year daily RPF for the period of 2016-2019 (FReg). Alternatively, an ARIMA model was created using the same data of 2011-2015; later a series of ARIMA model based forecasts were performed using different updating options: First, ARIMA-Stable and ARIMA-Sliding methods in itself and second regression which is based on special dates and events throughout the year. Later, these forecasts were verified with Measure of Effectiveness defining their error terms. Flow chart of the methodology is presented in Figure 4.2. There are 2 forecast methods for ARIMA: ARIMA-Stable and ARIMA-Sliding. ARIMA-Stable calculates dynamic, multi-step forecasts starting from the first period in the forecast sample. Previously forecasted values for the lagged dependent variables are used in forming forecasts of the current value. ARIMA-Sliding calculates a sequence of one-step ahead forecasts, using the real, rather than forecasted values for lagged dependent variables, if available.

Table 4.1 Variables used in the model

Variables	
D_{male}	1 if the passenger is male; 0 if female,
Age	Exact age of the passenger
D_{young}	1 if the passenger is less than 25 years old, 0 otherwise
$D_{midage1}$	1 if the passenger's age is between 25-44, 0 otherwise
$D_{midage2}$	1 if the passenger's age is between 45-60, 0 otherwise
D_{old}	1 if the passenger is more than 60 years old, 0 otherwise
D_{comm}	1 if the trip purpose is commute, 0 otherwise
D_{edu}	1 if the trip purpose is education, 0 otherwise
D_{work}	1 if the trip purpose is travel for work, 0 otherwise
$D_{leisure}$	1 if the trip purpose is leisure, 0 otherwise
D_{trsm}	1 if the trip purpose is tourism, 0 otherwise
D_{shop}	1 if the trip purpose is shopping, 0 otherwise
D_{pers}	1 if the trip purpose is personal business, 0 otherwise
D_{VFF}	1if the trip purpose is visiting friends and family, 0 otherwise
D_{crry}	1 if the trip purpose is carrying or delivering goods, 0 otherwise
$D_{hmbased}$	1 if the trip is home based, 0 otherwise
D_{1day}	1 if the return is on the same day, 0 otherwise
TrpFrq	Trip frequency: 22 if daily, 4 if weekly, 1 if monthly, 0.5 if less than once a month, 0.1 if annually, 0.01 if non-periodic
D_{daily}	1 if the frequency of the trip is daily
D_{weekly}	1 if the frequency of the trip is weekly
$D_{monthly}$	1 if the frequency of the trip is monthly
$D_{lessmonth}$	1 if the frequency of the trip is less than once a month
$D_{annually}$	1 if the frequency of the trip is annually
$D_{nonperiod}$	1 if the trip is nonperiodic
D_{1way}	1 if the ticket type is single (one way), 0 if return
income	Monthly net household income
$D_{income1}$	1 if less than 500 Euro; 0 otherwise
$D_{income2}$	1 if between (500 - 1,000 Euro); 0 otherwise
$D_{income3}$	1 if between (1,000-2,000 Euro); 0 otherwise
$D_{income4}$	1 if (More than 2,000 Euro), 0 otherwise
D_{car}	1 if there is private car available for the trip, 0 if there is not
D_{HS}	1 if passenger is traveling with High-Speed Train, 0 if conventional

Using these methods, first the whole year of 2016 was forecasted. These are called DRPF forecast ARIMA Stable (FA-St) and DRPF forecast ARIMA Sliding (FA-Sld) respectively in this study. After that, ARIMA-Stable forecast of 14 days was made for the total of year 2016, feeding the data each time (Full year forecast-weekly updated). For example, 1st January - 14th January period was forecasted, 1-7 January was noted as week 1 (FA-St-1W) forecast and 8-14 was week 2 (FA-St-2W). Then, real values of 1-7 January were defined in the model and forecast for 8-21 January was made. This process was repeated until the end of 2016 each time. So weekly forecasts were obtained in ARIMA-Stable method with this.

After ARIMA calculations were finished, regression models were formed for forecasting. Special dates were defined and introduced in the model, according to the model, forecasts were made for the years 2016-2019. A growth rate is also defined in the model for the growing pattern of the total passenger numbers, allowing the data to be on trend.

After forecasts were made, the real values and forecasted values were compared and error terms were defined. Measures of Effectiveness (MoE) analysis was performed in order to see the achievement of the forecast models. Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) were calculated. Forecasted values of the regression model were plotted versus the observed values on the same graph, equation of the fitted line and R^2 values were determined.

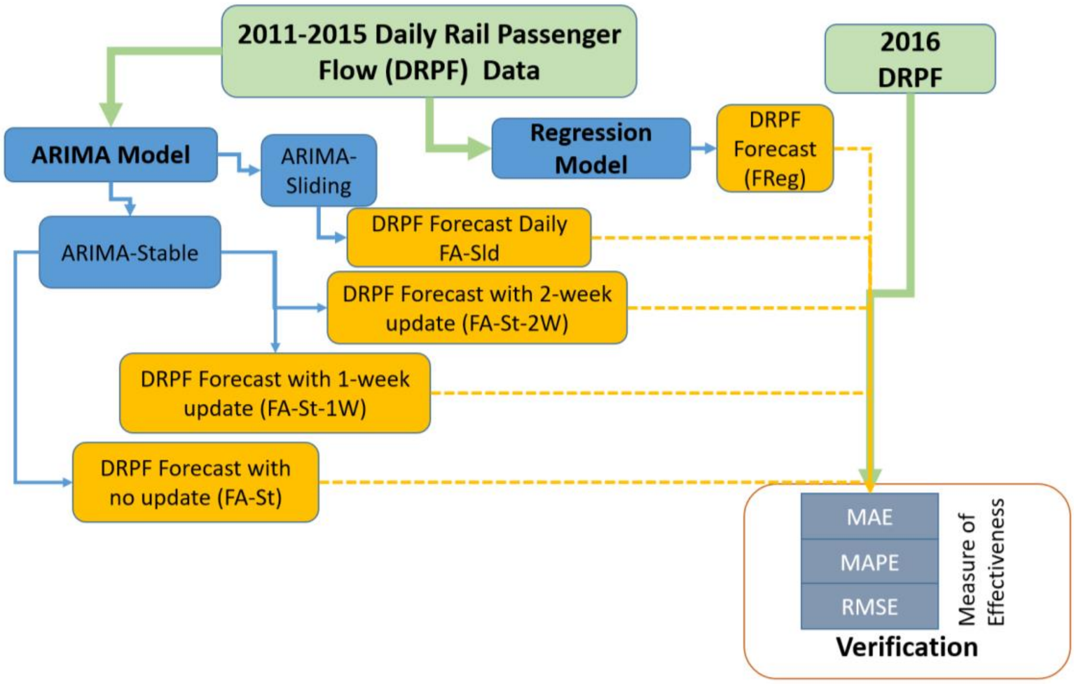


Figure 4.2 Comparative Rail Passenger Flow Forecasting Methodology

4.2.1 ARIMA Models

ARIMA was used in this study to forecast the number of passengers (NPax) using rail transport in Turkey. The most important part of the ARIMA forecasting process is analyzing the data set of the variable that is trying to be predicted. Box-Jenkins prediction algorithm was used for modeling. The stationary condition of the Box-Jenkins modeling method must be met during the determination of the model. Time series data is based on the number of passengers of Turkey rail transport between January of 2011 and December of 2015.

The forecasted data is compared with the data realized in 2016 as shown in Figure 4.3. Since the forecast is stable (with no update), it does not exactly match the actual data. However, sliding (with update) data shows very similar profile to the real data.

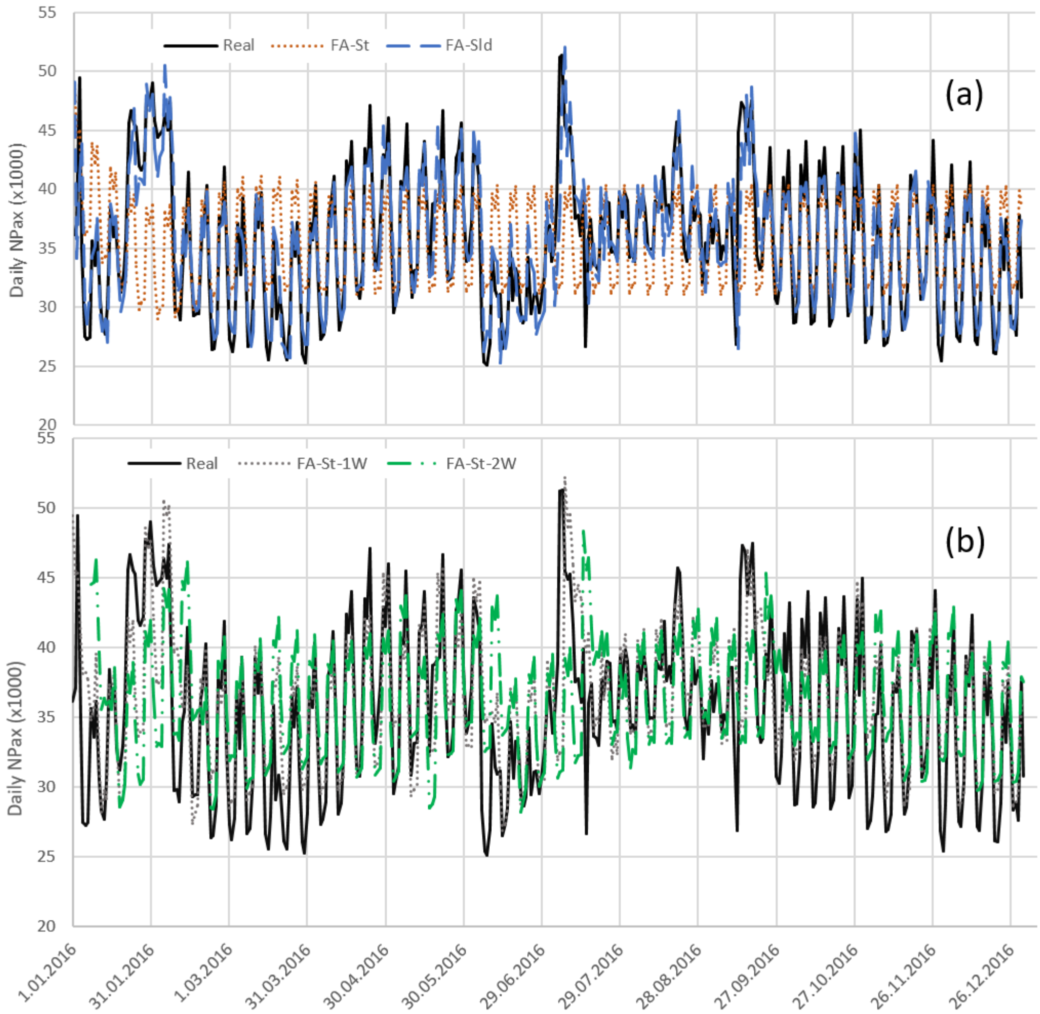


Figure 4.3 Comparison of actual and ARIMA forecasts for Daily Rail NPax for 2016 using (a) with no update (FA-St) and with daily update (FA-Sld) and b) weekly updated (FA-St-1W) and 2-weekly updated (FA-St-2W)

4.2.2 Regression Models

Regression model was applied to the data to see the effect of special events on the date. For example, religious holidays and school breaks were defined in the regression model and forecasts were made considering these special dates. Each day of the week has a unique travel pattern so each day (Mon, Tue, Wed…) was defined in the model. Similarly, solar calendar’s months are defined because national holidays and school breaks are formed according to the official calendar of Turkey.

Holidays in a year were divided into categories of short (if a holiday is shorter than 3 days, such as a weekend), medium (holidays lasting 3-14 days such as winter breaks) and long (longer than 2 weeks, such as summer holiday season). There are 2 official school breaks in a year in Turkey. First is winter break which is usually formed of 15 days, covering the last week of January and the first week of February. Summer break generally starts at the middle of June and ends at the second week of September.

When the national holidays correspond to Friday or Monday, the weekend holiday extends to 3 days and people tend to travel more. Therefore weekend duration is added to the model. Duration of the holiday is also assumed to be important because it might affect the tendency to go on holiday.

The holy month Ramadan, which is based on lunar calendar, is the month in which Muslims fast. Therefore, tendency to go out reduces and because of that, mobility decreases in this month. Also, in the holy days of Islam, Eid al Fitr and Eid al Adha, it is a ritual to go to visit relatives. Therefore, before these days, mobility increases but on the day of the Eid, because people are with their family, the mobility is not as much as the day before or the day later. Variables used in the regression model and their explanations are given in Table 4.2.

Table 4.2 Variables used in the model and explanations

Variable	Variable Explanation	
NPax	Number of daily rail passenger	
D_{Mon}, D_{Tue}, … D_{Sun}	Dummy for day-of- week	1 if it is the day considered; 0 otherwise
D_{jan}… D_{dec}	Dummy for month-of-the year	1 if it is the month considered; 0 otherwise
D_{sh}	D Short Holiday	1 if the holiday is shorter than 3 days, 0 otherwise
D_{mh}	D Medium Holiday	1 if the holiday is between 3 days and 14 days, 0 otherwise
D_{lh}	D Long Holiday	1 if the holiday is longer than 14 days, 0 otherwise
D_{wb}	D winter break	1 if it is winter break, 0 otherwise
D_{sb}	D summer break	1 if it is summer break, 0 otherwise
dur_wknd	Weekend duration	3 if long weekend (Monday or Friday included), 2 otherwise
dur_hldy	holiday duration	Duration of religious holidays
D_{Ram}	Ramadan Dummy	1 if it is a day of Ramadan, 0 otherwise
D_{eid1}	D eid al fitr	1 if it is Eid al Fitr (Ramadan) holiday; 0 otherwise
D_{eid2}	D eid al adha	1 if it is Eid al Adha (Qurban) holiday; 0 otherwise
GR	Growth Rate	Ratio of annual NPax compared to 2012

4.2.3 Measures of Effectiveness

Measures of Effectiveness are widely used for evaluating forecasting accuracy. As absolute errors are used, it is useful to avoid positive and negative errors cancelling each other.

First, *et* is error term, which is the difference between the forecasted demand and the observed one as $et = ft - dt$

MAE is Mean Absolute Error; $MAE = \frac{1}{n}\sum|et|$ where n is the number of historical period

MAPE is Mean Absolute Percentage Error; $MAPE = \frac{1}{n}\sum\frac{|et|}{dt}$

RMSE is Root Mean Squared Error; $RMSE = \sqrt{\frac{1}{n}\sum et^2}$

CHAPTER 5

RAIL PASSENGER FLOW (RPF) CHARACTERISTICS IN TURKEY

5.1 Railway Passenger Flow (RPF) Data

The RPF data in Turkey covers daily total number of passengers from station to station from 2011-2020: data format for 2011-2015 is slightly different from 2016-2020 period, which has HSR and ConvRail flows separately. To unify the dataset, pre-processing codes were developed in MATLAB to produce daily, weekly, monthly and yearly totals for station-to-station as well as city-to-city statistics. An example of the data format for 2011-2015 is given in Table 5.1 and for 2016 and later in Table 5.2. Each station has a unique code, which is later associated with the city it is located in using the provincial borders of the city.

Analysis of 2011-2015 period, which is used for model development step, showed a missing part at the end of 2011 for the two weeks of December 2011, which was not big to disrupt modeling efforts. Repeating fluctuations (highs and lows) in the time series of 2011-2019 (see Figure 5.1) were easily associated with the calendar of cultural and social events, such as winter break, the holy month Ramadan, which are later used in the modeling and verification steps.

Table 5.1 Format of the Passenger Data for 2011-2015

Number of Passenger	**Train Number**	**Origin**	**Destination**	**Date**
4	11015	2435	1512	20110101
1	11015	2435	1523	20110101
1	11015	1512	1560	20110101
3	11015	2435	1609	20110101
1	11016	1570	1520	20110101
1	11016	1624	1520	20110101
2	11016	1560	1523	20110101
3	11017	1520	1512	20110101
1	11017	1523	1512	20110101
3	11017	2435	1512	20110101

Table 5.2 Format of the Passenger Data for 2016 and later

Origin		**Destination**		**Date**	**Npax**	
					Conventional	**HSR**
Adana	6503	Ankara	2503	1.01.2016	32	0
Adana	6503	Araplı	2506	27.01.2016	1	0
Adana	6503	Ayran	6518	1.01.2016	3	0
Adana	6503	Ayran	6518	2.01.2016	6	0
Adana	6503	Ayrancı	6519	30.01.2016	3	0
Adana	6503	Bahçe	6521	1.01.2016	36	0
Ankara	2503	Arifiye	1512	10.01.2016	6	6
Ankara	2503	Bilecik HT	1712	10.01.2016	16	16
Ankara	2503	Bozüyük HT	1715	9.01.2016	21	21

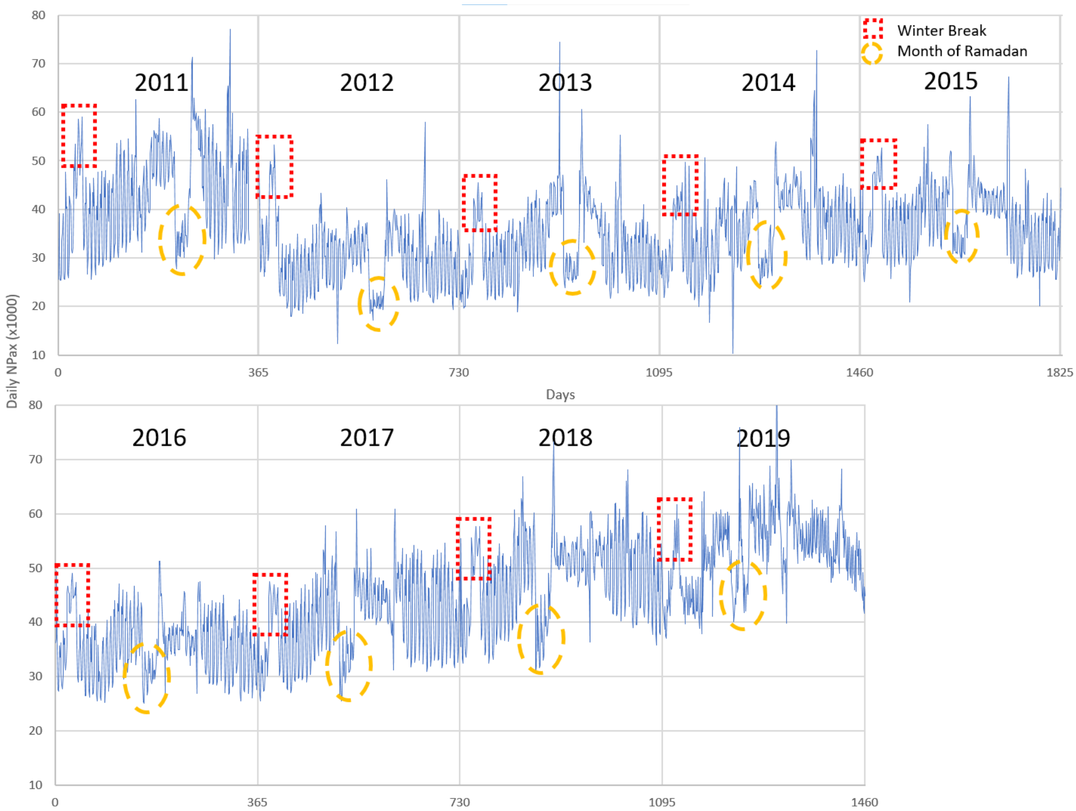


Figure 5.1 2011-2019 data of daily intercity RPF

If a trip was made between two stations in the same provincial border, it is counted as "intracity" trip, which was later omitted in the analysis of the intercity RPFs. The total of flows from all stations in a city constituted the production/attraction, while origin-destination (O-D) based RPFs were created by taking the total flows departing from all the stations in the origin city to all the stations in the destination city. Whenever necessary, daily intercity flows were created by adding up all the O-D flows.

There is generally a growing trend in the intercity passenger data after 2012 as seen in Figure 5.2. However, 2016 is an exception due to some restrictions throughout the country in the second half of the year. The same trend is not applicable to the intracity traffic so it is possible to say that intracity and intercity travel show different behavior in terms of growth according to years. Year 2011 is also an exception as it shows higher volume than the following years. As 2012 shows an average profile it was determined to be used as a basis.

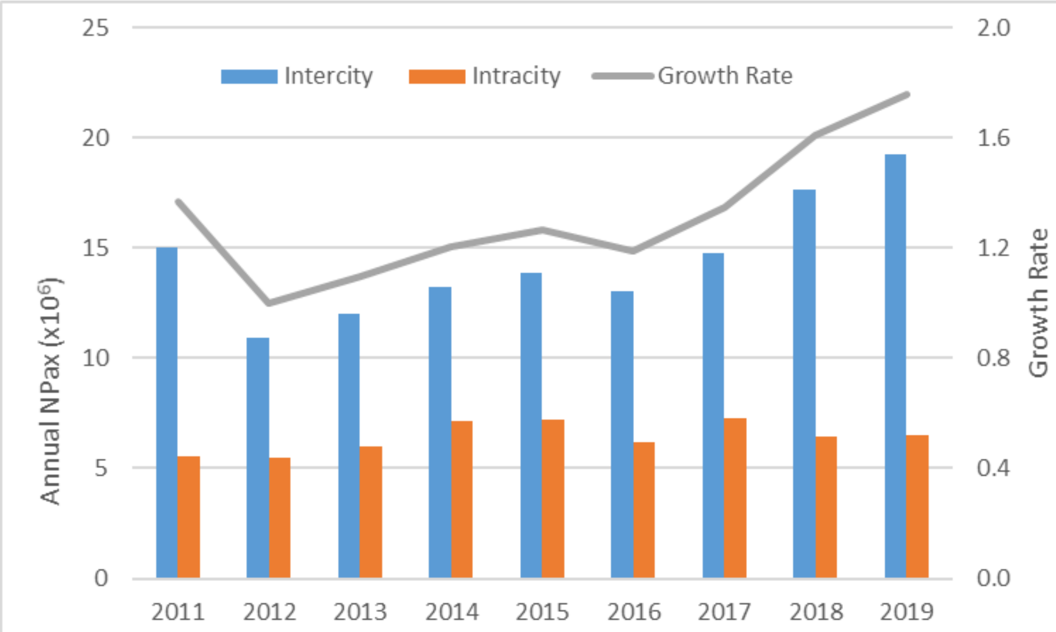


Figure 5.2 2011-2019 Annual Passenger Volumes and Growth Rate

Although winter and summer breaks corresponded to close dates in the yearly calendar, religious events (month of Ramadan and Eids) came approximately 10 days earlier each year due to use of lunar calendar for religious events. When the daily passenger profiles are plotted for two successive years in Figure 5.3, the effect of lunar calendar-based shifts are clearly observed.

