



**T.C.
İSTANBUL UNIVERSITY
INSTITUTE OF GRADUATE
STUDIES IN SCIENCE AND
ENGINEERING**



Ph.D. THESIS

**DETERMINING SPEED OF VEHICLE FOR ECONOMICAL
FUEL CONSUMPTION ON SPECIFIED ROUTE
ACCORDING TO THE SLOPE OF THE ROAD**

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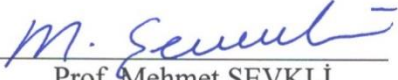
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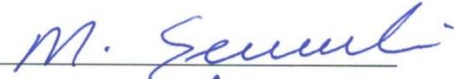
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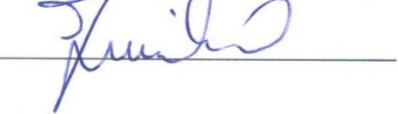
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LIST OF SYMBOLS AND ABBREVIATIONS

Symbols	Explanation
Cc	:Cubic centimeters
CO₂	:Carbon dioxide
$F_a(t_a)$	:Acceleration mode fuel consumption
$F_c(t_c)$	:Cruise mode fuel consumption
$F_d(t_d)$	:Deceleration mode fuel consumption
$F_i(t_i)$	:Idle mode fuel consumption
f_i	:Fuel Consumption Rate
g	:gram
g/h	:Gram per hour (fuel)
kg	:Kilogram
Km	:Kilometre
Km/h	:Kilometer per hour
kW	:Kilo Watt
M	:Mass of vehicle
ml/h	:Milliliter per Hour
ml/kJ	:Milliliter per Kilo Joule
ml/km	:Milliliter per Kilometer
ml/s	:Milliliter per second
Mtoe	:Million Tonnes of Oil Equivalent
RPM	:Revolutions Per Minute
P	:The actual engine power
α	:Idle Fuel Consumption Rate
β_1	:Efficiency Parameter
β_2	:Energy-acceleration efficiency Parameter
ξ	:Drag Fuel Consumption Parameter
ω	:Slope Angle

Abbreviations	Explanation
ARTEMIS	:Assessment and reliability of transport emission models and inventory systems
ASFCM	:Average Speed Fuel Consumption Model
CARB	:California Air Resources Board
COPERT	:Computer program to calculate emission values of road transport
COST346	:Emissions and Fuel Consumption from Heavy Duty Vehicles
CP	:Payload Capacity
CPFM	:Comprehensive Force-Based Fuel Consumption Models
CU	:Capacity utilization
ECF	:Final energy consumption
ECOTRANSIT	:Ecological Transport Information Tool
ECU	:Final Energy Consumption
ECUEC	:Energy related upstream energy consumption
EEA	:European Environment Agency
EGR	:Exhaust Gas Recirculation
EMFAC	:Emission factors modeling software
EMIT	:Traffic Mode Emission
EPA	:Environmental Protection Agency
GHG	:Greenhouse Gas
GPS	:Global Positioning System
GREET	:The Greenhouse Gases, Regulated Emissions
HBEF	:Handbook for Emission Factors
HBEFA	:The European Handbook of Emission Factor for Road Transport
IEA	:International Energy Agency
IVE	:International Vehicle Emissions Model
LEM	:Lifecycle Emissions Model
LR	:Linear Regression
MDV	:Mid-size vehicle
MEET	:Methodology for Calculating Emission and Energy Consumption
MOBILE	:Mobile Source Emission Model
MOVES	:Motor Vehicle Emission Simulator
NAEI	:National Atmospheric Emissions Inventory

NTM	:National Transport Model
OBD	:On Board Diagnostic
OFCM	:Oguchi fuel consumption Model
PEMS	:Predictive Emissions Modeling System
PERE	:Physical Emission Rate Estimator Model
PHEM	:Emissions Model in Passenger and Heavy Vehicles
RPM	:Revelations Per Minute
SVM	:Support Vector Machine
SVR	:Support Vector Regression
VERSIT-LD	:Roadway emissions model based on Light Duty Vehicle
VSPM	:Vehicle specific power model
VT-Micro	:Virginia Technique Microscopic

ÖZET

ARAÇLARDA MEVCUT ROTA ÜZERİNDE YOLUN EĞİM BİLGİSİNE GÖRE EKONOMİK YAKIT TÜKETİMİ İÇİN HIZ BELİRLEME

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Literatürde sayı ve çeşit olarak yakıt tüketimi modelleri önerilmesine rağmen, onların gerçek hayat verileri kullanılarak doğrulandığı çalışmalar sınırlıdır. Bu tezde ilk olarak, iki yolcu aracı ve üç farklı güzergâh üzerinde bir cep telefonu uygulaması ile gerçek zamanlı olarak toplanan veriler kullanılarak altı farklı matematiksel model sayısal olarak karşılaştırılmış ve yorumlanmıştır. Özellikle, rota seçimlerinde ve sonuçların analizlerinde yolun eğiminin yakıt tüketimine etkisine odaklanılmıştır. İkinci olarak, bu çalışmada bir aracın yakıt tüketimini tahmin etmek için, doğrusal regresyon, yapay sinir ağları ve destek vektör makineleri dahil olmak üzere üç farklı regresyon modeli geliştirilmiş ve performansları incelenmiştir. Üç güzergahta ve üç farklı binek araçla toplanan gerçek veriler kullanılarak literatürdeki beş anlık yakıt tüketimi modellerinin karşılaştırmalı sonuçları gösterilmiştir. Elde edilen sonuçlar, anlık yakıt tüketimi modellerinin tahmin değerleri doğruluğu veri setlerine göre değişkenlik gösterirken, regresyon modellerinin veri girişindeki değişikliklere karşı önemli ölçüde daha iyi ve daha güçlü olduğu gösterilmiştir. Üçüncü olarak, bir aracın başlangıç ve bitiş noktaları arasında gidebileceği tüm rotalar için yolun eğim bilgileri de göz önünde bulundurularak toplam yakıt tüketimlerinin hesaplandığı, bu rotalardan en ekonomik olanın tespit edilmesi ve seçilen rota üzerinde sürekli seyir hızlarını bulmanın mümkün olduğu bir dinamik programlama yaklaşımı açıklanmıştır.

Mayıs, 2016, 131 sayfa.

Anahtar kelimeler: Ekonomik Yakıt Tüketimi, Enerji Verimliliği, Regresyon modelleri, Yolun Eğimi, Dinamik Programlama, Mobil Yazılım.

SUMMARY

DETERMINING SPEED OF VEHICLE FOR ECONOMICAL FUEL CONSUMPTION ON SPECIFIED ROUTE ACCORDING TO THE SLOPE OF THE ROAD

Ph.D. Thesis

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Despite the number and variety of fuel consumption models proposed in the literature, studies on their validation using real-life data are limited. This dissertation firstly, reviews and numerically compares six such models against data collected in real-time from a passenger vehicle on three routes, using a mobile phone application. A particular focus has been placed on testing the effect of the road gradient on fuel consumption in the selection of the routes and the analysis of the results. Secondly, it describes the development of three types of regression models to estimate fuel consumption of a vehicle, including linear regression, artificial neural network and support vector machines. The thesis presents comparison results with five instantaneous fuel consumption models from the literature using real data collected from three passenger vehicles on three routes. The results indicate that while the prediction accuracy of the instantaneous fuel consumption models varies across the data sets, those obtained by the regression models are significantly better and more robust against changes in input data. Thirdly, it describes a dynamic programming approach able to find the most economical route, total fuel consumption estimate and the continuous optimal travelling speeds for a vehicle travelling from origin to destination with a set of possible routes.

May, 2016, 131 pages.

Keywords: Economic Fuel Consumption, Energy Efficiency, Regression Models, Slope of the Road, Dynamic Programming, Mobile Software.

1. INTRODUCTION

Oil consumption around the world and the share of oil consumption in transportation are increasing every passing day. While total oil consumption was 2250 Mtoe in 1973, the amount spent for transport was 1022.41 Mtoe with 45.4%, at the beginning of 2013 total oil consumption has risen to 3716 Mtoe, and the amount spent for transport was 2370.81 with 63.8%. The amount of oil consumed for transport in 2013 increased in respect of both total consumption and share and went beyond the total oil consumption in 1973. (iea.org, Key World Energy Statistics, 2015)

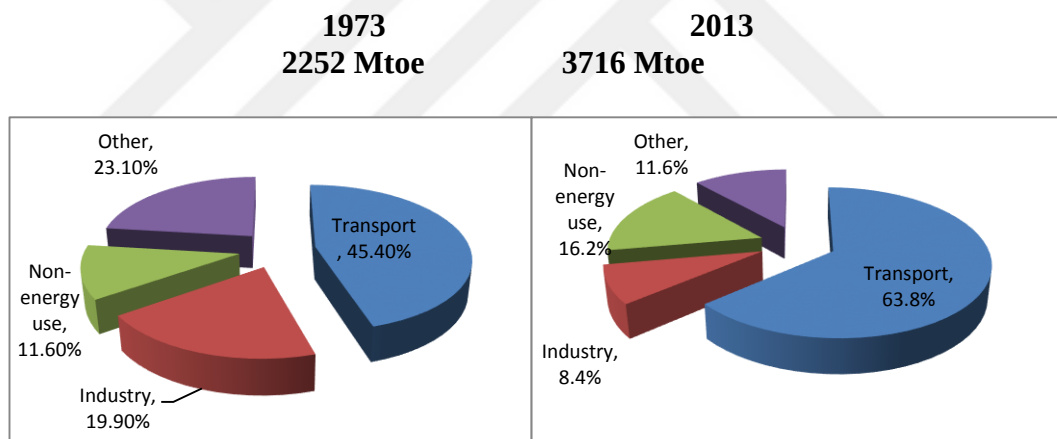


Figure 1.1 Shares of world fuel consumption.

*Includes agriculture, commercial and public services, residential, and non-specified other.

Over one third of global energy usage is due to transportation (Ahn & Rakha, 2008; (Rakha, Ahn, Moran, Saerens, & Bulck, 2011) , the majority of which is obtained through petroleum products. Consumption of fuel by vehicle engines results in greenhouse gas (GHG) emissions, the most prominent of which is CO₂, all of which have detrimental effects on the environment. The second largest source of CO₂ emissions is the combustion of gasoline and diesel in vehicles used in transportation ("Carbon Dioxide Emissions | Climate Change | US EPA", 2016) . To reduce environmental externalities, it is imperative that fuel efficiency of vehicles is improved.

To this end, whilst renewable fuel sources and alternative fuel vehicles might be a solution in the long-term, reducing emissions and fuel consumption of vehicles operating under existing technologies should be the goal in the short to medium term.

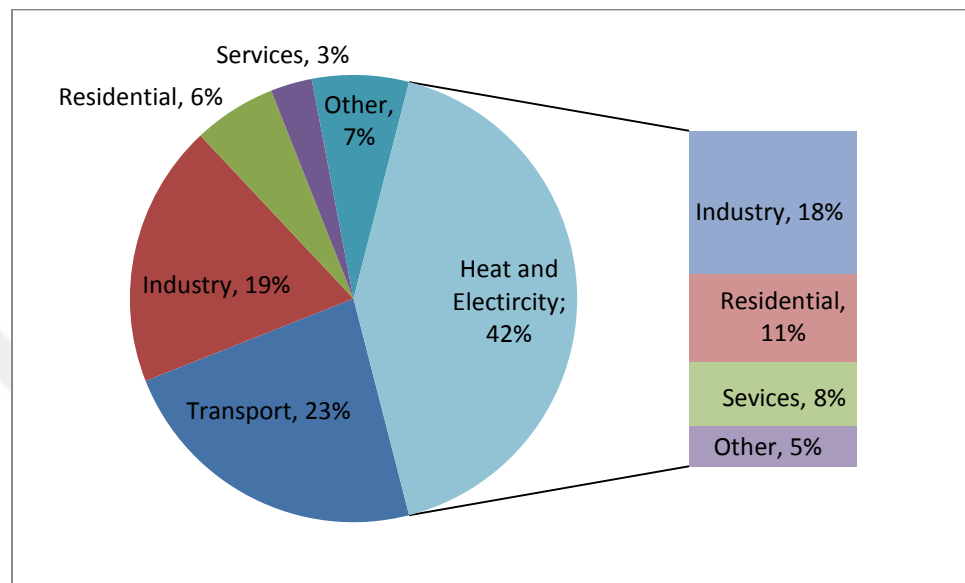


Figure 1.2 World CO₂ emissions by sector in 2013.

Note: Figure 1.2 also shows allocation of electricity and heat to end-use sectors. *
Other includes agriculture/forestry, fishing, energy industries other than electricity and heat generation, and other emissions not specified elsewhere.

Two sectors produced nearly two-thirds of global CO₂ emissions in 2013: electricity and heat generation, by far the largest, which accounted for 42%, while transport accounted for 23%. (iea.org, Key World Energy Statistics, 2015)

The amount of CO₂ emissions from a vehicle is proportional to the amount of fuel consumed by the engine. Fuel efficiency depends on the driving mode, which in turn is dependent on several factors. There are many different ways to estimate emissions using the information on fuel consumption. However, the choice of the nature of emission functions becomes crucial for when accurate estimates are needed in planning for transportation, be it at operational, tactical or strategic levels. The literature is relatively rich in describing models to estimate fuel consumption of vehicles, but

numerical validation results are limited, are described only for some of these models, and in isolation. Further empirical studies using real data are needed not only to gauge the quality of the estimations suggested by such models, but also to be able to provide comparison results across the various models.

(Ardekani et al., 1996); (Bigazzi and Bertini, 2009); (Demir et al., 2011) and (Alwakiel, 2011) have showed the factors affecting fuel consumption by dividing into various categories in their studies (see Figure 1.2).



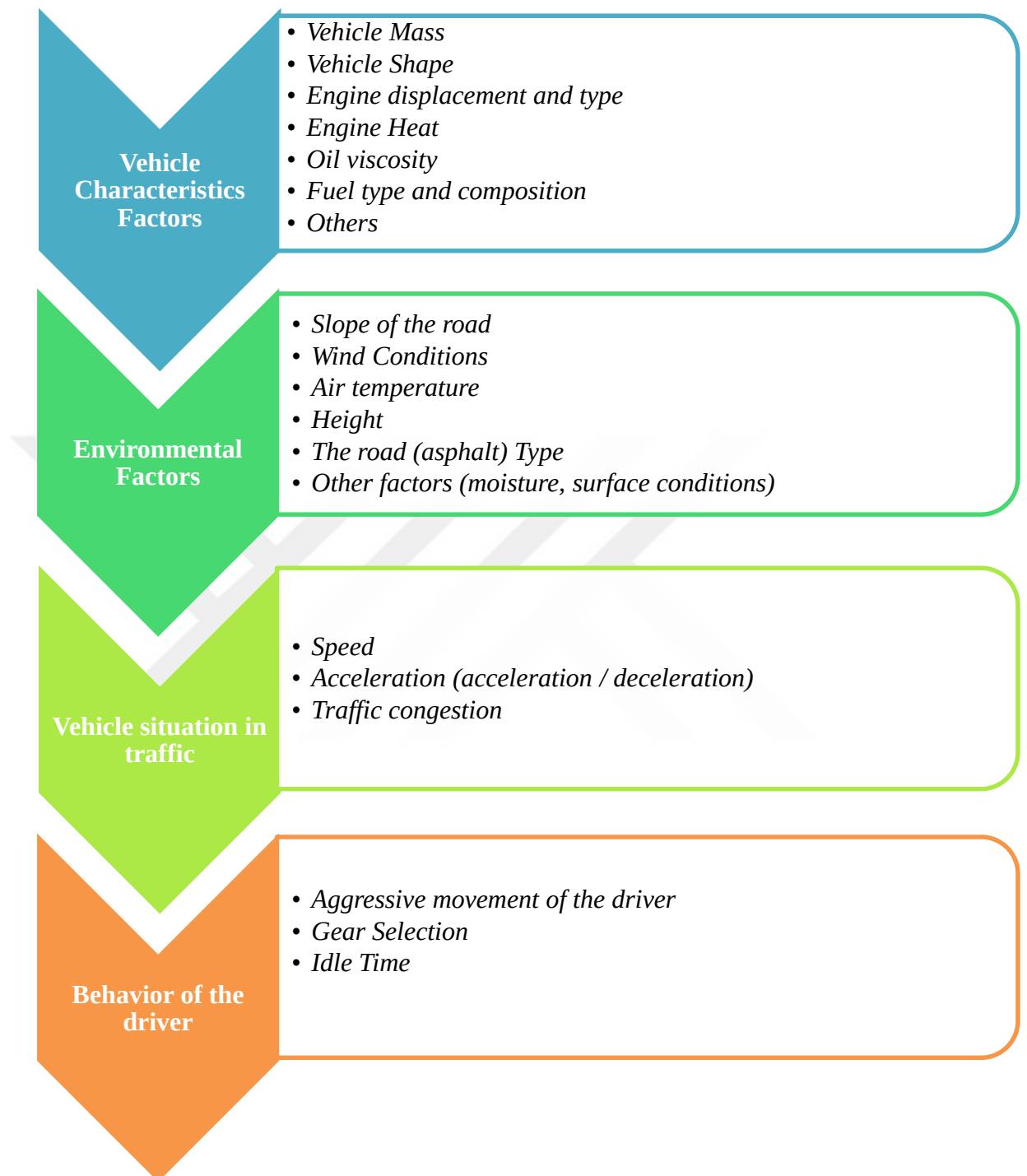


Figure 1.3 Factors affecting fuel consumption.

The most significant one among these factors is speed. It is also seen that the speed factor is examined at most when the recent studies are considered (Demir et al., 2014).

(Samaras et al., 2012), has expressed the impact of the rate of fuel consumption in vehicles with Euro 4 type oil engines with engine capacity of 1400cc and less as seen in Figure 1.3.

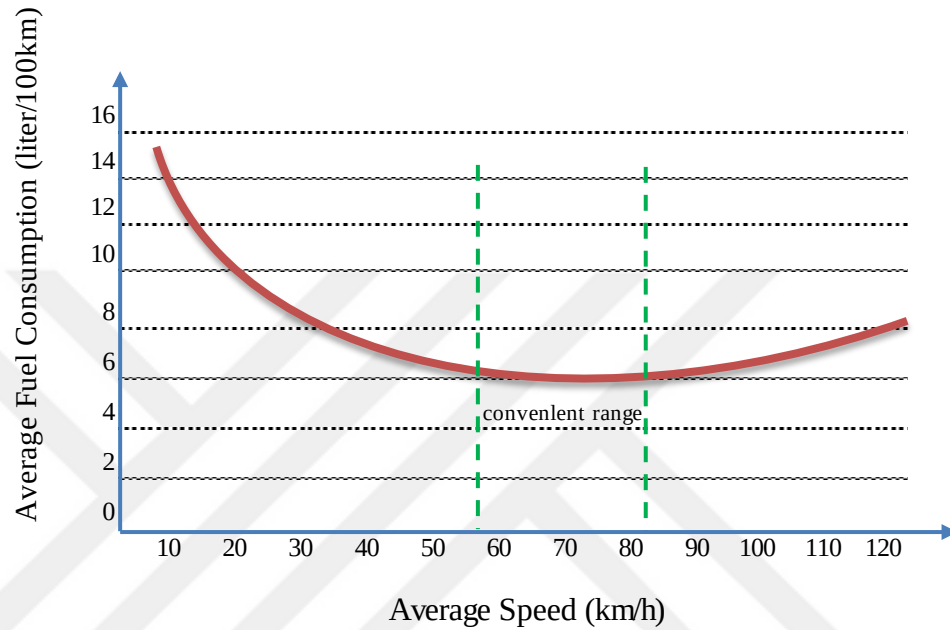


Figure 1.4 Fuel Consumption by average speed.

Another significant factor in fuel consumption is the road's inclination. (Demir et al., 2011) have shown that 6 liters of more consumption occurs per each 100 km in Mid-Size Vehicles (MDV) going uphill with 1% inclination angle and in the same way 6 liters of less consumption occurs per each 100 km in Mid-Size Vehicles (MDV) going downhill with 1% inclination angle.

These are precisely the aims of the dissertation. In particular, the first contribution of this thesis is to test the performance of microscopic vehicle emission models from the literature against real-time data that is collected from a passenger car using existing on-board diagnostics (OBD2), a Bluetooth interface and a smartphone. The results also allow providing a numerical comparison across the microscopic models. Second contribution of this thesis is the literature by proposing regression models for use in estimating fuel consumption of passenger vehicles and shows that they provide more accurate estimations as compared to some of the available models in the literature. The

regression models we develop range from simple linear regression to more sophisticated models, such as artificial neural networks and support vector machines. We also present real data collected from a passenger vehicle using existing on-board diagnostics (OBD2), a Bluetooth interface and a smartphone. This data is used in the numerical comparison of five existing consumption models and three new regression models. Third contribution of this thesis is the following; the speed which is required for a vehicle, has been determined by taking into consideration the conditions such as the type, weight, geographical location on a certain route for the most economic fuel consumption.

In this method, the fuel consumption model calculations recommended for dynamic programming and collection of data required for validation of them were carried out. Some part of these data; are the data directly received from the vehicle depending on the condition of road and the vehicle's brand and model such as coefficient of friction between the wheels and road, engine size, front surface area, weight of the vehicle. And some part are the data which is required to be collected from the vehicles momentarily while the vehicle is going along a route designated like current speed, acceleration, position of the vehicle, slope of the road, engine RPM. To determine the most appropriate mathematical fuel consumption model; to compare the fuel consumptions calculated by mathematical models with actual fuel consumption data is only possible through correct collection of these data.

The Four-Mode Elemental Fuel Consumption Model (FMEFCM) was used for calculation of the most economic fuel consumption with dynamic programming. During selection of this model, 12 macroscopic and 13 microscopic fuel consumption models were analyzed in the literature and the accuracy of these models were tested with actual data, in the end it was selected because of being the most appropriate model for dynamic programming.

2. LITERATURE SURVEY MATHEMATICAL MODEL FOR ECONOMICAL FUEL CONSUMPTION

2.1 REVIEW OF THE EXISTING WORK

Relevant work on the topic dates back to the late 80s, one of which is by Biggs and Akçelik (1987) who compared central districts with urban and non-urban areas by using different size vehicles. The accuracy in prediction of fuel consumption rate against CO₂ emissions has been validated and implemented in many national institutions (Wang et al., 2008). A study by (Wang et al., 2008) found that driving patterns might play an important role on fuel consumption. They show that fuel consumption rates increase significantly when the vehicles accelerate but change little during deceleration. (Oh et al., 2014) presented a comparison of 10 different passenger vehicles for seven driving modes based on simulated data. They show that the gross weight and the speed of the vehicle have significant effects on fuel consumption, whereas those of rolling resistance, frontal area and air drag are negligible. Further research on fuel consumption models has also shown that the vehicle speed, load, and road gradient have a significant effect on the fuel consumption (Demir et al., 2011). (Chaim and Smerling, 2013) looked at fuel consumption estimation under urban operating conditions, and calculated fuel consumption as a function of the degree of power utilization and four different operating modes, namely average speed, accelerations, decelerations and idle mode. (Chaim et al., 2013) looked at vehicle fuel consumption under two different operating modes, namely cruising at constant speed and acceleration. They showed that the fuel consumption depended on instantaneous engine efficiency under each mode. (Oduro et al., 2013) conducted experiments to model the relationship between the tire pressure and fuel consumption, and showed that by using a recommended tire pressure, fuel consumption can be reduced by 17.6%, which lowers

emissions by similar amounts. (Da Rocha et al., 2013) studied the relevance of microscopic traffic models for estimating the impact of traffic strategies on fuel consumption. (Smit et al., 2008) used the three average speed models, namely COPERT III, MOBILE 6, EMFAC 2000 to estimate emissions and fuel consumption from road traffic and include the effects of congestion. The authors suggested that a congestion algorithm might be incorporated in to the model to improve current average speed models. They also evaluated the effect various vehicle parameters, local traffic conditions and driving behavior on vehicle emissions and fuel consumption for conventional vehicles.

A study by (Van Mierlo et al., 2004) found that driving style might play an important role on fuel consumption and emissions. (Li and Sun, 2014) proposed a model of vehicle-pedestrian interactions and the effect on traffic fuel economy and emissions. On-ramp can enhance each vehicle's fuel consumption on the main road and that the increments are related to the traffic state of the main road and the inflow of the on-ramp (Tang et al., 2015). Ho et al Emissions and fuel consumption estimation models play a key role in the evaluation of the environmental impacts of intelligent transportation systems strategies (Ho et al., 2014) formulated a representative driving cycle, with consideration of distance, road type and duration, for passenger cars in Singapore in order to reduce the emissions and fuel consumption. Euro 4 petrol car driven on four typical urban routes in Hong Kong (Tsang et al., 2011), Euro III and IV buses fueled on diesel and compressed natural gas in Beijing (Wang et al., 2011), gasoline passenger cars in Bangkok (Tamsanya and Chungpaibulpatana, 2009) were analyzed to obtain the effects of on-road emissions and fuel consumption.

There exists research looking at the effect of street characteristics, driver category and car performance on urban driving patterns (Freij and Ericsson, 2005), high altitude on fuel consumption of a gasoline passenger car (Zervas, 2011), driving behaviors, road slope and vehicle load factor on bus fuel consumption and air pollutant emissions (Carrese et al., 2013), route choice decisions on vehicle energy consumption and emissions (Ahn and Rakha, 2008), and the effect of a driver support tool, the acceleration advisor, on fuel consumption and emission (Larsson and Ericsson, 2009). In (Saboochi and Farzaneh, 2009), controlling speed and selecting an appropriate gear ratio with respect to different engine loads were considered for implementation of

optimal driving strategy to minimize the fuel consumption. A study by (Aksoy et al., 2014) showed that the fuel consumption and CO₂ emission amount has direct correlation with the type of vehicle chosen and the distance traveled.

At the local and regional levels, a significant portion of freight transportation is carried out by trucks, which emit a large amount of pollutants. In (Demir et al, 2014), a review of recent research on green road freight transportation is presented. (Walnum and Simonsen, 2015) studied the known and potential factors for reducing fuel consumption in heavy-duty vehicles, and suggest that modifying driving behavior can potentially lower fuel consumption. Other studies have looked at on-road emissions for a heavy-duty public transit buses using different fuel systems in Beijing using portable emission measurement systems (Zhang et al., 2014) and for light-duty passenger vehicles in three cities in China with a particular focus on fuel consumption (Zhang et al., Energy, 2014).

A number of studies have highlighted the significant effects road grade can have on actual fuel usage and on exhaust emissions (Boriboonsomsin and Barth, 2009; Boroujeni and Frey, 2014; Zhang and Frey, 2006; Sahlholm and Johansson, 2010). In (Boriboonsomsin and Barth, 2009), the effect of road grade on vehicle fuel consumption and CO₂ emissions was evaluated for light-duty vehicles both at the roadway link level and at the route level (Boriboonsomsin and Barth, 2009). (Ragione et al., 2014) evaluated the emissions trend with two cars with gasoline fuelled on a particular path road characterized by uphill and downhill gradient variability. They show that a maximum emission value was reached on uphill phase. (Wyatt et al., 2014) investigated the impact of road grade on CO₂ emission of a passenger car with PEMS. They suggested that transport management and urban planning approaches should incorporate road grade into their analysis where prediction of vehicle emission and fuel consumption was required. Despite the mentioned studies, however, the evidence on the effect of road gradient on fuel consumption is still limited, and more research is needed to fill this gap, and one which the present study contributes to.

2.2 FUEL CONSUMPTION MODELS

As such, it can be said that current speed and the inclination of the road play an important role among the factors affecting fuel consumption.

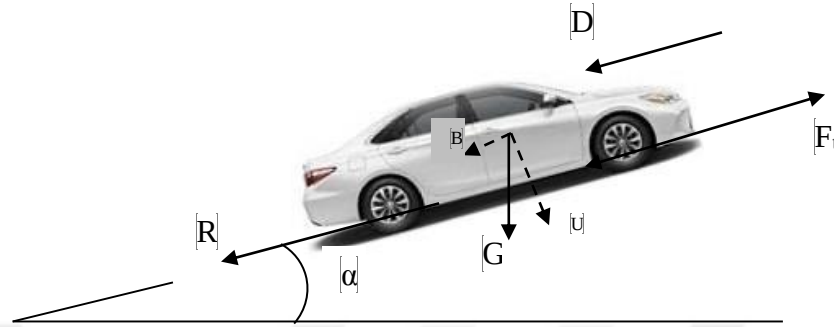


Figure 2.1 Forces Affecting Vehicle in an Inclined Road.

The vehicle's traction force (F_T) can be expressed as follows by taking Figure 2.1 into consideration. (Hucho, 1998):

$$F_T = D + R + m \frac{dV}{dt} + mgsin\alpha \quad (2.1)$$

where D is the air resistance force, R is the tire rolling resistance, m is the vehicle's mass, V is vehicle speed, g is the acceleration of gravity, and α is the slope angle of the road. The $m \frac{dV}{dt}$ is termed acceleration resistance and $mg.sin\alpha$ is climbing resistance. All resistances will reduce the power of the engine production.

D: Force of Air Resistance

Air resistance is the resistance of the force affecting in the opposite direction of movement direction of objects moving in air. Air Resistance Force depends on the size of a vehicle which is characterized by a vehicle's frontal area. The Air Resistance Force D can be expressed as (Hucho, 1998) :

$$F_d = C_d \frac{1}{2} \rho v^2 A \quad (2.2)$$

where C_d is the coefficient of air resistance drag, ρ is the air density (NTP for 1,293 kg/m³ air), A is the vehicle's frontal area and the square of the velocity of the vehicle V .

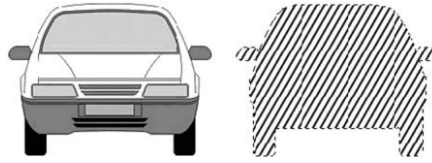


Figure 2.2 The Vehicle's Frontal Surface Area.

Air Resistance Coefficient is a function that depends on several parameters such as shape of the object and Froude number , Mach number and surface roughness.

Air resistance coefficients of objects have been generally determined as a result of experiments. Air resistance coefficients of some objects are provided in Table 2.1.

Table 2.1 Air Resistance Coefficients.

Type of Object	Air resistance Coefficient, C_d
Subsonic Transport Aircrafts	0,012
Airplane Wing, normal position	0,05
Airplane Wing, stop position	0,15
Sports cars, sloping rear	0,2-0,3
Average cars (e.g. Toyota Corolla)	0,29
Convertible cars, roadster	0.6 -0.7
Bus	0.6 -0.8
Classic Cars like T –ford	0.7 -0.9
Bicycle	0.9
Tractors	0.96
Trucks	0.8-1.0

Example - A normal car's air resistance

Air resistance force that occurs in a family car with front surface area of 2 m² and with air resistance coefficient 0.29 and going with a speed of 90 km/h per hour is calculated as follows:

$$F_d = 0.29 * \frac{1}{2} * (1.2 \text{ kg/m}^3) * ((90 \text{ km/h}) * (1000 \text{ m/km}) / (3600 \text{ s/h}))^2 * (2 \text{ m}^2) = 217.5 \text{ N}$$

R: Rolling (Friction) Resistance Force

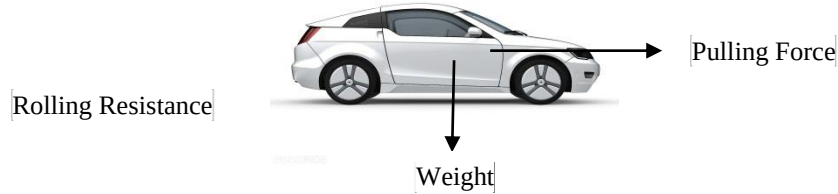


Figure 2.3 Rolling Resistance Force.

Force applied by the surface to the opposite direction of the object's movement is named rolling resistance or rolling friction.

Rolling resistance (F_r) is expressed by this equation (Hucho, 1998):

$$F_r = c W \quad (2.3)$$

Where, c is Rolling Resistance Coefficient (dimensionless (CRF)) and W is the weight of the object,

$W = m \cdot g$, where m is mass of the object and g is gravity (9.81 m/s^2)

Rolling resistance can be described as follows if the wheel's radius is taken into account:

$$F_r = c_l W / r \quad (2.4)$$

Where c_l is length of size and rolling resistance coefficient (rolling friction coefficient) (mm) and r is wheel radius (mm)

Rolling Resistance in Cars

Rolling resistance coefficient with a tire with full air on dry road is calculated as follows:

$$c = 0.005 + 1/p (0.01 + 0.0095(v/100)^2)$$

where c is rolling coefficient, p is tire pressure (bar) and v is speed (km/h)

Example- Calculating the rolling resistance force of a car on asphalt road

Rolling resistance force on an asphalt surface with 1500 kg of weight and with rolling resistance coefficient of 0,03 is calculated as follows.

$$F_r = 0.03 (1500 \text{ kg}) (9.81 \text{ m/s}^2) = 441 \text{ N}$$

Table 2.2 Rolling resistance coefficients.

Rolling Resistance Coefficient, C	
Train wheels and steel rails	0.001 -0.002
Bicycle wheel and wooden floor	0,001
Bicycle tires concrete road	0,002
Bicycle tires asphalt road	0,004
Tramway rails	0,005
Truck wheel and asphalt road	0,006-0,01
Ordinary vehicle tires and concrete road	0,01 -0,015
Car tires and asphalt road	0,03
Car tires and solid sand	0,04 to 0,08
Car tires and loose sand	0,2-0,4

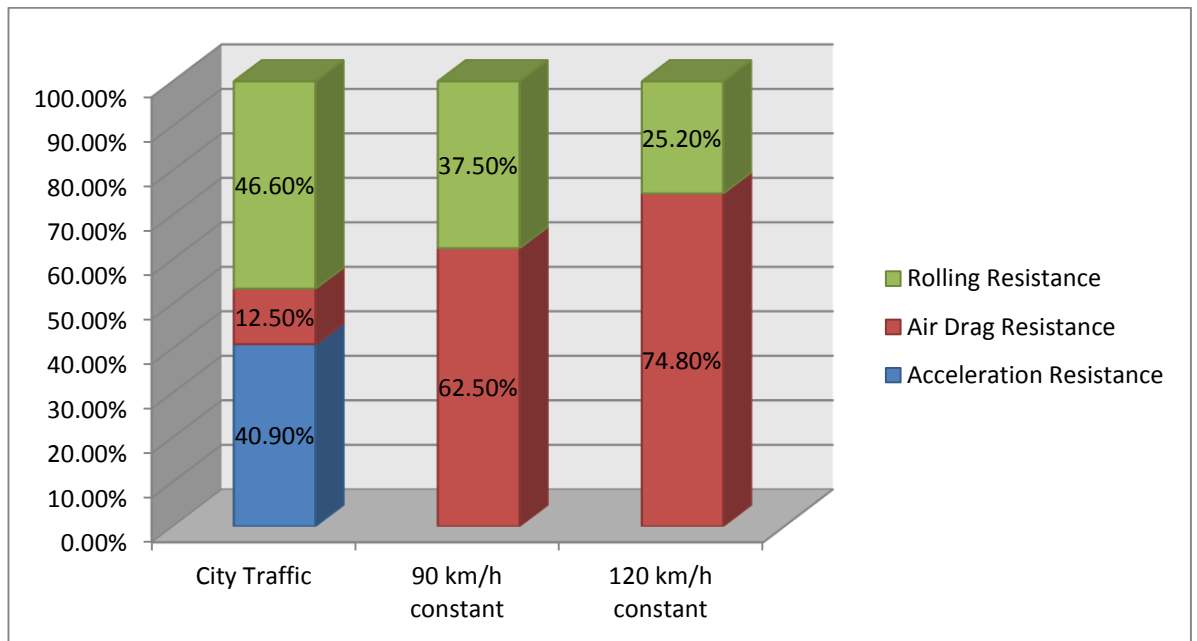


Figure 2.4 Contribution of Tire Rolling Resistance to Vehicle Fuel Economy versus Speed

Additionally, the contribution of tire rolling resistance to fuel economy varies with the speed of the vehicle. At lower speeds, tire rolling resistance represents a larger percentage of the fuel consumption (Figure 2.4) (Reimpell, and Stoll, 2001) than at higher speeds.

Fuel consumption information can be accessed in three ways. (Wu and Liu 2011)

- Factory data
- Fuel consumption estimation modeling by taking into consideration factors given here in above
- Performance Analysis

Fuel can cause consumption. Factory fuel consumption modeling can be divided into 3 main categories as Factor, microscopic and macroscopic modeling. Factor modeling includes simple fuel consumption models. Microscopic modeling provides the instantaneous fuel consumption value while macroscopic modeling gives the total amount of fuel consumed on the route.

The most comprehensive research for macroscopic and microscopic models has been carried out by Demir et al (2014) in the last decade.

2.2.1 Macroscopic Models

13 macroscopic (average speed) models are discussed. These models can be utilized in calculations and development of national and regional emissions data inventories.

Similar variables were used in all models in order to eliminate the repeat in variables. Vehicle speed (km/h) and total distance were shown as D (kilometer).

2.2.1.1 Transport emissions and energy consumption method. (MEET)

The MEET method used for calculation of emissions and energy consumption in the heavy freight were identified as transport emission factors in road transport (INFRAS, 1995), published by (Hickman et al., 1999) in European Commission. Real road path

and the test parameters were used. The vehicles were classified by weight as vehicles lighter than the weight of 3.5 tons, vehicles between the weight of 3.5 and 7.5 tonnes, vehicles between the weight of 7.5 and 16 tonnes and vehicles over 16 tonnes.

CO₂ emission measurement of vehicles lighter than the weight of 3.5 tons was conducted according to speed by this regression formula.

$$er(v) = 0,0617v^2 - 7,8227v + 429,51 \quad (2.5)$$

Table 2.3 Parameters Used in the MEET Method.

Weight Class	K	A	b	c	D	E	f
3.5<Weight<7.5	110	0	0	0.000375	8702	0	0
7.5<Weight<16	871	-16.0	0.143	0	0	32031	0
16<Weight<32	765	-7.04	0	0.000632	8334	0	0
Weight>32	1576	-17.6	0	0.00117	0	36067	0

The following formula is used for other vehicle classifications in the MEET method:

$$er(v) = K + av + bv^2 + cv^3 + d/v + e/v^2 + f/v^3 \quad (2.6)$$

here $er(v)$ gives the CO₂ emission value in kind of (gram/kilometer) for a road

If we want to take into account the inclination of the road inclination verification factor formula is written as follows.

$$GC(v) = A_6 v_6 + A_5 v_5 + A_4 v_4 + A_3 v_3 + A_2 v_2 + A_1 v + A_0 \quad (2.7)$$

All the coefficients from A_0 to A_6 are given in Table 2.3

Table 2.4 Inclination Formula Coefficients

Weight Class	A ₆	A ₅	A ₄	A ₃	A ₂	A ₁	A ₀	Slope
Weight≤7.5	0	-3.01E-9	5.73E-07	-4.13E-05	1.13E-03	8.13E-03	9.14E-01	[0,4]
Weight≤7.5	0	-1.39E-10	5.03E-07	-4.18E-06	1.95E-05	3.68E-03	9.69E-01	[-4,0]
7.5<Weight≤16	0	-9.87E-10	-2.01E-09	1.91E-05	-1.63E-03	5.91E-02	7.70E-01	[0,4]
7.5<Weight≤16	0	-6.04E-11	-2.36E-08	7.76E-06	-6.83E-04	1.79E-02	6.12E-01	[-4,0]
16<Weight≤32	0	-5.25E-09	9.93E-07	-6.74E-05	2.06E-03	-1.96E-02	1.45E+00	[0,4]

16<Weight≤32	0	-8.24E-11	-2.91E-08	-2.58E-06	5.76E-05	-4.74E-03	8.55E-01	[-4,0]
Weight<32	0	-2.04E-09	4.35E-07	-3.69E-05	1.69E-03	-3.16E-02	1.77E+00	[0,4]
Weight<32	0	-1.10E-09	2.69E-07	-2.38E-06	9.51E-04	-2.24E-02	9.16E-01	[-4,0]

If the vehicle is assumed to be loaded the load verification formula is written as follows.

$$LC(v) = k + nv + pv^2 + qv^3 + r/v + s/v^2 + t/v^3 + u/v \quad (2.8)$$

all the coefficients from k to u are given in Table 2.4.

Table 2.5 The Coefficients in the Formula Used for the Loaded Vehicle.

<i>Weight Class</i>	<i>k</i>	<i>n</i>	<i>p</i>	<i>q</i>	<i>r</i>	<i>s</i>	<i>T</i>	<i>u</i>
3.5<Weight<7.5	1.27	0.0614	0	-0.00110	-0.00235	0	0	-1.33
7.5<Weight<16	1.26	0.0790	0	-0.00109	0	0	-2.03E-07	-1.14
16<Weight<32	1.27	0.0882	0	-0.00101	0	0	0	-0.483
Weight>32	1.43	0.121	0	-0.00125	0	0	0	-0.916

Because the MEET method was calibrated again in 1999 it may be needed to revise it again according to the new engine and aerodynamic technology.

2.2.1.2 Network Model for Transport and Environment (NTM)

This model has been created by a Swedish non-profit organization in 1993 (Road NTM, 2010). It has been created with an eye to find a common method of environmental performance calculating in various modes of transport. NTM aims to create carbon footprints of the environmental impact of all the actors in the transport sector. NTM takes into consideration distance, load factor, form of the mode of transportation, positioning, topography, form of the road (urban, suburban, highway, etc.). The load factor, consumption of fuel (kilometers/liter) f (LF) i and form of the road (urban, suburban, highway, etc.) are shown with i .

$$f(lf)_i = F(full) + (F(full) - F(empty)) \quad (2.9)$$

$F(\text{empty})$ denotes fuel consumption when vehicle is completely empty (liters/kilometer) and $F(\text{full})$ means fuel consumption when vehicle is loaded (liters/kilometer). For different types of vehicles $F(\text{full})$ and $F(\text{empty})$ values (Road NTM, 2010) are calculated.

2.2.1.3 Computer program to calculate emission values of road transport (COPERT)

(COPERT) is an emission model financed by the European Economic Area for making measurement according to the type of vehicle and engine class (Kouridis et al, 2010). Class of vehicle, engine technology and speed and emission values are managed by the database. A regression function is used in (COPERT) according to the weight of vehicles for estimating the fuel consumption as in (MEET) method.

Calculation of total fuel consumption (g) in different load and inclinations:

$$F(v, D) = (e + (a \exp(-bv)) + (c \exp(-dv))) \cdot D \quad (2.10)$$

variables are defined from a and e and a data set is shown in Table 2.6 also for Euro-5 diesel trucks of 20-26 tones.

Table 2.6 Coefficients according to some load and road inclination for the (COPERT) method.

<i>Payload</i> (%)	<i>Gradient</i> (%)	<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>	<i>e</i>
0	0	530.707	0.0634	2704.528	0.512	157.588
0	-2	546.477	0.064	9599.652	0.766	61.960
0	+2	1051.552	0.424	-67.668	0.084	0
50	0	505.770	0.051	4762.796	0.609	180.436
50	-2	479.620	0.047	7858.071	0.677	40.246
50	+2	2074.874	1.008	-0.534	0	0
100	0	502.941	0.041	9343.090	0.729	195.202
100	-2	1144.824	0.981	-0.400	0	0
100	+2	1882.813	1.006	-0.422	0	0

2.2.1.4 Ecological Transport Information Tool (ECOTRANSIT)

(ECOTRANSIT) is a limited regional model developed in Europe in 2003. The new version EcoTransIT World model, applying to all countries of the world and predicting the effects of worldwide transportation on ecology was published in 2011 (Knörr, Seum, Schmied, Kutzner, & Anthes, 2011). This model of energy consumption includes emissions of greenhouse gases and air pollution. All calculations are performed in three steps. In the first step, final energy consumption is calculated in kilometers per net ton. $ECF \text{ ton kilometer} = ECF_{\text{kilometer}} / (CP * CU)$. Here $ECF_{\text{kilometer}}$ shows the final energy consumption in kilometers for each ton, and CP shows the load capacity in (tonnes) and U shows the used Capacity in (%). Secondly, source energy usage is calculated. final energy consumption per net tone in kilometers. $ECU \text{ ton kilometer} = ECF_{\text{kilometer}} * ECUEC$. Here ECUEC shows the use of energy connected to energy source. The third step is the calculation of total energy consumption in (Megajoul).

$F(D;M) = D * M * (ECF_{\text{ton kilometer}} + ECU_{\text{ton kilometer}})$. Here M shows the weight of the load being carried in (t) and D shows the length of the total distance (km) taken. Energy consumption and emissions, of course, changes according to the type, inclination of the road as well as the way of driving. With (HBEFA) effect of the load factor, according to the modeling, the effect of a vehicle's being one-third full or completely full is more than the inclination of the road and driver's characteristics on fuel consumption.

2.2.1.5 National Atmospheric Emissions Inventory (NAEI)

NAEI has been developed for wide range of applications including agriculture, local activities, as well as industrial and transportation (NAEI, 2012). It takes into account everything from the calculation of emissions of road transport, total fuel consumption data, fuel specifications or data of the driver and traffic conditions. Fuel consumption data (liters/100 kilometers), in average speed and when exhaust is hot, can be calculated for each vehicle category with NAEI.

$$F(v) = k(a + bv + cv^2 + dv^3 + ev^4 + fv^5 + gv^6)/v \quad (2.11)$$

Here all the letters from k to g are coefficients and these coefficients for trucks between 20-26 tons are given in Table 2.7.

Table 2.7 Parameters for certain engine types for NAEI model.

<i>Fuel Type</i>	<i>k</i>	<i>a</i>	<i>b</i>	<i>c</i>	<i>D</i>	<i>E</i>	<i>f</i>	<i>G</i>
Pre Euro I	0.037	13690.286	390.990	54.374	-2.587	0.048	0	0
Euro I	0.037	13661.548	-220.208	85.38	-3.401	0.060	0	0
Euro II	0.037	4747.573	1341.727	-23.117	0.103	0.002	0	0
Euro III	0.037	9584.751	464.510	42.172	-2.069	0.038	0	0
Euro IV	0.037	10297.467	210.752	53.532	-2.367	0.043	0	0
Euro V	0.037	10537.515	220.217	54.175	-2.404	0.043	0	0
Euro VI	0.037	10537.515	220.217	54.175	-2.404	0.043	0	0

2.2.1.6 Other Macroscopic Models

In addition to the models specified hereinabove there are 7 models in the literature in which calculation of fuel consumption and emission figures are made according to speed.

MOBILE is a model developed by Environmental Protection Agency (EPA) and published in 1978 by the Office of Transportation and Air Quality. Latest version 6.2 MOBILE has been developed by using both the inspection and maintenance emission test data collected from EPA, CARB of vehicles produced recently and car producers of vehicles in various places (EPA, 2003). MOBILE table output is the amount of dirty emissions in grams per kilometer for each vehicle in traffic. EPA's official emission estimation tool has become Motor Vehicle Emission Simulator (MOVES) as from 2010 instead of MOBILE.

MOVES model has been developed by (EPA, 2013). The purpose of this tool is to predict emission values coming from a user-defined wide range. When the model is

could it makes a series of calculations to start or go on idling to reflect the vehicles usage process correctly and estimate emissions correctly.

HBEF Europe is a database for vehicle emission factors and a handbook for emission factors for road transport. This model was introduced in 1995 (Hausberger et al, 2009). Current version of HBEF 3.1 was published in 2009. This model includes emission factors for all current vehicle categories in road transport in addition to all EU emissions standards as well as a wide range of traffic conditions.

GREET is a transport model developed in Argonne National Laboratory for greenhouse gases, regulated emissions and a full life-cycle improved as energy. (Wang model 1999).

LEM is a model which predicts energy use, polluting emissions and CO₂ emissions from types of transport and energy life cycle (Delucchi, 2003). This models contains a wide range of passenger and freight transport modes. VERSIT-LD is a model for improved predicting traffic flow emissions in light vehicles in various traffic situations. (Smit et al., & Rabe, 2007).

IVE International Vehicle Emissions Model is designed to estimate the emissions of motor vehicles. (ISSRC, 2008). This model predicts local air pollutants, toxic contaminants and greenhouse gas emissions.

EMFAC is an emission model developed by the California Weather Prediction Council and its current version is EMFAC2011. (CARB, 2011). EMFAC emission rates are the average speed functions of the vehicles.