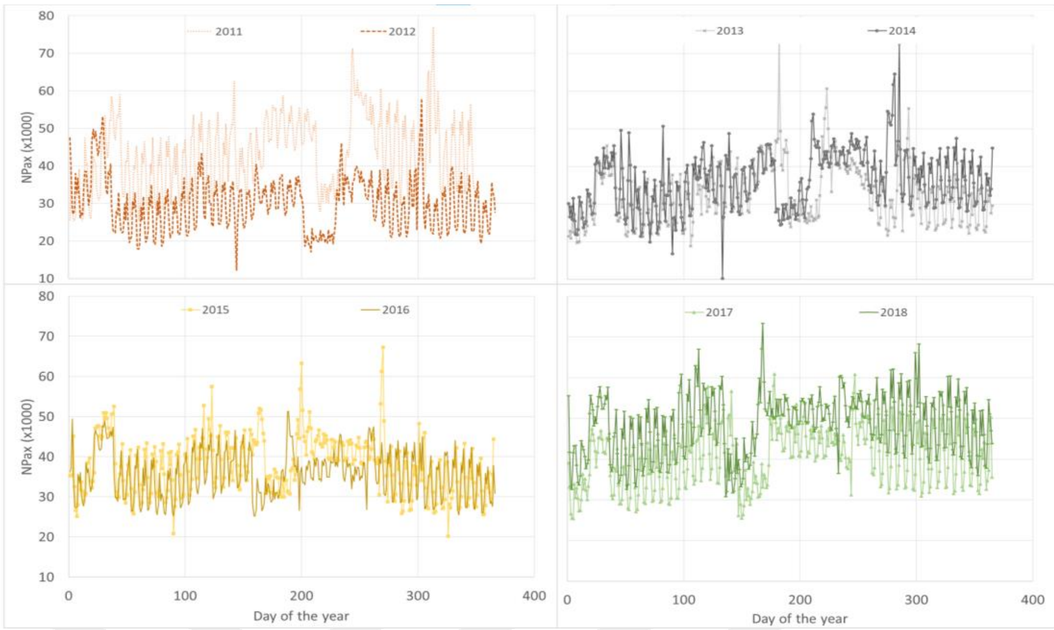


Figure 5.3 Intercity Daily Number of Passengers (2011-2018)

5.1.1 RPF Daily Profile

To be able to see the regular daily profile, day of the week graphs were drawn for the years 2015 and 2016. Average daily number of passengers of each day of week in overall ($\overline{dd}_{dow}$): Average of daily passenger volume for each day of week (average of Mondays, average of Tuesdays, average of Wednesdays…). The figures for $\overline{dd}_{dow}$ were calculated and given in Figure 5.4.

When the number of passengers is examined, first of all, regular increases draw attention on certain days. The systematic occurrence of rises in certain periods creates the impression that this time series data is exposed to seasonal effects. In general, it shows a higher course on weekends than weekday traffic. There are “M” shapes in the daily passenger data. The first shoulder of the “M” corresponds to Friday, and the middle drop is Saturday, and the last shoulder accounts for Sunday peak. This “M” shape shows up on almost all weeks in the whole data, except when there are special events or holidays. Likely, air travel shows similar M-shape profile in daily passenger transportation. However, Thursdays and Mondays show quite higher profile comparing to railway passenger flow. (TSA, 2021) Also, same M-shape day-of-the-week pattern is seen in the study by Luo and others (2015). As noted by Luo et al. (2015), in one cycle of the week, passenger volume on Monday, Tuesday, Wednesday and Thursday are relatively lower. On Friday, due to the effect of the weekend, the volume is at the highest point that many businessmen return to their home and tourists go on a trip. Saturday is lower than Friday and Sunday; and Sunday is high as it is the date of return of these tourists who left their home on Friday and business people who need to turn back to their work places.

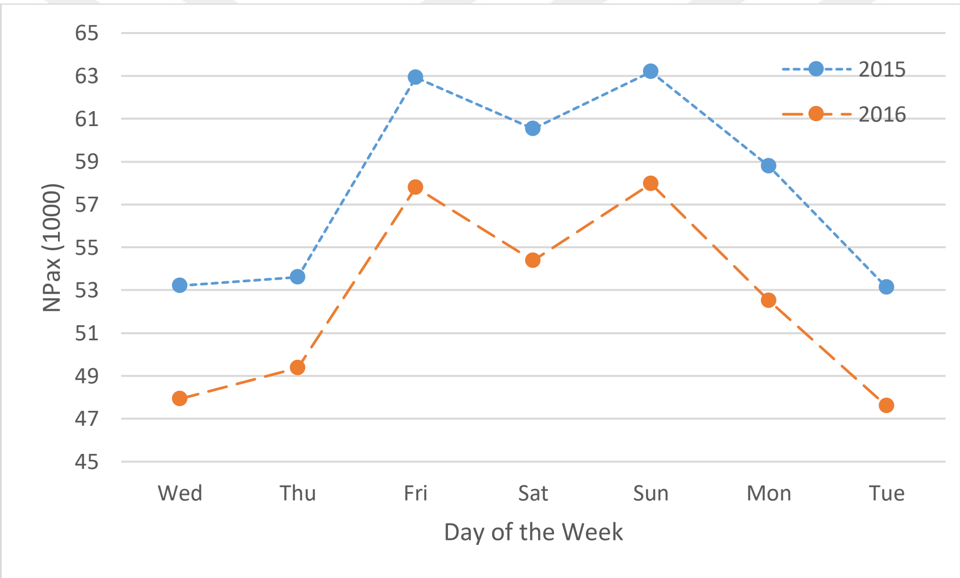


Figure 5.4 Annual average daily number of passengers for each day of week ($\overline{dd}_{dow}$)

5.1.2 RPF Weekly Profile

Analysis of weekly total flows (see Figure 5.5) for 2011-2016 period showed that winter breaks (mostly taking place between the 3rd-6th week of the year), had quite high values compared to school semester weeks. This suggests that closing of schools enabled people to travel more at the intercity level (for vacationing or visiting back home purposes). The holidays during Eids, religious festivals, people had more mobility via rail services, though not as high as winter break level. More specific pattern was observed as in the first day of the Eid, passenger traffic was lower than the following days, which is due to the fact that this auspicious day is generally spent with family at home before visiting other relatives in other cities. Also, as mentioned earlier, there is a steady growth in the intercity passenger number each year.

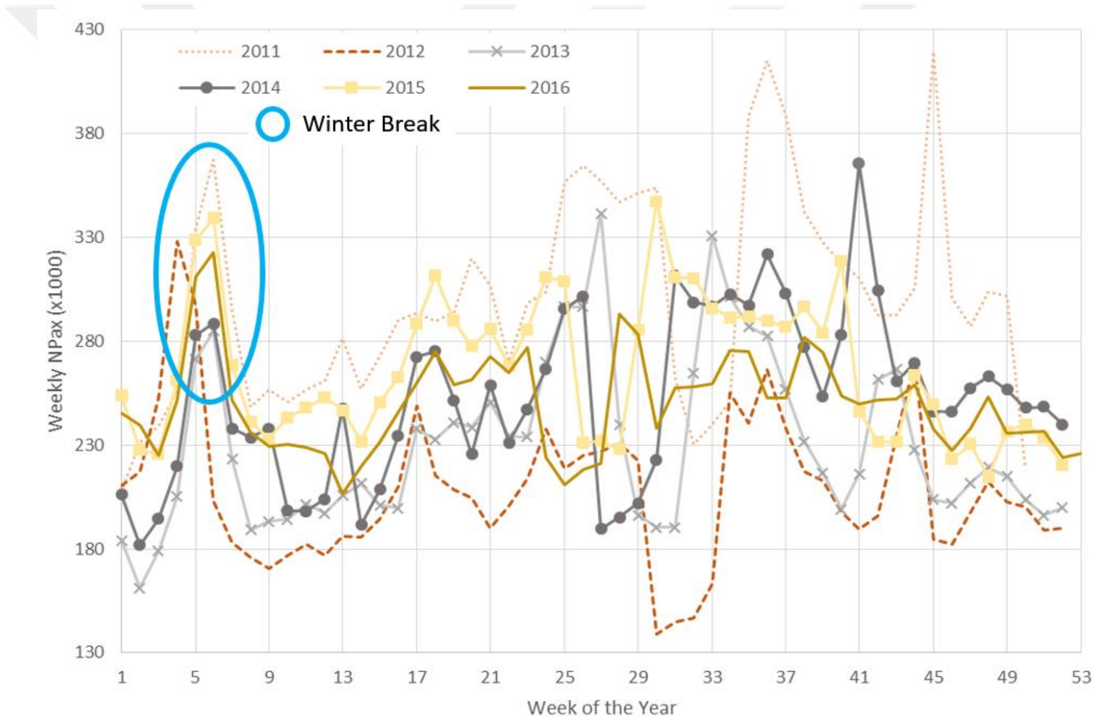


Figure 5.5 2011-2016 Weekly Intercity Railway Passenger Numbers

5.1.3 RPF Daily Analyses

Data was obtained from 2011 to 2020, but since NTMP surveys were performed in 2016, the rail passenger data for 2016 was shown as an example to understand the nature of the data.

Total daily number of passengers (dd_i) (for each month and for the whole year): This figure shows the total number of passengers transported in a day. Firstly, data for 366 days in 2016 were analyzed and seasons were defined (Figure 5.6). The classification of seasons are according to regularity and level of the volume. They are shown in detail in Figure 5.7 to Figure 5.15.