2.2.2 Microscopic Models

In this section, instantaneous emission models for estimating vehicle emissions in warmed-stabilized condition (in time t) will be reviewed. It is necessary to estimate more accurate traffic emissions in the instant models. These are based on instantaneous vehicle kinematics variables velocity collected in a more detailed way such as acceleration or; at constant speed, or positive, it is snapshot tool for each traffic modes such as time spent on negative acceleration. Some indications are combined with a view

to improve the readability and comprehensibility of the models: v denotes vehicle's velocity (m / sec), T denotes the total journey time (seconds), M denotes total weight of the vehicle (kg), a denotes instant acceleration (meters / second²), ω gradient (%), g denotes constant (m/sec², approximately 9.81), Δ denotes air intensity (kilograms/meter³ is typically between 1.1455 and 1.4224), A denotes front surface area (m², typically between 3.91 and 5.88 for large vehicles), C_d denotes aerodynamic coefficient number (typically between 0.7 and 0.9), μ friction coefficient, C_r denotes rolling resistance (typically between 0.006 and 0.01). (Bowyer, 1985) has taken microscopic models of fuel consumption in four steps:

- Instantaneous fuel consumption model
- Four-mode element fuel consumption model
- Operating speed fuel consumption model
- Average fuel consumption model

(Kent, Tomlin and Post, 1982) have made studies on instantaneous fuel consumption model before (Bowyer while Akçelik, 1983) has conducted studies element model and (Watson, 1981) has carried out studies on operating speed model, studies were made. In addition to them following studies been carried out:

- Vehicle Specific Power (VSP), (Jimenez-Palacios, 1998)
- Traffic Mode Emission (EMIT), (Cappiello, Chabini, Nam ve Lue, 2002)
- Virginia Technique Microscopic (VT-Micro), (Ahn, Rakha, Trani, Van Aerde, 2003)
- Oguchi fuel consumption Model (OFCM) (Oguchi et al., 2002)
- Physical emission rate estimator (PERE) model
- Comprehensive Force-Based Fuel consumption Models (CPFMs)
- Emissions Model in Passenger and Heavy Vehicles (PHEM)

2.2.2.1 An Instantaneous Fuel Consumption Model (IFCM)

IFCM is described by (Bowyer et al. 1985) as an energy-based model, according to which the instantaneous fuel consumption $f(t)$ of a vehicle of weight M moving at speed v can be calculated (in milliliter/second) as

$$f(t) = \begin{cases} \alpha + \beta_1 R(t)v + (\beta_2 Ma^2 v / 1000) & \text{for } R_t > 0 \\ \alpha & \text{for } R_t \leq 0 \end{cases}, \quad (2.12)$$

where $R(t)$ is the total tractive force (kilo-newton) calculated as $R(t) = b_1 + b_2 v^2 + Ma/1000 + gM\omega/100000$, in which α is the constant idle fuel rate (in milliliter/second, typically between 0.37 and 0.56), β_1 is the fuel consumption per unit of energy (in milliliter/kilojoules, typically between 0.09 and 0.08), β_2 is the fuel consumption per unit of energy-acceleration (in milliliter/(kilojoules $\times$ meter/second²), typically between 0.03 and 0.02), b_1 is the rolling drag force (in kilo newton, typically between 0.1 and 0.7), and b_2 is the rolling aerodynamic force (in kilo newton/ (meter/ second²), typically between 0.00003 and 0.0015). With IFCM model, the total amount $F(T)$ of fuel consumption (milliliter) for a trip of duration T , with all other parameters such as speed remaining constant, can be calculated as

$$F(T) = \int_0^T f(t)dt. \quad (2.13)$$

The values of the parameters presented above are from (Bowyer et al.,1985) and (Akçelik and Besley, 1990; 2003).

2.2.2.2 A Four-Mode Elemental Fuel Consumption Model (FMEFCM)

FMEFCM is another model described by Bowyer et al. (1985) and can be regarded as a more detailed version of IFCM. For this reason, it uses the same set of parameters as with the IFCM, but includes additional ones reflecting initial and final speeds. This model explicitly takes into consideration the amount of fuel consumed in four modes (or phases) of driving, namely acceleration (a), deceleration (b), cruise (c) and idle (d), denoted by $F_a(t_a)$, $F_d(t_d)$, $F_c(t_c)$ and $F_i(t_i)$, respectively, where t_a , t_d , t_c and t_i are the times spent under each phase. The explicit calculations for each of the four modes are given below.

a. Acceleration mode: The fuel consumption during the acceleration phase is calculated as

$$F_a(t_a) = \max\{\alpha t_a + (\Gamma + k_1 B(v_i^2 + v_f^2) + \beta_1 M E_k + k_2 \beta_2 M E_k^2 + 0.0981 \beta_1 M \omega) x_a, \alpha t_a\} \quad (2.14)$$

where E_k shows the change in kinetic energy per unit distance during acceleration and is calculated as $E_k = 0.3858 (10)^{-4} (v_f^2 - v_i^2) / x_a$ and where v_f is final speed and v_i is initial speed of vehicle. In addition, $k_1 = 0.616 + 0.000544 v_f - 0.0171 \sqrt{v_i}$, $k_2 = 1.376 + 0.00205 v_f - 0.00538 v_i$, Γ is a parameter (in milliliter/kilometer) typically between 21 and 100, and B is another parameter (in (milliliter/kilometer)/(kilometer/hour)² typically taking a value between 0.0055 and 0.018. If the travel distance x_a and the travel time t_a are not known, they can be estimated using $x_a = m_a (v_f + v_i) t_a / 3600$, where $m_a = 0.467 + 0.00200 v_f - 0.00210 v_i$ and $t_a = (v_f - v_i) / (2.08 + 0.127 \sqrt{v_f - v_i} - 0.0182 v_i)$.

b. Deceleration mode: The fuel consumption in this case is

$$F_d(t_d) = \max\{\alpha t_d + (k_x \Gamma + k_y k_1 B(v_i^2 + v_f^2) + k_a \beta_1 M E_k + k_x \beta_1 M E_k^2 + 0.0981 \beta_1 M \omega) x_d, \alpha t_d\} \quad (2.15)$$

Where; $k_x = 0.046 + 100/M + 0.00421 v_i - 0.00260 v_f + 0.544 \omega$, $k_y = k_x^{0.75}$, $k_a = k_x^{3.81} (2 - k_x^{3.81})$ and $k_1 = 0.621 + 0.000777 v_i - 0.0189 \sqrt{v_f}$.

c. Cruise mode ($F_c(t_c)$): The fuel consumption in this mode is given by

$$F_c(t_c) = \max\left\{\frac{f_i}{v_c} + \Gamma + B v_c^2 + k_{E1} \beta_1 M E_{k+} + k_{E2} \beta_2 M E_k^2 + 0.0981 k_G \beta_1 M \omega, \frac{f_i}{v_c}\right\} x_c \quad (2.16)$$

where f_i denotes the idle fuel rate (in milliliter/hour), v_c is the average cruise speed (kilometer/hour), x_c stands for the travel distance (kilometer) and $E_{k+} = \max\{0.258 - 0.0018 v_c, 0.10\}$ and the other calibration parameters are $k_{E1} =$

$\max\{12.5/V_c - 0.000013v_c^2, 0.63\}$, $k_{E2} = 3.17$ and $k_G = 1 - 2.1E_{k+}$ for $\omega < 0$ and $k_G = 1 - 0.3E_{k+}$ for $\omega > 0$.

d. Idle mode: The amount of fuel consumption when the vehicle is idle is calculated as $F_i(t_i) = \alpha t_i$, where t_i is the idle time spent (seconds), and α is the idle fuel rate (milliliter/second).

With FMEFCM, the total fuel consumption (milliliter) using the all four modes can be calculated as;

$$F(t_a, t_d, t_c, t_i) = \int_0^{t_a} F_a(t_a) dt + \int_0^{t_d} F_d(t_d) dt + \int_0^{t_c} F_c(t_c) dt + \int_0^{t_i} F_i(t_i) dt. \quad (2.17)$$

2.2.2.3 Physical emission rate estimator (PERE) model

PERE was first presented by Nam and Giannelli (2005) to measure vehicle emissions, according to which the fuel consumption (kilogram/second) is calculated as:

$$f_{pr}(t) = \xi \{kNV + (P_b(v)/\eta_t + P_{acc})/\eta\}/41.7 \quad (2.18)$$

where ξ is the fuel air equivalence ratio (typically 1), k is the engine friction (typically between 0.15 and 0.25), N is the engine speed (typically between 15 and 80 RPS), V is the engine displacement volume (typically between 1 and 7), η_t is a transmission and final drive efficiency (typically between 0.4 and 0.45), P_{acc} is the power draw of accessories (typically 0).

The power demand (watts) can be calculated as

$$P_b(v) = C_r v + B v^2 + C_d v^3 + M v(a + g\omega) \quad (2.19)$$

where A , B , C are model specific constants calculated as $A = C_{R0}Mg$, $B = 0.0$, $C = C_d A_r \rho / 2 + C_{R2}Mg$, and C_{R0} and C_{R2} are the zero and second order in speed rolling resistance force terms, respectively. Using PERE, the total fuel consumption (kilogram) over a trip of duration T is calculated as

$$F_{pr}(T) = \int_0^T f_{pr}(t)dt. \quad (2.20)$$

2.2.2.4 A comprehensive modal emission model (CMEM)

CMEM was formulated by Scora and Barth(2006) and Barth and Boriboonsomsin (2008) for heavy-goods vehicles, and consists of three modules relevant to engine power, engine speed and fuel rate, respectively. We explain these modules further in the below.

The engine power module: The total tractive power is the base of the power demand function $P_{tract}(t)$ (kilowatt) calculated as follows.

$$P_{tract}(t) = (Ma + Mg \sin \omega(\theta) + 0.5 C_d \rho A v^2 + Mg C_r \cos \omega(\theta)) v / 1000 \quad (2.21)$$

The transformation from tractive power to engine power is shown by the expression below,

$$P(t) = P_{tract}(t) / \eta_{tf} + P_{acc}, \quad (2.22)$$

where $P(t)$ is the second-by-second engine power output (kilowatt), and η_{tf} is the vehicle drive train efficiency.

The engine speed module: Engine speed is related to vehicle speed in the following way,

$$N(v) = S \left(\frac{R(L)}{R(L_g)} \right) v_i, \quad (2.23)$$

where $N(v)$ is the engine speed (in rpm), S is the engine-speed/vehicle-speed ratio in top gear L_g , $R(L)$ is the gear ratio in gear $L = 1, \dots, L_g$, and η is the efficiency parameter for engines.

The fuel rate module: The fuel rate (gram/second) is formulated as

$$F_{cm}(t) = \xi (kN(v)V + P(t)/\eta) / 41.7 \quad (2.24)$$

According to CMEM, the total fuel consumption (in grams) by a vehicle for a trip of duration T is given by:

$$F_{cm}(T) = \int_0^T f_{cm}(t)dt \quad (2.25)$$

2.2.2.5 A running speed fuel consumption model (RSFCM)

The running speed fuel consumption model is derived from FMEFCM and was presented by Bowyer et al.(1985). The model evaluates fuel consumption individually during driving modes when a vehicle is running idle. Within this model, all driving modes are accounted for simultaneously within a single function. The RSFCM estimates the total fuel consumption $F(t_i, t_s)$ of a vehicle traveling over a total distance of x_s at an average running speed v_r (kilometer/hour) as follows:

$$\begin{aligned} F(t_i, t_s) &= \max\{\alpha t_i + (f_i/v_r + A + Bv_r^2 + k_{E1}\beta_1 ME_{k+} + k_{E2}\beta_2 ME_k^2 \\ &\quad + 0,0981k_G\beta_1 M\omega)x_s, \alpha t_s\} \end{aligned} \quad (2.26)$$

where is the total fuel consumption (milliliter), respectively. The average speed is calculated as $v_r = 3600x_s/(t_s - t_i)$ with t_s and t_i representing the travel and idle times, respectively. In addition, $E_{k+} = \max\{0.35 - 0.0025v_r, 0.15\}$, $k_{E1} = \max\{0.675 - 1.22/v_r - 0.5\}$ and $k_{E2} = 2.78 + 0.0178v_r$. The data requirements of the RSFCM are much less than FMEFCM, but the model provides less accurate fuel consumption estimations.

2.2.2.6 Vehicle specific power model

The vehicle specific power model (VSPM) proposed by Jimenez-Palacios (1998) is a microscopic model to estimate vehicle fuel consumption and emission rates on a second-by-second basis. The vehicle specific power is dependent on the load of a vehicle and is defined as the power per unit mass to overcome road gradient, rolling and aerodynamic resistance, and acceleration, for which factors such as instantaneous speed,

acceleration and road gradient are used. The vehicle specific power at a given point in time t , denoted by $VSP(t)$ and expressed in kilowatt/ton, can be calculated using an equation given by United States Environmental Protection Agency and is given as below.

$$VSP(t) = v(a(1 + \epsilon_m) + g \sin(\arctan(\omega) + gC_r) + 0.5 C_d \rho A v^3 / M) \quad (2.27)$$

In (17), ϵ_m is the mass factor (typically between 0.1 and 0.2).

The power demand $P_{vsp}(t)$ (kilowatt) calculated as follows.

$$P_{vsp}(t) = VSP(t) M/1000 \quad (2.28)$$

The fuel rate (gram/second) is formulated as

$$f_{vsp}(t) = \xi \{ kNV + (P_{vsp}(t)/\eta_t + P_{acc})/\eta \} / 41.7 \quad (2.29)$$

P_{acc} is the power draw of accessories (typically 0).

Total fuel consumption (in grams) by a vehicle for a trip of duration T is given by:

$$F_{vsp}(T) = \int_0^T f_{vsp}(t) dt. \quad (2.30)$$

VSPM is also used as a base model to measure power demand in different emission models.

2.2.2.7 Average speed fuel consumption model (ASFCM)

This model is another extension of the (IFCM) model of and has been presented by Bowyer et al (1985) The model is related to fuel consumption per distance in average speed. In this model, the total fuel consumption (ml) can be estimated as $F_s(D) = f(v_s)D$; and here fuel consumption per unit distance is shown as $f(v_s) = f_i/v_s + Ck$. And here v_s shows the average travel speed (km/h) and D indicates the total distance. Also, K shows the adjustment factors for different tools; c which is the regression coefficient and parameters from K_1 to K_5 are given in table 2.8 based on the actual road data.

$$K=1-K_1 (1-M/1200)-K_2(1-\beta_1/0,090)- K_3(1-\beta_2/0,045)- K_4(1-b_1/0,000278M)- K_5(1-b_2/0,000108)$$

Table 2.8 Example parameters for ASFCM.

<i>Driving enviroment</i>	<i>c</i>	<i>K₁</i>	<i>K₂</i>	<i>K₃</i>	<i>K₄</i>	<i>K₅</i>
City center	70.6	0.893	0.79	0.21	0.421	0.109
Urban	73.8	0.72	0.867	0.134	0.406	0.280

Bowyer et al. have explained how to calculate these values (1985).

2.2.2.8 Traffic Mode Emission (EMIT)

EMIT, which is a statistical model based on physical systems for fuel consumption of light commercial vehicles, has been found by Cappiello et al., (2002). Fuel rate can be calculated as (grams/second).

$$f_e(t) = \begin{cases} \alpha_{fr} + \beta_{fr}v + \gamma_{fr}v^2 + \delta_{fr}v^3 + \zeta_{fr}av & \text{if } P_{tract}(t) > 0 \\ \alpha'_{fr} & \text{if } P_{tract}(t) = 0 \end{cases} \quad (2.31)$$

Here $P_{tract}(t) = A_{fr}v + B_{fr}v^2 + C_{fr}v^3 + Mav + Mgsin(\omega(\theta))v$, A_{fr} denotes rolling resistance (kilowatt/(meter/second)²), B_{fr} denotes speed verification of the rolling resistance coefficient (kilowatt/(meter/second)²), C_{fr} denotes air resistance coefficient (kilowatt/(meter/second)³). More detailed knowledge about other variables $\alpha_{fr}, \beta_{fr}, \gamma_{fr}, \delta_{fr}, \zeta_{fr}$ can be found from Cappiello et al. (2002). Total fuel consumption (grams)

$$F_e(T) = \int_0^T f_e(t)dt \quad (2.32)$$

This model gives reasonable results in actual measurements. Do not forget that the developed EMIT model has been calibrated without engine, heat, zero road gradient and accessories. If the conditions of use are started with a cold engine it does not correspond to the emissions.

2.2.2.9 Virginia Technique Microscopic (VT-Micro)

This model has been developed by Ahn, Rakha, Trani, Van Aerde (2003) by using speed and acceleration levels and chassis dynamometer in light commercial vehicles are a result of numerous trials by using combinations of polynomials. Fuel consumption rate for accepted

free flow rate with Ω inclination and equal to the fixed running speed is calculated as follows:

$$f_v(t) = \exp \left(\sum_{i=1}^3 \sum_{j=1}^3 L_{i,j} v f^i (g\omega)^j \right) \quad (2.33)$$

Here $L_{i,j}$ model denotes regression coefficients, i denotes speed exponential and j denotes acceleration exponential. Total fuel consumption (liters) is calculated as follows:

$$F(D_I) = 3600 f_v(t) D_I / (vf)^I, \quad (2.34)$$

D_I denotes length of I connection (kilometers) and $(vf)^I$ denotes free flow speed (kilometer/hour).

2.2.2.10 Oguchi, Katakura, and Taniguchi (2002) fuel consumption Model (OFCM)

OFCM is developed by Oguchi et al. (2002). The function consistent of the five components: idle consumption, friction, loss of height variation, air friction loss and deceleration. Total fuel consumption $F_o(T)$ (milliliters) can be calculated as follows by using OFCM:

$$\begin{aligned}
F_o(T) = & f_{idle}T \\
& + E \sum_{j=1}^J \left\{ \mu Mg \int_{t_{js}}^{t_{je}} v dt \right. \\
& + \sin\theta Mg \int_{t_{js}}^{t_{je}} v dt \\
& \left. + C_d \int_{t_{js}}^{t_{je}} v^3 dt + (M + m)(0,5v_{je}^2 - 0,5v_{js}^2) \right\}
\end{aligned} \tag{2.35}$$

Here f_{idle} denotes basic consumption, T denotes travel time, E denotes fuel energy equivalent, μ denotes coefficient of friction number and J denotes number of range. j_s and j_e denote start and end of the parametre range and m denotes internal resistance of the range. When the vehicle is idle the fuel consumption is equal to the fuel used for transmission, air conditioning and the inertial resistance of some electrical parts and the engine. Other components estimate the energy lost by vehicle's movement.

2.2.2.11 Comprehensive Power Fuel Consumption-Based Models (CPFilms)

Two power-based second degree polynomial models were created by Rakha, Ahn Moran, Saerens and Van Bulck (2011). These models were created by being inspired from one of the Wong (2001) base models which are within the mechanical engineering literature. It is not needed to give any engine data for the first model; it is a function of vehicle speed and acceleration energy level used by a vehicle. The second model requires engine data in addition to external data due to the use thereof in modeling of eco-drive and gearshift strategies. Both models can be formulated as follows:

$$F_1(t) = \alpha_0 + \alpha_1 P(t) + \alpha_2 P(t)^2, \tag{2.36}$$

Here $\alpha_0, \alpha_1, \beta_0, \beta_1$ and β_2 are specific fixed values given for each vehicle separately.

$P(t) = ((R(t) + 1,04ma(t))/3600\eta_d)v(t)$ equation measures total force exerted by the vehicle at t time in the driving route (kW); here $R(t)$ denotes total resistance force

(Newton), and η_d denotes the productivity of moving parts. In addition, the total resistance force is calculated as follows:

$$R(t) = (\rho/25,92)C_dC_hAv^2(t) + 9.8066mC_r\{c_1v(t) + c_2\} + 9.8066mG(t) \quad (2.37)$$

Details regarding the coefficients in calculations are shown in the article of Rakhavd. (2011).

2.2.2.12 Emissions Model in passenger and heavy vehicles (PHEAI)

PHEM, the microscopic emission model, has been designed for fuel consumption simulation. It is a measurement program which has been created again for different engines and vehicles as a result of the collaboration between ARTEMIS (Boulter & McCrae, 2009), COST346 (Rexeis, Hausberger and Riemersma, 2005) and HBEFA (Hausberger et al, 2009). PHEM is the fuel consumption interpolation obtained from engine maps according to engine power demand and engine speed. The actual engine power (P) can be calculated as follows:

$P = P_{rr} + P_{ar} + P_{acc} + P_{gr} + P_{au} + P_{tl}$, here $P_{rr} = Mg(fr_0 + fr_1v + fr_2v^2 + fr_3v^3 + fr_4v^4)v$ denotes rolling resistance, $P_{ar} = 0,5C_dA\rho v^3$ denotes air resistance, $P_{ac} = (M + M_{rot})av$ denotes acceleration while $P_{gr} = Mg\omega 0,01v$ denotes slope resistance, $P_{au} = P_0 + P_{rated}$ denotes the power claimed by accessories and $P_{tl} = P_{dr}/\eta_t - P_{dr}$ shows the loss of transmission. Here from fr_0 to fr_4 denotes coefficients of rolling resistance, m_{rot} denotes the reduced mass of the rational expedited parts, P_0 denotes the power demand of auxiliary values, P_{rated} denotes nominal power ratio and P_{dr} denotes the power to overcome the driving resistance. The total emissions under the transition conditions can be calculated as follows:

$$E_{trans}(t) = E_{qs} + P_{rated}F_{trans}, \quad (2.38)$$

Here E_{qs} is the equation of interpolation from half steady state emissions to steady-state emissions (g / h), P_{rated} denotes nominal motor power (kW) (without the normalized emission values of the nominal power) $F_{trans}(t)$ denotes dynamic correction function ((g

/ h) / kW nominal power). More information can be found in the article of Boulter and McCrae (2009)

2.3 EXPERIMENTAL SET-UP AND DATA COLLECTION

A Toyota Corolla and Volkswagen Passat have been instrumented with torque Pro, a Bluetooth adaptor is plugged in the OBD2 socket of the vehicle. The specifications of the vehicle are given in Table 2.8.

In order to numerically test and compare the fuel consumption models above, data was collected in real-time from two passenger vehicles, namely a 2013 Toyota Corolla 1.4D-4D multimode running on a diesel engine and Volkswagen Passat dsg on a diesel engine. Vehicles properties are given Table 2.9. The vehicle was driven over three different routes using six different levels of fixed speeds, ranging from 45 km/h to 120 km/h in increments of 15 km/h.

Table 2.9 Vehicles properties.

	Fuel Type	Engine Displacement (ml)	Frontal Surface Area(m²)	Aerodynamic Drag Coefficient	Vehicle Weight (kg)
Toyota Corolla	Diesel	1396	2.09	0.27	1425
Volkswagen Passat	Diesel	1596	2.15	0.29	1600

All three routes, namely Route 1, 2 and 3, are located in Istanbul, Turkey, and are shown on the maps that appear in Figures 2.5 to 2.7, respectively, along with their elevation graphs. The maps show the beginning and end of each route with the letters A and B.

The routes primarily differ with respect to their road gradient, in particular Route 1 is almost flat, Route 2 has a negative gradient and Route 3 has a positive gradient.

Route 1 is part of what is known as the Basin Ekspres road, and is of 3.5 km length. The latitude and longitude coordinates of the start and end points of the route are (41.0094, 28.8128) and (41.01717, 28.81229), respectively.

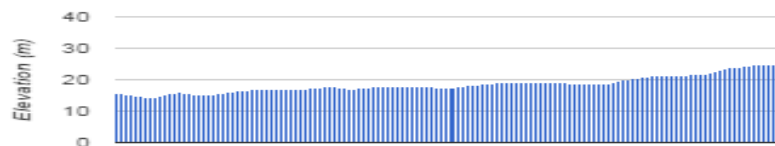
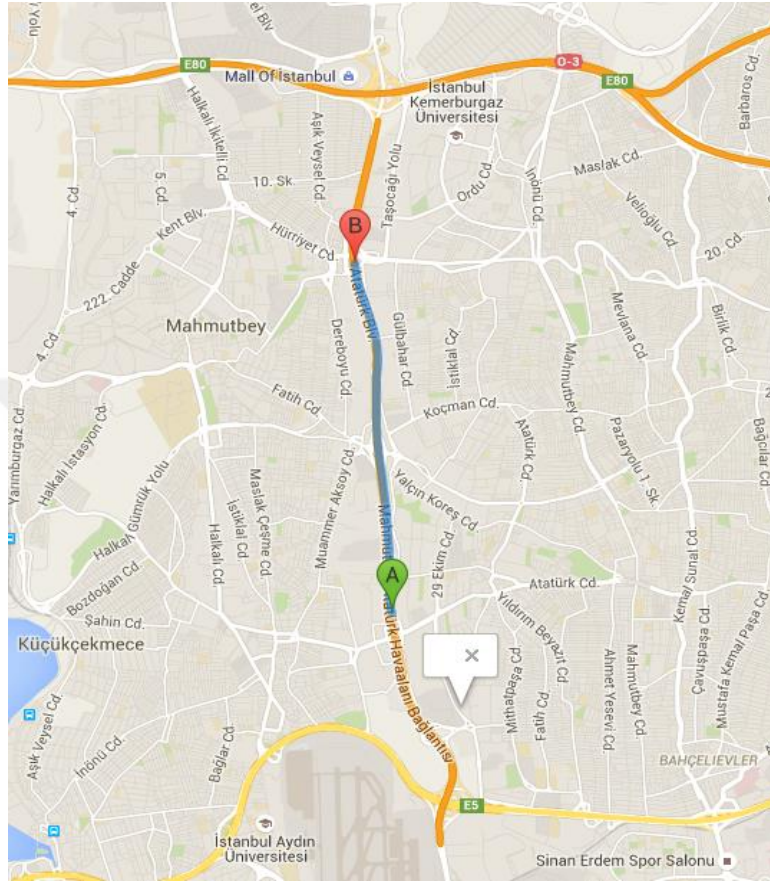


Figure 2.5 Route 1 and its elevation graph.

Route 2 is part of the highway TEM E80 between Hadımköy and Bahçeşehir, and is of 7.8 km length. The latitude and longitude coordinates of the start and end points of the route are (41.0867, 28.6354) and (41.0583, 28.7053), respectively.

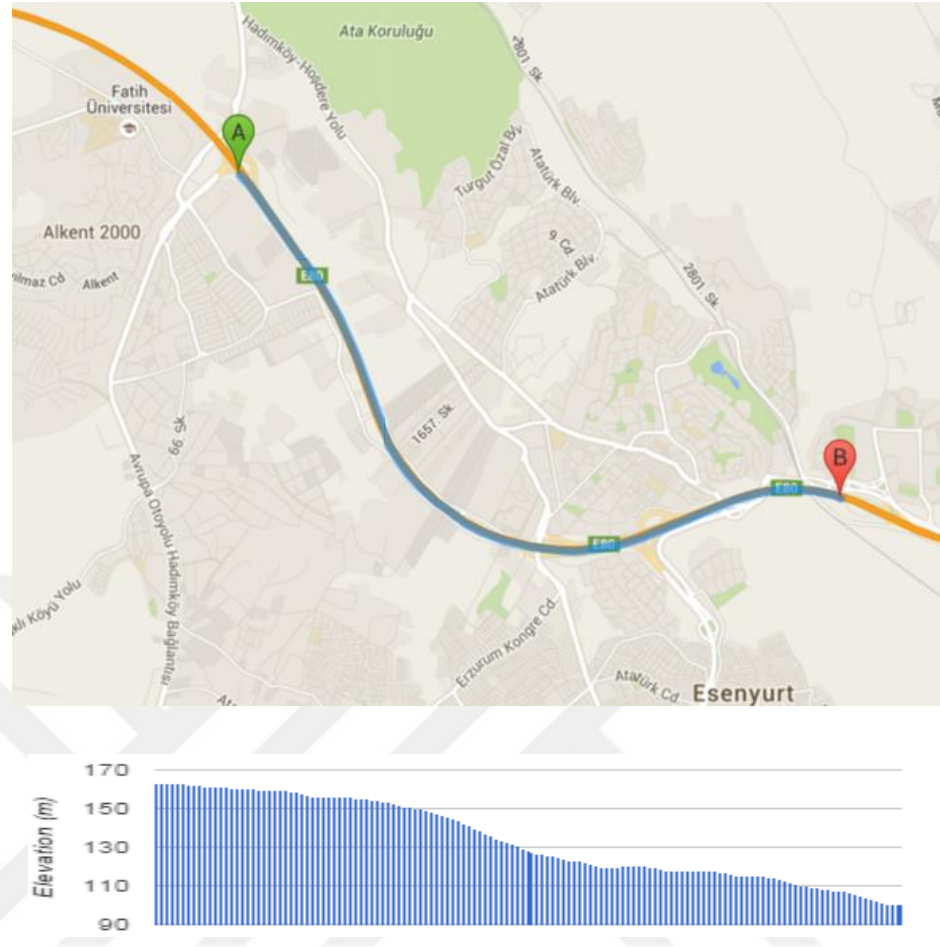


Figure 2.6 Route 2 and its elevation graph.

Route 3 is the same as Route 2 on the TEM E80 but in the reverse direction from Bahçeşehir to Hadımköy. The latitude and longitude coordinates of the starting and ending points of the test route are (41.0583, 28.7053) and (41.0867, 28.6354), respectively.

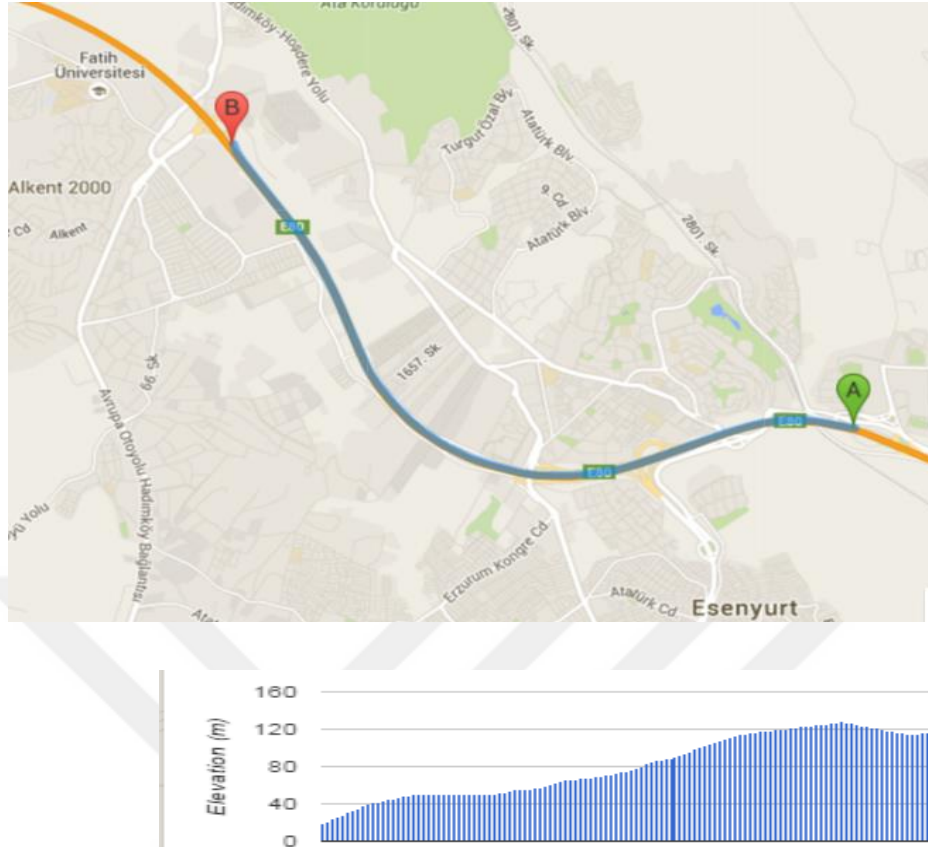


Figure 2.7 Route 3 and its elevation graph.

Data from the vehicle has been collected in real-time using existing on-board diagnostics (OBD2), a Bluetooth interface and a smartphone. An OBD2 protocol allows accessing the vehicle's Engine Control Unit (ECU) easily through a Bluetooth OBD2 connector (see Figure 2.8). Instant data are obtained via (Torque Pro,2015) that uses the OBD2 connector. Many recently manufactured vehicles support the use of OBD2. The diagnostic socket should be fitted to the vehicle using an adapter plug prior to instant data collection.

Torque Pro is a tool for performance and diagnosis, and runs on the Android phones of any kind. The tool keeps the driver informed via several sensors located within the Engine Management System of the vehicle. Through OBD2, it is possible to access data from the ECU and OBD2 itself becomes an extremely useful source of information for screening and solving problems with the vehicle.

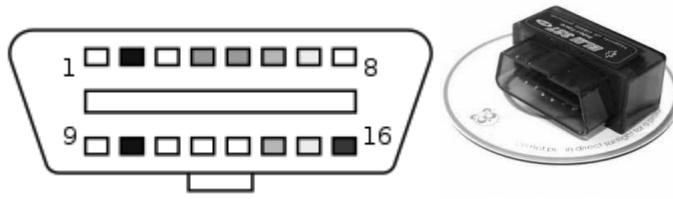


Figure 2.8 An OBD2 connector and a Bluetooth adaptor.

In order to capture the parameters needed by the fuel consumption models via Torque Pro, a Bluetooth adaptor is plugged into the OBD2 socket of the vehicle, through which parameters such as the vehicle weight and engine displacement are input into the Torque Pro application on the smart phone.

Finally, we present in Table 2.10 all the parameters used for input to the six models for calculation and comparisons.

Table 2.10 Input data used for the fuel consumption models.

Parameters	CMEM	PERE	FMEFCM	IFCM	RSFCM	VSPM
Mass, m (kg)	1425	1425	1425	1425	-	1425
Gravity Force, $g(m/s^2)$	9.81	9.81	-	9.81	-	9.81
FrontalArea, A (m^2)	2.09	2.09	-	-	-	2.09
Aerodynamic Drag Coefficient, C_d	0.29	0.29	-	-	-	0.29
Chemical efficiency, η	0.4	0.4	-	-	-	0.4
Air Density, ρ (kg/m^2)	1.293	1.293	-	-	-	1.293
Engine Displacement, $V(L)$	1.396	1.396	-	-	-	1.396
Rolling Resistance Coefficient, Cr	0.0135	0.0135	-	-	-	0.0135
Transmission efficiency, η_{tf}	0.88	0.88	-	-	-	0.88
k	0.25	0.25	-	-	-	0.25
Idle Fuel Consumption Rate, F_i (mL/h)	-	-	888.8	888.8	888.8	-
Idle Fuel Consumption Rate, α (mL/s)	-	-	0.2469	0.2469	0.2469	-

Efficiency Parameter, β_1 (mL/kJ)	-	-	0.926	0.926	0.926	-
Energy-acceleration efficiency Parameter, β_2 mL/(kJ.m/s ²)	-	-	NA	NA	NA	-
b_1 , kN	-	-	-	0.1316	-	-
b_2 , kN/(m/s) ²	-	-	-	0.00050	-	-
Drag Fuel Consumption Parameter Mainly Related To Aerodynamic Drag, Γ (ML/km)	-	-	12.2	-	12.2	-
Drag Fuel Consumption Parameter Mainly Related To Aerodynamic Drag, B (mL/km)/(km/h) ²	-	-	0.0036	-	0.0036	-
Specific Gravity of Deisel g/cm ³	0.85	0.85	-	-	-	0.85

2.4 RESULTS OF MATHEMATICAL MODELS

In this section, we present comparisons of the consumption values given by the six models on the three routes with the fuel usage values measured in real-time. The results are shown in Tables 2.11, 2.13., 2.15, 2.17, 2.19 and 2.21. for Routes 1, 2 and 3, for two different vehicle, respectively, in which we present, under column “real-time data”, the actual fuel consumption (in liters) measured under different speed values. We also present the the estimations obtained by the six models under their respective columns. We then calculate the Mean Absolute Error (MAE) by calculating the absolute difference between the figures given by the fuel consumption model and the real-time measurement for each model and speed level separately, and then taking the average, all of which are provided in Tables 2.12, 2.14, 2.16, 2.18, 2.20 and 2.22 In these tables, the values yielding the best results are highlighted in bold font. For the sake of consistency, all the results are adjusted to a route of 6 km length. Finally, Figures 2.9, 2.10, 2.11, 2.12, 2.13 and 2.14 provide a visual depiction of the comparison results, where the horizontal axes are the speeds (in km/h) and the vertical axes show the fuel consumption (in liters).

Table 2.11 Comparisons on Route 1 measurements for Toyota Corolla.

km/h	Fuel Consumption (liters)						
	real-time data	CMEM	PERE	FMEFCM	IFCM	RSFCM	VSPM
45	0.287	0.519	0.172	0.314	0.689	0.332	0.375
60	0.214	0.319	0.180	0.343	0.593	0.264	0.268
75	0.206	0.324	0.196	0.371	0.518	0.371	0.236
90	0.236	0.338	0.269	0.461	0.595	0.461	0.245
105	0.294	0.370	0.308	0.519	0.672	0.519	0.268

Table 2.12 MAE values of the models on Route 1for Toyota Corolla.

Mean Absolute Error						
speed (km/h)	CMEM	PERE	FMEFCM	IFCM	RSFCM	VSPM
45	0.232	0.115	0.027	0.402	0.045	0.087
60	0.104	0.035	0.129	0.379	0.050	0.053
75	0.118	0.010	0.166	0.312	0.166	0.030
90	0.102	0.033	0.225	0.360	0.225	0.010
105	0.076	0.013	0.225	0.378	0.225	0.026
MAE	0.126	0.041	0.154	0.366	0.142	0.041

Table 2.13 Comparisons on Route 1 measurements for Volkswagen Passat.

km/h	Fuel Consumption (liters)						
	real-time data	CMEM	PERE	FMEFCM	IFCM	RSFCM	VSPM
45	0,187	0,290	0,140	0,352	0,439	0,236	0,194
60	0,225	0,361	0,153	0,406	0,381	0,240	0,187
75	0,130	0,230	0,151	0,272	0,193	0,222	0,156
90	0,218	0,363	0,182	0,396	0,332	0,241	0,166
105	0,196	0,318	0,291	0,384	0,182	0,365	0,225

Table 2.14 MAE values of the models on Route 1for Volkswagen Passat.

Mean Absolute Error						
speed (km/h)	CMEM	PERE	FMEFCM	IFCM	RSFCM	VSPM
45	0,103	0,048	0,165	0,252	0,049	0,006
60	0,136	0,072	0,182	0,156	0,016	0,038
75	0,100	0,021	0,143	0,064	0,092	0,026
90	0,146	0,035	0,179	0,115	0,023	0,051
105	0,122	0,095	0,188	0,015	0,169	0,029
MAE	0,121	0,054	0,171	0,120	0,070	0,030

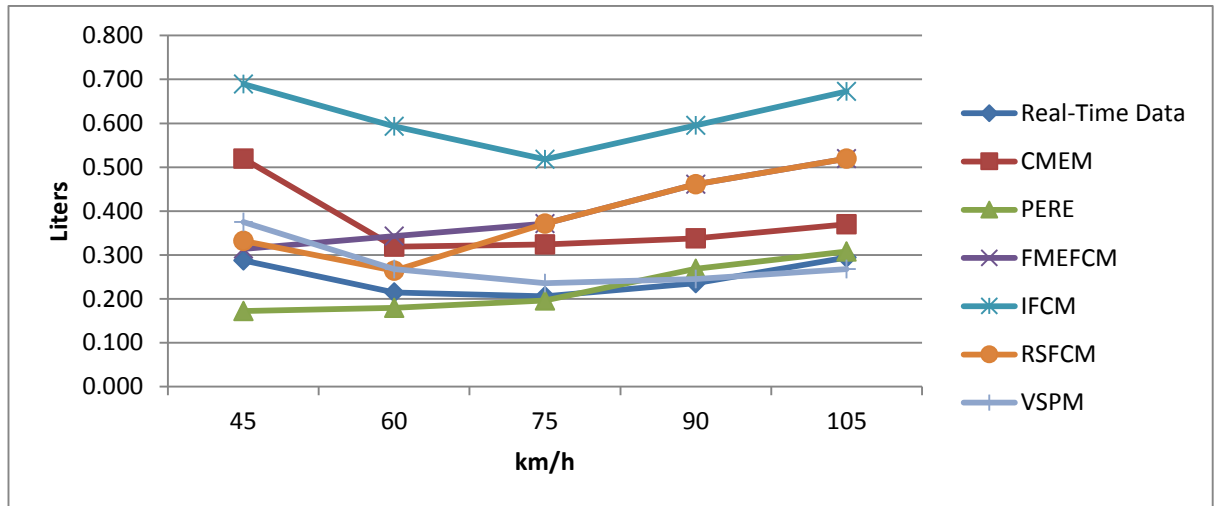


Figure 2.9 . Fuel consumption curves of all models on Route 1for Toyota Corolla.

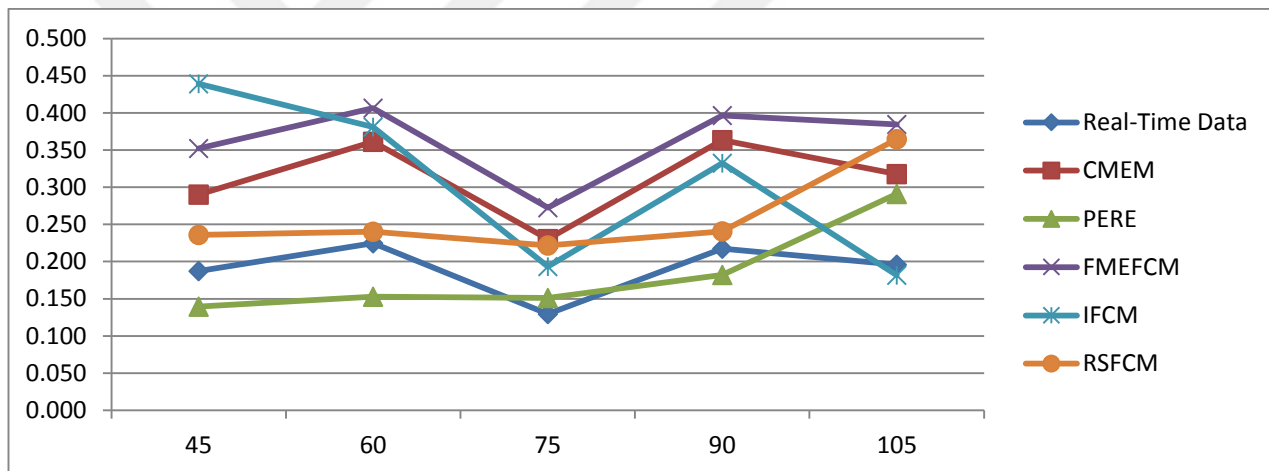


Figure 2.10 . Fuel consumption curves of all models on Route 1for Volkswagen Passat.

The results shown in Tables 2.11, 2.12, 2.13, and 2.14, and Figure 2.9, 2.10, for Route 1 indicate that PERE and VSPM yield estimations for Toyota corolla and VSPM yield estimations for Volkswagen Passat that have the least MAE when compared with real data on average. In particular, both models have an MAE equal to 0.041 for Toyota corolla., which is significantly less than those of the other four, which range between 0.126 and 0.366. VSPM model has a MAE equal to 0.30 for Volkswagen Passat It is interesting to note that, in this case, CMEM, FMEFCM and RSFCM provide similar MAE figures, whereas IFCM has the highest.

Table 2.15 Comparisons on Route 2 measurements for Toyota Corolla.

km/h	real-time data	Fuel Consumption (liters)					
		CMEM	PERE	FMEFCM	IFCM	RSFCM	VSPM
45	0.085	0.190	0.163	0.309	0.297	0.255	0.153
60	0.081	0.205	0.164	0.273	0.217	0.243	0.154
75	0.091	0.202	0.197	0.270	0.172	0.268	0.152
90	0.141	0.207	0.239	0.280	0.136	0.310	0.157
105	0.167	0.223	0.285	0.320	0.123	0.367	0.166
120	0.258	0.295	0.355	0.400	0.170	0.445	0.213

Table 2.16 MAE values of the models on Route 2 for Toyota Corolla.

speed (km/h)	Mean Absolute Error					
	CMEM	PERE	FMEFCM	IFCM	RSFCM	VSPM
45	0.106	0.078	0.224	0.213	0.170	0.068
60	0.123	0.082	0.192	0.136	0.161	0.072
75	0.110	0.105	0.179	0.080	0.177	0.061
90	0.066	0.098	0.139	0.004	0.169	0.017
105	0.057	0.118	0.154	0.043	0.200	0.001
120	0.036	0.097	0.142	0.088	0.187	0.046
MAE	0.083	0.097	0.171	0.094	0.177	0.044

Table 2.17 Comparisons on Route 2 measurements for Volkswagen Passat.

km/h	Fuel Consumption (liters)						
	real-time data	CMEM	PERE	FMEFCM	IFCM	RSFCM	VSPM
45	0,141	0,234	0,135	0,310	0,378	0,237	0,191
60	0,093	0,226	0,138	0,278	0,278	0,241	0,183
75	0,064	0,253	0,187	0,298	0,214	0,269	0,189
90	0,152	0,256	0,232	0,297	0,205	0,308	0,201
105	0,156	0,291	0,246	0,338	0,195	0,361	0,231
120	0,212	0,310	0,324	0,391	0,220	0,409	0,238

Table 2.18 MAE values of the models on Route 2 for Volkswagen Passat.

Mean Absolute Error						
speed (km/h)	CMEM	PERE	FMEFCM	IFCM	RSFCM	VSPM
45	0,093	0,007	0,168	0,237	0,095	0,050
60	0,133	0,045	0,185	0,185	0,147	0,089
75	0,189	0,123	0,234	0,150	0,205	0,126
90	0,104	0,081	0,146	0,054	0,156	0,049
105	0,135	0,090	0,182	0,039	0,205	0,075
120	0,098	0,112	0,179	0,008	0,196	0,026
MAE	0,125	0,076	0,182	0,112	0,168	0,069

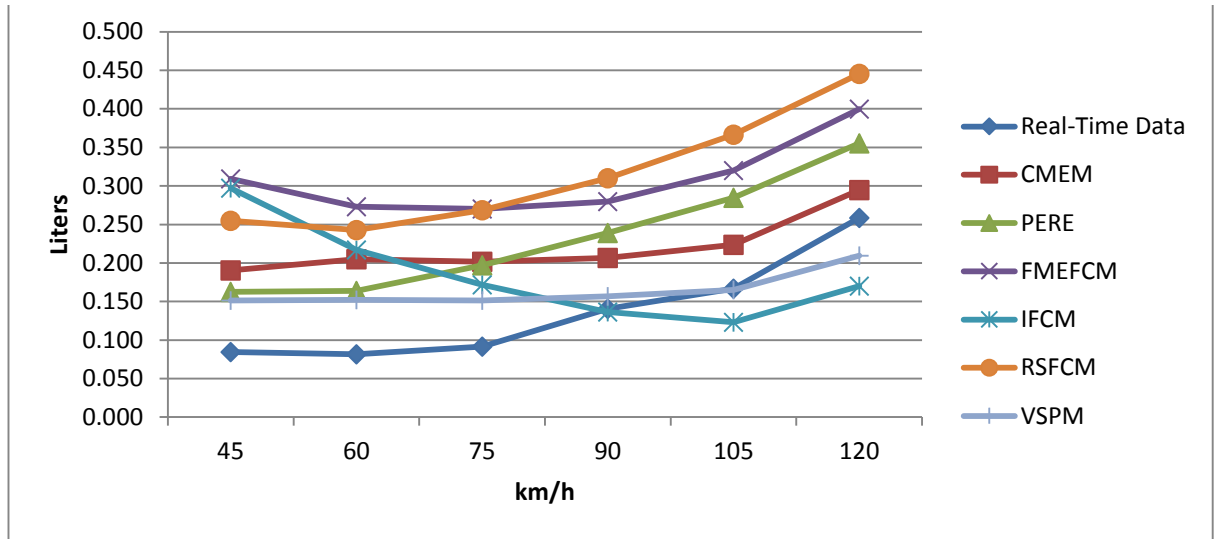


Figure 2.11 Fuel consumption curves of all models on Route 2 for Toyota Corolla.

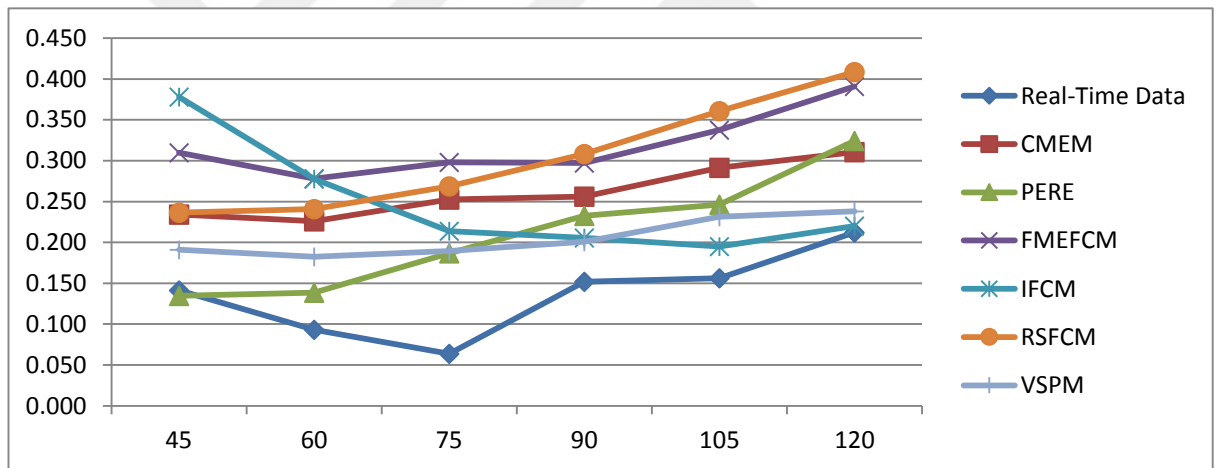


Figure 2.12 Fuel consumption curves of all models on Route 2 for Volkswagen Passat.