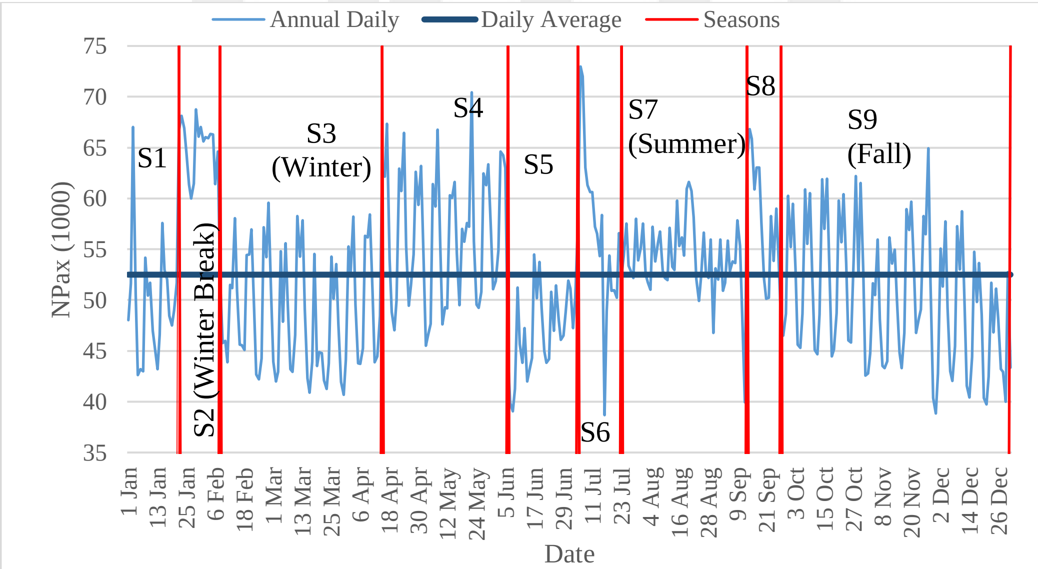


Figure 5.6 2016 Annual Daily Number of Passengers

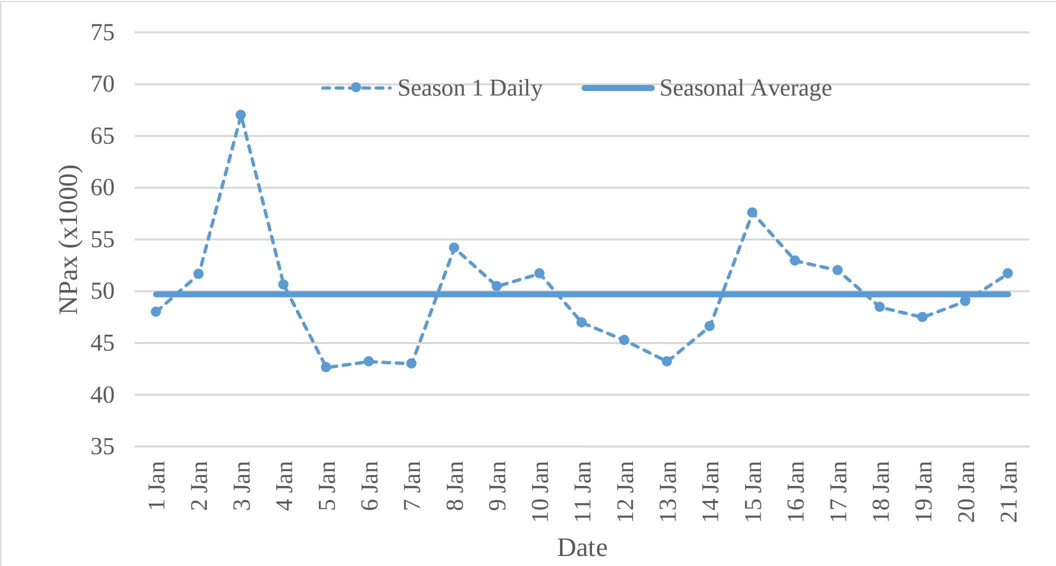


Figure 5.7 Season 1 (1 Jan - 21 Jan) Daily Passenger Volume

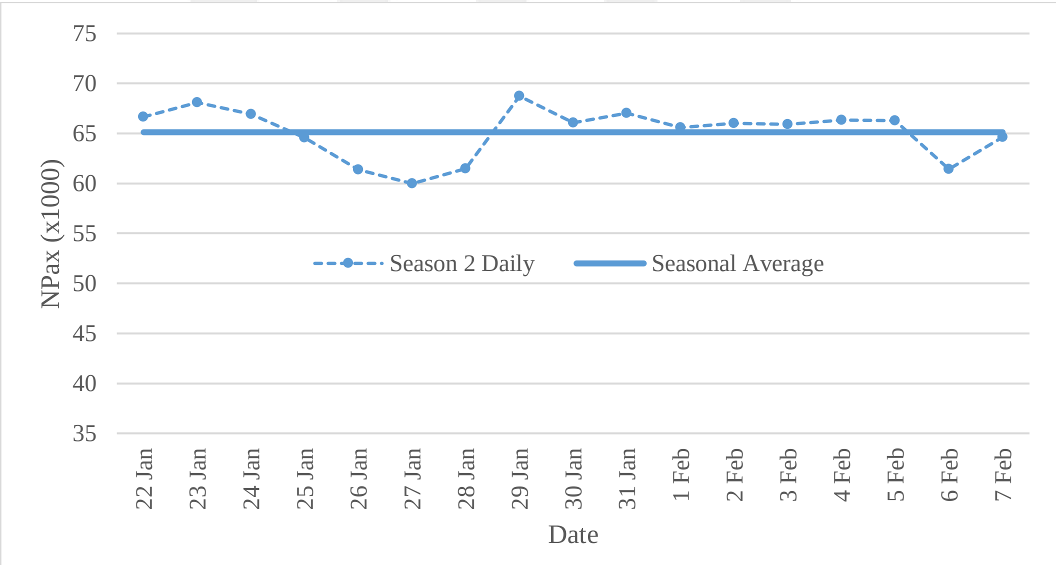


Figure 5.8 Season 2 (22 Jan - 7 Feb) Daily Passenger Volume

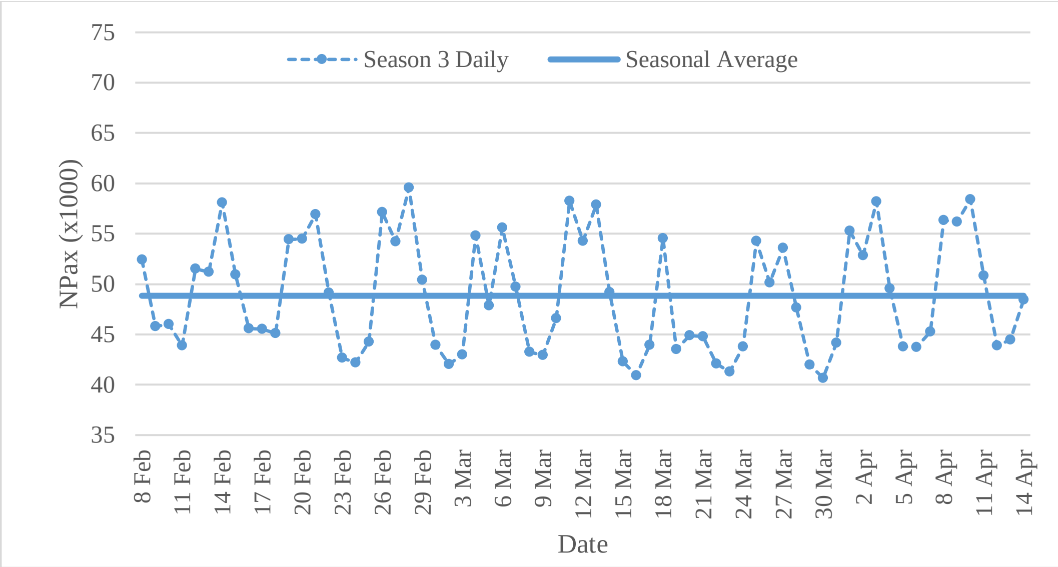


Figure 5.9 Season 3 (8 Feb - 14 Apr) Daily Passenger Volume

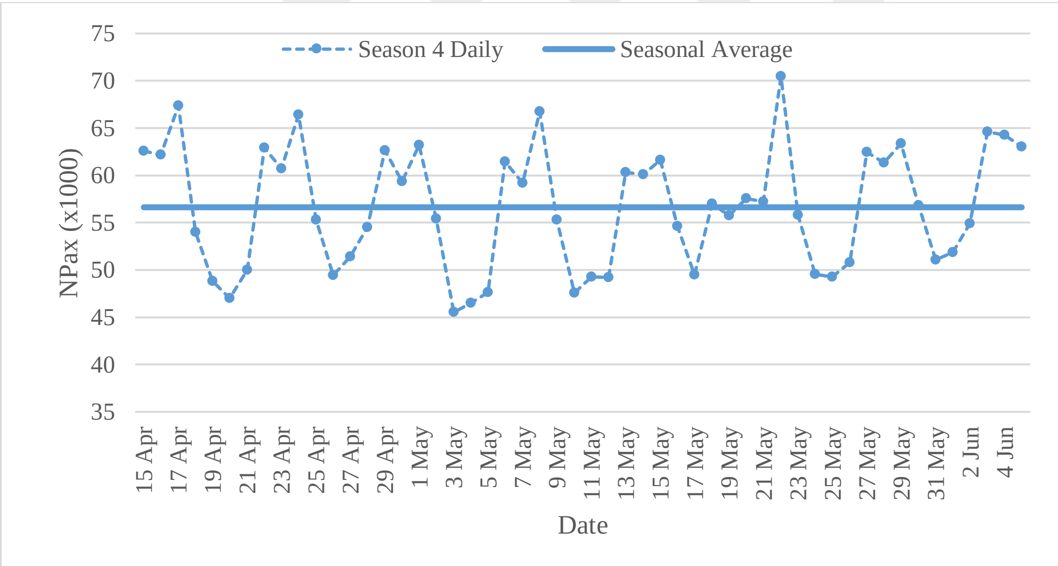


Figure 5.10 Season 4 (15 Apr - 5 Jun) Daily Passenger Volume

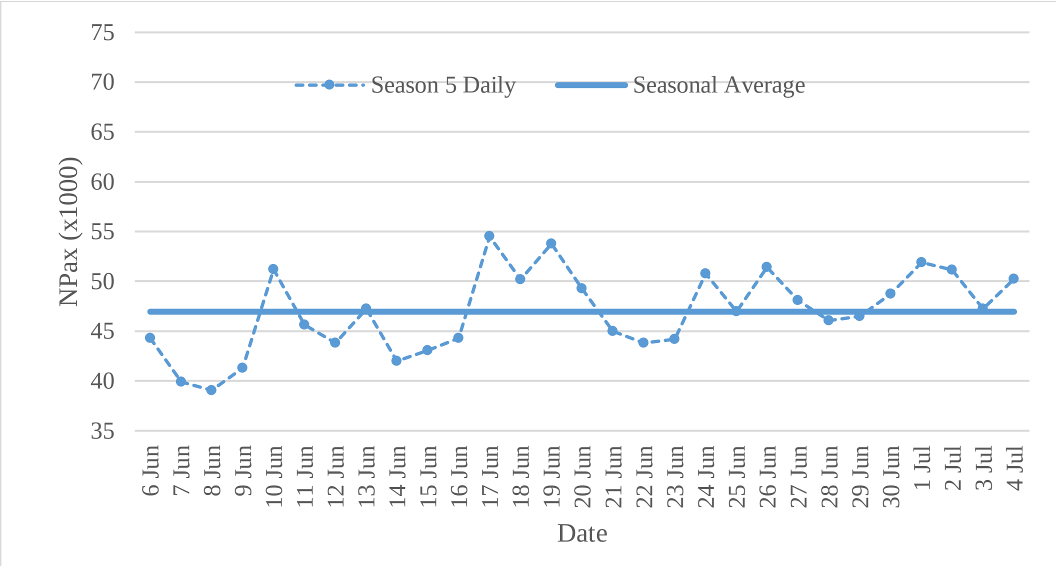


Figure 5.11 Season 5 (6 Jun - 4 Jul) Daily Passenger Volume

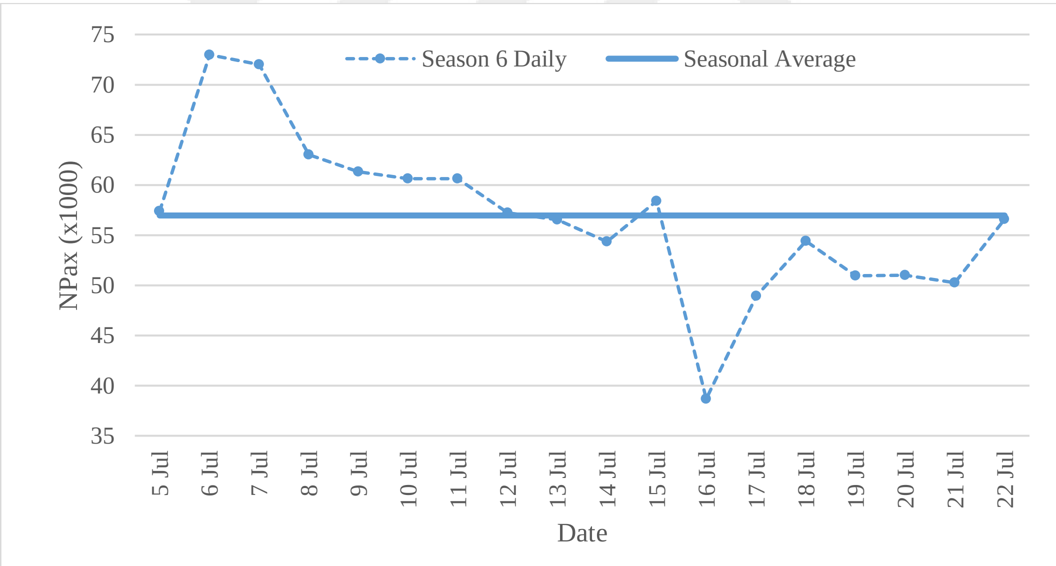


Figure 5.12 Season 6 (5 Jul - 22 Jul) Daily Passenger Volume

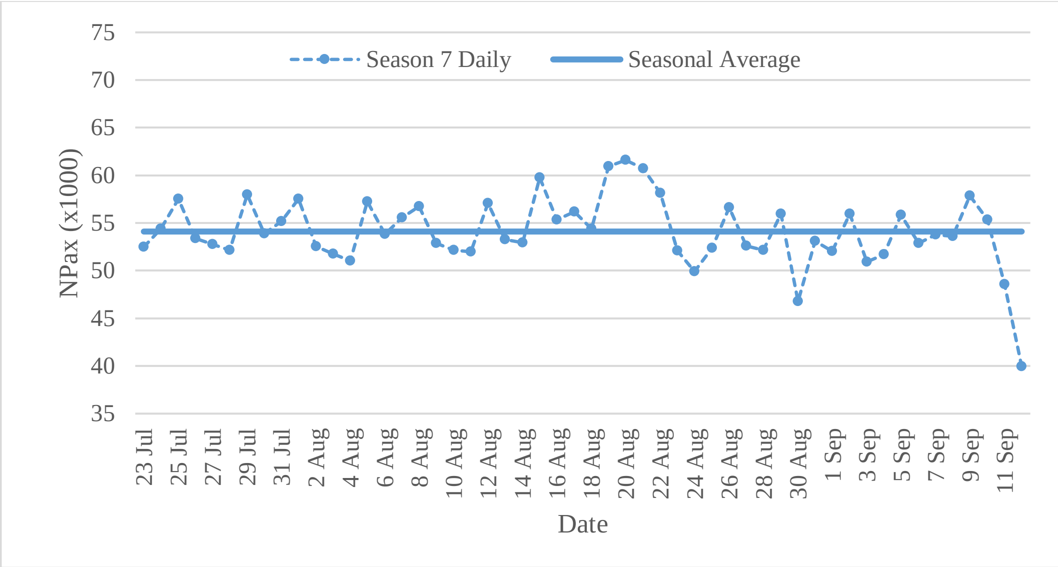


Figure 5.13 Season 7 (23 Jul - 12 Sep) Daily Passenger Volume

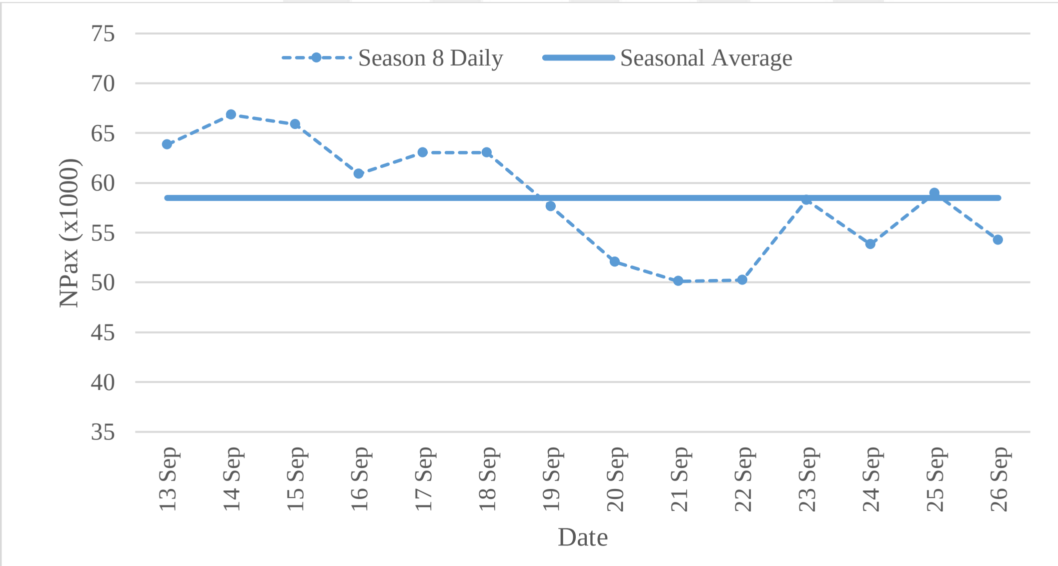


Figure 5.14 Season 8 (13 Sep - 26 Sep) Daily Passenger Volume

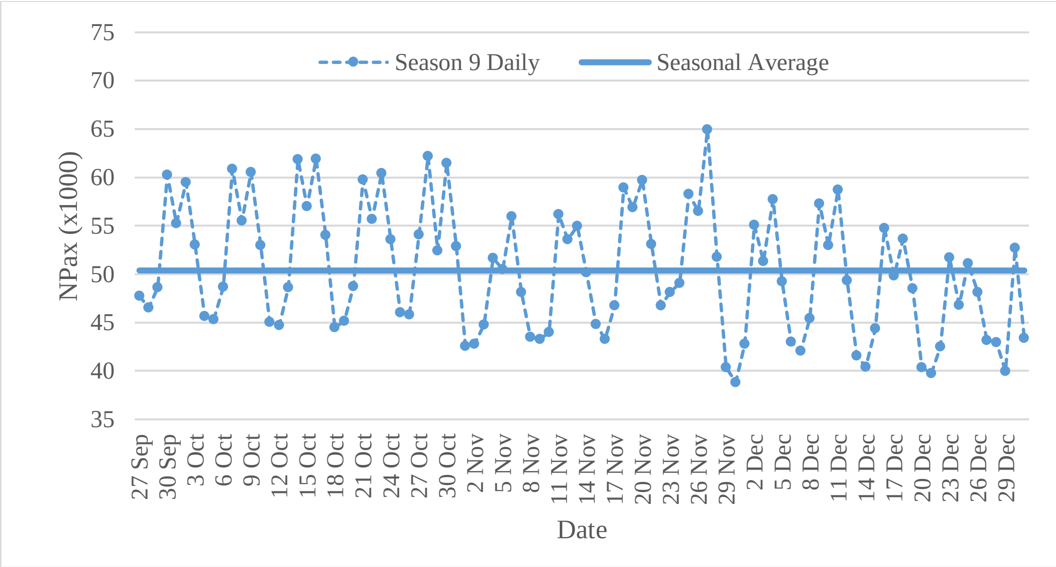


Figure 5.15 Season 9 (27 Sep - 31 Dec) Daily Passenger Volume

<u>Overall vs HSR</u>

When total and HSR figures put together on the same graph in Figure 5.16, it is seen that trend is quite similar as variations such as jumps and drops match in the both lines. However, M-shape of the day of the week profile in HSR is not so distinct as in total. Relatively, peaks at weekends are smoother in HSR profile as understood from Figure 5.17.

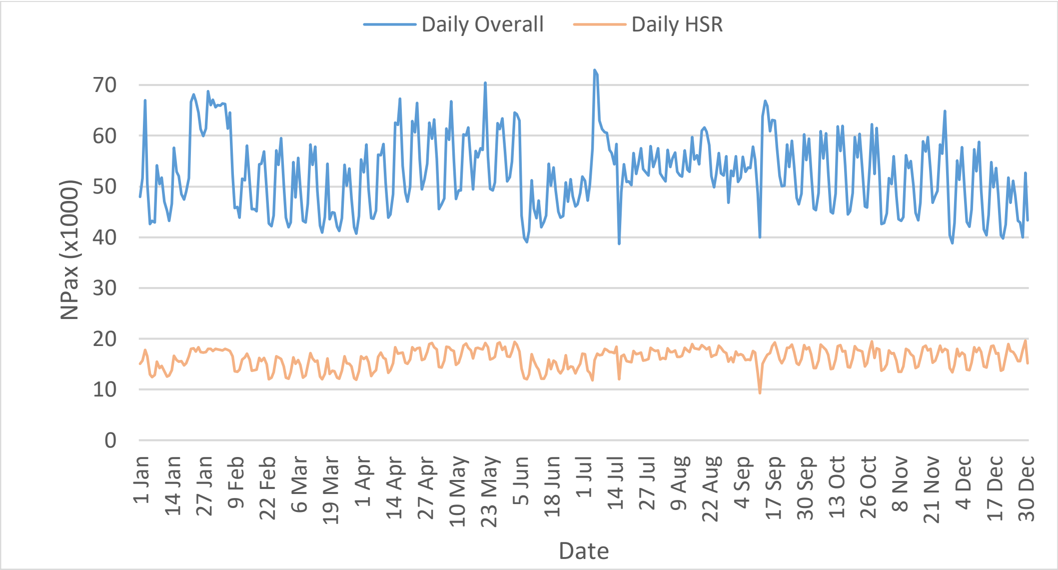


Figure 5.16 2016 Daily Number of Passengers Overall vs HSR only

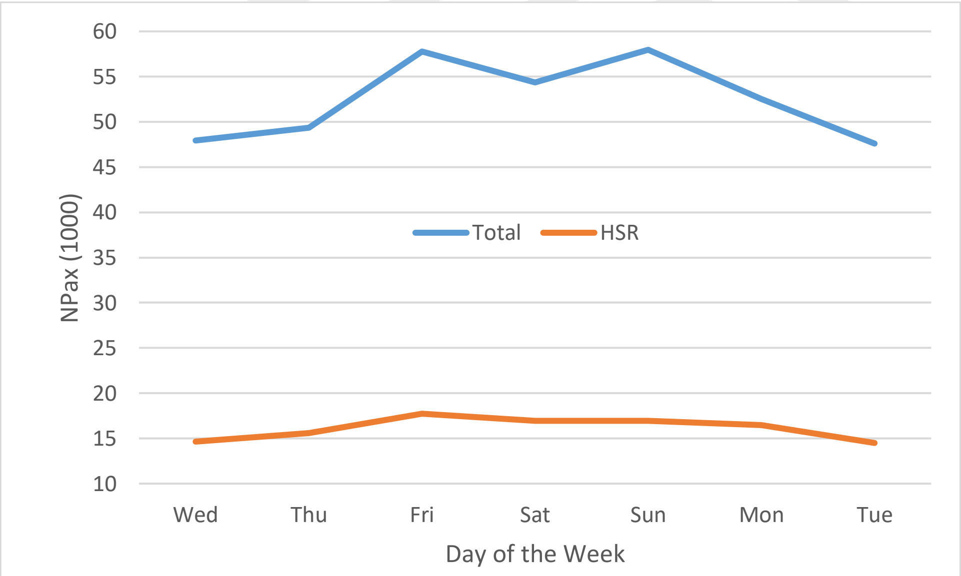


Figure 5.17 2016 average daily number of passengers for each day of week

5.1.4 RPF Monthly Analyses

For comparison, 2015 RPF data is shown in the monthly analyses. It is seen from 2015 data that month May has the highest amount of passengers that used railways in their intercity trips. The monthly variation is shown in Figure 5.18.

Total monthly number of passengers (dmj): It is the summation of number of passengers transported each day of the month. It can be formulated as follows:

$$dmj = \sum_{i=1}^{nj} (dd_i) \qquad (Eq. 5.1)$$

$$dd_i = Total\ NPax\ for\ day\ i$$
$$dmj: Total\ NPax\ for\ month\ j$$
$$nj = number\ of\ days\ in\ the\ month\ j$$
$$j = 1,12$$

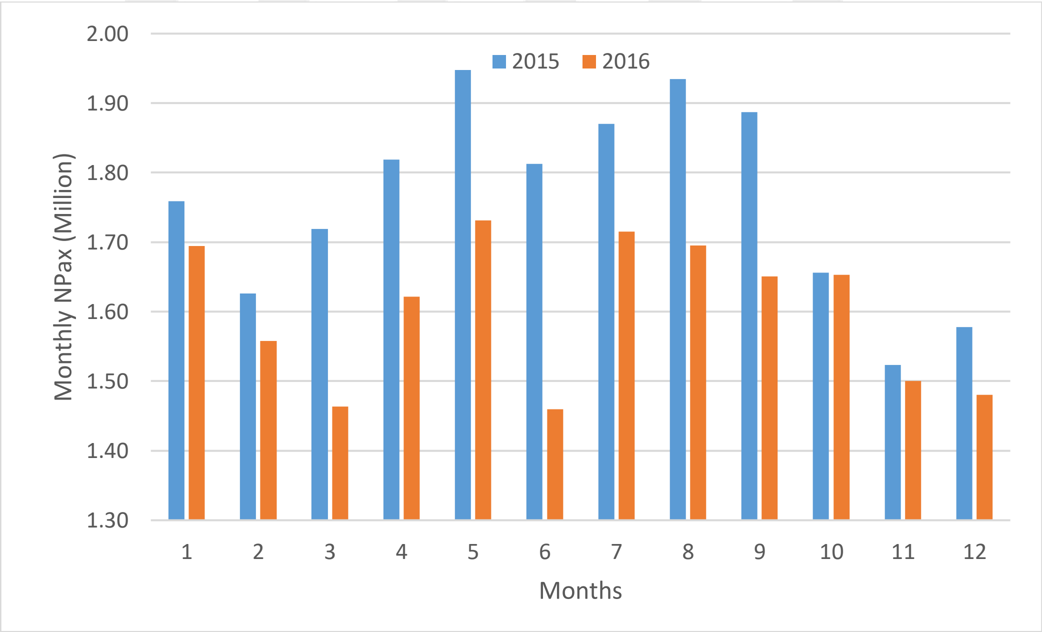


Figure 5.18 Monthly Rail Passenger Data in 2015 and 2016

When average daily number of passengers of each month is analyzed, it is seen in Figure 5.19 that the data has peaks in month May and month September. There is a drop in month March in both years but June is another significant drop in 2016. Average daily number of passengers of each month ($\overline{ddȷ}$): It is the average of number of passengers transported each day of the month. It can be formulated as follows:

$$\overline{ddȷ} = \frac{\sum_{i=1}^{nj} ddi}{\text{nj}} \qquad (Eq. 5.2)$$

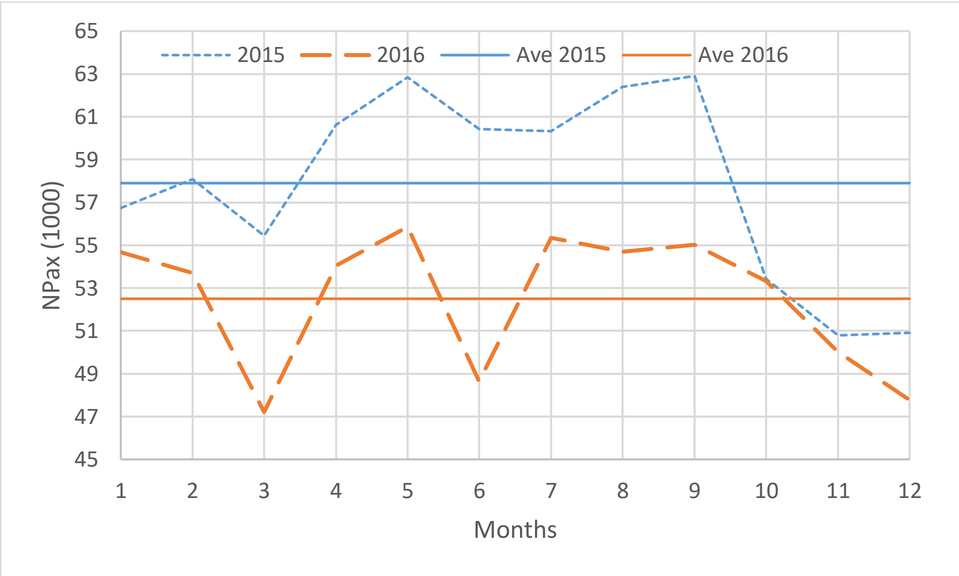


Figure 5.19 Average Daily Number of Passengers in 2015 and 2016's Months

5.1.5 City-based Rail Passenger Production-Attraction Analyses

Production of each station was calculated. Number of passengers who boarded at that station was found for every month and for the whole year. Then top production stations were found in the RPF data. Same procedure was applied to the alighting number of passengers and attraction of each station was found (Table 5.3).

Table 5.3 Top Production and Attraction Stations in 2016

Top Production Stations			Top Attraction Stations		
	Station	**Annual Total Production (x10^6)**		**Station**	**Annual Total Attraction (x10^6)**
1	Ankara	2.15	1	Ankara	2.21
2	Mersin	1.68	2	Mersin	1.56
3	Eskişehir	1.54	3	Eskişehir	1.53
4	Adana	1.42	4	Adana	1.42
5	Konya HZ	1.18	5	Konya HZ	1.18
6	Tarsus	0.96	6	Tarsus	1.07
7	İstanbul (Pendik)	0.85	7	İstanbul (Pendik)	0.88
8	İzmir (Basmane)	0.65	8	İzmir (Basmane)	0.52
9	Aydın	0.49	9	Manisa	0.51
10	Manisa	0.49	10	Aydın	0.5
11	Sincan	0.37	11	Sincan	0.32
12	Nazilli	0.3	12	Nazilli	0.3
13	Ödemiş Şehir	0.28	13	Adnan Menderes H.	0.25
14	Denizli	0.24	14	Ödemiş Şehir	0.25
15	Selçuk	0.17	15	Denizli	0.24
16	Gaziemir	0.17	16	Salihli	0.21
17	İzmit HT	0.17	17	Selçuk	0.2
18	İzmir (Alsancak)	0.16	18	İzmit HT	0.17
19	Turgutlu	0.14	19	İzmir (Alsancak)	0.16
20	Alaşehir	0.14	20	Alaşehir	0.16
Others		7.24	Others		7.15
Total		20.79	Total		20.79

Production and attraction figures were summed and total activity was found for each station. The top stations in terms of total activity are given in Table 5.4. Station locations were analyzed. Provincial borders of each station's location was discovered. Province of each station was notedTable 5.5). After that, production of each province was found. Number of intracity trips were extracted from the total number of passengers boarded and data was categorized as intercity production (P_{xc}) and intracity production ($P_{ıc}$) as well as intercity attraction (A_{xc}) for each city (Table 5.6). The busiest OD corridors were found in terms of total number of passengers traveling on that corridor in the year. (Station-to-station and city-to-city) (Table 5.7).

Table 5.4 Total Activity (Production + Attraction) Stations (2016 Annual)

Rank	Station	Total Activity (P+A) ($x10^6$)
1	Ankara	4.36
2	Mersin	3.24
3	Eskişehir	3.08
4	Adana	2.84
5	Konya HZ	2.36
6	Tarsus	2.03
7	İstanbul (Pendik)	1.73
8	İzmir (Basmane)	1.17
9	Manisa	0.99
10	Aydın	0.99
11	Sincan	0.69
12	Nazilli	0.60
13	Ödemiş Şehir	0.54
14	Denizli	0.48
15	Adnan Menderes H.	0.39
16	Selçuk	0.38
17	Salihli	0.34
18	İzmit HT	0.34
19	Gaziemir	0.33
20	İzmir (Alsancak)	0.32
Others		14.38
Total		41.58

Table 5.5 Provincial borders of stations

St. Code	St. Name	St. City
1502	Adapazarı	Sakarya
1509	Enveriye	Eskişehir
1512	Arifiye	Sakarya
1525	Büyükderbent	Kocaeli
1552	Gebze	Kocaeli
1588	Köseköy	Kocaeli
1601	Mithatpaşa	Sakarya
1609	İstanbul (Pendik)	İstanbul
1615	Sapanca	Sakarya

Table 5.6 City-based Intercity (XC) and IntraCity (IC) Production (P) and Attraction (A) Values for Year 2016 (x1000)

City	Total P	P_{xc}	P_{ic}	Total A	A_{xc}
Ankara	2869.0	2409.9	459.1	2853.9	2394.8
Mersin	2777.5	1371.4	1406.1	2810.1	1404.0
İzmir	2445.8	918.1	1527.7	2453.4	925.7
Adana	1611.5	1534.8	76.7	1563.9	1487.2
Eskişehir	1549.0	1544.3	4.7	1537.8	1533.1
Manisa	1404.9	448.8	956.1	1419.3	463.2
Aydın	1382.5	539.1	843.4	1362.7	519.3
Konya	1274.3	1265.4	8.9	1274.7	1265.8
İstanbul	867.5	867.3	0.2	893.4	893.2
Zonguldak	437.7	16.6	421.1	436.4	15.3
Denizli	270.0	259.5	10.5	263.7	253.2
Kocaeli	237.9	231.3	6.5	237.4	230.9
Sivas	212.5	90.8	121.7	223.0	101.3
Kütahya	151.3	129.2	22.2	151.3	129.1
Sakarya	135.8	134.8	1.0	136.1	135.1
Diyarbakır	135.1	65.9	69.2	144.0	74.8
Karaman	125.0	123.3	1.7	121.2	119.5
Erzincan	117.3	32.0	85.3	117.2	31.9
Malatya	115.0	93.9	21.1	109.6	88.5
Kayseri	114.0	112.1	1.9	103.8	102.0
Balıkesir	104.2	29.1	75.0	104.9	29.9
Uşak	94.5	60.8	33.6	96.6	63.0
Osmaniye	92.4	79.2	13.3	95.5	82.3
Kars	85.4	21.3	64.1	86.7	22.6
Yozgat	67.7	60.8	7.0	72.2	65.2
Batman	67.2	65.4	1.7	58.9	57.2
Niğde	62.0	57.3	4.7	73.3	68.6
Bilecik	61.2	61.0	0.2	61.3	61.1
Elazığ	50.8	38.8	12.0	51.9	40.0
Erzurum	45.4	37.7	7.7	45.2	37.5
Afyon	44.4	38.3	6.1	47.6	41.5
Kırıkkale	42.1	37.1	5.0	42.1	37.1
Hatay	35.8	35.5	0.3	37.9	37.6
Karabük	30.9	15.3	15.6	32.2	16.6
Gaziantep	28.6	28.4	0.3	28.3	28.0
Tekirdağ	22.2	18.7	3.5	20.1	16.6
Adıyaman	11.1	10.9	0.2	12.0	11.7
Bingöl	8.8	4.7	4.1	8.9	4.8
Kırklareli	8.7	7.2	1.4	8.4	7.0
Kahramanmaraş	7.9	6.9	1.0	8.8	7.8
Edirne	7.7	6.8	0.9	8.4	7.6
Siirt	5.7	5.6	0.1	4.0	3.9
Nevşehir	2.9	2.9	0.0	2.8	2.8
Muş	2.6	2.5	0.1	2.7	2.6
Bitlis	0.5	0.4	0.0	0.7	0.7

Table 5.7 ODs Station to Station and City to City (2016 Annual)

Rank	OD Station to Station	Total NoP ($x10^3$)	Rank	OD City to City	Total NoP ($x10^3$)
1	Mersin-Adana	891.9	1	İzmir-İzmir	1527.7
2	Adana-Mersin	859.6	2	Mersin-Mersin	1406.1
3	Eskişehir-Ankara	849.4	3	Adana-Mersin	1335.3
4	Ankara-Eskişehir	824.0	4	Mersin-Adana	1292.7
5	Konya HZ-Ankara	770.1	5	Ankara-Eskişehir	965.9
6	Ankara-Konya HZ	741.7	6	Eskişehir-Ankara	964.4
7	Mersin-Tarsus	675.6	7	Manisa-Manisa	956.1
8	Tarsus-Mersin	573.7	8	Ankara-Konya	856.8
9	Adana-Tarsus	316.7	9	Konya-Ankara	856.3
10	Ankara-İstanbul (Pendik)	297.2	10	Aydın-Aydın	843.4
11	İstanbul (Pendik)-Ankara	293.5	11	Ankara-Ankara	459.1
12	Tarsus-Adana	286.6	12	Zonguldak-Zonguldak	421.1
13	Eskişehir-İstanbul (Pendik)	259.8	13	Aydın-İzmir	390.6
14	İstanbul (Pendik)-Eskişehir	250.7	14	İzmir-Aydın	373.1
15	İzmir (Basmane)-Ödemiş Şehir	155.1	15	İzmir-Manisa	371.8
16	Ödemiş Şehir-İzmir (Basmane)	133.9	16	Manisa-İzmir	351.5
17	Konya HZ-İstanbul (Pendik)	120.8	17	Ankara-İstanbul	336.4
18	İstanbul (Pendik)-Konya HZ	115.7	18	İstanbul-Ankara	322.0
19	Sincan-Eskişehir	107.4	19	Eskişehir-İstanbul	259.9
20	Polatlı-Sincan	106.6	20	İstanbul-Eskişehir	250.7
21	Eskişehir-Kütahya	105.3	21	Aydın-Denizli	148.5
22	Kütahya-Eskişehir	102.6	22	Denizli-Aydın	146.3
23	Aydın-Nazilli	95.6	23	Sivas-Sivas	121.7
24	Nazilli-Aydın	94.7	24	Konya-İstanbul	120.8
25	Sincan-Konya HZ	88.6	25	İstanbul-Konya	115.7
26	Sincan-Polatlı	86.3	26	Eskişehir-Kütahya	114.1
27	Eskişehir-Konya HZ	85.4	27	Kütahya-Eskişehir	111.0
28	Konya HZ-Eskişehir	85.2	28	Karaman-Konya	100.0
29	Manisa-Salihli	83.6	29	Denizli-İzmir	99.9
30	Eskişehir-Sincan	82.3	30	Konya-Karaman	97.6
Others		11250.4	Others		5073.5
Total		20790.0	Total		20790.0

5.2 NTMP Data

332142 passenger interviews were done in the scope of National Transport Master Plan study for Turkish Republic in 2016. The distribution of the surveys according to survey type is shown in Table 5.8. The survey data collated was used for a range of purposes within the model building process in NTMP, including development of:

- Trip matrices using Origin-Destination data from Roadside Interview (RSI) expanded to section counts, and public transport surveys;
- Trip generation model using total traffic values leaving towns,
- Trip distribution model using the RSI and passenger interview data,
- Mode choice model using parameters derived from SP surveys,
- Calibration and validation of modeled traffic flows using key inputs from section counts.