The results for Route 2 that has a negative gradient suggest that VSPM once again performs the best with respect to the MAE both two vehicles. It is outperformed slightly by IFCM for the speed 90 km/h and by CMEM for the speed 120 km/h but the difference is not significant. CMEM in this case is the second best with a MAE equal to 0.083, followed by IFCM with a MAE equal to 0.094. The results also suggest that PERE and RSFCM are more sensitive to the increases in speed as compared to real-time data, whereas VSPM has a relatively stable curve as can be seen from Figure 2.10. All

models, with the exception of IFCM for speeds of 105 km/h or above, overestimate the fuel consumption.

Fuel consumptions and MAE values for all models on third route are given in Table 2.19, 2.20, 2.21 and 2.22 . The Fuel consumption comparison results are also depicted in Fig. 2.13, and Fig.2.14.

Table 2.19 Comparisons on Route 3 measurements for Toyota Corolla.

km/h	Fuel Consumption (liters)						
	real-time data	CMEM	PERE	FMEFCM	IFCM	RSFCM	VSPM
45	0.316	0.397	0.167	0.512	0.516	0.241	0.298
60	0.292	0.453	0.185	0.500	0.421	0.237	0.326
75	0.283	0.419	0.187	0.483	0.351	0.259	0.302
90	0.336	0.442	0.232	0.509	0.337	0.298	0.320
105	0.426	0.456	0.271	0.553	0.324	0.350	0.331
120	0.610	0.521	0.334	0.611	0.367	0.412	0.417

Table 2.20 MAE values of the models on Route 3 for Toyota Corolla.

speed (km/h)	Mean Absolute Error					
	CMEM	PERE	FMEFCM	IFCM	RSFCM	VSPM
45	0.081	0.149	0.196	0.200	0.075	0.018
60	0.162	0.107	0.209	0.130	0.054	0.035
75	0.136	0.096	0.199	0.068	0.024	0.018
90	0.106	0.104	0.173	0.001	0.038	0.016
105	0.031	0.154	0.128	0.101	0.076	0.095
120	0.089	0.276	0.001	0.244	0.199	0.193
MAE	0.101	0.148	0.151	0.124	0.078	0.063

Table 2.21 Comparisons on Route 3 measurements for Volkswagen Passat.

km/h	Fuel Consumption (liters)						
	real-time data	CMEM	PERE	FMEFCM	IFCM	RSFCM	VSPM
45	0,361	0,425	0,131	0,521	0,589	0,239	0,190
60	0,389	0,371	0,118	0,502	0,479	0,237	0,189
75	0,388	0,438	0,180	0,492	0,423	0,266	0,192
90	0,387	0,491	0,229	0,552	0,432	0,307	0,206
105	0,399	0,515	0,287	0,592	0,390	0,360	0,221
120	0,464	0,558	0,351	0,628	0,388	0,414	0,250

Table 2.22 MAE values of the models on Route 3 for Volkswagen Passat.

speed (km/h)	Mean Absolute Error					
	CMEM	PERE	FMEFCM	IFCM	RSFCM	VSPM
45	0,064	0,230	0,160	0,228	0,122	0,171
60	0,018	0,270	0,113	0,090	0,152	0,172
75	0,051	0,208	0,104	0,036	0,122	0,169
90	0,104	0,158	0,166	0,046	0,080	0,155
105	0,115	0,112	0,193	0,009	0,039	0,140
120	0,094	0,114	0,164	0,076	0,050	0,111
MAE	0,074	0,182	0,150	0,081	0,094	0,153

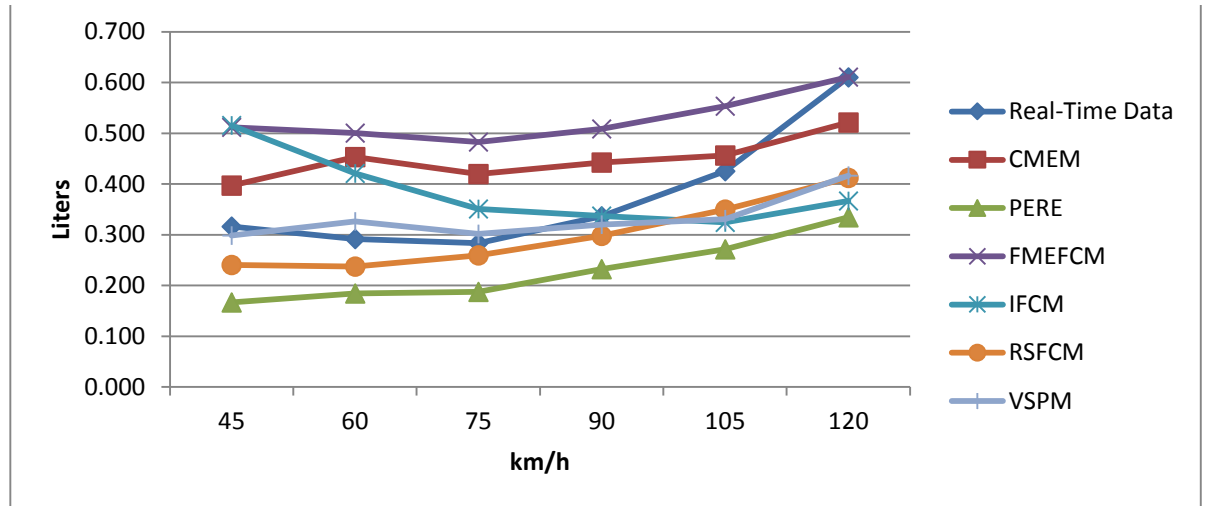


Figure 2.13 . Fuel consumption curves of all models on Route 3 for Toyota Corolla.

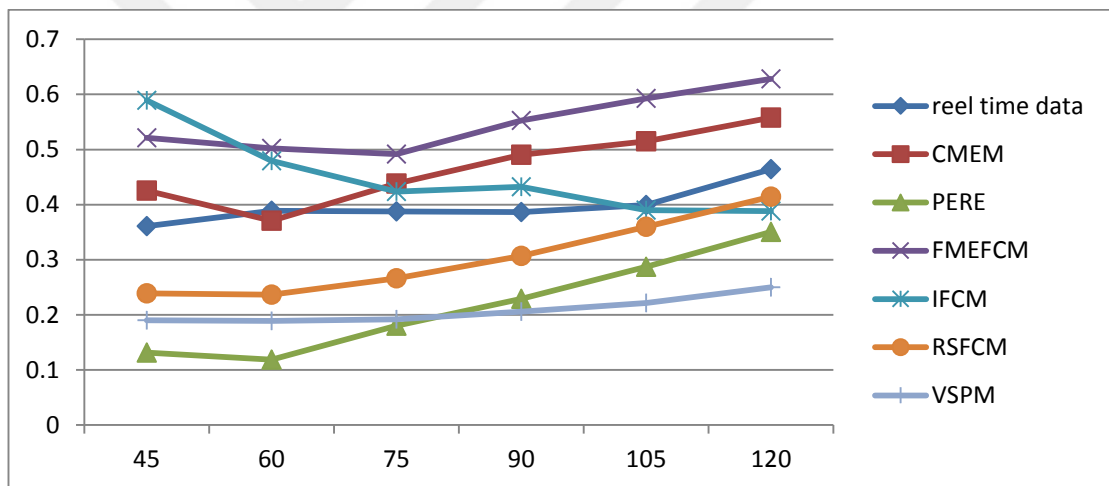


Figure 2.14 . Fuel consumption curves of all models on Route 3 for Volkswagen Passat.

The results concerning Route 3 suggest that whilst VSPM once again provides the lowest MAE, the quality of the estimation deteriorates for speeds higher than 105 km/h. For such speeds, CMEM, FMEFCM or IFCM provide better results. In contrast, IFCM performs poorly on low speeds. For this experiment, it can be seen from Figure 2.13 that FMEFCM and CMEM consistently overestimate fuel consumption and are not sensitive to the changes in speed, whereas IFCM, RSFCM and PERE are. In particular, the latter to consistently underestimate fuel consumption for all speed levels, and show a steady increase with increasing speed levels.

To be able to see the effect of various degrees of road gradient and speed levels on fuel consumption, we present Figure 2.15 that shows the fuel usage over the three routes with flat, negative and positive road gradients. In this figure, the horizontal axis shows the speed (in km/h) and the values on the vertical axis shows fuel usage (in liters).

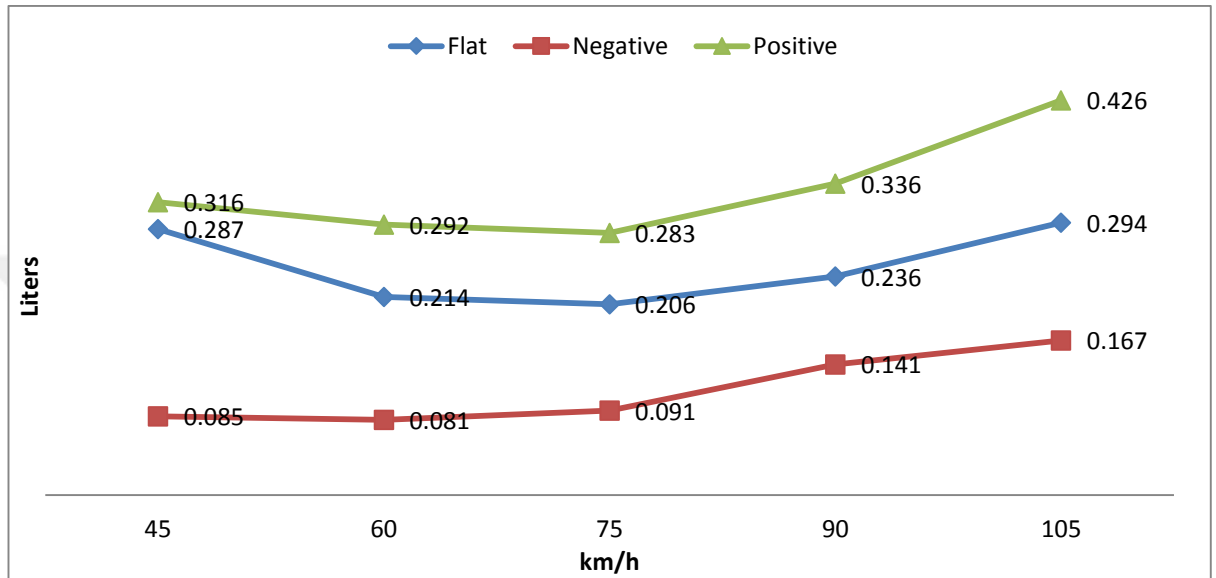


Figure 2.15 . Actual fuel consumption values with varying speeds and road gradients.

It can be seen from Figure 2.15 that there is a considerable increase in fuel consumption in the case of a positive road gradient. It is interesting to note that with positive or flat road gradients, the fuel consumption suggests a U-shaped curve where fuel consumption decreases with increasing speed until around 75 km/h, and starts increasing with higher speeds. This is not so much the case with a negative road gradient, which remains relatively stable between 45–75 km/h and only starts increasing for higher speed values.

The final results we present in this section pertain to the MAE values yielded by the six fuel consumption models for the three routes, as shown in Figure 2.16. As the figure indicates, VSPM consistently provides the lowest MAE for all the three routes when compared with real data. VSPM also has the minimum MAE across the five models for nearly all speed levels. PERE has the second best prediction accuracy. FMEFCM yields very similar MAE values for each route, but is the least accurate when they are

compared with real-time data. Finally, IFCM yields the highest MAE for Route 1, but performs better than FMEFCM for the other two routes.

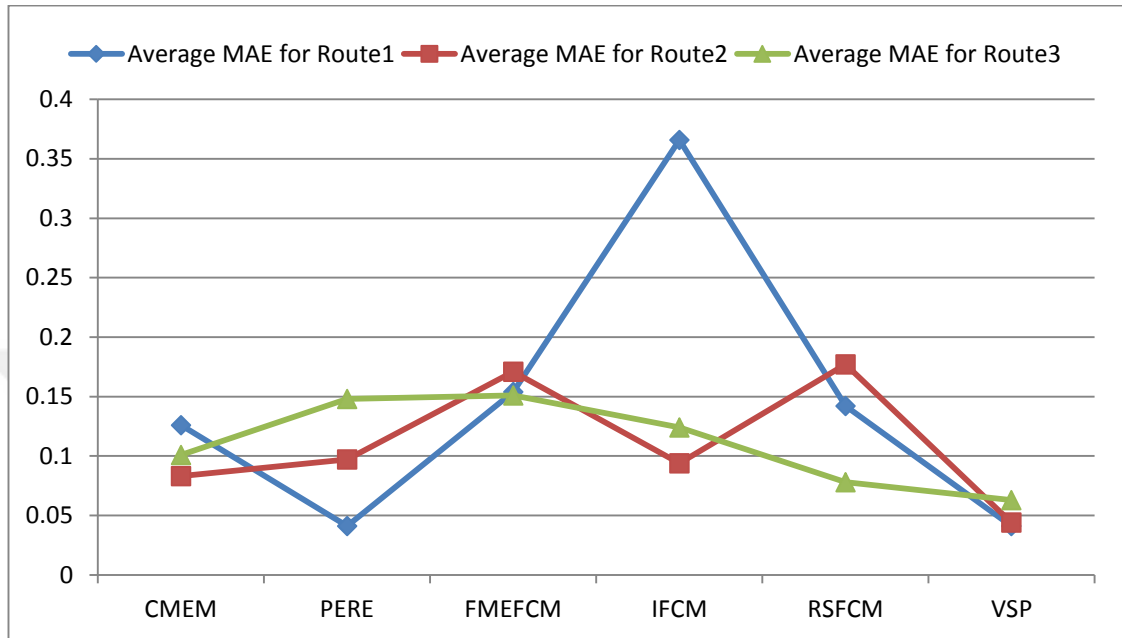


Figure 2.16 . Average MAE Comparison within the routes.

3. ESTIMATING THE FUEL CONSUMPTION OF PASSENGER VEHICLES USING REGRESSION MODELS

3.1 INTRODUCTION

Transportation uses more than one third of global energy (Ahn & Rakha, 2008; Rakha, Ahn, Moran, Saerens, & Bulck, 2011) that is obtained from petroleum products. Fuel consumption in vehicles results in greenhouse gas emissions, in particular CO₂, with detrimental effects on the environment. The combustion of gasoline and diesel in vehicle engines is the second largest source of CO₂ emissions, the amount of which is proportional to the amount of fuel consumed by the engine.

The rate at which fuel is consumed by an engine depends on a wide range of factors, including those that are vehicle specific (such as the engine speed or vehicle mass) and those that are trip specific (such as rolling resistance or road gradient). A number of fuel consumption models have been developed in the literatures that differ from one another in the way in which they incorporate these factors into the calculation.

When fuel consumption estimations are needed, the choice of the model becomes crucial. Whilst accuracy is the main criterion affecting the choice, simplicity is (and should be) another. As for the former, the more numerical validations are available, the better it is to be able to evaluate model accuracy. As for the latter, some models are increasingly complex in their data requirements, which might limit their practical applicability.

This thesis contributes to the literature by proposing regression models for use in estimating fuel consumption of passenger vehicles and shows that they provide more accurate estimations as compared to some of the available models in the literature. The regression models we develop range from simple linear regression to more sophisticated models, such as artificial neural networks and support vector machines. We also present real data collected from a passenger vehicle using existing on-board diagnostics (OBD2), a Bluetooth interface and a smartphone. This data is used in the numerical comparison of five existing consumption models and three new regression models.

The rest of the this chapter is structured as follows. In Section 3.2, we provide a brief overview of the relevant literature. Section 3.3 describes the statistical models of fuel consumption. In Section 3.4, experimental set-up and process of data collection is described. Numerical results are presented in Section 3.5 .

3.2 REVIEW OF THE EXISTING WORK

Much work has been done on the modeling of fuel consumption for vehicles. We will not present a detailed exposition of the this chapter but instead refer the interested reader to Chapter 2 of the this dissertation and the review papers (Demir et al.2011; Demir et al.2014), where detailed descriptions of fuel consumption models can be found. In summary, these models tend to come in two flavors: (1) macroscopic models, suitable for modeling wide-area emissions and require aggregate parameters, and (2) microscopic models, which are instantaneous models described to provide a second-by-second basis fuel consumption of a moving vehicle, and are to be used mostly for short-trips. The former class includes models that are simpler and with less number of input parameters than the latter.

Recent years have seen the application of artificial neural networks (ANNs) in automotive engineering, including forecasting engine characteristic under different working conditions. (Wu and Liu, 2011) studied a predictive system for car fuel consumption using a back propagation neural network (Wu and Liu, 2011) and a radial basis function neural network (Wu and Liu, 2012). The engine style, weight of car, vehicle type and transmission system type were used as input parameters for training the neural network training and forecasting fuel consumption forecasting procedure in both (Wu and Liu , 2011, Wu and Liu , 2012). Togun and Baysec presented an artificial neural network model (Togun and Baysec, 2010), and genetic programming model (Togun and Baysec, 2010) to predict the torque and fuel consumption of a gasoline engine. Numerous studies have been undertaken to predict the performance and exhaust emission characteristics of internal combustion engines by using ANNs (Parlak et al., 2006; Alonso et al., 2007; Sayin et al., 2007; Cay , 2013; Martinez and Palacios, 2015; Chakraborty et al., 2016; Bera, 2013; Roy et al., 2014). In (Rahimi andAbbaspour, 2014), the tractor fuel consumption was estimated on the basis of engine speed, throttle

and load conditions, chassis type, total tested weight by using ANN. The authors of (Kakaee et al., 2015) combined ANN and multi-objective optimization to reduce fuel consumption of and emissions from a heavy-duty diesel engine. These prediction results demonstrated the proposed system using the neural network is effective and the performance is satisfactory in terms of fuel consumption prediction.

There exist studies featuring alternative ways to model transportation CO₂ emissions. For example, (Velázquez-Martínez et al., 2016) presented a statistical-mathematical methodology that allows companies to reduce transportation CO₂ emissions when delivering in regions with a variety of road and traffic conditions. (Wong et al., 2016) employed online time-sequence incremental and decremental least squares support vector machines for engine air-fuel ratio prediction. To our knowledge, there has not been any other work featuring the use of support vector machines for predicting engine related performance measures, such as fuel consumption and emissions.

3.3 STATISTICAL MODELS OF FUEL CONSUMPTION

3.3.1 Linear Regression

Linear Regression is the most widely used statistical model to construct a linear relationship between a given set of independent variables. Linear regression models assume that a *dependent* (or *response*) *variable* is a linear function of *independent variables* (or *parameters*). In multiple linear regression, there are several model parameters in order to predict the response variable as shown in the following equation.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n, \quad (3.1)$$

where β_0 is a constant term, $(\beta_1, \dots, \beta_n)$ are the coefficients of the independent variables $(x_1, \dots, x_n)$ coefficients, and y is the response variable.

3.3.1.1 Multiple linear regression analysis

When the relation between one dependent and one independent variable is examined in simple linear regression analysis, the functional relation between one dependent and multiple independent variables is examined in multiple linear regression analysis (Günaşdı, 2014).

The researcher has two main objectives in multiple linear regressions. One of them is to estimate the value of the dependent variable by virtue of the variables determined to affect the dependent variable while the other objective is to determine which of the independent variable(s) deemed to affect the dependent variable, affects the dependent variable more and to define the relation between them (Alpar, 2003).

According to the studies carried out, it is important to observe all the factors affecting the examined factor and determine in which direction and how the independent variables affect the dependent variable in order to obtain more reliable results. For example, factors such as air temperature, age of chicken, amount of the feed and duration of the illumination are effective as to egg production in laying hens. Multiple regression analysis is employed to estimate which of these factors are more effective as well as the monthly egg production according to these factors. Multiple linear regression models consist of at least two independent variables.

If the relation between Y dependent variable and p number of independent variable is linear and if there is n number of observation value of Y and X's the multiple linear regression model is as follows;

$$y = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_n x_{in} + e_i, \quad (i=1, 2, \dots, n) \quad (3.2)$$

$$Y = \beta_0 + \sum_{k=1}^n \beta_k x_{ik} + e_i \quad (3.3)$$

Here $\beta_0 + \beta_1 + \beta_2 + \dots + \beta_n$ unknowns are partial regression coefficients or briefly regression coefficients.

3.3.1.2 Estimation of multiple linear regression analysis coefficients

In multiple linear regression analysis, the condition of absence of multicollinearity between multiple independent variables is sought in addition to requirements to be fulfilled in general regression (Günaşdı, 2014).

In as much as errors are random variables some assumptions have to be made as to errors. These assumptions are as follows:

- i. Expected value of $E(\epsilon_j) = 0$, ϵ_j is zero.
- ii. $\text{Var}(\epsilon_j) = \sigma^2$.
- iii. $\text{Cov}(\epsilon_j, \epsilon_k) = 0$, $j \neq k$.

Here it is assumed that the error terms in ϵ vector have normal distribution. $p + 1$ number of b statistical values which is the estimator of β parameters in multiple linear regression model is obtained by virtue of Least squares method utilizing the following formula:

$$b = (X'X)^{-1}(X'Y)$$

T-distribution, freedom degree of which is $n-(p+1)$ is utilized in absence and alternative hypothesis tests in creation of confidence intervals parameters as to β .

Assumptions of the multiple linear regression models are as follows (Kılıçbay 1980; Koutsoyiannis 1992; Çömlekçi 1998; Gujarati 2005, Günaşdı 2014).

- i. The dependent variable is a random variable and shows a normal distribution.
- ii. Independent variables are not random variables. Values of independent variables are values predetermined through the researchers or values which are selected optionally or are fixed values.
- iii. Errors are independent from each other. In other words, there is no autocorrelation between them.
- iv. Errors of estimates are random and do not relate to each other. ($\text{Cov}(\epsilon_j, \epsilon_i) = 0$). At the same time the variance is $V(\epsilon) = \sigma^2$ and its average is zero. Diagonal elements of this matrix is σ^2 and other elements thereof are zero.
- v. There is no correlation between the error terms and independent variables.
- vi. $\text{Cov}(\epsilon_j, X_{ji}) = 0$, $j=1, 2, \dots, p$ ve $i=1, 2, \dots, n$

- vii. Simple linear correlation coefficients between independent variables should be 0 or very close to 0. This assumption is called not being multicollinearity.
- viii. It is assumed that the errors have a normal distribution to conduct hypothesis tests and generate confidence intervals.

The multiple correlation coefficients, indicated by R , are used to explain the strength of the relation between the independent variables and the dependent variables in multiple linear regression analysis. However, R^2 , which is the multi-determination coefficient, is more appropriate to make comments on this relation.

The following is written:

$R^2 = \text{Explained part of the total variation} / \text{Total variation}$

In other words, the following formula is found (Ertekin 2000):

$$R^2 = \frac{b'X'Y - \sum(Y)^2/n}{\sum Y^2 - \sum(Y)^2/n} \quad (3.4)$$

Theoretically infinite number of independent variables explaining the dependent variable can be found. But in practice, 1 or 2 or sometimes 3 independent variables explain a large part of the variance in dependent variable. It is considered for the value to be enough around 0.80 (Ünver and Gamgam 2008)

In this thesis, the response variable is the amount of fuel consumption. The initial set of parameters used includes speed, acceleration, engine RPM, volumetric Efficiency, EGR commanded and slope for a specific vehicle. We will refer to this as the full linear regression model, which will be tested in Section 5. When all the variables are used in analysis of linear regression, the correlation between observed values and predicted values is quite high. However, in terms of controllability, some of the parameters such as the engine RPM, volumetric efficiency and EGR Commanded are related to the vehicle and cannot be easily changed. Hence, we also consider an alternative and a

smaller regression model using speed, acceleration and slope only, which are easier to control, and will also be tested in the numerical analysis.