Table 5.8 Number of Surveys per Type

Survey Type	**Number of Surveys (#)**
Roadside Interviews for light vehicles (RSI-L)	150520
Roadside Interviews for heavy vehicles (RSI-H)	43364
Roadside Passenger Interviews (PSI)	40806
Heavy vehicle driver interviews at Strategic Points	25270
Bus terminus Passenger Interviews	10767
Train Station Passenger Interviews	7028
Port Passenger Interviews	4031
Airport Passenger Interviews	20154
Stated Preference Surveys (SPS)	30202
Total	332142

5.2.1 Rail Passenger Survey (RPS)

There are 7028 passenger interviews conducted at train stations in 2016. The interviews were conducted with the approval of terminal authorities. The survey was conducted with passengers waiting at the train stations. But, those who have longer to wait are more likely to agree to be interviewed, and to reduce the bias this might produce, interviews were undertaken for alighting passengers as well as boarding. The best way therefore of carrying out this survey was at the train station entrance where a mix of boarding and arriving passengers, covering a variety of services, could be intercepted. The duration of the survey was from 07:00 to 19:00 during neutral weekdays. Length of a single interview was around 3-4 minutes. The scope of the survey is shown in Table 5.9

Table 5.9 Scope of Rail Passenger Survey

Category	Content
Socio-demographic	Gender, Age, Income Level; Car Availability
Trip Details	Origin-Destination, Rail Service Type (HSR or Conventional), Trip Purpose, Access mode, Egress mode, Type of trip (home-based or non-home-based)
Rail Travel Characteristics	Travel frequency, Time of return

The 20 stations in which questionnaires were performed are as follows: Adana, Ankara-Sincan, Ankara Gar, Aydın-Nazilli, Aydın, Denizli, Erzincan, Eskişehir, İstanbul-Pendik, İzmir Basmane, Karaman, Kayseri, Konya YHT, Malatya, Manisa-Alaşehir, Manisa, Mersin-Tarsus, Mersin, Sivas and Zonguldak Train Stations. Data inconsistency checks included comparison of GPS location and stated survey location coming from using smart tablets which have GPS and internet. If the two value did not match, interviews were counted as inconsistent and removed from the data. Further logical checks were done after the basic descriptive evaluation of the data, such as origin-destination-survey location compatibility, first boarding – start point of trip, final alighting – end point of trip coherence. Example survey questions are given in the Appendix A of this study following the sample O-D of the RPS in the Appendix B. Also, results of other passenger surveys are given in the Appendix C.

5.2.2 RPS Participant Profile

Socio-demographic characteristics of all respondents were summarized in Table 5.10. Majority of participants are male with 61% ratio and 5219 out of 7028 respondents are making intercity trips. The rest (1809) are traveling inside provincial borders according to the results of Origin–Destination (O-D) analysis. Among all participants, 2147 people stated the service they are using at the time of the interview is high speed, and 4881 of them stated ConvRail service which corresponds to 69% of all sample. Majority of interviewees are in the middle age group (25-44) with 44% and youngsters follow that with 33%. Only 367 people were more than 60 years old (5%). Most of the travelers interviewed didn't have a car available for their trips. Only 16 percent stated they have a car to be used for this trip. Again, 16% of the respondents did not want to claim their monthly net household income. 74% of the respondents have monthly net household income lower than 3200 Turkish Liras (TL) (1000 €) and almost half of them have lower than 1600 TL (500 €). Income levels are defined as very low (VL) for less than 1600 TL, low for between 1600 and 3200 TL, middle (M) for 3200 – 6400 and high (H) for higher than 6400 TL (2000 €).

Table 5.10 Rail Passenger Survey – Participant Profile

		#	(%)
Gender	***Male***	4272	61
	Female	2756	39
Income Level	***Very Low***	2512	36
	Low	2696	38
	Middle	549	8
	High	130	2
	Not declared	1141	16
Car Availability	***Available***	1134	16
	Non-Available	5894	84

		#	(%)
Age	***<25***	2338	33
	25-44	3105	44
	45-60	1218	17
	>60	367	5
Rail Service Type	***HSR***	2147	31
	ConvRail	4881	69
Trip Type	***Inter-city***	5219	74
	Intra-city	1809	26
Total		7028	100

A series of descriptive statistical analyses were performed to investigate characteristics on a) O-D of the sample, b) Trip Purpose; c) Trip Frequency, d) Access/Egress Modes, e) Car Availability and Rail Preference Reasons. When doing these analyses, the difference of travel behavior among different age groups was investigated. Similarly, responses from different income levels were analyzed separately to see the difference on the travel characteristics. Also, travel behavior of HSR and ConvRail passengers were compared to see the effect of HSR.

5.2.3 Geographical Characteristics

According to results of the survey, origin and destinations of the sample was identified. Out of 7028 people, majority of them were captured starting (924 people) or ending (1018 people) their trip in Ankara but 125 of them reported to travel to a destination within Ankara province (i.e. Polatlı). Major destinations from Ankara were Eskişehir, Konya and İstanbul which are all HSR cities. The next big group was observed in Mersin, where almost one third of the participants were traveling within province (303 people) and more than half were commuting to Adana (567 people) which also had a big demand back to Mersin (347 people). However, though 413 people reported traveling from Mersin to Adana by HSR (and 215 from Adana to

Mersin), there is no HSR service in this corridor. On Adana-Mersin corridor, regional trains are running very frequently with 24 services per day in both ways, some of which are express services with fewer stops, and it is very likely that local people use “high-speed” term for the “express services”. This surely was a survey problem that the interviewers did not know the situation and noted down the stated responses blindly. Note: Such incorrect responses due to lack of knowledge was corrected in the data to prevent any bias in the following evaluations.

While P and A columns show total number of production and attraction in Table 5.11 and Table 5.12, intracity (IC) column gives the number of passengers traveling within the same provincial borders. ATD stands for average travel distance of the passengers in the corresponding row’s city.

Table 5.11 National Rail Passenger Survey- Trip Production Characteristics (N= 7028 participants-Raw Data)

City	A(Total)	P_{IC}	P_{XC}	HSR	Conv. Rail	Major Destinations	ATD (km)	Sampling Ratio*	Expected Sample*
ANK-Ankara[1]	1018	125	**799**	**547**	377	**ESK (311), KON (167), IST (141)**	**416.7**	**321.9**	717.7
IST-İstanbul	266	0	**439**	**304**	135	**ANK (197), ESK (89)**	**409.2**	**507.1**	216.4
KON-Konya	382	3	**364**	**302**	65	**ANK (282),** KRM (21)	330.2	**288.2**	318.3
ESK-Eskişehir	428	4	**360**	**301**	63	**ANK (194), IST (86)**	**264.5**	**235.0**	387.3
MER-Mersin[1]	662	303	**582**	-	885	ADN (567), OSM (5)	71.7	**320.1**	691.2
ADN-Adana	670	29	**374**	-	403	MER (347), OSM (10)	79.6	**252.4**	399.2
OSM-Osmaniye	23	1	**4**	-	5	MER (4)	171.8	**53.2**	23.5
MAN-Manisa[1]	419	386	**302**	-	688	IZM (182), USK (85)	155.8	**494.0**	348.2
AYD-Aydın[*]	586	267	**366**	-	633	IZM (229), DEN (137)	132.6	**473.4**	334.3
IZM-İzmir	853	286	**227**	-	513	AYD (135), DEN (61)	182	**203.4**	630.5
DEN-Denizli	210	5	**321**	-	326	AYD (183), IZM (129)	190.9	**1208.0**	67.5
			0						
SVS-Sivas	313	190	**104**	-	294	ERN (43), KYS (17)	**432.8**	**1419.9**	51.8
MLT-Malatya	40	30	**263**	-	293	DYB (152), SVS (33)	277	**2498.4**	29.3
KYS-Kayseri	39	0	**278**	-	278	ANK (132), SVS (75)	356.9	**2445.9**	28.4
ERN-Erzincan	132	35	**96**	-	131	ERM (75), KAR (19)	263.7	**1074.6**	30.5
DYB-Diyarbakır[2]	161	0	**0**	-	-	-	272.9	**-**	33.4
Others	1844	145	**340**		485	ZON (139), ERM(76), ERN (73),	301.1	**136.2**	890.0
Total	7028	1809	**5219**	**1454**	5574				

[1] There are 2 stations surveyed within the province borders.

[2] No station surveyed within the province borders.

[*] Sampling Ratio is calculated as $SR=P/P_{ridership}/10^6$ and Expected sample is calculated as $ES=250xP_{ridership}/10^6$

A: Attraction P: Production ATD: Average Travel Distance

Table 5.12 National Rail Passenger Survey- Trip Attraction Characteristics (N= 7028 participants-Raw Data)

City	P(Total)	A_{IC}	A_{XC}	HSR	Conv. Rail	Major Origins	ATD (km)	Sampling Ratio*	Expected Sample*
ANK-Ankara[1]	924	125	**893**	**624**	394	**KON (282), IST (197), ESK (194)**	394.9	**333.7**	762.7
IST-İstanbul	364	0	**266**	**215**	51	**ANK (141), ESK (86)**	491.1	**961.5**	69.2
KON-Konya	360	3	**379**	**202**	180	**ANK (167),** KRM (123)	292.5	**256.5**	372.4
ESK-Eskişehir	0	4	**424**	**332**	96	**ANK (311), IST (89)**	272.0	**288.2**	371.3
MER-Mersin[1]	374	303	**359**	-	662	ADN (347), OSM (4)	73.2	**123.8**	725.2
ADN-Adana	4	29	**641**	-	670	MER (567), KRM (28)	104.7	**352.4**	454.8
OSM-Osmaniye	5	1	**22**	-	23	ADN (10), MLT (7)	171.8	**232.0**	23.7
MAN-Manisa[1]	366	386	**33**	-	419	IZM (16), ANK (9)	359.3	**20.1**	410.0
AYD-Aydın*	227	267	**319**	-	586	DEN (183), IZM (135)	133.1	**196.7**	405.4
IZM-İzmir	321	286	**567**	-	853	AYD (229), MAN (182), DEN (129)	163.3	**202.5**	699.8
DEN-Denizli	0	5	**205**	-	210	AYD (137), IZM (61)	179.1	**919.5**	55.7
SVS-Sivas	263	190	**123**	-	313	KYS (75), MLT (33)	266.7	**355.6**	86.5
MLT-Malatya	278	30	**10**	-	40	ANK(4)	684.8	**61.1**	40.9
KYS-Kayseri	96	0	**39**	-	39	SVS (17)	404.6	**203.7**	47.9
ERN-Erzincan	131	35	**97**	-	132	SVS (43), ERM (35)	374.7	**736.4**	32.9
DYB-Diyarbakır[2]	0	0	**161**	-	161	-	272.8	-	37.5
Others	3315	145	**681**		826	ANK(117), IST (106), MAN(100)	311.1	**191.3**	1116.6
Total	7028	1809	**5219**	**1373**	5655				

[1]There are 2 stations surveyed within the province borders.

[2] No station surveyed within the province borders.

* Sampling Ratio is calculated as $SR=A/A_{ridership}/10^6$ and Expected sample is calculated as $ES=250xP_{ridership}/10^6$

A: Attraction P: Production ATD: Average Travel Distance

Desire lines for major origin-destinations are shown in Figure 5.20. They show the higher demand couples and provide information on average travel distance between them. Spatial distribution of these strong demand directions may provide insights about the regional associations of the cities producing/attracting rail demand. As seen from the figure, the strongest desire line is Mersin-Adana, followed by Ankara-Eskişehir. While short distance travels are more common in the western region of Turkey, Middle Anatolia shows longer ATD due to its HSR ownership.

As NTMP details have not been published yet, the intercity rail passenger O-D matrices calibrated by the rail ridership have not been included here. Thus, the aggregate evaluation of the rail passenger O-D had been limited to geographical distribution of the trips. If the demand distribution from the RPS sample was assumed to find the estimated destination volumes for the year 2016 data (see right-hand side of Table 5.13), it is easy to see the need to balance the O-D matrix during the calibration process. Based on the analyses performed on survey data, western region has the highest share of intracity trips. Mersin-Adana in the southern region comes to the forefront as the busiest corridor in Turkey. HSR region shows a more balanced distribution comparing to the others.

Sample O-D ratios were applied to the actual production data of 2016 (Table 5.13). Based on the analyses performed on survey data, western region has the highest share of intracity trips. Mersin-Adana in the southern region comes to the forefront as the busiest corridor in Turkey. HSR region shows a more balanced distribution comparing to the others.

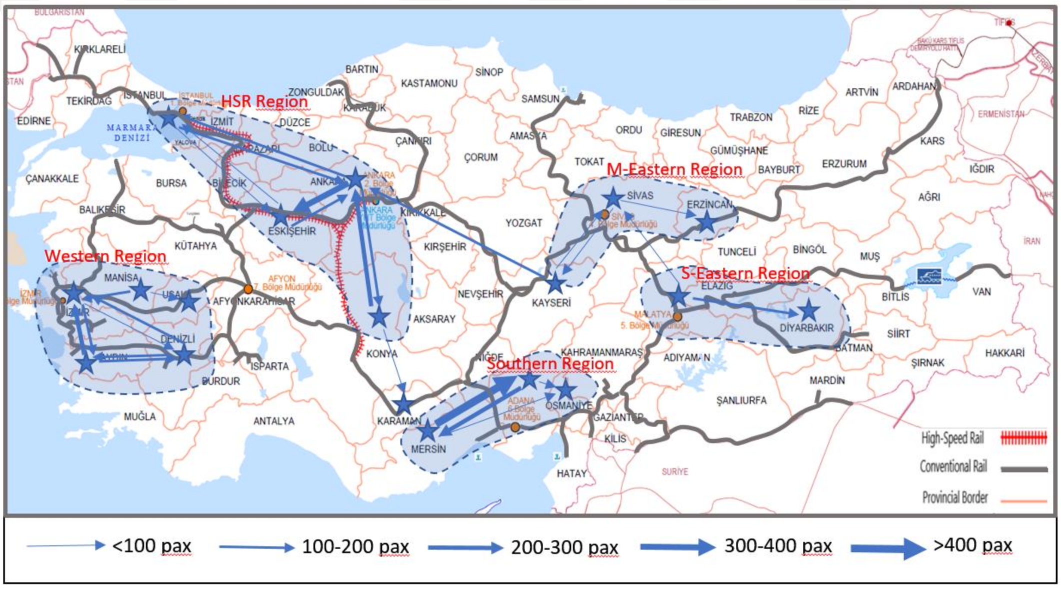


Figure 5.20 Desire Lines for Major Rail Passenger O-Ds in the National Rail Passenger Survey

Table 5.13 Demand distribution a) in the RPS sample and b) expected distribution of RPF in 2016

	Origin	Sample Destinations						P_{2016}	Estimated Demand ($x10^6$)			
HSR Region		**IST**	**ESK**	**ANK**	**KON**	**Other**	***Total***		**IST**	**ESK**	**ANK**	**KON**
	IST	--	20.5	**44.9**	10	24.6	***100.0***	**0.87**	--	0.18	0.39	0.09
	ESK	23.6	1.1	**53.3**	6.6	15.4	***100.0***	**1.55**	0.37	0.02	0.83	0.1
	ANK	15.3	33.7	13.5	18.1	19.5	***100.0***	**2.87**	0.44	0.97	0.39	0.52
	KON	5.4	3	**76.8**	0.8	13.9	***100.0***	**1.27**	0.07	0.04	0.98	0.01
Western Region		**IZM**	**MAN**	**AYD**	**DEN**	**Other**	***Total***		**IZM**	**MAN**	**AYD**	**DEN**
	IZM	**55.8**	3.1	26.3	11.9	2.9	***100.0***	**2.52**	1.41	0.08	0.66	0.3
	MAN	26.5	**56.1**	--	0.1	17.3	***100.0***	**1.39**	0.37	0.78	--	0
	AYD	36.2	--	**42.2**	21.6	0	***100.0***	**1.34**	0.48	--	**0.56**	0.29
	DEN	39.6	--	**56.1**	1.5	2.8	***100.0***	**0.27**	0.11	--	0.15	0.01
Southern Region		**MER**	**ADN**	**OSM**	**KRM**	**Other**	***Total***		**MER**	**ADN**	**OSM**	**KRM**
	MER	34.2	**64.1**	0.6	--	1.1	***100.0***	**2.76**	0.95	1.77	0.02	--
	ADN	**86.1**	7.2	2.5	--	4.2	***100.0***	**1.6**	1.37	0.11	0.04	--
	OSM	80	--	**20**	--	--	***100.0***	**0.09**	0.08	--	**0.02**	--
Eastern Region		**SVS**	**MLT**	**KYS**	**ERN**	**Other**	***Total***		**SVS**	**MLT**	**KYS**	**ERN**
	SVS	64.6	0.0	5.8	14.6	15.0	***100.0***	0.21	0.13	0.00	0.01	0.03
	MLT	11.3	10.2	2.0	0.0	76.5	***100.0***	0.12	0.01	0.01	0.00	0.00
	KYS	27.0	0.7	0.0	1.8	70.5	***100.0***	0.11	0.03	0.00	0.00	0.00
	ERN	0.8	0.0	0.0	26.7	72.5	***100.0***	0.12	0.00	0.00	0.00	0.03

CHAPTER 6

TRAVEL BEHAVIOR ANALYSIS FOR INTERCITY RAIL TRANSPORTATION

Rail passenger characteristics by different attributes are summarized in Table 6.1, which showed that majority of the respondents were young and middle age (<44 years old) and had very low or low income. Only 859 people stated that “having a car available for the realized trip” among whom 385 people had low income (these may be young people that have a car in the family or access to a car due to work place). Out of 1463 HSR passengers, more than half were younger than 44 years old and had again very low or low income, a pattern repeated among the ConvRail passengers, too.

All responses to “purpose of the trip” showed that 25.9% of them were done for “visiting friends and family (Visit F&F)”. When combined with leisure (2.7%,), tourism (14.0%) and shopping (2.7%), the total share of non-business trips reached a value of 45.3%. Despite a high number of daily regional services in some corridors such as Adana-Mersin, low share of “commute (4.8%)” in overall as well as among working age group of 25-44 years (5.5%) suggested a potential misunderstanding between the concept “business (16.0%)” and “personal business (17.2%)”, as for the latter there is no universally valid clear perception or description.

On the aspect of travel frequency, one third of the people stated they traveled the same route every month. There is no critical difference between age groups and income levels. As expected, everyday trips are the lowest in the intercity passengers. Daily traveling rail passengers were only 3.8% whereas weekly travelers were around 12.3%. These numbers support the low share of commuters in the previous findings, and reinforce the fact that intercity rail services mostly for non-business trips. People were asked about the last transportation mode they used when arriving to the train station and the first transportation mode they would use after they get off the train. Existence of flight and ferry as access/egress modes (even at low shares) raised concerns about survey problems as there is no there train station directly connected to a port/airport. It is considered that, these modes should be zero as there is no direct connection, however, this question might not have been understood well by the respondents who gave these answers.

Table 6.1 Rail Passenger Travel Characteristics (N= 5219 participants)

	Overall	**Age band**				**Income Level***			
		<25	**25-44**	**45-60**	**>60**	**VL**	**L**	**M**	**H**
Participants	5219	1854	2255	843	267	1740	2015	482	123
Car Availability	859	188	455	172	44	170	385	149	53
HSR Users	1463	568	629	193	73	327	450	218	81
ConvRail Users	3756	1286	1626	650	194	1413	1565	264	42
Trip Purpose (%)									
Commute	4.8	4	5.5	4	**7.9**	5	4.1	3.3	6.5
Education	**16.2**	**36.1**	7.1	1.8	1.1	**18.9**	14.1	12.7	10.6
Business	**16**	8.1	**21.9**	**19**	10.5	10.5	17.4	**29**	**38.2**
Leisure	2.7	3.1	2.8	2.1	1.1	3.3	3	1.7	0.8
Tourism	**14**	**15.6**	**14.7**	10.4	9.4	12.4	14.8	**18.5**	**18.7**
Shopping	2.7	1.9	3.5	3.1	0	3	3	1.9	2.4
Personal biz.	**17.2**	9.5	**19.5**	**26.3**	**23.6**	**18.3**	**17.9**	14.1	4.9
Visiting F&F	**25.9**	**21.5**	**24.6**	**33**	**46.4**	**28.1**	**25.3**	**18.9**	**17.9**
Carrying goods	0.3	0.2	0.5	0.2	0	0.4	0.4	0	0
Total	100	100	100	100	100	100	100	100	100
Trip Frequency (%)									
Daily	3.8	3.8	4.9	2.1	0.4	3.7	4.1	3.3	4.9
Weekly	12.3	14.2	12.1	8.8	11.6	13.9	11.4	12	11.4
Monthly	**34**	**35.5**	**33.6**	**33.3**	**30**	**33**	**38**	**29**	**40.7**
<Once a month	**24.3**	**22.6**	**24.4**	**27.4**	**26.2**	**23.7**	**24.1**	**30.5**	**22**
Annually	17	15.2	17.2	18.7	22.5	18.1	14.2	19.3	14.6
Other	8.5	8.7	7.9	9.6	9.4	7.6	8.1	5.8	6.5
Total	100	100	100	100	100	100	100	100	100
Access Mode Choice (%)									
Car	**21.4**	17.4	**24.4**	**23.7**	16.5	**21.4**	**21.4**	**26.6**	**26.8**
Rail	7.6	9.4	6	6.9	9.7	6.6	7.5	7.7	8.1
Bus	**21.5**	**24.7**	19.9	19.1	**21**	**21.3**	**22.9**	**25.1**	15.4
Walk	**29.1**	**29.4**	**28.3**	**30.6**	**28.5**	**32.8**	**28.6**	17.4	14.6
Taxi	8.6	6.6	10.3	8.5	8.2	6.7	8.1	11.8	**26.8**
Flight/Ferry	0.3	0.5	0.2	0.3	0.8	0.4	0.3	0	1.6
Other	11.5	12	11	10.8	15.4	10.8	11.1	11.4	6.5
Total	100	100	100	100	100	100	100	100	100
Egress Mode choice (%)									
Car	**24**	19.6	**26.5**	**25.5**	**28.5**	**22.9**	**22.8**	**30.1**	**36.6**
Rail	7.1	8.6	5.7	6.4	10.5	7	7.1	5.2	3.3
Bus	**21.4**	**24.3**	18.9	**21.6**	**21.3**	**23.2**	**22.9**	19.9	13.8
Walk	**24.1**	**26.9**	**23.1**	**21.5**	**22.1**	**27.9**	**24.5**	15.8	13.8
Flight/Ferry	0.6	0.5	0.8	1	0	0.4	0.5	1.2	2.4
Taxi	11.7	8.3	13.9	14.6	8.6	9.4	11.5	18.7	**26**
Other	11	11.8	11	9.5	9	9.3	10.7	9.1	4.1
Total	100	100	100	100	100	100	100	100	100

*Results of those who did not want to claim their income are not shown in this table.

6.1 Rail Preference Reasons of Car Available Passengers

People were asked if there was a private car available for the trip they were making. Only 859 of the intercity passengers said yes to this question. After that, rail preference reason was asked to those who said yes. Overall, cost, comfort and time were the main factors for choosing to travel by train. However, high income group are focusing on time and comfort much more than cost. Except very low income group, comfort is always the most important case for choosing rail. Considering ConvRail services are cheaper but longer in time comparing to other modes in general in Turkey, ConvRail passengers gave priority to comfort and cost almost equally and much more than the other factors. However, time is a very important factor for high speed rail passengers as seen in the results in Table 6.2.

Table 6.2 Rail Passenger Travel Characteristics (N= 859 participants)*

	Overall	Service type		Age band				Income Level			
		HSR	Conv.	<25	25-44	45-60	>60	VL	L	M	H
Rail Preference Reason (%)											
Cheaper	32.2	15.8	42.7	31.4	30.3	36.6	38.6	47.1	34.3	24.2	9.4
More comfort	37.0	29.0	42.2	36.2	33.8	44.8	43.2	31.8	44.2	34.9	37.7
Not fit in the car	2.4	1.5	3.1	2.7	3.1	1.2	0.0	2.9	3.1	1.3	0.0
Weather cond.	0.7	0.0	1.1	0.5	0.9	0.6	0.0	1.2	0.0	1.3	1.9
Shorter in time	17.7	40.0	3.4	14.9	22.9	8.7	11.4	11.2	12.7	26.8	45.3
Other	9.9	13.7	7.4	14.4	9.0	8.1	6.8	5.9	5.7	11.4	5.7

*N= 859 as rail preference reason was asked to those who have car available for this trip.

6.2 HSR versus ConvRail Passenger Comparison

When the difference between HSR passengers and ConvRail passengers in terms of trip purpose and trip frequency was investigated, it is seen that, both passenger profiles are quite similar on this point. However, the two purposes -business and personal business- are pretty different between the two groups. While business is much higher for HSR passengers, personal business rate is almost half of ConvRail passengers. Another marked difference between the two groups is in access and egress modes as walking is significantly higher for ConvRail passengers than HSR users. This is probably due to the fact that in small cities people can access to train stations in a smaller range and ConvRail serves to more small cities comparing to HSR. Results can be seen in the graphs in Figure 6.1. It is also seen that, very low and low income group have much higher rate among ConvRail passengers. While 22.4% of HSR users has very low income (<500 €) and 30. 8% low income (500 – 1000 €); these ratios are 37.6% and 41.7% for ConvRail users. However, rate of people who do not want to disclosure their monthly income is much higher for HSR users (26.5%) while only 12.6% of ConvRail passengers did not want to tell their income.

After conducting general analysis for all rail passengers, some determined corridors need to be investigated specially in detail. As an example, Ankara-Konya corridor was selected and the survey results were compared with the general results. There are some differences in the ratios of purposes but not significant. Graphs in Figure 6.2 show the trip purpose rates for all rail passengers and Ankara-Konya passengers only.

Another special treatment for Konya passengers in the analysis was on rail preference reason. Only 32 out of 169 Ankara-Konya passengers responded to this question and comfort is found as the most preferred reason for choosing railways. Summary of the analysis is shown in Table 6.3. Production figures from RPF data were compared to the survey data of NTMP in Table 6.4. Production percentage of the provinces was calculated as the ratio of production of the province in all departing passengers. (RPF share/survey share) ratios show how close the P-rates for rail-pax and for survey are.

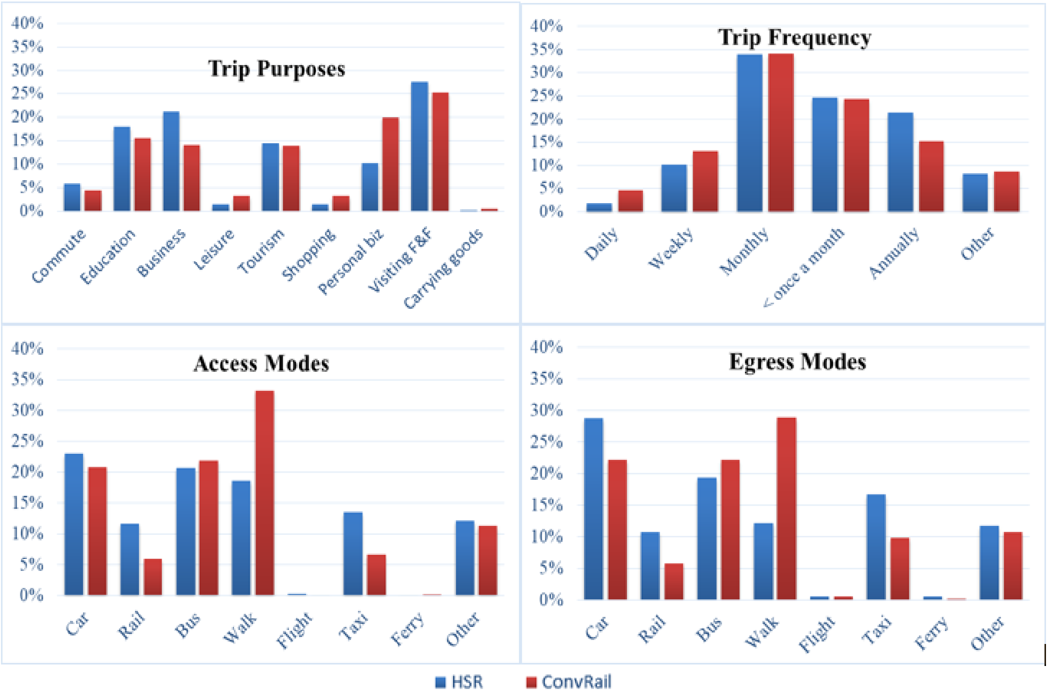


Figure 6.1 Comparison of HSR and ConvRail Passenger Characteristics

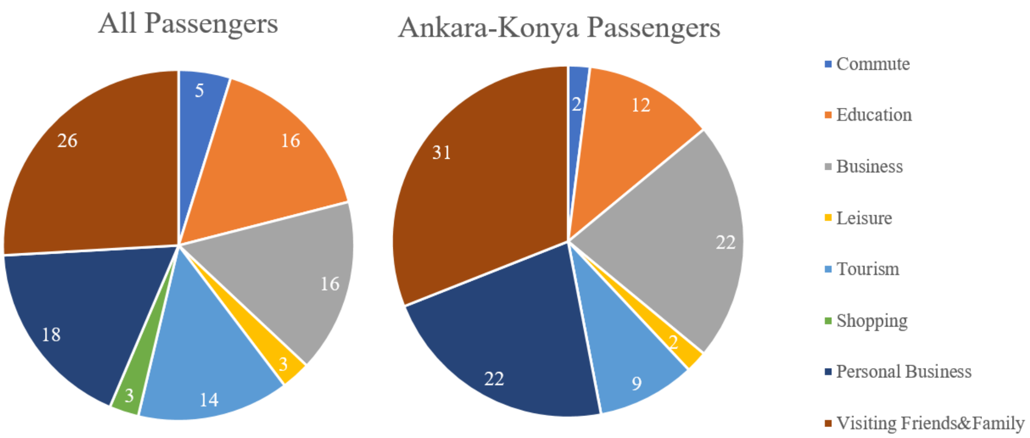


Figure 6.2 Trip Purpose Rates for all Rail Passengers and Ankara-Konya Rail Passengers

Table 6.3 Rail Preference Reasons for Ankara-Konya Rail Passengers

Ankara-Konya Passengers rail preference reason (32 respondents out of 169)	
S26.Why did you choose to travel by train?	
Train is cheaper	16%
More comfortable	44%
It would take longer by car	31%
Other (please specify)	9%

Table 6.4 RPF and survey data comparison in terms of net production

Survey				**Rail-Pax**		
Province	**Name**	**Net P**	**%**	**Net P ($x10^6$)**	**%**	**Rail-Pax% / survey%**
6	Ankara	799	15.3%	2.41	18.7%	1.2
33	Mersin	582	11.2%	1.37	10.6%	1.0
42	Konya	302	5.8%	1.27	9.8%	1.7
26	Eskişehir	366	7.0%	1.54	12.0%	1.7
1	Adana	227	4.4%	1.53	11.9%	2.7
20	Denizli	439	8.4%	0.26	2.0%	0.2
45	Manisa	374	7.2%	0.45	3.5%	0.5
38	Kayseri	364	7.0%	0.04	0.3%	0.0
34	İstanbul	360	6.9%	0.87	6.7%	1.0
70	Karaman	321	6.2%	0.12	1.0%	0.2
Others		1085	20.8%	3.06	23.6%	1.1

6.3 Regional Rail Passenger Travel Characteristics

To be able to understand the regional differences in the passenger characteristics, a separate evaluation was done on Southern Region (Mersin, Adana, Osmaniye, Karaman), HSR Region (Ankara, Istanbul, Eskisehir and Konya), Western Region (Aydın, Denizli, İzmir, Manisa) and Eastern Region (Erzincan, Kayseri, Malatya, Sivas).

Table 6.5, Table 6.6, Table 6.7 and Table 6.8 show travel characteristics of Southern Region, HSR Region, Western Region and Eastern Region respectively. The values 10% more than the whole data statistics given in Table 6.1 are shown in bold and 10% less are shown in italic in order to understand the very different characteristics between the regions.

The most significant difference in Southern Region travelers is the trip frequency. Since the trains are giving services in relatively shorter distances, people here use rail services more frequently. So daily and weekly travel numbers are higher than overall results. Also, bus is a very dominant access and egress mode in the Southern Region as understood from the high percentage of access mode and egress mode part of Table 6.5.

HSR region shows very similar profile to the general results (Table 6.6). Only significant difference is that older people tend to use rail more as an access mode and travel for leisure and shopping purposes are higher among HSR travelers. Also, walk is a less preferred access and egress mode in HSR passengers than in general.

In contrast to Southern Region travelers, Western Region passengers travel less frequently and use less bus but more walk for access and egress mode (Table 6.7). In the Eastern Side, rate of commuters is more than overall (Table 6.8). However, business purposes show less importance among Eastern Region travelers. Opposite to HSR travelers, walk is the most preferred access and egress mode with more than half ratio among Eastern Region travelers and rate of people using bus from/to train station is much less than general profile.

Table 6.5 Rail Passenger Survey - Travel Characteristics (Southern Region) (N=1297)

Southern Region	**Overall**	**Age band**				**Income Level**			
		<25	**25-44**	**45-60**	**>60**	**VL**	**L**	**M**	**H**
Trip purpose									
Commute	7.5	3.9	10.6	6.3	8.6	7.3	9.0	6.4	5.6
Education	13.6	29.3	5.3	0.6	5.7	15.4	12.8	6.4	16.7
Business	34.2	19.9	41.7	47.4	34.3	32.1	36.3	40.4	*22.2*
Leisure	44.8	46.9	42.5	45.7	51.4	45.2	41.8	46.8	**55.6**
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Trip Frequency									
Daily	**16.0**	**14.1**	**19.2**	**13.7**	0.0	**14.4**	**16.7**	**22.3**	11.1
Weekly	**25.3**	**28.8**	**24.0**	18.3	**34.3**	**30.2**	21.3	**24.5**	11.1
Monthly	28.5	**26.3**	28.6	30.9	**42.9**	30.4	*27.6*	23.4	33.3
<Once a month	*13.1*	*12.4*	*12.9*	*16.6*	*8.6*	*10.0*	14.8	*10.6*	16.7
Annually	*6.6*	6.2	*6.0*	9.7	*5.7*	*6.7*	6.0	10.6	5.6
Other	10.6	12.0	9.4	10.9	8.6	8.3	13.5	8.5	**22.2**
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Access Mode									
Car	13.4	10.0	16.0	14.3	11.4	11.5	13.7	19.1	22.2
Rail	4.6	6.4	3.0	4.6	8.6	2.9	6.8	1.1	**22.2**
Bus	**38.8**	**45.2**	**37.9**	24.6	**37.1**	**36.3**	**42.0**	**47.9**	16.7
Walk	32.2	29.5	31.2	**42.3**	37.1	37.7	27.0	22.3	5.6
Taxi	4.3	2.7	5.0	6.3	5.7	4.2	4.3	**3.2**	*11.1*
Flight/Ferry	0.7	1.0	0.2	1.7	0.0	0.6	0.9	0.0	0.0
Other	5.9	5.2	6.8	6.3	0.0	6.9	5.5	6.4	**22.2**
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Egress Mode									
Car	15	11.2	18.2	*15.4*	*8.6*	*11.5*	14.5	28.7	44.4
Rail	3.4	4.6	2.0	5.1	**2.9**	3.1	4.8	0.0	0.0
Bus	**41.6**	**49.6**	**36.7**	**35.4**	**48.6**	**42.9**	**42.0**	**46.8**	**27.8**
Walk	29.8	26.6	31.9	31.4	28.6	32.3	28.0	12.8	5.6
Taxi	4.2	1.9	5.8	5.7	2.9	4.2	4.4	*5.3*	*5.6*
Flight/Ferry	0.4	0.2	0.7	0.0	0.0	0.4	0.2	1.1	0.0
Other	5.6	6.0	4.8	6.9	8.6	5.6	6.1	5.3	**16.7**
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table 6.6 Rail Passenger Survey - Travel Characteristics (HSR Region) (N= 1698)

HSR Region	Overall	Age band				Income Level			
		<25	25-44	45-60	>60	VL	L	M	H
Trip purpose									
Commute	7.2	6.7	7.7	7.8	4.1	3.5	3.4	2.8	7.8
Education	18.1	37.0	9.6	1.3	0.0	21.2	18.6	15.3	8.9
Business	33.1	16.2	43.3	46.3	28.8	27.1	31.5	42.7	43.3
Leisure/shop	41.6	40.2	39.4	44.6	**67.1**	48.2	46.5	39.1	40.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Trip Frequency									
Daily	4.5	3.5	6.1	3.0	0.0	3.5	2.4	0.8	4.4
Weekly	10.1	10.2	11.1	7.8	6.8	9.4	8.8	12.9	11.1
Monthly	31.7	36.3	29.5	27.7	27.4	35.9	35.3	26.6	42.2
<Once a month	24.6	24.5	25.0	22.9	27.4	20.3	27.5	33.1	22.2
Annually	21.0	17.6	21.3	27.3	26.0	23.2	20.4	21.8	15.6
Other	8.1	7.8	7.0	11.3	12.3	7.6	5.6	4.8	4.4
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Access Mode									
Car	20.5	16.6	24.2	20.8	13.7	19.4	21.6	25.8	26.7
Rail	11.8	13.6	9.9	10.4	**20.5**	11.2	11.6	11.3	8.9
Bus	22.1	25.0	20.2	19.9	24.7	28.8	22.0	25.8	17.8
Walk	22.2	22.6	21.8	23.8	*17.8*	*21.5*	*17.6*	9.3	11.1
Taxi	13.5	11.2	15.0	15.2	13.7	10.0	14.2	15.3	30.0
Flight/Ferry	0.4	0.2	0.4	0.0	2.7	0.3	0.2	0.0	2.2
Other	9.5	10.9	8.6	10.0	6.8	8.8	13.0	12.5	3.3
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Egress Mode									
Car	26.1	23.2	28.1	26.0	31.5	23.2	27.3	28.2	32.2
Rail	9.5	12.6	8.2	5.2	9.6	11.5	7.8	8.5	4.4
Bus	18.9	21.0	16.6	19.0	24.7	27.4	19.6	15.3	10.0
Walk	18.4	21.4	16.6	17.7	*12.3*	16.8	15.0	13.3	14.4
Taxi	16.9	11.4	20.9	19.5	13.7	10.0	19.2	23.8	32.2
Flight/Ferry	0.8	0.5	1.0	1.3	0.0	0.3	1.0	0.4	1.1
Other	9.4	9.9	8.5	11.3	8.2	10.9	10.2	10.5	5.6
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table 6.7 Rail Passenger Survey - Travel Characteristics (Western Region) (N= 2017)

Western Region	Overall	Age band				Income Level			
		<25	25-44	45-60	>60	VL	L	M	H
Trip purpose									
Commute	1.8	1.5	2.2	1.1	3.5	1.8	1.7	2.1	0.0
Education	8.3	27.8	1.6	0.2	0.0	*8.4*	8.0	4.2	0.0
Business	40.0	21.9	45.5	49.4	**44.3**	37.6	42.1	**60.0**	75.0
Leisure/shop	49.9	48.8	50.7	49.2	52.2	52.1	48.2	33.7	25.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Trip Frequency									
Daily	2.8	3.7	2.9	1.8	0.9	2.7	2.7	3.2	0.0
Weekly	15.8	20.3	13.5	14.1	19.1	19.1	14.2	13.7	0.0
Monthly	36.5	35.5	37.4	37.1	31.3	30.4	43.0	**54.7**	25.0
<Once a month	25.4	19.7	26.3	29.6	29.6	30.4	22.9	*14.7*	25.0
Annually	*6.7*	8.8	*5.2*	*6.6*	*9.6*	*7.1*	4.4	*7.4*	50.0
Other	12.8	12.0	14.7	10.7	9.6	10.4	12.8	6.3	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Access Mode									
Car	18.5	14.0	20.5	20.7	15.7	12.4	23.3	35.8	0.0
Rail	8.5	8.8	8.6	9.3	2.6	9.8	9.5	6.3	0.0
Bus	14.4	*14.2*	13.2	16.9	16.5	14.2	16.7	15.8	25.0
Walk	39.0	**40.9**	37.7	38.0	**43.5**	**47.0**	33.3	**30.5**	50.0
Taxi	2.1	1.5	2.2	2.7	1.7	1.3	2.8	2.1	25.0
Flight/Ferry	0.1	0.0	0.1	0.5	0.0	0.0	0.3	0.0	0.0
Other	17.4	20.6	17.7	11.8	20.0	15.3	14.1	9.5	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Egress Mode									
Car	19.4	14.2	20.2	24.4	19.1	17.0	21.7	30.5	50.0
Rail	5.0	6.6	3.2	5.5	10.4	5.9	5.5	1.1	0.0
Bus	12.9	*11.8*	12.1	16.4	12.2	*13.0*	16.0	16.8	0.0
Walk	**37.3**	**38.1**	**36.3**	**36.4**	**45.2**	**44.6**	33.8	**28.4**	0.0
Taxi	4.1	3.3	4.0	5.5	3.5	2.8	5.4	*7.4*	25.0
Flight/Ferry	0.6	0.9	0.5	0.5	0.0	0.1	0.3	5.3	25.0
Other	20.6	25.0	23.7	11.4	9.6	16.4	17.2	10.5	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table 6.8 Rail Passenger Survey - Travel Characteristics (Eastern Region) (N= 437)

Eastern Region	Overall	Age band				Income Level (TL)			
		<25	25-44	45-60	>60	VL	L	M	H
Trip purpose									
Commute	12.1	4.9	14.1	**16.2**	**24.1**	**15.9**	8.5	0.0	0.0
Education	16.2	31.7	11.1	4.4	3.4	16.3	16.2	17.6	100.0
Business	25.2	16.2	*29.3*	*30.9*	27.6	22.0	26.2	*29.4*	0.0
Leisure/Shop	46.5	47.2	45.5	48.5	*44.8*	45.8	49.2	**52.9**	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Trip Frequency									
Daily	1.1	0.7	1.0	1.5	3.4	1.9	0.0	0.0	0.0
Weekly	9.4	8.5	8.6	8.8	20.7	8.3	8.5	5.9	0.0
Monthly	32.0	38.7	26.3	36.8	27.6	30.7	33.8	29.4	100.0
<Once a month	24.5	31.0	22.7	*14.7*	27.6	26.1	20.8	**52.9**	0.0
Annually	**30.9**	18.3	**39.4**	**36.8**	20.7	**31.8**	**35.4**	11.8	0.0
Other	2.1	2.8	2.0	1.5	0.0	1.1	1.5	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Access Mode									
Car	20.8	19.0	22.2	17.6	**27.6**	23.1	13.8	23.5	100.0
Rail	3.9	5.6	3.0	1.5	6.9	4.5	2.3	5.9	0.0
Bus	*10.3*	17.6	*6.1*	*8.8*	*6.9*	11.4	*9.2*	*11.8*	0.0
Walk	**55.1**	**46.5**	**59.6**	**64.7**	**44.8**	**54.2**	**63.8**	**29.4**	0.0
Taxi	5.0	5.6	5.1	2.9	6.9	3.4	4.6	**23.5**	0.0
Flight/ Ferry	0.7	0.0	0.5	0.0	6.9	0.4	0.8	0.0	0.0
Other	4.1	5.6	3.5	4.4	0.0	3.0	5.4	5.9	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Egress Mode									
Car	24.0	21.1	25.8	19.1	37.9	25.0	20.0	**41.2**	100.0
Rail	0.5	0.0	1.0	0.0	0.0	0.4	0.8	0.0	0.0
Bus	*5.0*	*7.7*	*3.5*	*2.9*	*6.9*	*5.3*	*6.2*	0.0	0.0
Walk	**63.2**	**60.6**	**62.6**	**73.5**	**55.2**	**64.4**	**66.9**	**41.2**	0.0
Taxi	6.4	9.2	6.1	*4.4*	0.0	4.5	5.4	17.6	0.0
Flight/Ferry	0.2	0.0	0.5	0.0	0.0	0.4	0.0	0.0	0.0
Other	*0.7*	*1.4*	*0.5*	0.0	0.0	0.0	0.8	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

6.4 Binary Logistic Regression Model for Intercity Rail Passenger Travels

Binary logistic regression is a type of regression analysis where the dependent variable is dichotomous (e.g., succeed/fail, live/die, graduate/dropout, vote for A or B), in other terms dependent variable can be represented as a dummy variable. It is useful in predicting the likelihood that a new case will be in one of the two outcome categories. (Berger, 2017)

Using rail passenger survey data, binary logistic regression analyses were performed to identify the passenger characteristics. Models were built in order to understand the profile of business trip passengers. Methodology of the process and definitions of the variables were given in Chapter 4. From the total of 7028 surveys conducted in 20 stations in Turkey, intercity passenger data was collected and the data was cleaned up. 859 out of 5219 intercity passengers did not want to disclose their income so these data were removed. The models are based on 4360 surveys. Ratio of the number of business travelers in total is 16%. As seen in Table 6.9 to Table 6.14, when trip purposes are added to the model, R^2 values are good but the significance of the trip purpose variables are quite low. However, when the trip purpose related variables are put out of the model, R^2 dramatically decreases.