3.3.2 Artificial Neural Network

"Intelligence can be defined as the ability of the mind to learn, benefit from the learned issues, adapt to new situations and find new solutions" (Copeland, 2015; Yıldırım, 2014) . Artificial intelligence can be defined as follows: "Artificial intelligence based on an idealized approach is an artificial operating system from which it is expected to carry out high cognitive functions or autonomic behaviors unique to human intelligence such as perception, learning, connecting multiple concepts, thinking, opining, problem-solving, communication, making inferences and deciding " (Copeland, 2015; Yıldırım, 2014) " The concept of intelligence has emerged in line with the studies conducted in order to answer the question of "Can this human-specific abstract thinking process be achieved through a machine?" People can give their decision on a subject thanks to their experiences and abilities to perceive. The human brain, having the ability of very strong realization, can do this process in a very short time. In contrast to this fact, decisions based on numerical processing are performed in a much more difficult way due to the realization ability of the brain and take longer time. Computers have abilities which are in contrast with the capabilities of the human brain. Decision-making mechanisms of computers based on numerical processing operate very quickly while they cannot make decisions based on understanding. This brings to mind the question whether the ability of realization can be created in computers. Studies as to this issue have been gathered under the umbrellla of artificial intelligence.

These are neural network structures which are artificial and inspired from the human brain. Each and every element forming the network is named as artificial neuron. ANN (Artificial Neural Network) consists of numerous interconnected by virtue of a variety of weighting. ANN comprises of simple processors each of which has its own memory. Neurons join together thanks to these processors to form a network structure. ANNs have some common basic features although they ahve different characteristics depending upon the network model applied:

First feature; Parallelness of the system and structural dispersion of additive functions in ANNs; ANNs consist of many neurons and these neurons work simultaneously thereby performing complex functions. In other words, complex functions are formed by virtue of the working of many neurons simultaneously. Even if any of these neurons lose their functions during the process, the system can continue to work within confidence limits.

The second feature is the generalization ability which in other words denotes the network's deduction of rough features depicting the mapping from the numerical data used during training and thus generation of meaningful answers for inputs which are not used during training.

The third feature is that the network functions can be non-linear. Certain types of non-linear subunits scattered along the structure especially make fulfillment of the function mathematically in a correct manner possible especially if the required mapping is non-linear as in control or defining processes.

The fourth feature is the implementability of ANNs designed in the digital environment in the hardware. This feature is perhaps an indicator that ANNs will enter into our lives even more during our daily lives (Efe and Kaynak, 2004, Yıldırım, 2014).

3.3.2.1 Biological Neurons

ANNs have been created through being inspired from the human brain. Therefore structure and the mode of operation of the biological nerve cells namely neurons must be well known for understanding the ANNs. A nerve cell, as seen in Figure 3.1, consists of three parts as axons, cell bodies and dendrites. The cell body is the part where there is the nucleus of a neuron. Dendrites, is the name given to the large number of branches coming out from the cell body. They are similar to the branches of a tree as structure. Their task is to transmit the alerts received from other nerve cells to cell body. Axon is the part coming out from the cell body and extending without branching. Each nerve cell has one axon. Their function is to transmit the stimulations received from nerve cells to cell body. Some axons are covered with a layer named myelin. The cited layer can be considered as a protective layer that allows the neurons to make the transmission faster.

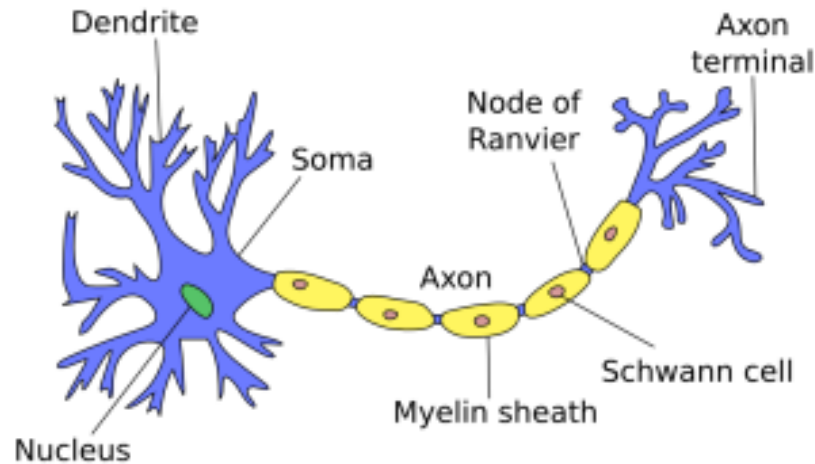


Figure 3.1 Structure of the biological nerve cells in a nervous system.

Communication between the nerve cells is a chemical process. During this chemical process, chemical energy is converted into electrical energy while electrical energy is converted into chemical energy. Dendrites collect all inputs to the cell. All the received signs are combined in the cells to decide whether an output should be produced or not. At the decision phase it is considered if the potential of the sign sent from one nerve cell to the other neurons nerve cell is above a certain threshold value. The sign is sent only if this condition is met. This occurrence is named as stimulation of the cell.

Each sending response during sending of the sign is called synapse. Synapses entering nerve cells are processed according to the properties of that cell and only one output is produced. This output is sent from the axon to the cell body.

3.3.2.2 Artificial Neural Networks and Biological Neurons

Technology imitates nature in many areas and aims to produce more superior products by trying to understand the structure thereof. Biological neurons are the elements which are based on also in the issue of artificial neural networks. In this respect it can be talked about similarities between the two structures. A biological neuron corresponds to a processing element in the artificial neural network. Furthermore dendrites, cell bodies, axon terminals and synapse gaps in biological neurons correspond to transfer functions, movement functions, output layers and weights in artificial neural networks respectively.

3.3.2.3 Main Elements of Artificial Neural Networks

It is necessary to know the structures named input, weight, addition function, threshold value, activity function and output for understanding the structure of the ANN. Inputs ($x_1, x_2, x_3, x_4 \dots$) denote the information received from the periphery of nerve cells. They can be received from outside world or other artificial neurons before the active nerves. All inputs in the artificial neural cell do not give the same impact on the network (Altun et al., 2014; Yıldırım, 2014). A weight value is determined to determine the degree of this effect for each input. w_1, w_2, w_3, w_4 values in the artificial neurons schematized in Figure 3.2 represent these weights.

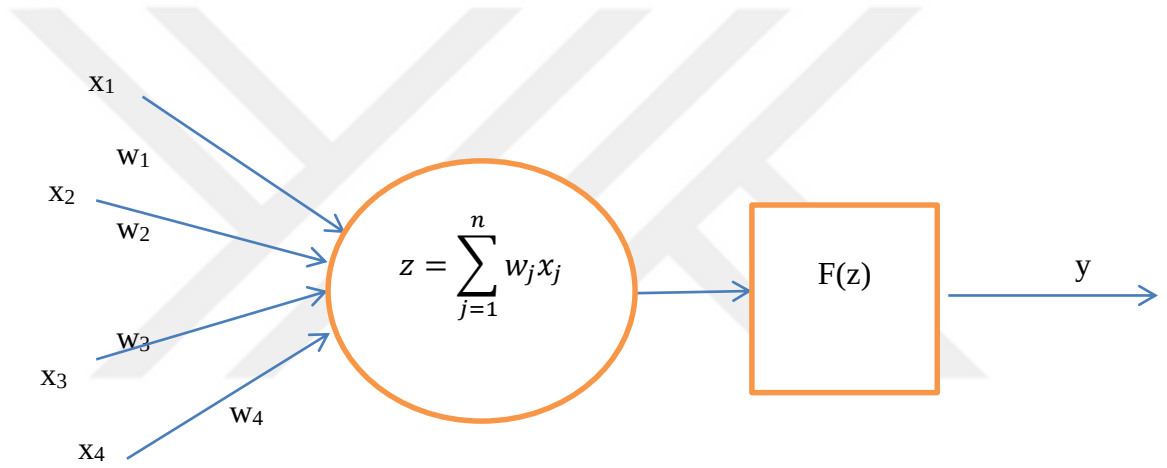


Figure 3.2 Artificial neuron

In line with the addition function, each weight in the neural cell is multiplied by the input to

which it belongs. All of the results obtained by multiplying these inputs by their weight are added. Result of the addition is added to the threshold value and sent to the activity function.

"w" gives the weights and "x" gives the values of input parameters in the calculation in Figure 3.1;

$$z = \sum_{j=1}^n w_j x_j \quad (3.5)$$

An artificial cell's weights is transmitted by passing the result of addition through the activity function. "The usage purpose of an activity is to allow the change of the output of the addition function when time information is in question " (Özbek, 2007; Yıldırım, 2014). As long as a nerve is below the threshold level of activity function, it does not produce an output. The nerves produce an output only if they are above the threshold level. This case is expressed with 1 and 0 output values

in Formula 3.6 .

$$y_i \begin{cases} 1 & \text{if } \sum_{i=1}^n x_i w_i \geq T \\ 0 & \text{if } \sum_{i=1}^n x_i w_i < T \end{cases} \quad (3.6)$$

"Results of activity function in the nodes can pass through scale or limit calculations. Scaling simply is the result obtained by multiplying a scale factor by the value of the activity. And limiting allows the scaled results not to go out of minimum and maximum borders " (Özbek, 2007; Yıldırım, 2014).

Output function (the elements shown by "y" symbol in Formula 3.6) distributes the result function obtained from activity function to the relevant places. There is only one output in a nerve. But this single output does not become an input to a single neuron. It combines with multiple artificial neurons and leads to the formation of the neural network.

3.3.2.4 Structure of Artificial Neural Networks

Neural networks which are created as a result of combination of artificial nerve cells are not created due to random processes. A specific format is necessary for the formation of neural networks. This format is determined by the layers within the ANN "There are 3 layers named as input layer, hidden layer and output layer " (Özbek, 2007).

Input layer:

This layer is the layer in which inputs to the artificial nerve cell from the outside world or other artificial neuron connected to it are accepted. The number of artificial nerve cells here is equal to the number of data to be accepted as input. In other words each input is formed in a way to carry one data. The layer after the input layer is the hidden layer.

Hidden layer:

The basic function of artificial neural networks is carried out at this layer. The hidden layer has more than one neuron. The number of neurons may vary according to the difficulty of the problem. Not only the number of neurons in hidden layers but also the number of hidden layers may also be increased to solve a difficult problem. The most important task of the hidden layer is transmission process of the input data received from the input layer to the output layer by producing an output as a result of processing with various functions (Altun et al., 2014).

The operations performed during the period when input data are received and output is produced in artificial neural networks are not known. This case is named as "black box feature of ANNs" in the literature. The issue of in which stage of output the artificial neural networks are produced is also mysterious. Therefore this section in which unknown processes are made is called black box.

Output layer:

The output layer which performs the transmission process of the data received from the hidden layer renders the learning process more efficient and effective in complex data sets by sending the weights calculated in the feedback network back into the input layer. These outputs are usually one however there may also be multiple outputs.

3.3.2.5 Transfer Functions

Transfer functions, which are also called as threshold function or sign functions, are functions which are capable of producing outputs within certain limits function for inputs which are considered as infinite. Their main task is to make the area limitation of the inputs. If the grading of inputs are made within proper limits, outputs will be

different. Otherwise, the outputs will be collected and tendency of the artificial neural network will be incomprehensible. Selection of the transfer function is carried out according to the work of the network model in artificial neural networks. The transfer functions which are commonly used include Tanget-Sigmoid (tansig), Logarithmic-Sigmoid (Logsig) and Purelin (Altun et al. , 2014).

3.3.2.5.1 Tangent Sigmoid Transfer Function

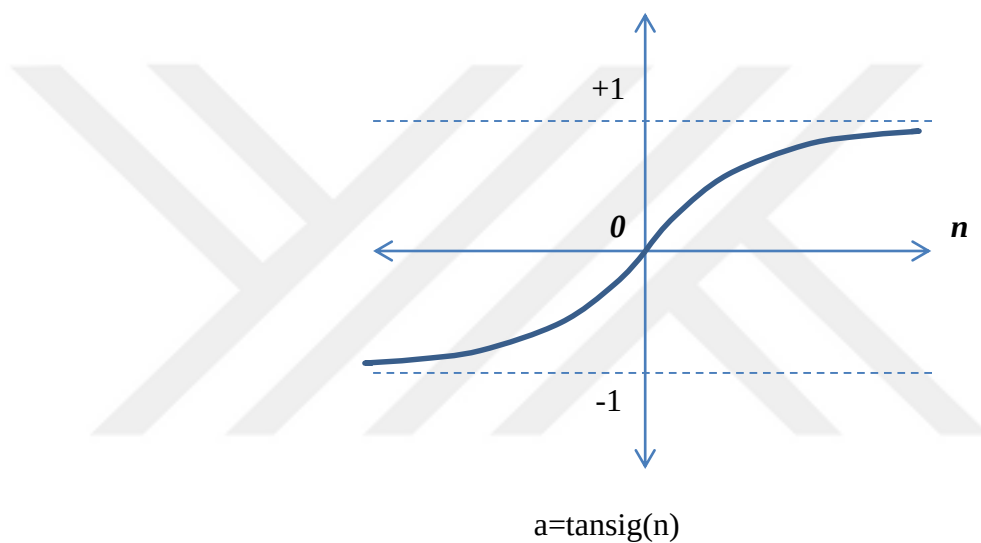


Figure 3.3 Tansig function graph

This function is a commonly used function in many artificial neural network applications. Its opening is in the form of Tangent-Sigmoid. It is also called as Tangent Hyperbolic function in many places. Tansig function, which is a bipolar function, is a function that extends the input space. Functional change for this transfer function is as in Figure 3.3. The function shows a non-linear change within the $[-1, +1]$ range (Altun et al. , 2014).

3.3.2.5.2 Logarithmic sigmoid transfer function

This function, which is also called as a sigmoid function, is used in cases when the response inputs of artificial neural cells require having a continuous function. Because

the backpropagation model requires a function, differential of which can be taken at every point,

Sigmoid function is suitable for backpropagation model (Altun et al. , 2014).

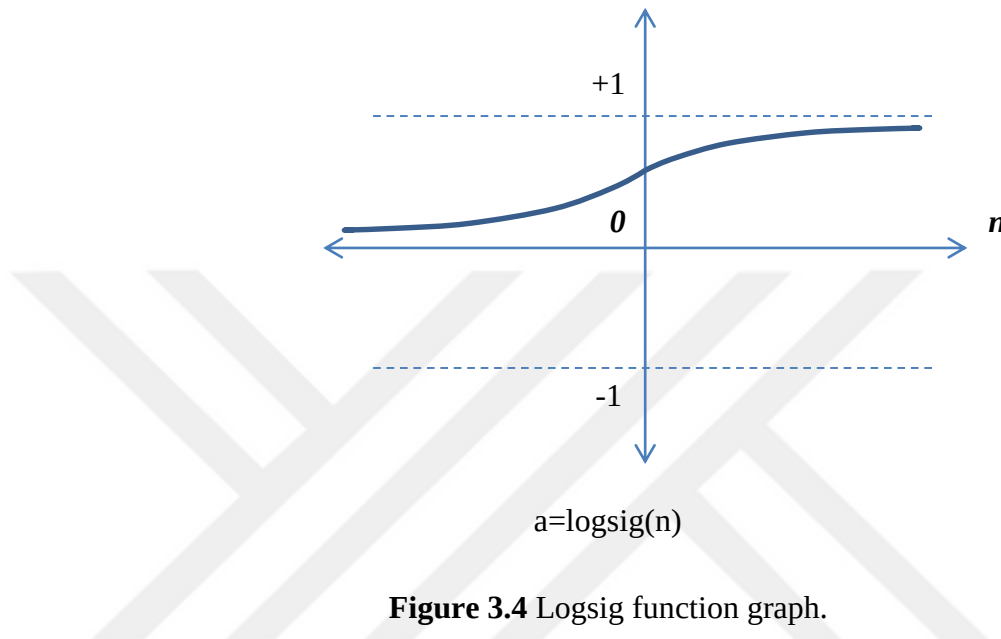
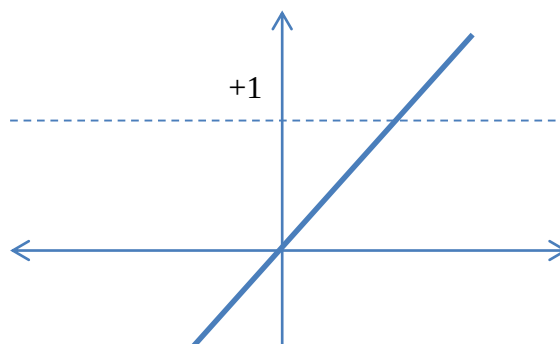


Figure 3.4 Logsig function graph.

The function does not produce outputs in the range of negative values as shown in Figure 3.4. The function shows a non-linear change at $[0,1]$ range which is the dynamic variation range of the function (Altun et al. , 2014).

3.3.2.5.3 Purelin transfer function



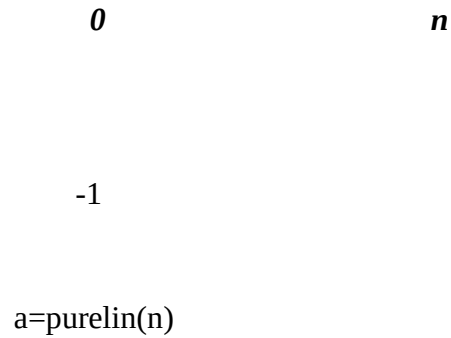


Figure 3.5 Purelin function graph.

The most important feature of the Purelin function which is also known as a linear function is its being linear as shown in Figure 3.5. Neuron is obtained as linear according to the change of the of the neurons' input. The change range of this function is [-1, +1] (Altun et al. , 2014).

3.3.2.6 Feedforward neural networks

Processor elements are usually divided into layers in the feedforward networks. Signs are transmitted from the input layer to the output layer by virtue of one-way links. Each processor element in one layer is connected to the next layer with all elements however there is no connection between the elements in the same layer. Therefore the connections between the processor elements in the feed-forward artificial neural networks cannot constitute a loop and these networks can quickly produce output to data entered.

The cells are arranged in layers in feedforward neural networks and the outputs of cells in one layer are given as input to the next layer. The input layer transmits the information it receives from outside to the cells in intermediate (hidden) layers without making any changes. Network output is determined by processing this information in the intermediate layer and output layer (Baş, 2006).

3.3.2.7 Feedback artificial neural networks

Feedback artificial neural networks also known as recursive artificial neural networks have a dynamic structure unlike feedforward networks. Feedback artificial neural networks have a structure in which the processor elements in the output or intermediate layers are fed back to the processor elements in input or previous intermediate layers. In this way, inputs are transmitted both in forward and reverse directions. Feedback artificial neural networks have dynamic memory and an output at one moment reflects both the input at that moment and the previous inputs.

In feedback artificial neural networks, at least one processor element output's is given as input to itself or the other processor elements and generally feedback is made via a delay element (element which carries the activation values in the intermediate layer or output layer as input to the next iteration). Feedback can be between processor elements in one layer or processor elements between layers. Feedback artificial neural networks, thanks to this structure, show a non-linear dynamic behavior. Thus, feedback artificial neural networks with different structures and behavior can be obtained according to the manner in which the feedback is performed (Baş, 2006).

An Artificial Neural Network (ANN) is a supervised learning technique that mimics biological neural networks. The complex structure of neural networks allows ANN to capture the non-linear structure of data accurately (Haykin, 1994). In an ANN, the input vectors (i.e., the independent variables) are propagated through layers of neurons in order to estimate corresponding output (i.e., the dependent variable) as shown in Figure 3.1.

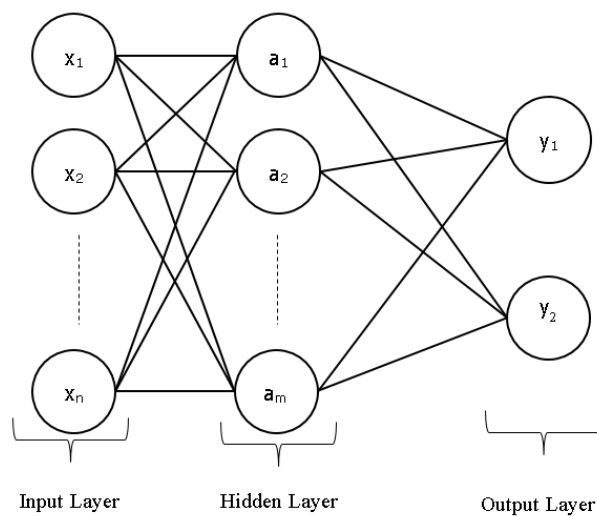


Figure 3.6 Representation of typical three-layer neural network architecture.

Figure 3.6 represents the ANN architecture with an n -dimensional input vector and m neurons in the hidden layer. Every element of the input vector has a relationship with all the neurons in the hidden layer. The strength of the relationship between an input x_i and neuron a_j is determined by weight w_{ij}^1 . The relationship between the neurons in the hidden layer and the output is represented with the weights in the second layer, denoted by w_{ij}^2 . The output vector y is predicted by forward propagating the input vector through layers of the network as shown in the following equation for one hidden layer neural network architecture (Kalogirou and Bojic , 2000).

$$a = f^1(w^1x) \quad (3.7)$$

$$y = f^2(w^2a), \quad (3.8)$$

where x is the vector of inputs, w^i is the weight matrix for layer i , and f^i is the activation function of layer i . In this thesis, the sigmoid function is selected as activation function for the first layer and linear function is utilized for the second layer (Ain et A., 1996).

3.3.3 Support Vector Machine

Support Vector Regression (SVR) is a variant of the Support Vector Machine (SVM), have been developed Russian mathematician Vladimir Vapnik on the basis of his works on statistical learning conducted from 1960s until the early 1990s. They were used for the first time in 1997 by Vapnik et al. (Vapnik et al.,1997), in a binary classification problem and have achieved their present position among heuristic methods by being developed gradually. In other words we can say that SVM has quite a strong theoretical background (Cristianini et al., 2001). Their basic logic is simple, but their results are very effective. In the simplest way in Support Vector Machines if we consider that there are two classes of data in a plane, it is possible here to separate the two data sets with one border line. This border passes through a mid point at the place where the data in two different groups are closest to each other and from the farthest point to the both data sets. SVM provides a successful method of classification by determining the best way of drawing these borders with minimal error (Erdal, 2011; Kartal, 2012).

SVM algorithm is a feedforward learning decision network mechanism (Alataş et al., 2004). It can be used effectively for many classification and prediction problems which are linear or nonlinear and in varying sizes. SVM also is a kernel-based method. That's why the SVM machines are called recently as "Kernel Machines". Core functions named "Kernel" SVM are the most important learning parameters of SVM (Lin et al. 2008). Considering the continued increase of developments in kernel-based methods, can be said that SVM will be a method which will give even better results.

3.3.3.1 Basic Theory of SVM

SVM is based on the statistical learning theory developed through V. Vapnik. This theory provides a useful infrastructure for artificial learning and SVM uses this infrastructure successfully. Vapnik-Chervonenkis (VC) method based on the error upper limit's in examples in statistical learning theory being the smallest utilizes SRM (Structural Risk minimization) and ERM (Empirical Risk Minimization) concepts. (Vapnik, 1982). Vapnik and Lerner-Chervonenkis (VC) dimension: a data set containing N points can be labeled in 2^N ways as positive and negative differently, VC is a scalar maximization corresponding to value which does not disrupt the separability of this data set in a way not to be greater than N (Alpaydm, 2011). The low size of VC represents low expected error and it becomes greatly possible to get rid of the extreme learning problem encountered in learning problems with SRM. In this way, the learning pattern is more simplified and comploututy is reduced. However, this can lead to compromise on success in learning to a certain extent. Nevertheless, because it provides a better generalization, it saves the model from extreme learning problem. ERM minimizes the classification error and maximizes the distance between the nearest different classes of SVM. This does not guarantee a single decisive solution but it is a way needed to achieve the best solution (Erdal, 2011; Kartal, 2012).

The major advantage of SVM compared to other statistical methods is that instead of making classification only in statistical evaluations it utilizes a geometric approach which is based on planar separation. In this way, SVM ensures getting rid of dependence on statistical distribution estimations (Tolun, 2008). It is aimed to have the maximum distance between the two closest samples at the border of the two classes,

between two different classes and the best separating plane providing this is tried to be determined. This plane is called as "the best separating high-level" and the closest vectors in two sides of the plane which determine this are called as support vectors (Erdal, 2011; Kartal, 2012).