Table 6.9 Binary Model Results (Model 1 – Model 3)

D_business	**Model 1**		**Model 2**		**Model 3**	
Chi-sq	3795.86		393.63		383.89	
R-sq	0.982		0.146		0.142	
(-2) Log likelihood	113,294a		3515,523a		3525,259a	
Variables	**Beta**	**Sig**	**Beta**	**Sig**	**Beta**	**Sig**
D_male	0.671	0.224	0.636	0.000	0.640	0.000
Age	0.082	0.203	0.028	0.002	-	-
D_young	-10.083	0.990	1.009	0.033	-0.266	0.264
D_midage1	-11.090	0.989	1.632	0.000	0.669	0.003
D_midage2	-11.200	0.989	1.016	0.000	0.580	0.016
D_old	-	-	-	-	-	-
D_comm	-62.336	0.979	-	-	-	-
D_edu	-60.735	0.965	-	-	-	-
D_leisure	-48.435	0.986	-	-	-	-
D_trsm	-62.873	0.965	-	-	-	-
D_shop	-49.519	0.986	-	-	-	-
D_pers	-60.532	0.963	-	-	-	-
D_VFF	-61.554	0.960	-	-	-	-
D_crry	-	-	-	-	-	-
D_hmbased	-1.859	0.089	-0.607	0.000	-0.603	0.000
D_1day	1.058	0.127	0.263	0.014	0.254	0.017
TrpFrq	-0.082	0.782	-0.057	0.208	-	-
D_daily	16.476	0.989	2.212	0.009	0.997	0.000
D_weekly	0.450	0.613	0.557	0.000	0.371	0.053
D_Monthly	-0.763	0.495	0.048	0.779	0.045	0.791
D_lessmonth	-	-	-	-	-0.226	0.213
D_Annually	13.265	0.981	-0.227	0.238	-0.214	0.264
D_nonperiod	-	-	-	-	-	-
D_1way	0.660	0.430	-0.044	0.715	-0.059	0.624
income	0.000	1.000	0.000	0.221	-	-
D_income1	-14.769	0.993	-0.737	0.037	-1.357	0.000
D_income2	-13.924	0.990	-0.400	0.103	-0.893	0.000
D_income3	-	-	-	-	-0.280	0.211
D_income4	-	-	-	-	-	-
D_car	-0.245	0.724	0.171	0.109	0.176	0.098
D_HS	14.349	0.978	0.290	0.005	0.271	0.009
constant	26.594	0.990	-3.676	0.000	-1.163	0.002

Table 6.10 Binary Model Results (Model 4 – Model 6)

D_business	**Model 4**		**Model 5**		**Model 6**	
Chi-sq	179.18		272.95		378.35	
R-sq	0.068		0.103		0.140	
(-2) Log likelihood	3729,976a		3636,207a		3530,801a	
Variables	**Beta**	**Sig**	**Beta**	**Sig**	**Beta**	**Sig**
D_male	-	-	0.667	0.000	0.699	0.000
Age	0.014	0.000	-	-	-	-
D_young	-	-	-	-	-	-
D_midage1	-	-	0.631	0.000	0.684	0.000
D_midage2	-	-	-	-	-	-
D_old	-	-	-	-	-	-
D_comm	-	-	-	-	-20.240	0.994
D_edu	-	-	-	-	-	-
D_leisure	-	-	-	-	-	-
D_trsm	-	-	-	-	-	-
D_shop	-	-	-	-	-	-
D_pers	-	-	-	-	-	-
D_VFF	-	-	-	-	-	-
D_crry	-	-	-	-	-	-
D_hmbased	-	-	-0.488	0.000	-0.468	0.000
D_1day	-	-	-	-	-	-
TrpFrq	0.052	0.000	-	-	-	-
D_daily	-	-	1.092	0.000	1.598	0.000
D_weekly	-	-	-	-	-	-
D_Monthly	-	-	-	-	-	-
D_lessmonth	-	-	-	-	-	-
D_Annually	-	-	-	-	-	-
D_nonperiod	-	-	-	-	-	-
D_1way	-	-	-	-	-	-
income	0.001	0.000	-	-	-	-
D_income1	-	-	-0.690	0.000	-0.691	0.000
D_income2	-	-	-	-	-	-
D_income3	-	-	-	-	-	-
D_income4	-	-	-	-	-	-
D_car	-	-	-	-	-	-
D_HS	-	-	0.365	0.000	0.365	0.000
constant	-2.898	0.000	-1.910	0.000	-1.931	0.000

Table 6.11 Binary Model Results (Model 7 – Model 9)

D_business	**Model 7**		**Model 8**		**Model 9**	
Chi-sq	464.54		354.00		563.81	
R-sq	0.171		0.132		0.205	
(-2) Log likelihood	3444,617a		3555,151a		3345,343a	
Variables	**Beta**	**Sig**	**Beta**	**Sig**	**Beta**	**Sig**
D_male	0.697	0.000	0.662	0.000	0.628	0.000
Age	-	-	-	-	-	-
D_young	-	-	-	-	-	-
D_midage1	0.944	0.000	0.879	0.000	0.539	0.000
D_midage2	0.811	0.000	0.775	0.000	0.367	0.006
D_old	-	-	-	-	-	-
D_comm	-20.375	0.994	-	-	-	-
D_edu	-	-	-	-	-19.574	0.989
D_leisure	-	-	-	-	-	-
D_trsm	-	-	-	-	-	-
D_shop	-	-	-	-	-	-
D_pers	-	-	-	-	-	-
D_VFF	-	-	-	-	-	-
D_crry	-	-	-	-	-	-
D_hmbased	-0.497	0.000	-0.520	0.000	-0.524	0.000
D_1day	-	-	-	-	-	-
TrpFrq	-	-	-	-	-	-
D_daily	1.632	0.000	1.082	0.000	1.341	0.000
D_weekly	-	-	-	-	-	-
D_Monthly	-	-	-	-	-	-
D_lessmonth	-	-	-	-	-	-
D_Annually	-	-	-	-	-	-
D_nonperiod	-	-	-	-	-	-
D_1way	-0.173	0.147	-0.175	0.134	-0.194	0.104
income	-	-	-	-	-	-
D_income1	-1.130	0.000	-1.100	0.000	-1.109	0.000
D_income2	-0.680	0.000	-0.636	0.000	-0.650	0.000
D_income3	-	-	-	-	-	-
D_income4	-	-	-	-	-	-
D_car	0.212	0.047	0.220	0.037	0.177	0.099
D_HS	0.223	0.029	0.222	0.028	0.285	0.006
constant	-1.566	0.000	-1.555	0.000	-1.087	0.000

Table 6.12 Binary Model Results (Model 10 – Model 12)

D_business	**Model 10**		**Model 11**		**Model 12**	
Chi-sq	397.13		610.05		397.65	
R-sq	0.147		0.221		0.147	
(-2) Log likelihood	3512,025a		3299,108a		3511,508a	
Variables	**Beta**	**Sig**	**Beta**	**Sig**	**Beta**	**Sig**
D_male	0.656	0.000	0.647	0.000	0.645	0.000
Age	-	-	-	-	-	-
D_young	-	-	-	-	-	-
D_midage1	0.886	0.000	0.897	0.000	0.899	0.000
D_midage2	0.773	0.000	0.700	0.000	0.793	0.000
D_old	-	-	-	-	-	-
D_comm	-	-	-	-	-	-
D_edu	-	-	-	-	-	-
D_leisure	-19.523	0.996	-	-	-	-
D_trsm	-	-	-19.837	0.990	-	-
D_shop	-	-	-	-	-19.552	0.996
D_pers	-	-	-	-	-	-
D_VFF	-	-	-	-	-	-
D_crry	-	-	-	-	-	-
D_hmbased	-0.554	0.000	-0.593	0.000	-0.518	0.000
D_1day	-	-	-	-	-	-
TrpFrq	-	-	-	-	-	-
D_daily	1.077	0.000	0.872	0.000	1.041	0.000
D_weekly	-	-	-	-	-	-
D_Monthly	-	-	-	-	-	-
D_lessmonth	-	-	-	-	-	-
D_Annually	-	-	-	-	-	-
D_nonperiod	-	-	-	-	-	-
D_1way	-0.170	0.149	-0.239	0.048	-0.182	0.123
income	-	-	-	-	-	-
D_income1	-1.086	0.000	-1.252	0.000	-1.084	0.000
D_income2	-0.621	0.000	-0.727	0.000	-0.624	0.000
D_income3	-	-	-	-	-	-
D_income4	-	-	-	-	-	-
D_car	0.224	0.035	0.158	0.146	0.253	0.017
D_HS	0.194	0.056	0.253	0.015	0.199	0.050
constant	-1.501	0.000	-1.114	0.000	-1.528	0.000

Table 6.13 Binary Model Results (Model 13 – Model 15)

D_business	**Model 13**		**Model 14**		**Model 15**	
Chi-sq	664.23		793.81		359.06	
R-sq	0.239		0.281		0.134	
(-2) Log likelihood	3244,928a		3115,342a		3550,097a	
Variables	**Beta**	**Sig**	**Beta**	**Sig**	**Beta**	**Sig**
D_male	0.694	0.000	0.639	0.000	0.662	0.000
Age	-	-	-	-	-	-
D_young	-	-	-	-	-	-
D_midage1	1.025	0.000	0.933	0.000	0.883	0.000
D_midage2	1.022	0.000	0.938	0.000	0.774	0.000
D_old	-	-	-	-	-	-
D_comm	-	-	-	-	-	-
D_edu	-	-	-	-	-	-
D_leisure	-	-	-	-	-	-
D_trsm	-	-	-	-	-	-
D_shop	-	-	-	-	-	-
D_pers	-19.866	0.989	-	-	-	-
D_VFF	-	-	-19.882	0.986	-	-
D_crry	-	-	-	-	-19.408	0.998
D_hmbased	-0.520	0.000	-0.443	0.000	-0.518	0.000
D_1day	-	-	-	-	-	-
TrpFrq	-	-	-	-	-	-
D_daily	0.926	0.000	0.833	0.000	1.074	0.000
D_weekly	-	-	-	-	-	-
D_Monthly	-	-	-	-	-	-
D_lessmonth	-	-	-	-	-	-
D_Annually	-	-	-	-	-	-
D_nonperiod	-	-	-	-	-	-
D_1way	-0.166	0.173	-0.073	0.552	-0.179	0.127
income	-	-	-	-	-	-
D_income1	-1.063	0.000	-0.957	0.000	-1.096	0.000
D_income2	-0.607	0.000	-0.527	0.000	-0.630	0.000
D_income3	-	-	-	-	-	-
D_income4	-	-	-	-	-	-
D_car	0.217	0.047	0.321	0.004	0.224	0.034
D_HS	0.097	0.351	0.341	0.001	0.216	0.033
constant	-1.438	0.000	-1.517	0.000	-1.555	0.000

Table 6.14 Binary Model Results (Model 16 – Model 18)

D_business	**Model 16**		**Model 17**		**Model 18**	
Chi-sq	1261.49		1652.62		1652.61	
R-sq	0.424		0.533		0.533	
(-2) Log likelihood	2647,666a		2256,538a		2256,548a	
Variables	**Beta**	**Sig**	**Beta**	**Sig**	**Beta**	**Sig**
D_male	0.685	0.000	0.615	0.000	0.615	0.000
Age	-	-	0.015	0.005	0.015	0.005
D_young	-	-	-	-	-	-
D_midage1	1.181	0.000	0.524	0.000	0.523	0.000
D_midage2	1.484	0.000	0.415	0.036	0.414	0.036
D_old	-	-	-	-	-	-
D_comm	-	-	-	-	-	-
D_edu	-	-	-20.352	0.989	-20.352	0.989
D_leisure	-	-	-	-	-	-
D_trsm	-	-	-	-	-	-
D_shop	-	-	-	-	-	-
D_pers	-20.476	0.988	-20.765	0.988	-20.765	0.988
D_VFF	-20.355	0.986	-20.713	0.986	-20.712	0.986
D_crry	-	-	-	-	-	-
D_hmbased	-0.417	0.001	-0.382	0.003	-0.382	0.003
D_1day	-	-	-	-	-	-
TrpFrq	-	-	-	-	-	-
D_daily	0.543	0.005	0.730	0.001	0.726	0.001
D_weekly	-	-	-	-	-	-
D_Monthly	-	-	-	-	-	-
D_lessmonth	-	-	-	-	-	-
D_Annually	-	-	-	-	-	-
D_nonperiod	-	-	-	-	-	-
D_1way	-0.005	0.973	0.014	0.922	-	-
income	-	-	-	-	-	-
D_income1	-0.820	0.000	-0.740	0.000	-0.741	0.000
D_income2	-0.433	0.001	-0.391	0.005	-0.391	0.005
D_income3	-	-	-	-	-	-
D_income4	-	-	-	-	-	-
D_car	0.364	0.003	0.297	0.022	0.296	0.022
D_HS	0.178	0.116	0.327	0.007	0.324	0.007
constant	-1.481	0.000	-1.146	0.000	-1.132	0.000

Several models were formed and the best model (Model 19) is summarized in Table 6.15. -2loglikelihood of the chosen model is equal to 3623.622. Being male, getting older, returning same day, trip frequency, income, car ownership and taking high-speed service have positive impact on likelihood of making a work trip. On the other hand, home based trip has a negative effect on making work trip.

Table 6.15 Best Model (Model 19) for Business-Trip Passengers

Variables	β	Wald	Sig.	Exp(β)
D_{male}	0.619	42.352	0	1.857
Age	0.013	17.727	0	1.013
$D_{hmbased}$	-0.637	31.968	0	0.529
D_{1day}	0.381	14.418	0	1.464
TrpFrq	0.046	28.802	0	1.048
income	0.001	93.798	0	1.001
D_{car}	0.297	8.113	0.004	1.346
D_{HS}	0.209	4.478	0.034	1.233
Constant	-2.92	289.831	0	0.054
-2 Log likelihood	3623,622[a]			
Cox & Snell R^2	0.063			
Nagelkerke R^2	0.107			

For male: $e^{0.619} = 1.857$ …males are more likely to be a business-trip passenger by a factor of 1.857.

Age: $e^{0.013} = 1.013$ …for every year of age, the odds of making a business-trip increases by a factor of 1.013.

Home based: $e^{-0.637} = 0.529$ …home based travelers are less likely to make a business-trip by a factor of 0.529.

1day: $e^{0.381} = 1.464$ …same day return travelers are more likely to be a business-trip passenger by a factor of 1.464.

Trip Frequency: $e^{0.046} = 1.048$ …the frequency of the trip increases the odds of a business-trip by a factor of 1.048.

Income: $e^{0.001} = 1.001$ …increase in income affects the odds of a business-trip by a factor of only 1.001.

Car ownership: $e^{0.297} = 1.346$ …car owners are more likely to make a business-trip by a factor of 1.346.

HS service: $e^{0.209} = 1.233$ …HSR passengers are more likely to be a business-trip passenger by a factor of 1.233.

The business-trip passenger profile is therefore a frequently traveling adult man who is on a non-home based trip and returning same day, with high income and having a car available for the trip but using HSR service. The results seem logical, considering the fact that an intercity business trip is made more likely by an adult shown by a positive association with age. Secondly, employment rate of men is higher than women (Eurostat, 2021), increasing the likelihood of male travelers making business trips, who would most likely to be made from office locations, explaining the negative impact of home-based departures. Also, time is an important factor for business people so as to make their way on time to catch up on a meeting or start the work on a certain time. Therefore, HSR is preferred for being faster by business passengers. Most of the business travelers are making frequent trips, differentiating them from non-repeating vacation or leisure trips. Car ownership is positively related with income, therefore a business-trip traveler is more likely to have higher income than vacation/leisure travelers (including young people, retirees, etc.)

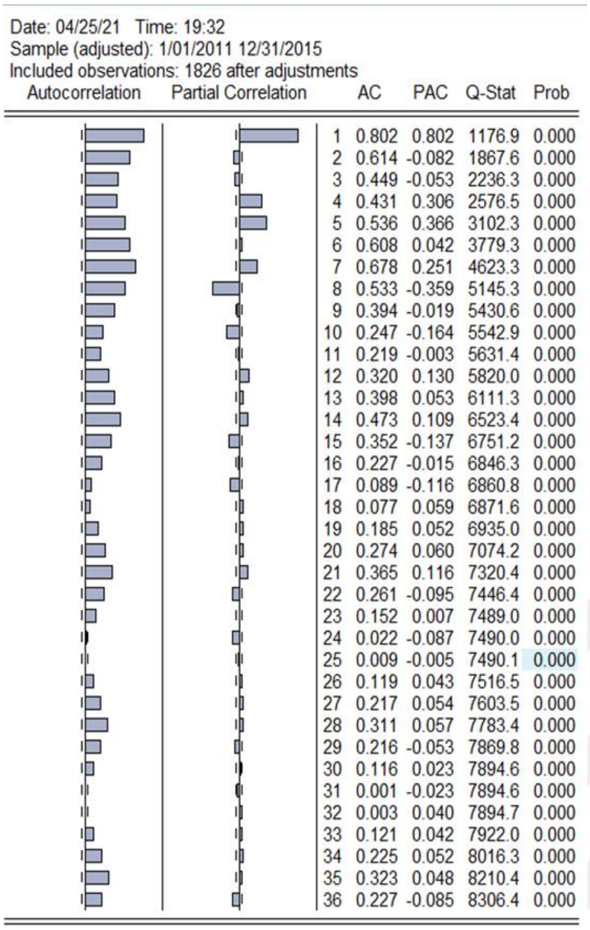
CHAPTER 7

FORECASTING RAIL PASSENGER FLOW (RPF)

7.1 ARIMA Models

Autocorrelation (ACF) and partial autocorrelation (PACF) functions of the series are given in Figure 7.1 by the help of the Eviews package program. When the graphs of the raw series are examined, the sine fluctuation in the ACF graph with lags shows that there is a seasonal effect, but when evaluated together with the PACF, it cannot be said that the series is non-stationary (Tortum et al., 2014). It was subjected to unit root test analysis to evaluate whether the series was stationary or not in the light of real data. For this, Augmented Dickey-Fuller (ADF) test was performed on the data and the results are given in Figure 7.1.

The critical value of -5.65, which is the value of the test statistic, is smaller than -2.86. Therefore, the series can be called stationary. Box-Jenkins modeling will be possible. Within the scope of the method presented in the theoretical framework, the most suitable ARIMA models were tried to be determined for the time series consisting of the daily passenger numbers of railway transportation for the years 2011-2015 and the parameters of the prediction model were calculated (Table 7.1). Accordingly, the series can be modeled as ARMA (11,12) or ARIMA (11,0,12).



Date: 04/25/21 Time: 19:32
Sample (adjusted): 1/01/2011 12/31/2015
Included observations: 1826 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.802	0.802	1176.9	0.000
		2	0.614	-0.082	1867.6	0.000
		3	0.449	-0.053	2236.3	0.000
		4	0.431	0.306	2576.5	0.000
		5	0.536	0.366	3102.3	0.000
		6	0.608	0.042	3779.3	0.000
		7	0.678	0.251	4623.3	0.000
		8	0.533	-0.359	5145.3	0.000
		9	0.394	-0.019	5430.6	0.000
		10	0.247	-0.164	5542.9	0.000
		11	0.219	-0.003	5631.4	0.000
		12	0.320	0.130	5820.0	0.000
		13	0.398	0.053	6111.3	0.000
		14	0.473	0.109	6523.4	0.000
		15	0.352	-0.137	6751.2	0.000
		16	0.227	-0.015	6846.3	0.000
		17	0.089	-0.116	6860.8	0.000
		18	0.077	0.059	6871.6	0.000
		19	0.185	0.052	6935.0	0.000
		20	0.274	0.060	7074.2	0.000
		21	0.365	0.116	7320.4	0.000
		22	0.261	-0.095	7446.4	0.000
		23	0.152	0.007	7489.0	0.000
		24	0.022	-0.087	7490.0	0.000
		25	0.009	-0.005	7490.1	0.000
		26	0.119	0.043	7516.5	0.000
		27	0.217	0.054	7603.5	0.000
		28	0.311	0.057	7783.4	0.000
		29	0.216	-0.053	7869.8	0.000
		30	0.116	0.023	7894.6	0.000
		31	0.001	-0.023	7894.6	0.000
		32	0.003	0.040	7894.7	0.000
		33	0.121	0.042	7922.0	0.000
		34	0.225	0.052	8016.3	0.000
		35	0.323	0.048	8210.4	0.000
		36	0.227	-0.085	8306.4	0.000

Number of non-converged estimations: 0				
Selected ARMA model: (11,12)(0,0)				
AIC value: 19.5370971282				
Augmented Dickey-Fuller test statistic			t-Statistic	Prob.*
			-5.65425	0.0000
Test critical values:	1% level		-3.433773	
	5% level		-2.862939	
	10% level		-2.567562	
*MacKinnon (1996) one-sided p-values.				

Figure 7.1 ACF and PACF Functions

The determination of the number of ARMA terms is typically done by determining the maximum AR or MA coefficients, then estimating each model up to these maximums, and then evaluating each model using the information criterion. Akaike information criterion (AIC) is a quality measure of statistical relative model for a given dataset. That is, given the collection of data models, AIC estimates each model quality relative to each of the other models. Hence, AIC provides a means of model selection.

Table 7.1 Model Forecast Criteria

Dependent Variable: D(INTERCITY)			
Method: ARMA Maximum Likelihood (BFGS)			
Date: 04/18/21 Time: 16:43			
Sample: 1/02/2011 12/31/2015			
Included observations: 1825			
Convergence not achieved after 500 iterations			
Coefficient covariance computed using outer product of gradients			
Variable	**Coefficient**	**Prob.**	
C	-0.5908	0.945	
AR(1)	-0.4580	0.000	
AR(2)	0.1439	0.000	
AR(3)	-0.3817	0.000	
AR(4)	-0.5069	0.000	
AR(5)	0.1051	0.000	
AR(6)	-0.3502	0.000	
AR(7)	0.6608	0.000	
AR(8)	0.5691	0.000	
AR(9)	-0.2443	0.000	
AR(10)	-0.0750	0.000	
AR(11)	0.4205	0.000	
MA(1)	0.3070	0.000	
MA(2)	-0.4677	0.000	
MA(3)	0.1090	0.000	
MA(4)	0.3745	0.000	
MA(5)	-0.1543	0.000	
MA(6)	0.2067	0.000	
MA(7)	-0.7571	0.000	
MA(8)	-0.5898	0.000	
MA(9)	0.3854	0.000	
MA(10)	0.2383	0.000	
MA(11)	-0.4183	0.000	
MA(12)	-0.1471	0.000	
SIGMASQ	17376913	0.000	
R-squared	0.539629	Mean dependent var	10.30795
Adjusted R-squared	0.533491	S.D. dependent var	6145.419
S.E. of regression	4197.411	Akaike info criterion	19.54762
Sum squared resid	3.17E+10	Schwarz criterion	19.62309
Log likelihood	-17812.2	Hannan-Quinn criter.	19.57546
F-statistic	87.91218	Durbin-Watson stat	1.998686
Prob(F-statistic)	0		

Demand forecasting for future times in railway passenger transportation can be performed by passenger flow estimation with ARIMA models, which are based on the total number of trips from their own internal dynamics and are one of the univariate time series analyses, independent of the factors affecting the railway transport demand. Based on the past values of the variable, we can define it as an effort to estimate and predict the future values.

Provided that the basic assumptions and criteria of the Box-Jenkins methodology are met exactly, the methodology was followed step by step, and the model that best describes the daily passenger series was found to be ARMA (11,12) (0,0). Based on the number of daily trips between 2011 and 2015, the number of daily trips for 2016 was forecasted over the model. When the number of trips realized is compared to the predicted values obtained from the model created, it is seen that ARIMA-Sliding and ARIMA-Stable models perform differently.

Accordingly, it is considered that it may be appropriate to use different models in order to match the estimation values established on the model created with the reality. It is thought that regression models to be made by including the effect of important dates, school closures, public holidays, etc. in the analysis can give more realistic results for this time series in the long term. Therefore, regression analyses were performed on the data. The details of the regression analyses are given in Chapter 7.2.

7.2 Regression Models

RPF is influenced by many factors. Time, seasonal factors, holidays have great importance on passenger flow forecasting so it is not easy to predict the railway passenger flow accurately. With the help of a regression model where significant factors are defined it is possible to make a reasonable prediction of railway passenger flow but the significant factors should be able to explain the variations in the railway passenger flow data.

A growth rate for the years was defined into the model. Because the year dummy is not known for the future years, growth rate is introduced as the ratio of the total number of intercity passenger of that year to the total number of intercity passenger of the year 2012. While 2011 shows a higher profile, it was not chosen for the base year, 2012 shows an average profile and determined to be used as a basis. The growth rate is determined to estimate the total RPF for a forecast year (or a target total yearly RPF value can be assumed for future planning). The selected model gives R^2 value of 0.734 and 24 statistically significant variables.

The equation of the selected model is as follows:

$$[NPax] = 7{,}60 + 5.25 * Dmon + 0.91 * Dthu + 8.72 * Dfri + 6.99 * Dsat + 10.00 * Dsun$$

$$-6.92 * Djan - 6.75 * Dfeb - 6.69 * Dmar - 3.12 * Dapr - 2.00 * Dmay - 1.14 * Daug - 2.20 * Doct - 3.43 * Dnov - 4.47 * Ddec$$

$$-13.21 * Dram - 13.87 * Deid1 - 15.31 * Deid2$$

$$+13.27 * Dwb + 4.90 * Dsb + 3.99 * Dsh + 9.15 * Dmh + 0.79 * durhldy + 34.47 * GR$$

After the model was formed, estimation was made to find the RPF for 2016. For the growth rate, total of the year's intercity passenger number was divided to the total of 2012. As the annual leaves of public officers were restricted between 15th July and 9th August 2016, it affected the intercity RPF in 2016. Therefore, the first half of the year 2016 gives better forecast results than the second half. The observed and forecasted data of 2016 are shown together in Figure 7.2.

The model has given a very reasonable R^2 value. For the first half, equation is $y = 0.8821x+2.7104$ and R^2 is 0.8194. When forecasted and real data are put together in one graph, it is seen that the both show quite similar profile and it can be said that model performs well. However, as mentioned before, due to the effect of the restrictions, the full year does not perform as well as the first half of 2016. Second half model gives the equation y = 1.1042x-0.1361 and R^2 decreases to 0.489. The model results are shown in Figure 7.3.

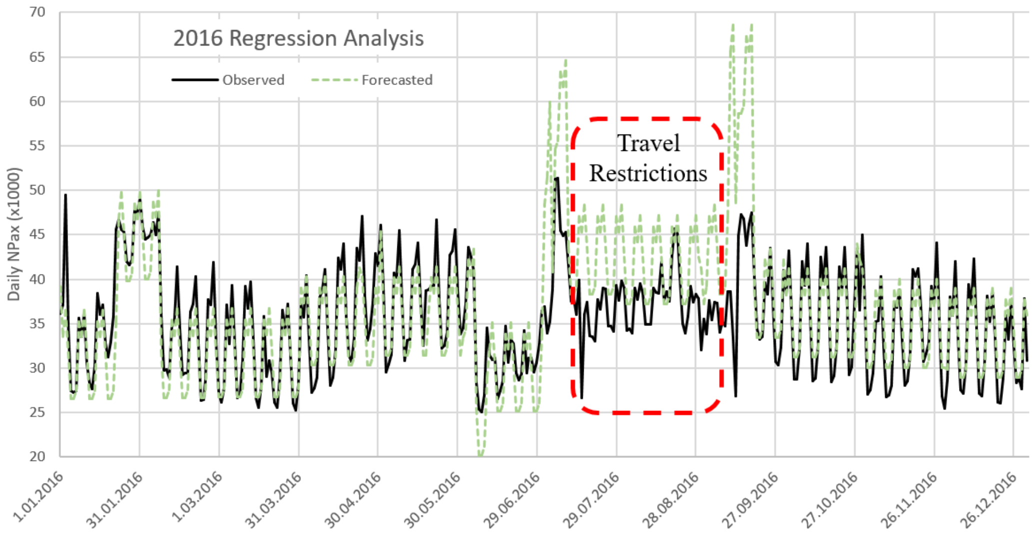


Figure 7.2 Analysis of the Selected Regression Model for the Year 2016

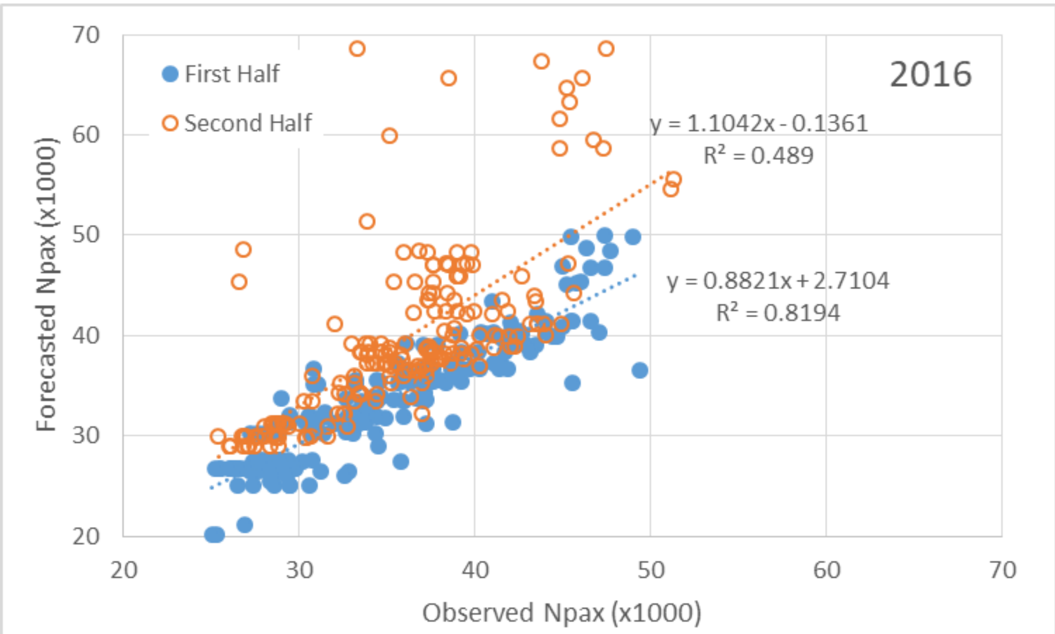


Figure 7.3 Forecasted and Real Data Comparison for the Year 2016

7.3 Overall Comparison of ARIMA and Regression Forecasts

In order to compare the models, error terms were defined. As seen in Table 7.2, ARIMA-Sliding model gives the best-fit, as it forecasts for very short term. ARIMA-Sliding forecast (FA-Sld) is made feeding the data for each day and it estimates the day after. Secondly, ARIMA-Stable weekly updated (FA-St-1W) shows a quite good fit, while ARIMA-Stable 2-Weekly Updated (FA-St-2W) is far behind that. Regression comes after FA-St-1W forecasts and that shows ARIMA is not very useful for the forecasts more than 1 week. Regression should be preferred for long term forecasts. Also, same procedure was applied for 2017, 2018 and 2019 data. Similarly, Table 7.3 shows while ARIMA-Sliding is the best model for the very short term (daily), regression should be preferred for long term forecasts.

Table 7.2 Error Terms for 2016 Forecast

	ARIMA FA-St-1W	ARIMA FA-St-2W	ARIMA FA-St	ARIMA FA-Sld	Regression
			MAE		
2016 First Half	3064.3	4020.4	4274.9	**1794.9**	2326.3
2016 Whole Year	**2902.1**	3802.4	3757.2	**1961.5**	3356.3
			MAPE		
2016 First Half	0.0919	0.1180	0.1229	**0.0520**	0.0659
2016 Whole Year	**0.0842**	0.1093	0.1063	**0.0554**	0.0930
			RMSE		
2016 First Half	4135.2	5178.6	5359.9	**2553.9**	3043.3
2016 Whole Year	**4093.0**	**5012.4**	**4913.1**	**2854.9**	5461.7

Table 7.3 Error Terms for 2017-2019 Forecasts

	MAE		**MAPE**		**RMSE**	
	ARIMA FA-Sld	**Regression**	**ARIMA FA-Sld**	**Regression**	**ARIMA FA-Sld**	**Regression**
2017	**2223.3**	3464.6	0.054	0.087	3428.1	4404.7
2018	**2440.3**	4092.6	0.050	0.086	3826.2	5072.2
2019	**2698.5**	5760.4	0.051	0.113	4221.6	7694.7

7.4 Prediction Power of Major Events

When there is an interruption to the system due to an unexpected event, regression does not perform well but ARIMA can adopt quickly. It is seen in the 2016 data while there was disruption in the services due to restrictions, regression was overestimating the data but ARIMA could catch the real trend quickly. With the help of prediction in the long term by regression, disruption related ridership loss can be estimated.

Some examples from model comparison in certain dates are shown in Figure 7.4. There were some restrictions on annual leaves of public servants between 15th July and 9th August 2016. However, its effect on mobility continued until the Eid-al-Adha Holiday. While religious festivals increase mobility, holy month Ramadan’s effect is the opposite. Ramadan of the year 2017 is between 27th May and 24th June while 25th June 2017 is the first day of Eid-al-Fitr. While summer break of the year 2018 started on 8th June and ended on 17th September, winter break of the year 2019 is starting from 19th January and ending on 3rd February. Although regression forecast may overestimate in some cases, it is still performing well in the long term comparing to ARIMA forecast for the long term.

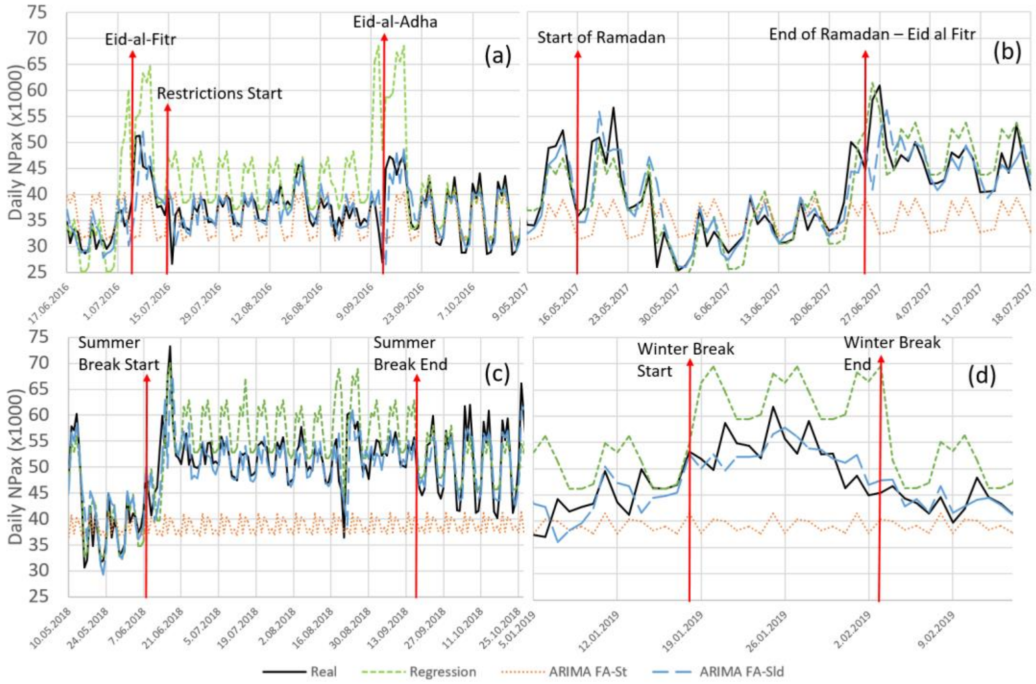


Figure 7.4 Comparison of Models in Special Dates a) Eids and Restrictions Effect in 2016 b) Ramadan and Eid Effect in 2017 c) Summer Break Effect in 2018 d) Winter Break Effect in 2019

7.5 Data-driven policies

The analyses and comparisons above showed that different modeling approaches had different strengths and weaknesses. Regression models definitely show the impact of repeating events/periods on the RPF directly, such as holidays, weekends, etc. and can even help to detect the impact of any major change/disruption in the rail services. However, they are not capable of responding to such changes while the event occurs, thus, incapable of producing any real-time short-term predictions for operational purposes. Thus, they are better for long-term planning and pricing policies.

ARIMA is better to make forecasts in the daily passenger data for the short term e.g. at most 1 week, while regression model should be used for the long term forecasts. With these forecasts, resource allocation can be performed accordingly and also dynamic pricing can be introduced in Turkish Railways. Knowing the approximate number of the potential passengers allows the authority to design its schedule and manage the revenue. When there is a less traffic foreseen, some promotions can be introduced on that day especially, or just as the reverse, when a high demand is forecasted, ticket prices can be increased. Personnel annual leave programs can be determined in advance. Operation strategies can be formed for the next steps. Train schedules, fleet allocation, capacity planning, personnel shift programs, maintenance work plans can be made according to the forecast model in order to set a good revenue management and for efficient services.

CHAPTER 8

CONCLUSIONS AND FURTHER RECOMMENDATIONS

8.1 Summary of the Study

This study focused on development of an overview of rail passenger travel characteristics in Turkey. It mainly used two data sources: i) Rail Passenger Flow (RPF) data providing station-to-station daily ticket numbers and ii) Rail Passenger Survey (RPS) data collected at the selected intercity train stations during the National Transport Master Plan studies. While the former was primarily used to develop regression and time series-based forecasting models, it also enabled the development of demand patterns (daily, weekly, seasonal etc.) additionally. The latter was used to develop descriptive statistics for socioeconomic structure and travel characteristics of different intercity rail passengers (HSR versus conventional travelers, business travelers, etc.).

After a comprehensive literature review, Turkey's railway sector was evaluated in general with its history and today. It was supported with comparison of Turkey with EU countries in terms of rail travel statistics. Number of passengers traveling daily, weekly, monthly and yearly was analyzed, intercity ratio in total rail travels was investigated in order to perform analyses on intercity RPF data. An assessment on rail passenger characteristics enabled to detect general profile of a business purpose rail traveler. It is important to know characteristics of travelers in building planning and operating strategies. RPF forecast is also another important topic in these strategies. ARIMA and Regression models were built in order to forecast the number of passengers in short term and long term.

Turkey is not far behind Europe in terms of rail transportation, but as a developing country, it has to enlarge its national network and increase the rail share in total transportation to reach rail passenger modal shares in Europe. Although it is not on the last rank in rail length, Turkey is lower than any European country in terms of rail density (railway length per 1000 km^2 area).

In addition to population, there are other factors affecting rail passenger demand generation: Most populated cities in Turkey are not the main generators in rail passenger demand. Although Istanbul has more than 15 million population (almost 3 times of the second populated city Ankara) it is on the 7^{th} rank in number of passenger list. There are other factors such as local connections, convenience of the station, easy access/egress, car ownership, per capita income, etc. affecting number of travelers in different cities.

8.2 Main Findings based on RPS Data Analysis

Intercity rail passenger mobility is higher among youngsters and middle age people than the elderly, as expected. Majority of the rail passengers interviewed were from very low- and low-income groups and, most of them did not have a car available for their trips. The major origin/destination cities in the sample data included Ankara, which has both HSR and conventional rail connection to many cities. Secondly, although connected via conventional rail service to Adana, a nearby major city, Mersin had an unexpectedly high intercity rail passenger mobility connection. Manisa, Aydın and İzmir are creating a desire region in the Aegean coast of Turkey. This shows how research question 1 is responded in this thesis.

Having analyzed the national rail passenger survey, the effect of HSR is clearly seen as the major destinations and busy O-D pairs are HSR cities although HSR network length is only 10% of the total conventional line length. However, there is not much difference between HSR and conventional rail passengers in terms of travel characteristics. Main purpose of intercity rail trips was found visiting friends and family in overall and this is followed by personal business, education, business and tourism in the descending order. Business trips are higher on HSR services, which also increases parallel to income levels. Despite low pricing of HSR services which is closer to conventional rail ones, travelers of HSR are found to have higher income than the others, as they have more longer distance and business trip characteristics compared to the shorter distance travels on the conventional lines, which resemble to same-day commute trips in suburban regions. HSR and conventional rail passenger characteristics were analysed as a response to research question 3.

HSR origins also have higher average travel distance than the others in general, but the main parameter would be the speed and geographic location of the services. In HSR region, Ankara acts like a hub reaching to big cities located further away (i.e. Konya, Istanbul) easily. Despite the service type, there are also important differences between travel characteristics of different regions: While southern region has lower rail travel distances and more frequently traveling passengers, eastern side has higher distances with less frequently traveling passengers. Access and egress modes also differ between the regions. Southern region has more bus as access and egress modes, HSR Region has more car and Western and Eastern Regions have more walk. These show that there are significant regional differences in travel characteristics so each region needs to be analyzed in itself after a general analysis.

Binary logistic regression results responding to research question 4 showing that likelihood of making a business trip increases with such factors as being male, getting older, returning same day, trip frequency, income, car ownership and taking high-speed service while home based trip has a negative effect on making business trip.

8.3 Main Findings based on RPF Data Analysis

When daily rail passenger volumes from 2011 to 2019 were evaluated, it is found out that Tuesdays and Wednesdays generally form the lowest points in a day of week profile while Fridays and Sundays have a peak, on the other side special events such as school breaks or national holidays show very different profile than neutral days. Analysis based on service type showed that, In Turkey, a developing country with limited HSR network,

- HSR lines got higher ridership significantly,
- Total demand did not change as demand on conventional lines reduce significantly,
- Travelers are mostly non-business: HSR slightly has higher business travelers. It may be due to the fact that HSR network is very limited, not well connected with the city centers. Thus, travel time reduction power is low therefore not competing against air yet (HSR Lines (e.g. ANK-ESK ANK-KON) relatively short distance trips)
- Southern region in Turkey especially Mersin-Adana corridor is very successful as it is short and fast but conventional line. Differences between regions in travel characteristics are analyzed as a response to research question 2.
- Although HSR and conventional rail are analyzed in separate categories in some analyses, they are complementary systems of each other. They need to be taken into account as a whole when the rail system is wanted to be analyzed.

As a result of the travel demand forecasting model development efforts, it was shown that it is possible to predict rail passenger demand for future based on,

a) yearly event/activity calendar, such as holidays, winter/summer breaks, etc. via regression models
b) time series data of past periods, using ARIMA analyses.

The ticket number series were found stationary which means it is integrated at level zero. The **ARMA** terms were also found as **AR(11)** and **MA(12)** according to Akaike Information Criteria of the models tried. So, the best model was defined as **ARIMA (11,0,12)**. Using this model, forecasts were made first for the year 2016 and then the forecast was extended up to 2019. When 2016 forecast was made, ARIMA-Stable and ARIMA-Sliding methods were used in order to compare the estimation power of the model. While ARIMA-Sliding forecast (FA-Sld) shows a good fit as it uses the real values feeding the data for each day, ARIMA-Stable model does not show a good performance for the estimations more than a week.

The regression model, introducing date and event characteristics as independent variables, (i.e. day of the week, month of the year, growth rate of the year, duration and time of school breaks and national holidays, religious month Ramadan and religious festivals, etc.) was developed based on data from 2011 to 2015, and used to forecast for 2016 to 2019, to be verified with real daily volumes to test the power of the model comparing with the real values for the forecasted years. It is seen that regression model performs well in the long term while the estimation power of ARIMA model is better in the very short term.

8.4 Recommendations for Further Research

These results are valuable as they show travel behavior of inter-city rail passengers in Turkey. Survey data is the backbone of all steps of classical 4-step transport modeling. Trip generation, trip distribution and mode choice models use survey data with calibrations and validations; assignment model uses the data produced after these steps. Therefore, a robust survey data and proper analysis are very important in transportation engineering. The Rail Passenger Survey data collected at the major train stations had more than 7000 participants, giving strong descriptive statistics results, however, it was still not enough to capture the whole rail mobility in Turkey. Furthermore, the sampling was not totally satisfying randomness expectations, where some regions were overrepresented. Thus, it is not possible to develop any traditional travel demand forecasts, but, it can be used to detect characteristics of intercity rail passenger flow up to a limit. The survey data used in this study can be validated with ticketing data of Turkish State Railways (TCDD) from station to station in a further research study and can generate fruitful results for transportation engineering academia.

8.5 Recommendations for Planning/Operating Strategies

It is important to expand the network and increase the rail share in transportation and catch the average of EU to be able to have higher standards for EU integration.

Obligation for TSIs and EN standards must continue in both design and operation stages of rail lines. In parallel with these consistence, 2035 targets of the Government can be reached if HSR rail network is expanded in accordance with the choices of travelers. Also, in compliance with the liberalization process, planning studies are required to be based on passenger and travel characteristics. In order to assure competence in the sector and to keep step with the EU countries, nature of the trips and travelers must be well-understood. Therefore, comprehensive survey studies need to be performed regularly and the results should be analysed carefully. A further recommendation can be for a comparative study of EU and Turkey's passenger characteristics. That can reveal the differences similar to the regional differences performed in this study. Planning and operating strategies can be shaped with the examples from the EU.

It has to be noted that the choice of travelers shapes the basis of planning in transportation. The passenger characteristics must be understood well both in overall and from regional perspective. If there are different characteristics for a specific region, the planning or development must be shaped accordingly. Because sometimes it is impossible to define single gravity model for the whole of the country, the significant regional characteristics must be evaluated separately and specific trip generation models can be formed for each specific region. It is also essential to support the planning decisions with further customer satisfaction surveys as it is a must to see the system from an eye of the user in order to establish a successful system.

With the ongoing renaissance in Turkey's railway sector since 2009, investments in rail (especially HSR) has been playing an important role in governmental policy. However, investments bring more responsibility in management of services and resource planning. While investments on HSR services play a significant role in transportation sector, conventional railways should not be forgotten and they have to be kept open and contemporary. In order to ensure a better management in this sector, proper analyses for demand forecasting need to be performed. A railway company has to fulfil the tasks of capacity planning and revenue management with its operating strategies to be able to maintain its existence. With this importance, the focus of the study was determined as forecasting intercity passenger demand in Turkey's railways.

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APPENDICES

A. Roadside Interview Questionnaire Form

a) Site code	b) Direction Specify EB, WB, NB or SB Towards which city	c) Date Day Month Year	d) Hour (24-hour format) Hour Minutes	e) Weather	1. Clear 2. Cloudy 3. Rain	f) Sheet No.