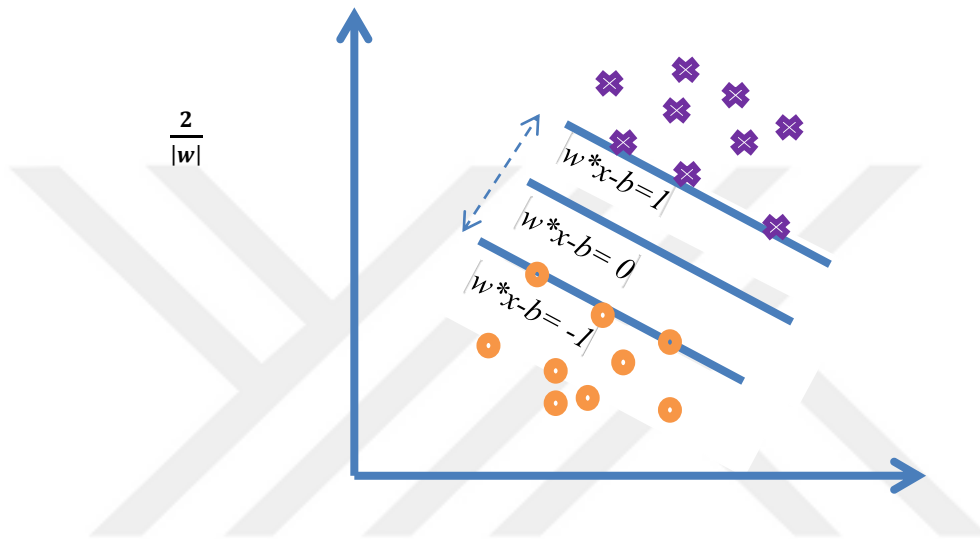


Figure 3.7 Separation of a two-dimensional plane.

Data which is possible to be classified as linear can be easily separated in this way. Those which cannot be classified as linear are transferred into a multidimensional space. Thus, principle of finding the same "best separating high-level" is applied in this higher dimensional space and classification of data is performed (Coates, 2011).

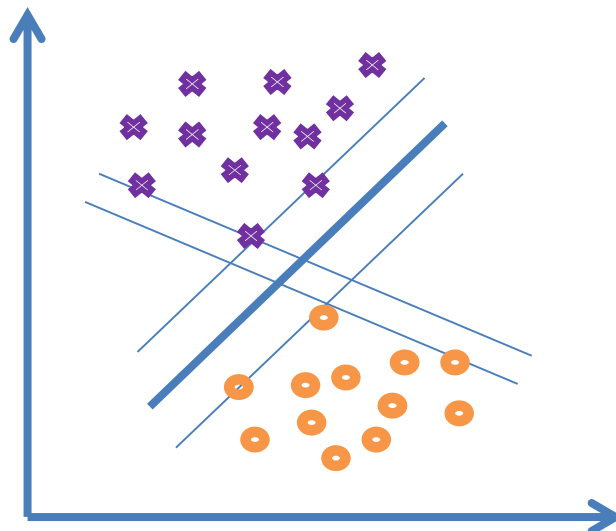


Figure 3.8 Two different separator plane.

SVM prefers the one with the widest range of borders (margins) in determining the best possible plane among many planes which separates the two different data sets.

SVM's main advantages can be listed as follows;

- It is based on structural risk minimization however it also utilizes empirical risk minimization. Thus, it tries to provide a balance between extreme compliance and extreme generalization.
- Problems created for finding a hyperplane is a convex optimization problem. In other words it is in a soluble form by utilizing the quadratic programming. Thus problem of encountering with local minima is eliminated.
- Classifiers created at the end of learning, can be expressed in the form of support vectors or kernel functions.
- Can make relatively good generalizations without the need of a lot of data for an adequate learning. Error level can be predetermined on learning data.

3.3.3.2 SVM Binary Classification Approach

Let's assume that we specify the inputs in a binary classification problem as, X and $Y_i = \pm 1$ And let's suppose all the X_i and Y_i pairs are specified as $i = 1, 2, \dots, m$

Any X_i here defines a distance of the "input space" specified as i . in the dataset.

Although compliance with input in Kernel type selection and in arrangement of parameters has ben researched for the SVM method a standard and defined method has not been defined for this.

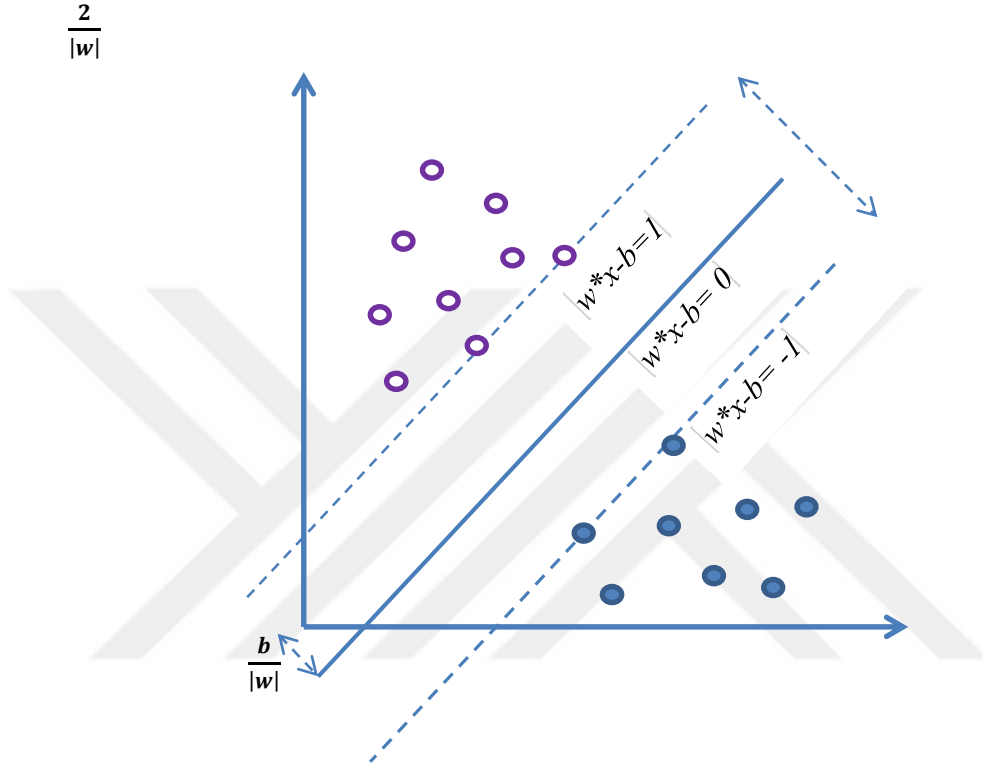


Figure 3.9 Support vectors of two classes.

A differential plane as “ w ” a weight and “ b ” a bias probability value can be stated in an arbitrary dimensional space as follows:

$$w.x + b = 0 \quad (3.9)$$

$D(x)$ which is a sign is expressed as follows:

$$D(x) = \text{sign}(w.x + b) \quad (3.10)$$

Sign function in equation (3.10) is a function that can give decision in the form of (+) or (-). $D(X)$ decision function here can be written for all the support vectors as follows:

$$\begin{cases} wX_1 + b = +1 \\ wX_1 + b = -1 \end{cases} \quad (3.11)$$

(3.12) and (3.13) are obtained when the equations given in (3.12) is subtracted from each other.

$$w(X_1 - X_2) = 2 \quad (3.12)$$

$$(X_1 - X_2) = 2/w \quad (3.13)$$

Function for data set consisting of the n elements separable linearly from the expressions can be shown as in (3.14)

$$D = \{(x_i, y_i) | x_i \in R^p, y_i \in \{-1, 1\}\}_{i=1} \quad (3.14)$$

The expression of the most separating plane for the full sample also becomes a quadratic problems expressed in (3.15) and (3.16) from here.

$$\min \max \left\{ \frac{1}{2} \|w\|^2 - \sum_{i=1}^n \alpha_i [y_i (w \cdot x_i - b) - 1] \right\} \quad (3.15)$$

$$w, b \quad \alpha \geq 0$$

$$w = \sum_{i=1}^n \alpha_i y_i x_i \quad (3.16)$$

This problem is a problem which can be solved by the Karush-Kuhn-Tucker conditions. SVM, in addition, utilizes statistical learning theory and multidimensionality in this binary system.

There are two important reasons for this:

- i. The upper limit in generalization errors in the theory is not dependent on the number of dimensions.
- ii. This margin of error can be minimized maximizing the total of distance of the high-level, which separates the two classes, to the nearest points of two classes

When the problem is linearly inseparable, dimension increase and kernel functions are utilized.

3.3.3.3 SVM Kernel Functions

It may not be possible simply to separate the data linearly or a separation with enough quality may not be provided while SVM makes classification. And for this SVM kernel functions are utilized. Inputs of all sampling are separated according to the kernel functions used in SVM. Different kernel functions carry the data to a higher dimensional feature space. Each feature is defined by vectors in this high dimensional space. A kernel matrix with inner product of vectors of all properties is used. Thus a non-linear classification problem in small size can be classified via a linear algorithm in feature space with higher dimension by virtue of the kernel function.

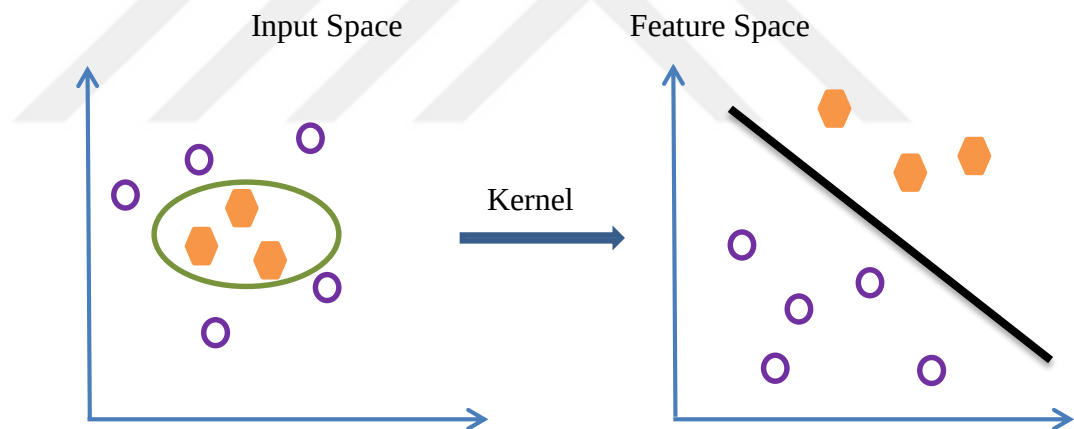


Figure 3.10 Kernel function

The type of function selected for kernel is highly effective in estimation and classification performance of SVM. However, in addition to type of function selected there are also other parameters affecting the performance. Factors affecting the training and prediction performance are as follows (Tolun, 2008):

- i. The type of the Kernel function,
- ii. Kernel parameter

- iii. C parameter,
- iv. Parameter.

Although compliance with input in Kernel type selection and in arrangement of parameters has ben researched for the SVM method a standard and defined method has not been defined for this.

Given a set of input-output pairs $(x_1, x_2 \dots, x_n, y_1, y_2 \dots, y_n)$, SVR aims to approximate the following function,

$$f(x) = wx + b, \quad (3.17)$$

by minimizing the following objective function,

$$\frac{1}{2} \|w\|^2 + C \frac{1}{n} \sum_{i=1}^n L(x_i, y_i) \quad (3.18)$$

where $\|w\|$ is a regularization term, $L(x_i, y_i)$ is the loss function and C is the trade-off between model complexity and error on training dataset. A graphical representation of SVR can be seen in Figure 3.11

The advantage of SVR is its ability to represent a convex solution space, resulting in a unique solution.

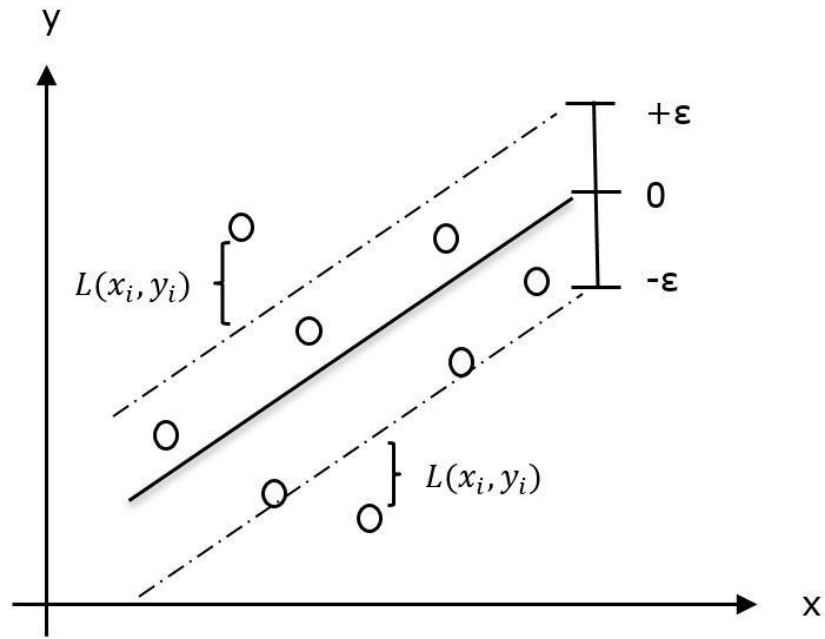


Figure 3.11 The graph of Support Vector Regression.

The data points are not always in a linear classification. The kernel functions enable us to transform the nonlinear dataset into a linear separation format. Figure 3.12 shows the transformation of nonlinear dataset to linear dataset by using the following kernel functions.

$$y = \sum_{i=1}^N (\alpha_i - \alpha_i^*) K(x_i, x) + b \quad (3.19)$$

where y is output, α_i and α_i^* are lagrange multipliers, x_i is the input vector, $K(x_i, x)$ is the kernel function, and b is the bias.

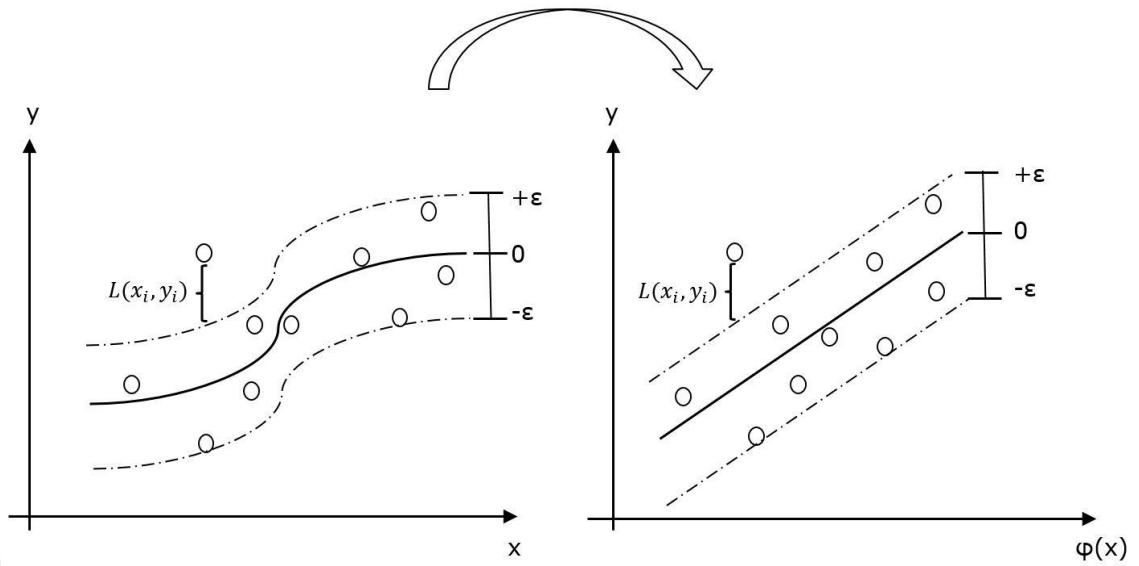


Figure 3.12 The transformation of nonlinear dataset to linear dataset by using Kernel functions.

3.4 REAL TIME DATA COLLECTION

All the numerical experiments conducted here use real-data with three different vehicles, the names of which are shown in the first column of Table 3.1. The rest of the columns define further specifications. The data were collected when the drivers were in the normal course.

Table 3.1 Vehicle properties.

	Fuel Type	Engine Displacement (ml)	Frontal Surface Area (m ²)	Vehicle Weight (kg)	Trip Distance (km)	Average Speed (km/h)
Toyota Corolla	Diesel	1396	2.09	1425	139.23	140
Kia Ceed	Diesel	1582	2.25	1800	432.42	100
BMW X3	Diesel	1980	2.66	2610	361.81	120

Data from the vehicles was collected in real-time using existing on-board diagnostics (OBD2), a Bluetooth interface and a smartphone.

The three vehicles were driven on three different routes listed in Table 3 2. The first route is between two cities in central Turkey, namely from Ankara to Bolu, and is of 139.23 km in length. The second route is from the city Ankara to the city Kayseri, again in Turkey, and is of 432.42 km in length. Finally, the third route is from Istanbul to Gerede, both in Turkey, and is of 361.81 km length. The latitude and longitude coordinates of the origins and destinations of the three routes are given in Table 3 2.

Table 3.2 Route coordinates.

	Origin		Destination	
	longitude	latitude	longitude	latitude
Route 1 by Toyota Corolla	32.60486	40.11768	31.64131	40.76668
Route 2 by Kia Ceed	32.25257	40.60962	35.54927	38.75007
Route 3 by BMW X3	28.734311	41.05889	32.25309	40.60868

3.5 RESULTS OF REGRESSION MODELS

In this section, it is presented numerical results obtained by five fuel consumption models from the literature and the three regression models developed in this thesis. These results are not only used to test the accuracy of the models against real data, but also compare the prediction accuracy eight models. The former category consists of five microscopic models, including an instantaneous fuel consumption model (IFCM) and a four-mode elemental fuel consumption model (FMEFCM) both described by (Bowyer et al. ,1985), physical emission rate estimator (PERE) model presented by (Nam and Giannelli, 2005), a comprehensive modal emission model (CMEM) for

heavy-goods vehicles described by (Scora and Barth, 2006) and (Barth and Boriboonsomsin, 2008), and vehicle specific power (VSP) proposed by (Jimenez-Palacios, 1998). These models were explained in detail by (Şevkli et al., 2016), but the same description is provided in the Appendix for the sake of completeness. The input parameters used for the five fuel consumption models for calculation and comparisons are presented in Table 3.3.

As for the statistical models, linear regression (LR), neural networks (NN) and support vector regression (SVR) are tested and compared with each other and against the five models above.

Table 3.3 Input data used for the fuel consumption models.

Parameters	CMEM	PERE	FMEFCM	IFCM	VSP
Gravity Force, $g(m/s^2)$	9.81	9.81	-	9.81	9.81
Chemical efficiency, η	0.4	0.4	-	-	0.4
Air Density, ρ (kg/m ³)	1.293	1.293	-	-	1.293
Rolling Resistance Coefficient, C_r	0.0135	0.0135	-	-	0.0135
Transmission efficiency, η_{tf}	0.88	0.88	-	-	0.88
K	0.25	0.25	-	-	0.25
Idle Fuel Consumption Rate, F_i (mL/h)	-	-	888.8	888.8	-
Idle Fuel Consumption Rate, α (mL/s)	-	-	0.2469	0.2469	-
Efficiency Parameter, β_1 (mL/kJ)	-	-	0.926	0.926	-
Energy-acceleration Efficiency Parameter, β_2 mL/(kJ.m/s ²)	-	-	N/A	N/A	-

b_1 , kN	-	-	-	0.1316	-
b_2 , kN/(m/s) ²	-	-	-	0.0005	-
Drag Fuel Consumption Parameter					
Mainly Related To Aerodynamic Drag, Γ (MJ/km)	-	-	12.2	-	-
Drag Fuel Consumption Parameter					
Mainly Related To Aerodynamic Drag, $B(\text{mL/km})/(\text{km/h})^2$	-	-	0.0036	-	-

3.5.1 Numerical Results Obtained By Fuel Consumption Models

The fuel consumption on the three routes described above was estimated via the five fuel consumption models by providing the input data. The results are given in Table 3.4, where the second column presents the actual amount of fuel consumed (in liters) on the three routes and the rest of the columns present the predicted amounts for each of the five models.

Table 3.4 Real time data and models calculations (total consumption).

Models	Real-time					
	data	IFCM	FMEFCM	PERE	CMEM	VSP
Toyota-Corolla	15.946	29.904	15.100	13.301	12.541	8.462
Kia-Ceed	30.175	54.534	33.227	25.696	29.901	17.244
BMW-X3	35.012	63.347	37.094	32.675	36.734	14.527

Based on the results presented in Table 3.5, the mean absolute percentage error (MAPE) is calculated and presented them in where the best result is presented are bold.

Table 3.5 MAPE values of the all models.

Models	IFCM	FMEFCM	PERE	CMEM	VSP
Toyota-Corolla	87.530	5.306	16.589	21.354	46.936
Kia-Ceed	80.726	10.115	14.843	0.907	42.852
BMW-X3	80.931	5.948	6.675	4.920	58.508
Average	83.062	7.123	12.702	9.060	49.432

As Table 3.5 indicates, FMEFCM, PERE and CMEM provide comparatively better estimates of total fuel consumption than the others. FMEFCM yields the minimum average MAPE out of the five models.

To investigate the reason behind the relatively large differences between the estimated total fuel consumption value and the actual fuel consumption figure given in Table 3.6, I have conducted further analyses to measure correlation between the instant real time data and the estimated fuel consumption values. The results are shown in Table 3.6.

Table 3.6 Correlation of calculated data with real-time data.

Models	IFCM	FMEFCM	PERE	CMEM	VSP
Toyota-Corolla	0.8063	0.6386	0.2267	0.8803	0.8854
Kia-Ceed	0.8648	0.7020	0.3755	0.8656	0.8740
BMW-X3	0.7749	0.5695	0.4907	0.7476	0.7622
Average	0.8153	0.6367	0.3643	0.8312	0.8405

It can be seen from Table 3.6 that IFCM, CMEM and VSP are more sensitive to changes to instant consumption through time, whereas IFCM and VSP had the worst results in total consumption. Furthermore, even though PERE has low MAPE in the total consumption, this model does not yield good correlation with instant consumption.

3.5.2 Numerical Results Obtained With the Statistical Models

In order to predict the fuel consumptions with the regression models, speed, acceleration, engine RPM, volumetric efficiency, EGR commanded and slope of the road are used as input variables for the full regression model. When all the variables are used in analysis, the correlation between real data and predicted data is quite high. However, although all variables are used in the analysis, not all of them are controllable. Given that speed and acceleration are controllable by driver and the slope is dependent on route selection, further analysis was conducted with these three parameters alone. This applies to the three regression models tested here.

In developing the three regression models, and prior to applying the statistical methods, the data was first normalized. The least squares method was used to find parameters for linear regression (LR). For the artificial neural network (ANN), a one hidden layer architecture is used with 10 neurons in the hidden layer. The sigmoid activation function (Cybenko, 1989) is used within the hidden layer and a linear activation function is used for the output layer. The (Levenberg–Marquardt algorithm Levenberg, 1944; Marquardt, 1963) is implemented to find the weights which will minimize the least square error. In developing the SVR, the epsilon-SVR is applied with radial basis kernel function (Basak et al., 2007). Both the epsilon value in the loss function and gamma value in radial basis kernel function is specified as 0.1, and the cost parameter C is set as 1.

Random subsampling was used for testing the performance of statistical models. In particular, a randomly selected 80% of the data is used for training and 20% for testing for each run. The procedure is repeated for 1000 times. The average and standard deviation (in parenthesis) of the R values are given in Table 3.7 for each statistical model, separately for training and for testing. The results presented under columns 3–5 pertain to the full regression (with all variables), whereas columns 6–8 relate to the

smaller regression with only the three independent variables, namely speed, acceleration and slope.

Table 3.7 Results of Statistical Models.

		All Variables			Speed, Acceleration and Slope		
Models		LR	ANN	SVR	LR	ANN	SVR
Toyota-Corolla	Training	0.89	0.96	0.97	0.85	0.93	0.93
		(0.005)	(0.007)	(0.001)	(0.006)	(0.007)	(0.002)
	Testing	0.89	0.95	0.96	0.85	0.91	0.92
		(0.019)	(0.021)	(0.007)	(0.022)	(0.029)	(0.013)
Kia-Ceed	Training	0.78	0.92	0.94	0.75	0.90	0.91
		(0.014)	(0.014)	(0.002)	(0.015)	(0.013)	(0.004)
	Testing	0.76	0.89	0.92	0.74	0.88	0.90
		(0.056)	(0.048)	(0.014)	(0.057)	(0.033)	(0.018)
BMW-X3	Training	0.90	0.93	0.95	0.76	0.80	0.80
		(0.004)	(0.010)	(0.002)	(0.011)	(0.019)	(0.006)
	Testing	0.90	0.91	0.92	0.75	0.78	0.79
		(0.015)	(0.037)	(0.011)	(0.043)	(0.044)	(0.026)

As seen from the Table 3.7, SVR provides the best results for all three vehicles as compared with ANN and linear regression. SVR outperforms other models in terms of

both accuracy and consistency, as indicated by the average and standard deviation of correlation coefficient (R) values. Even when only speed, acceleration and slope are used as input values, SVR delivers better results.