ROADSIDE DRIVER INTERVIEW - Light Vehicles

	No.	Q1. Vehicle Type	Q2. No. of pass.	Q3. Trip origin	Q4. Trip destination	Q5. Trip purpose	Q6. Type of Trip	Q7. Time of return/outward trip (if applicable)	Q8. Trip frequency	Q9. MONTHLY Household income group AFTER tax and other deductions (net income)	Q10. Cost for this journey	Q11. Phone Number of the respondent	Q12. Gender	Q13. Age
		1. Private Car 2. Taxi 3. LGV	No. of passengers including driver	Indicate the trip star point? (country, province, district)	Indicate the trip ending point? (country, province, district)	1. travel to/ from the place I work fro 2. education 3. Travel for work purposes/ for my employer's bussiness or for my own that I earn money /business meetings etc 4. leisure (recreation) 5. tourism (Holiday/Day Trip) 6. Shopping 7. Personal business of my own or family (Hospital,doctor,bank,...) 8. visiting friends and family 9. Carrying or delivering goods	1. From Home 2. To Home 3. Other / Non Home	Indicate the time of: the return trip to home (If Q6 is 1) or the outward trip from home (If Q6	1. daily 2. weekly 3. monthly 4. less than once a month 5. annually 6. other (specify)	1. Less than 500 Euros 1. < 1600 Turkish Liras 2. 500 - 1,000 Euros 2. 1600-3199 Turkish Liras 3. 1,000-2,000 Euros 3. 3200-6399 Turkish Liras 4. More than 2,000 Euros 4. >6400 Turkish Liras	Specify the trip cost (tolls, parking) Currency (Euro, Lira, etc)	For verification purposes	1. Male 2. Female	1. <25 2. 25-45 3. 45-60 4. >60
Time	1							Same Day ☐ Other Day ☐ Time am ☐ pm ☐			Tolls Currency Cost			
Time								Same Day ☐ Other Day ☐ Time am ☐ pm ☐			Parking Currency Cost			
Time								Same Day ☐ Other Day ☐ Time am ☐ pm ☐			Currency Cost			
Time	4							Same Day ☐ Other Day ☐ Time am ☐ pm ☐			Currency Cost			

Interviewer:	Supervisor:	Processed:

Figure A.1 RSI Light Vehicles Interview Questions

a) Train Station	b) Terminal	c) Date	d) Hour (24-hour format
		Day Month Year	Hour Minutes

TRAIN PASSENGER INTERVIEW AT INTERCIT

No.	Q1. Service	Q2. Trip origin?	Q3. Access Mode (from origin)	Q4. Trip destination?	Q5. Egress Mode (to destination)	Q6. Trip purpose	Q7. Type of Trip
	Indicate the train route no. AND tick the box in case of high speed Indicate stops used FROM - TO	Indicate the trip starting point? (country, province, district)	how did you get to this train? 1. Car 2. Train/Metro/Tram 3. Bus 4. Walk 5.Flight 6. Taxi 7. Ferry 8. Other (specify)	Indicate the trip ending point? (country, province, district)	How will you get there when you get off this train? 1. Car 2. Train/Metro/Tram 3. Bus 4. Walk 5.Flight 6. Taxi 7. Ferry 8. Other (specify)	1. travel to/ from w 2. education 3. travel for work / business 4. leisure (recreation) 5. tourism (Holiday/Day Trip) 6. Shopping 7. Personal business 8. visiting friends and family 9. Carrying or delivering goods	1. From Home 2. To Home 3. Other / Non Home-based
1	Route No. High speed ☐ First boarding stop: Final alighting stop:		specify (if 2,3,5,7,8):		specify (if 2,3,5,7,8):		
2	Route No. High speed ☐ First boarding stop: Final alighting stop:		specify (if 2,3,5,7,8):		specify (if 2,3,5,7,8):		
3	Route No. High speed ☐ First boarding stop: Final alighting stop:		specify (if 2,3,5,7,8):		specify (if 2,3,5,7,8):		
4	Route No. High speed ☐ First boarding stop: Final alighting stop:		specify (if 2,3,5,7,8):		specify (if 2,3,5,7,8):		

Interviewer:	Supervisor:

Figure A.2 Train Passengers Interview Questions (1-7)

t)	e) Weather	1. Clear 2. Cloudy 3. Rain	f) Sheet No.

'Y ROUTES

Q8. Time of return/outward trip (If applicable)	Q9. Trip frequency	Q10. Cost / Type of ticket for this journey	Q11. MONTHLY household income group AFTER tax and other deductions (net income)	Q12. Private car availability	Q13. Phone Number of the respondent	Q14. Gender	Q15. Age
Indicate the time of: the return trip to home (if Q7 is 1) or the outward trip from home (if Q7 is 2)	1. daily 2. weekly 3. monthly 4. less than once a month 5. annually 6. other (specify)	Specify the ticket type (single, return etc) Specify the ticket cost Currency (Euro, Lira, etc)	1. Less than 500 Euros 1. < 1600 Turkish Liras 2. 500 - 1,000 Euros 2. 1600-3199 Turkish Liras 3. 1,000-2,000 Euros 3. 3200-6399 Turkish Liras 4. More than 2,000 Euros 4. >6400 Turkish Liras	Was there a private car available for this trip? 1. Yes 2. No If yes, why did you choose the train? 1. Train is cheaper 2. More comfortable 3. Because the people I am traveling w 4. Because of weather conditions 5. It would take longer by car 6. Other (please specify)	For verification purposes	1. Male 2. Female	1. <25 2. 25-45 3. 45-60 4. >60
Same Day Other Day Time am pm		Ticket Type: Currency Price		car availability Justification for the use of train (if 1)			
Same Day Other Day Time am pm		Ticket Type: Currency Price		car availability Justification for the use of train (if 1)			
Same Day Other Day Time am pm		Ticket Type: Currency Price		car availability Justification for the use of train (if 1)			
Same Day Other Day Time am pm		Ticket Type: Currency Price		car availability Justification for the use of train (if 1)			
		Processed:					

Figure A.3 Train Passengers Interview Questions (8-15)

B. Rail O-D Matrix from Survey NTMP Raw Data

Table B.1 O-D Matrix of the Survey (Destination Cities 1-31)

O-D Matrix	1	2	3	4	5	6	7	8	9	10	11	16	17	18	20	21	23	24	25	26	27	31
1	23		1			1												1			1	2
2	1																					
3															1							
4				1																		
6	15		3	2	3	127				1	5	2	5	1	1	3		12	23	330		
9									273						138							
16																						
20			4						181						5					1		
23																						
24						1												35	77			
25						7												39	1			
26			2			200					2	1			3					3		
27	1																					
31	1																					2
33	573																					7
34						196					12									92		
35						2			136	8					62							
36						7												3				
38	3					134										1		4	12			
41																						
42			2			300	1	1			3	1								10		
43						1									1							
44	27	9				8										156	16				1	
45			10			7				2										5		
51																						
54																						
58						16												43	16			1
64																						
66																						
67																						
70	34					25														3		
80																						
empty																						
Total	678	9	22	3	3	1032	1	1	590	11	22	4	5	1	211	160	16	137	129	444	2	12

Table B.2 O-D Matrix of the Survey (Destination Cities 31-80)

O-D Matrix	31	33	34	35	36	38	39	40	41	42	43	44	45	46	51	54	58	62	64	65	66	67	70	71	72	78	80	empty	Total
	2	358				1				4					2						2						10		406
																													1
																													1
																	1												2
			128	10	12	7			15	169	8	4	9		3	2	6		4	1	4		6	1	2			1	925
				233																								1	645
										1																			1
				139							1																		331
												2																	2
					18												1												132
			2			7		1									5												62
			101	1					15	29	27	1	2			7													394
																													1
	2	2																											5
	7	306								2					2												5		895
									28	42						63													433
				287						3			8																506
					1	1											1												13
			10		2	1	1					2					78				32			3				1	284
									1	1																			2
		1	20	4					5	4			4			2			4				22						384
			1									1																	4
						7						34		7			36							1			8		310
				184						7	2		406						87									1	711
										2																			2
																1													1
	1				10	17						1					191												295
				1														1											2
																	1												1
																						144				8			152
		1	5	3					1	132					3								1						208
		4																									1		5
empty																												379	379
Total	12	672	267	862	43	41	1	1	65	396	38	45	429	7	10	75	320	1	95	1	38	144	29	5	2	8	24	383	7495

C. Other Surveys

Other than rail passengers, roadside surveys, bus terminal surveys and air passenger surveys were analyzed in a similar way to rail passenger survey analysis. Participant profiles are given in tables from Table C. 1 to Table C. 6 for each type:

Table C. 1 RSI-L Survey Participant Profile

<table>
<tr><th colspan="2">RSI-L</th><th>#</th><th>(%)</th><th></th><th></th><th>#</th><th>(%)</th></tr>
<tr><td rowspan="2">Gender</td><td>Male</td><td>138665</td><td>92</td><td rowspan="4">Age</td><td><25</td><td>10683</td><td>7</td></tr>
<tr><td>Female</td><td>11855</td><td>8</td><td>25-44</td><td>95406</td><td>63</td></tr>
<tr><td rowspan="5">Income Level</td><td>Very Low</td><td>29842</td><td>20</td><td>45-60</td><td>36956</td><td>25</td></tr>
<tr><td>Low</td><td>64406</td><td>43</td><td>>60</td><td>7475</td><td>5</td></tr>
<tr><td>Middle</td><td>25391</td><td>17</td><td rowspan="2">Trip Type</td><td>Inter-city</td><td>87712</td><td>58</td></tr>
<tr><td>High</td><td>6070</td><td>4</td><td>Intra-city</td><td>62808</td><td>42</td></tr>
<tr><td>Not declared</td><td>24811</td><td>16</td><td colspan="2">Total</td><td>150520</td><td>100</td></tr>
</table>

RSI-L surveys were conducted with drivers of the light vehicles. As expected, number of male drivers is significantly higher than female drivers. Majority of the drivers are middle aged and have low to middle income. Slightly more than half of the respondents stated that they are doing an inter-city trip in this type of survey. Result of bus passenger surveys which were conducted at terminals show that these passengers are younger and have lower income in general comparing to car drivers. Almost all surveys were conducted with inter-city passengers. Passenger profile slightly changes in the roadside bus surveys comparing to terminal bus surveys. Rate of provincial trips is much higher than terminal passengers. However, income and age profile show similarity with the bus terminal survey respondents.

Table C. 2 Bus Terminal Survey Participant Profile

Bus terminal		**#**	**(%)**			**#**	**(%)**
Gender	***Male***	24412	63	**Age**	***<25***	14296	37
	Female	14460	37		***25-44***	18681	48
Income Level	***Very Low***	11239	29		***45-60***	5148	13
	Low	12919	33		***>60***	747	2
	Middle	3543	9	**Trip Type**	***Inter-city***	37692	97
	High	418	1		***Intra-city***	1180	3
	Not declared	10753	28	**Total**		38872	100
Car Availability	***Available***	5179	13				
	Non-Available	33693	87				

Table C. 3 Bus Terminal Survey Participant Profile

Bus roadside		**#**	**(%)**			**#**	**(%)**
Gender	***Male***	9009	71	**Age**	***<25***	2891	23
	Female	3692	29		***25-44***	7242	57
Income Level	***Very Low***	3966	31		***45-60***	2082	16
	Low	4777	38		***>60***	486	4
	Middle	1346	11	**Trip Type**	***Inter-city***	10146	80
	High	166	1		***Intra-city***	2555	20
	Not declared	2446	19	**Total**		12701	100
Car Availability	***Available***	705	6				
	Non-Available	11996	94				

Table C. 4 Air Survey Participant Profile

Air		**#**	**(%)**			**#**	**(%)**
Gender	***Male***	11542	57	**Age**	***<25***	4257	21
	Female	8595	43		***25-44***	12064	60
Income Level	***Very Low***	1213	6		***45-60***	3177	16
	Low	5677	28		***>60***	639	3
	Middle	6410	32	**Trip Type**	***Inter-city***	20137	100
	High	1867	9		***Intra-city***	0	0
	Not declared	4970	25	**Total**		20137	100

All air travels are intercity logically and income profile of the travelers is significantly different than the other modes' passengers. Air passengers have higher income as expected. Gender distribution is more equal but still ratio of male passengers is slightly higher than females.

Travel characteristics of bus passengers are given in Table C.5 and Table C.6. When bus roadside and bus terminal surveys were compared, it is seen that trip purposes show differences between two types' passengers. While business and tourism are higher in roadside bus passengers, education and visiting friends & family purposes are much lower than terminal bus passengers. Another remark is on access and egress modes. Car and walk have higher ratios among roadside passengers while bus and rail share of bus terminal passengers are significantly higher. This is because public transport is served in all cities for bus terminals and roadside surveys can catch passengers who get on the bus from the street in small towns. Therefore, it is easier to walk to the boarding point for the bus in small places.

Also, bus and rail passenger profiles show some differences such as trip frequency and access/egress modes. Rail passengers seem more frequent travelers and they use more public transport while they access to and egress from station. Share of car in access/egress mode is significantly lower amongst rail passengers.

Table C. 5 Bus (Terminal) Passenger Travel Characteristics (N= 37962 participants)

Bus terminal	**Overall**	**Age band**				**Income Band***			
		<25	**25-44**	**45-60**	**>60**	**VL**	**L**	**M**	**H**
Participants	37692	**13837**	**18132**	5005	718	**10641**	**12589**	3490	413
Car Available	5030	1322	2702	906	100	850	2090	965	169
Trip Purpose									
Commute	4.8	4.6	5.1	4.3	4.7	5.1	4.8	4.1	2.2
Education	16.7	**35.7**	6.7	2.8	1.1	22.6	11.6	12.3	10.7
Business	17.1	10.3	22.1	18.4	11.4	15.8	20.4	23.2	26.4
Leisure	3.3	2.6	4	2.9	1.5	3.2	3.9	3.9	3.1
Tourism	11.2	10.8	12.3	8.9	9.5	9.7	11.5	13.7	14.5
Shopping	1	0.5	1.3	1.2	1	0.9	1.2	1.4	2.4
Personal business	15.7	10.4	18.3	19.7	21.6	14.7	16.3	14.3	14.3
Visiting friends &family	29.7	24.8	29.6	**41.1**	**48.1**	27.5	29.8	26.5	25.7
Carrying/delivering goods	0.5	0.2	0.7	0.8	1.1	0.5	0.5	0.5	0.7
Total	100	100	100	100	100	100	100	100	100
Trip Frequency									
Daily	0.6	0.4	0.8	0.6	0.1	0.5	4.1	0.9	0
Weekly	5	5.4	5.2	3.8	3.3	5.5	11.4	5.8	6.8
Monthly	22.4	27.4	20.2	17.2	15.3	23	**38**	21.9	22.3
<Once a month	29.3	28	30.3	30.1	24	31.1	24.1	32.8	33.2
Annually	31.5	25.1	**34.3**	**36.9**	**45.5**	28.2	14.2	26.5	23.2
Other	11.2	13.6	9.3	11.4	11.7	11.7	8.1	12	14.5
Total	100	100	100	100	100	100	100	100	100
Access Mode									
Car	36.9	33.4	39.2	38.4	37.2	33.1	35.8	37.2	37
Rail	12.3	13.8	11.5	11.2	11.7	10.6	12.2	14.7	18.2
Bus	15.8	18.6	14.1	14.4	13	20.9	15.7	13.9	11.1
Walk	6.1	6.5	6.3	4.6	4.2	8.4	5.5	5.5	3.4
Flight	0.2	0.2	0.2	0.2	0.3	0.2	0.3	0.3	0.7
Taxi	11	9.2	12.3	11.5	10.2	8.4	10.7	12.9	17.9
Ferry	0.2	0.2	0.2	0	0.1	0.1	0.2	0.2	0.5
Other	17.5	18.1	16.2	19.6	23.4	18.3	19.6	15.2	11.1
Total	100	100	100	100	100	100	100	100	100
Egress Mode									
Car	**40.7**	**37.9**	**41.9**	**43.6**	**45.4**	**38.6**	**40.3**	**40.9**	**43.1**
Rail	2.7	3.1	2.6	2.3	2.1	3.1	2.7	3.3	3.6
Bus	8.8	10	8	8	7.4	11.6	8.7	9.7	6.5
Walk	13.8	16.4	12.8	10.4	12.8	16.9	12.7	11.1	10.2
Flight	0.2	0.2	0.2	0.2	0.1	0.1	0.2	0.3	0
Taxi	16.8	13.9	18.9	17.6	13	13.3	16.6	18.7	21.3
Ferry	0.2	0.2	0.3	0.1	0.3	0.2	0.3	0.3	0.2
Other	16.8	18.2	15.3	17.7	18.9	16.2	18.5	15.8	15
Total	100	100	100	100	100	100	100	100	100
Bus Preference Reason									
Cheaper	**46.9**	**47.9**	**48.1**	**43**	35	**57.3**	**46.4**	**40.8**	29
More comfort	29.7	23.7	30.1	**36.4**	**38**	26.1	31.7	31.3	**36.1**
Not fit in the car	5.1	5.6	5.1	4.4	4	2.8	6.3	5.2	8.9
Weather cond.	1.7	2.2	1.7	1	1	1.2	1.7	2.2	4.1
Shorter in time	3.8	2.6	4.3	4.3	3	3.2	3.6	4.6	4.7
Other	12.9	18.1	10.8	10.8	19	9.4	10.4	16	17.2
Total	100	100	100	100	100	100	100	100	100

*Results of those who did not want to claim their income are not shown in this table.

Table C. 6 Bus (Roadside) Passenger Travel Characteristics (N= 10146 participants)

Bus Roadside	**Overall**	**Age band**				**Income Band***			
		<25	**25-44**	**45-60**	**>60**	**VL**	**L**	**M**	**H**
Participants	10146	2375	**5850**	1585	336	2684	**4031**	1230	157
Car Available	580	95	352	114	19	112	247	103	11
Trip Purpose									
Commute	4.3	5.5	4.4	2.5	2.4	8.6	2.7	2.4	2.5
Education	9.2	25.1	4.9	3	1.2	13.1	5.5	6.7	9.6
Business	21.5	15.1	23.8	23.7	16.1	17.7	22.5	27.2	26.1
Leisure	5.8	3.6	7.3	4.3	4.2	4.2	7.5	8.7	5.1
Tourism	18.5	15.6	19.9	18.1	17	13.3	20.3	24.7	34.4
Shopping	1.4	0.8	1.6	1.2	0.9	0.7	1.7	2.2	2.5
Personal business	19.3	15.5	20.5	19.3	23.5	19.9	20.9	13.8	8.9
Visiting friends &family	19.6	18.4	17.1	27.8	**34.2**	22.1	18.6	13.8	9.6
Carrying/delivering goods	0.4	0.3	0.5	0.3	0.6	0.3	0.3	0.4	1.3
Total	100	100	100	100	100	100	100	100	100
Trip Frequency									
Daily	3.7	4.1	3.8	2.8	2.4	5.1	3.2	3.6	8.9
Weekly	12.3	12.7	13.1	9.9	7.1	13.1	11	18.9	21.7
Monthly	29	30.3	30.4	22.6	25.9	28.6	30.3	**36.2**	30.6
<Once a month	19.8	18	20.3	21.3	17.3	21.2	19.4	17.9	14.6
Annually	31.6	28.3	30	**39.9**	**43.2**	28.1	33.4	21.3	21.7
Other	3.6	6.7	2.4	3.4	4.2	3.9	2.7	2.2	2.5
Total	100	100	100	100	100	100	100	100	100
Access Mode									
Car	**41.1**	**39.8**	**44.9**	31.2	31	**42.5**	**38.4**	**49.4**	**54.1**
Rail	2.9	6.3	1.6	2.6	2.4	3.3	2.5	2.9	4.5
Bus	2.8	5	1.9	3.1	3.3	3.8	1.8	2.4	5.1
Walk	25	21.6	26.6	24.4	23.5	24.5	29.6	23.2	7
Flight	0.6	0.5	0.8	0.3	0.3	0.4	0.5	1.7	5.7
Taxi	7.5	6.1	8.4	6.4	6.5	5.3	8	10.5	16.6
Ferry	0.2	0.1	0.2	0.3	0	0.2	0.2	0.2	0
Other	19.8	20.5	15.6	31.7	33	20	19	9.6	7
Total	100	100	100	100	100	100	100	100	100
Egress Mode									
Car	**40.6**	**42.2**	**43.3**	30.2	32.4	**42.3**	**37.4**	**47.2**	**55.4**
Rail	0.7	1.1	0.5	0.9	0.9	0.9	0.6	0.5	0.6
Bus	2.5	4.7	1.8	2.2	2.4	3.2	1.7	3.1	3.2
Walk	26.3	24	27.2	26.6	25.6	26.5	30.8	24.6	15.9
Flight	0.6	0.5	0.8	0.4	0.3	0.4	0.5	1.9	3.8
Taxi	9.3	6.4	10.9	8.3	7.4	6.8	9.9	14.1	11.5
Ferry	0.1	0.1	0.1	0	0	0.1	0	0.1	0
Other	19.7	21	15.4	31.4	31	19.9	19	8.6	9.6
Total	100	100	100	100	100	100	100	100	100
Bus Preference Reason									
Cheaper	**51.4**	**47.4**	**54.5**	**43**	**63.2**	**54.5**	**57.9**	**39.8**	0
More comfort	29.8	28.4	28.7	**36.8**	15.8	30.4	27.9	28.2	**81.8**
Not fit in the car	8.8	10.5	7.7	9.6	15.8	4.5	8.5	16.5	9.1
Weather cond.	0.5	1.1	0.3	0.9	0	0	0	1	0
Shorter in time	3.4	5.3	3.1	3.5	0	3.6	2.4	3.9	0
Other	6	7.4	5.7	6.1	5.3	7.1	3.2	10.7	9.1
Total	100	100	100	100	100	100	100	100	100

*Results of those who did not want to claim their income are not shown in this table.

CURRICULUM VITAE

EDUCATION

Degree	Institution	Year of Graduation
MS-2	Gazi University Civil Engineering	2017
MS	University of Birmingham Railway Systems Engineering and Integration	2013
BS-2	Anadolu University Business Management	2016
BS	Gazi University Civil Engineering	2011
High School	Atatürk Anatoliam High School, Ankara	2007

WORK EXPERIENCE

Year	Place	Enrollment
2016-Present	Ministry of Transport and Infrastructure of Turkey	Civil Engineer
2014-2016	Turkish State Railways (TCDD)	Civil Engineer
2013 December	Network Rail	Intern Railway Systems Engineer

FOREIGN LANGUAGES

Advanced English

PUBLICATIONS

Conference Proceedings

1. Ekici, Ü. and Akay, M.E. (2019) Two Generation in One Place: Ankara Gare & Ankara High Speed Train Station. Presented at UIC 7th International Conference on Railway Stations. Tehran

2. Görk, S. and Ekici, Ü (2018) High Speed Rail Comparison between Turkey and European Countries in terms of Network, Operation and Investments. Presented at 4th International Symposium on Railway Systems Engineering. Karabük

3. Ekici, Ü. (2018) Applicability of AASHTO Seismic Design Criteria to a High-speed Railway Bridge and a Comparison with Turkish DLH Code. Presented at UIC 10th World Congress on High Speed Rail. Ankara

4. Ekici, Ü. (2016) Are We Missing Aesthetics in Bridge Design? Presented at Istanbul Bridge Conference 2016

5. Ekici, Ü. (2015) Illustrating and Discussing the Determinants of Railway Complexity. Presented at UIC 9th World Congress on High Speed Rail. Tokyo

HOBBIES

Cinema, Music, Fitness, Swimming, Tennis