In the next set of experiments, it is presented more general results instead of constructing a model for each kind of vehicle. These models are constructed by considering additional input variables such as frontal area, engine displacements, and mass of vehicle. The new model can be applied all kinds of vehicles. Table 3.8 shows result of the new model for each statistical model. In the table, “all variables” indicate that the independent variables are those used in the full regression model as well as the additional variables above. On the other hand, “extended controllable variables” include vehicle characteristics (frontal area, vehicle weight and engine displacement) as well as the slope, instantaneous acceleration and speed.

Table 3.8 Results of a generalized statistical model for all vehicles.

	All Variables			Extended Controllable Variables		
	LR	NN	SVR	LR	NN	SVR
Training	0.87	0.95	0.96	0.81	0.90	0.90
	(0.004)	(0.005)	(0.001)	(0.006)	(0.006)	(0.002)
Testing	0.86	0.94	0.95	0.80	0.88	0.90
	(0.016)	(0.019)	(0.005)	(0.022)	(0.024)	(0.009)

Similar to Table 3.7, Table 3.8 shows that SVR outperforms other methods in both cases, where in the first case all variables are used as input, and in the second in addition to. ANN also provides competitive results, however SVR yields more robust results especially for testing data which can be seen from standard deviations of the R values.

This section is concluded by presenting Figures 3.4, 3.5 and 3.6, which depict the fuel consumption rate as predicted by the three models compared with the observed data on the three vehicles, namely Toyota, BMW and Kia, respectively. Speed, acceleration and the slope are used as inputs for all models. The horizontal axis shows the distance traveled in *km* whereas the vertical axis shows the rate of fuel consumption in *liter/hour*. The solid lines in all three graphs are the actual fuel consumption rates, whereas the dashed line shows the the prediction made with SVR, the dotted line is the prediction made with ANN and the dash-dot line is the prediction made with linear regression.

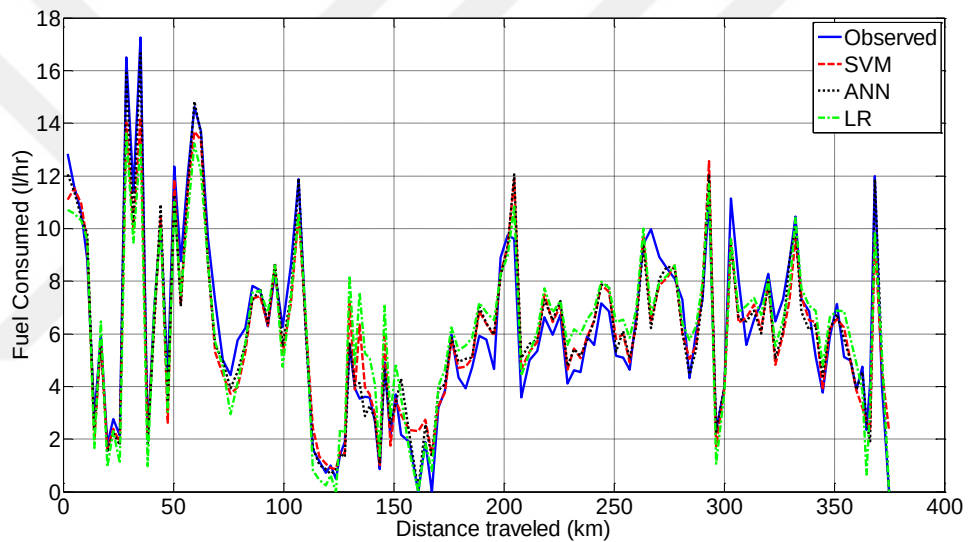


Figure 3.13 Prediction of fuel consumption by the three models for the Toyota vehicle.

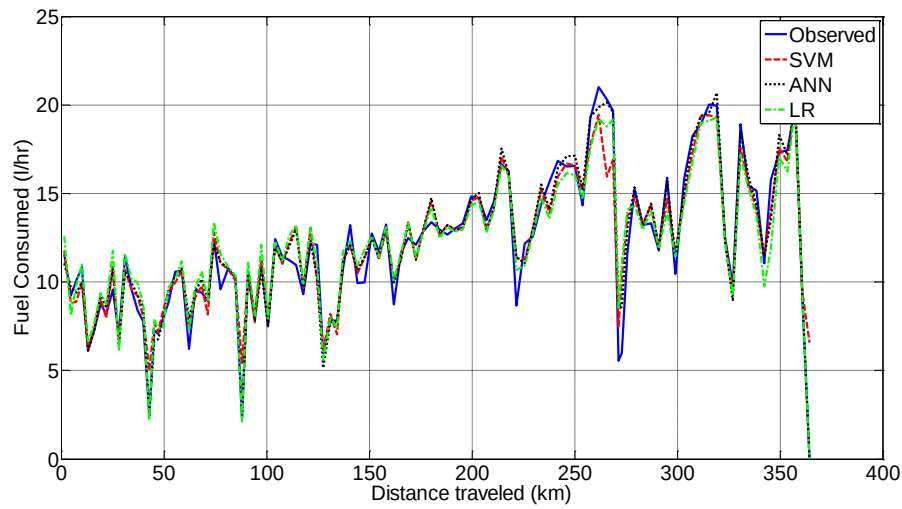


Figure 3.14 Prediction of fuel consumption by the three models for the BMW vehicle.

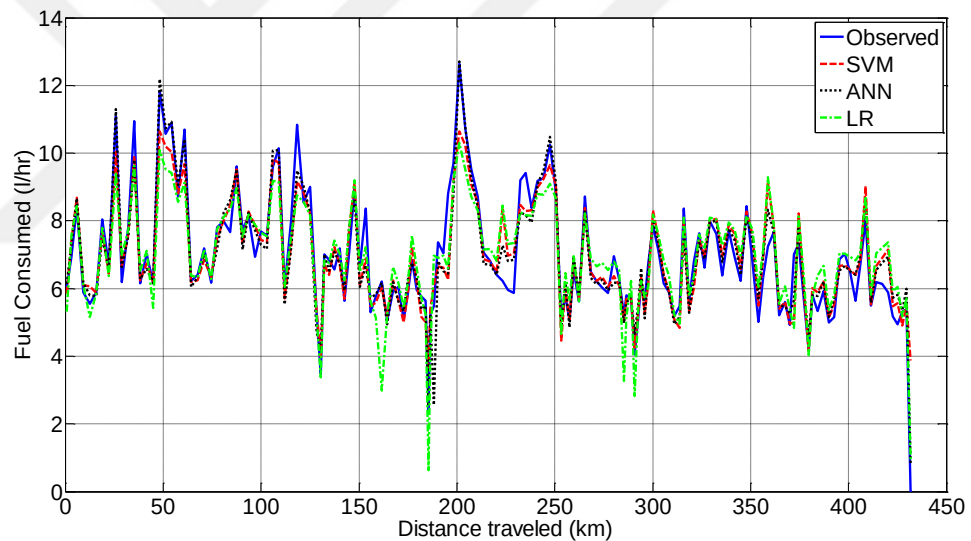


Figure 3.15 Prediction of fuel consumption by the three models for the Kia vehicle.

Figures 5–7 show that SVR and ANN makes highly accurate predictions to actual observed data, and outperform the linear regression. The results verify that machine learning techniques can be used as reliable tools for instantaneous fuel consumption calculation in route planning purposes, and only use speed, acceleration and slope as input.

4. A DYNAMIC PROGRAMMING APPROACH FOR OPTIMIZING PATH AND SPEED FOR PASSENGER CARS TO REDUCE FUEL CONSUMPTION

4.1 INTRODUCTION

In this section, the speed which is required for a vehicle, has been determined by taking into consideration the conditions such as the type, weight, geographical location on a certain route for the most economic fuel consumption. The proposed system is divided in 8 steps shown in Figure 2, Receiving vehicle position information from GPS, entering the destination location and vehicle information, acquire the possible routes, receiving elevation and distances data of possible routes, calculating route slope and partitioned of the route, cost estimation where for a given route the minimum fuel cost is calculated using a dynamic programming approach, select the most economical route, and lastly, proposed a velocity by the vehicle location.

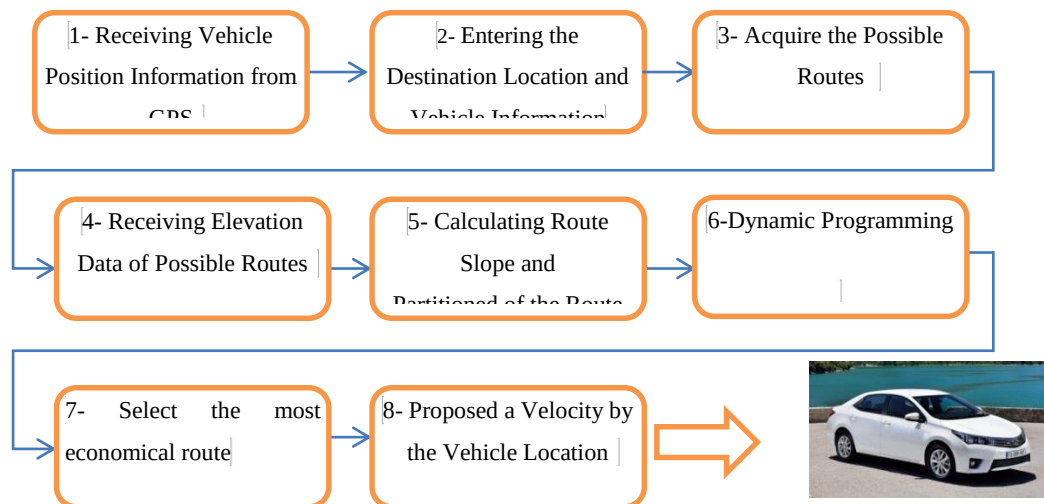


Figure 4.1 Methodology of proposed fuel economy system.

In this method, the fuel consumption model calculations recommended for dynamic programming and collection of data required for validation of them were carried out. Some part of these data; are the data directly received from the vehicle depending on the condition of road and the vehicle's brand and model such as coefficient of friction between the wheels and road, engine size, front surface area, weight of the vehicle. And some part are the data which is required to be collected from the vehicles momentarily while the vehicle is going along a route designated like current speed, acceleration, position of the vehicle, slope of the road, engine RPM. To determine the most appropriate mathematical fuel consumption model; to compare the fuel consumptions calculated by mathematical models with actual fuel consumption data is only possible through correct collection of these data.

The Four-Mode Elemental Fuel Consumption Model (FMEFCM) was used for calculation of the most economic fuel consumption with dynamic programming. During selection of this model, 13 microscopic fuel consumption models were analyzed in the literature and the accuracy of these models were tested with actual data, in the end it was selected because of being the most appropriate model for dynamic programming.

In Section 4.2, the fuel consumption model used for estimation of economic fuel consumption was explained. In Section 4.3, respectively dynamic programming, dynamic programming algorithm advised by us and adaptation of mathematical fuel consumption model into dynamic programming were demonstrated. In Section 4.4, dynamic programming and suggestion of necessary speed according to the position of the vehicle for minimum fuel consumption was explained with an example. In Section 4.5, the fuel consumption that was calculated by choosing a variety of routes was compared to actual fuel consumption. And in the last Section 4.6, the results obtained were assessed.

4.2 FUEL CONSUMPTION MODEL

In this chapter is based on the four-mode elemental fuel consumption model (FMEFCM) by (Bowyer et al., 1985), which consists of four modes, acceleration, deceleration, cruise and idle denoted by $F_a(t_a)$; $F_d(t_d)$; $F_c(t_c)$ and $F_i(t_i)$, respectively, where t_a ; t_d ; t_c and t_i are the times spent in each mode. The FMEFCM is an extension

of the instantaneous fuel consumption model (IFCM) also introduced by (Bowyer et al., 1985). While the IFCM is better suited for short trip estimations, the FMEFCM is capable of performing long trip distance estimations by adding initial speed, final speed and energy-related parameters. (Demir et al., 2014) review the different consumption models. (See the part 2.2.2.2 for more information)

4.3 DYNAMIC PROGRAMING MODEL

Dynamic Programing (DP) was a concept introduced by (Bellman, 1962). DP (Biegler, 2007; Bertsekas, 2000; Binder et al., 2001) applies dynamic system models to minimize an objective function, with multiple constraints taken into consideration. DP is an optimization method which solves complex problems by converting into simple forms. In order to use DP the given problem must either be transformed into a simpler problem without losing the original problem's characteristics (transform and conquer) or the problem should be breakable into sub problems (divide and conquer).

One of the first studies (Schwarzkopf and Leipnik, 1977) paper was developed computational method of optimal control problem for a conventional vehicle model for minimizing fuel consumption and specific solutions are obtained for various grades. (Saerens et al., 2009) paper was suggested that the dynamic programming model for optimization of fuel consumption consisting of two state variables: pressure in the engine intake manifold pressure and the engine speed. The experiment for validation of the control algorithm for fuel consumption minimization used dynamic programming was introduced (Nagy et al., 2013). (Onori et al., 2012) paper was suggested that finding the optimal velocity profile to minimize the fuel consumption with a dynamic programming. (Chang and Morlok, 2005) discussed the question of what optimal speed profile for minimize fuel consumption of a conventional vehicle under various road topographies. In (Hellstrom, et al., 2006) introduced a model of predictive cruise controller (CC). The model was suggested numeric optimization like dynamic programming for minimization of fuel consumption a heavy truck over different roadway characteristics. (Hellstrom et al., 2009) paper was developed look-ahead information system which is included a dynamic programming algorithm of the optimal

velocity profile with respect to a criterion formulation that weighs trip time and fuel consumption. (Jiménez and Montiel, 20014) paper is introduced an optimization system based on Dynamic Programming theory has been achieved to accomplish energy and minimization of fuel consumption in conventional vehicles. In (Monastyrsky and Golownykh ,1993), the effect of road slope, acceleration from rest to cruising speed and driving between stop signs on vehicle fuel consumption was evaluated with dynamic programming for various vehicle masses on short road segments. Analytical studies of the situation when this relation is nonlinear were conducted in (Froberg and Nielsen , 2007).

4.3.1 Minimum Fuel Cost Calculation With Dynamic Programming

To calculate the fuel cost of a trip, we first choose the starting and ending geographical points, the algorithm then finds all possible routes between the two points using Google Application programming interface (API). For each route, the elevation map is extracted and then sampled into 50, 100, 256 or 512 equal segments. The optimum speed for minimum fuel cost for each segment can be calculated by DP technique.

The DP technique uses the acceleration, deceleration and cruise modes of FMEFCM. As assume that vehicle is always on motion, idle mode is ignored.

The proposed DP formulation uses the following terms:

Stages in DP terminology is defined as the links within a multi-hop path from source to destination are indexed from 0 to M respectively ($k = 0, 1, 2, \dots, M$).

i and j represent speed values (km/h), ranging from 5 km/h to 120 km/h in increments of 5 km/h (5,10,15,..., 120 ($i,j,..., N$)) for each state.

The fuel consumption cost for each state is calculated as follows:

$$cost(i, j) = \begin{cases} F_a, & \text{if } i < j \\ F_d, & \text{if } i > j \\ F_c, & \text{otherwise} \end{cases} \quad (4.1)$$

where F_a , F_d and F_c denote the acceleration, deceleration and cruise fuel consumptions in equations (2.14), (2.15), (2.16) respectively.

The procedure of proposed DP can be modelled in (4.2), (4.3), (4.4) and (4.5).

$$f_0^*(0) = 0 \quad (4.2)$$

$$f_1^*(i) = cost(0, i) \quad \forall i \in N \quad (4.3)$$

$$f_k^*(i) = \min(cost(j, i) + f_{k-1}^*(j)) \quad \forall i, j \in N \quad (4.4)$$

$$f_M^*(i) = \min(cost(j, 0) + f_{M-1}^*(j)) \quad \forall j \in N \quad (4.5)$$

The cost function is calculated as the cumulative costs incurred along the communication path. The next stage depends on the current state of the network and the selected decision vector. The direct application of the DP approach starts from the final state $f_M^*(i)$ and steps backward until reaching the initial state $f_0^*(0)$. At each step the cost function is evaluated and the optimal speed value $f_k^*(i)$ is selected such that the total cost function is minimized. In general, the optimal costs for all possible speeds at a particular hop k have to be calculated, $f_k^*(i)$ and passed to the previous hop, $k-1$.

4.4 AN ILLUSTRATIVE EXAMPLE OF PROPOSED DYNAMIC MODEL

As an illustrative example, following route seen in Figure 4.2 is taken. In the Figure 4.2, A-B, C-D and E-F segments of the route are flat, the slope between B-C segment is negative 3%, and the slope between D-E segment is positive 3%. In the example all

segments have the same distance which is 0.2 km and totally 1 km. The vehicle starts from point A (assuming $v_i = 0$) and stops at point F. Our objective is to find the optimum velocities for each segment to minimize total fuel consumption by considering slope values.

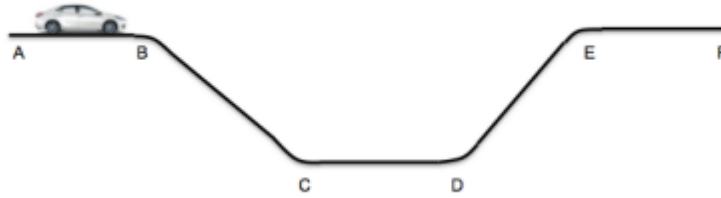


Figure 4.2 Sample vehicle travelling route

Taking the route in Figure 4.2 as an example, we will calculate the optimum speed for minimum fuel cost using the DP technique.

The values in Table 4.1 are remaining input data used for the fuel consumption model.

Table 4.1 Input data used for the fuel consumption model.

Parameters	FMEFC M
Mass, m (kg)	1425
Idle Fuel Consumption Rate, f_i (mL/h)	888.8
Idle Fuel Consumption Rate, α (mL/s)	0.2469
Efficiency Parameter, β_1 (mL/kJ)	0.926
Energy-acceleration efficiency Parameter, β_2 mL/(kJ.m/s ²)	NA
Drag Fuel Consumption Parameter Mainly Related To Aerodynamic Drag, ζ (Ml/km)	12.2
Drag Fuel Consumption Parameter Mainly Related To Aerodynamic Drag, B (mL/km)/(km/h) ²	0.0036

Table 4.2 Slope and distance for each level.

SECTION	Level (k)	Slope (%)	DISTANCE(km)
A-B	0	0	0.2
B-C	1	-3	0.2
C-D	2	0	0.2
D-E	3	3	0.2
E-F	4	0	0.2

Below are some constants and variables used in the calculation. These values are based on our test vehicle (Toyota Corolla D-4D automatic 2013).

Table 4.3 Vehicle properties.

	Fuel Type	Engine Displacement (ml)	Frontal Surface Area(m ²)	Aerodynamic Drag Coefficient	Vehicle Weight (kg)
Toyota Corolla	Diesel	1396	2.09	0.27	1425

Calculated speed values for each segment are given in the following tables. Each row presents initial velocities v_i (km/h), and each columns represent the final velocities v_f (km/h) for each segment (level k). All fuel consumption values in tables are calculated based on four-mode fuel consumption model by Bowyer et al. ,1985. In table 4.4, the four-model $F_a(t_a)$ acceleration formula in Equation 1 has been used for local cost calculation $f_1^*(i) = \text{cost}(0, i)$. In other words, since initial velocity $v_i=0$ km/h at level 0. Fuel consumption are separately calculated for each final velocities which are 20km/h, 30km/h, 40 km/h, 50 km/h, 60km/h, 70 km/h, 80km/h and 90km/h.

Table 4.4 Fuel consumption calculation with DP for A-B segment (level 0).

v_i (km/h) \ v_f (km/h)	20	30	40	50	60	70	80	90
0	22.68	19.84	21.21	25.00	30.62	37.83	46.50	56.57

According to Table 4.4, since the vehicle has stopped at point A, when the vehicle reach to point B with velocity of 20km/h (v_f), fuel consumption has been calculated as $F_a(t_a) = 22,68$ ml with the acceleration formula. At level 0 fuel consumption values have been calculated through utilization of equation 4.1 and 4.3.

Table 4.5 Fuel consumption calculation with DP for B-C segment (level 1).

v_i (km/h) \ v_f (km/h)	20	30	40	50	60	70	80	90
20	33.78	29.79	29.99	34.67	40.78	48.28	57.11	67.25
30	26.95	26.46	24.92	28.50	34.74	42.32	51.21	61.38
40	27.13	26.29	25.76	25.60	31.94	39.57	48.50	58.70
50	30.14	29.44	28.95	28.55	30.55	38.24	47.19	57.42
60	36.42	35.44	34.33	33.85	33.78	37.70	46.68	56.92
70	46.02	44.90	43.38	41.70	40.57	40.98	46.70	56.95
80	59.76	58.40	56.31	53.70	51.03	48.98	49.95	57.38
90	78.83	77.17	74.32	70.52	66.21	62.10	59.23	60.65
MIN	26.95	26.29	24.92	25.60	30.55	37.70	46.68	56.92

For level 1, 2 and 3 ($k = 1, 2$ and 3) minimum fuel consumption costs are calculated through utilization of equations 4.1 and 4.4 Total costs at this level $f_k^*(i)$; are obtained by addition of fuel consumption cost at this level $\text{cost}(j, i)$ with the cost of the previous level's minimum consumption cost $\text{cost}(j, i)$. Here if the vehicle was accelerating as shown in Equation 4.1, i.e. ($v_i < v_f$) calculation was made by using equation 2.14 $F_a(t_a)$; if the vehicle was decelerating ($v_i > v_f$) calculation was made by using equation 2.15 $F_d(t_d)$; if the vehicle was going at a constant speed ($v_i = v_f$) calculation was made by using equation (2.16) $F_c(t_c)$. In each level, all minimum values and their respective transition

velocities are kept in memory and are used during the backward step. Table 4.5, Table 4.6 and Table 4.7 have been created as described here in above.

Table 4.6 Fuel consumption calculation with DP for C-D segment (level 2).

v_i (km/h) \ v_f (km/h)	20	30	40	50	60	70	80	90
20	42.71	39.88	42.99	47.66	53.78	61.27	70.10	80.24
30	34.16	37.89	38.78	43.66	49.91	57.48	66.37	76.54
40	32.14	31.19	34.79	38.03	44.37	52.01	60.94	71.14
50	33.16	32.12	31.28	34.80	39.87	47.56	56.52	66.74
60	39.91	38.59	37.20	36.15	39.68	46.35	55.33	65.57
70	51.05	49.28	47.09	44.93	43.49	47.15	55.28	65.53
80	67.31	64.91	61.67	58.04	54.73	52.78	56.76	66.27
90	89.54	86.35	81.78	76.30	70.64	65.85	63.33	67.89
MIN	32.14	31.19	31.28	34.80	39.68	46.35	55.28	65.53

Table 4.7 Fuel consumption calculation with DP for D-E segment (level 3).

v_i (km/h) \ v_f (km/h)	20	30	40	50	60	70	80	90
20	56.03	53.78	56.89	61.56	67.68	75.17	84.00	94.14
30	42.84	50.98	52.41	57.29	63.53	71.11	79.99	90.17
40	42.58	41.85	49.39	53.12	59.45	67.09	76.02	86.22
50	46.79	45.77	45.21	52.28	57.79	65.48	74.44	84.66
60	53.90	52.34	50.92	50.30	57.13	64.19	73.18	83.41
70	65.17	62.81	60.21	58.05	57.31	64.18	72.65	82.90
80	82.25	78.87	74.76	70.62	67.45	66.60	73.78	83.59
90	105.80	101.17	95.22	88.67	82.52	78.12	77.19	84.96
MIN	42.58	41.85	45.21	50.30	57.13	64.18	72.65	82.90

For the level 4, Fuel consumption $f_M^*(i)$ was calculated by using the equations 4.1 and 4.4. As shown Table 4.8, the vehicle will stop at point F which is the last point ($v_f=0$); When initial speed at point E is respectively $v_i= 20\text{km/h}$, 30km/h , 40 km/h , 50 km/h , 60km/h , 70 km/h , 80km/h and 90km/h respectively (because $v_i > v_f$ is always at this level) fuel consumption is calculated by slowing formula $F_d(t_d)$ for each speed separately. All calculated values are accumulated by previous level values. The value of $f_M^*(i)$ is minimum of the sum of $\text{cost}(j, 0)$, and the optimum value of the previous level $f_{M-1}^*(j)$

Table 4.8 Fuel consumption calculation with DP for E-F segment (level 4).

v_i (km/h) \ v_f (km/h)	0
20	60.74
30	54.38
40	55.41
50	60.07
60	68.34
70	79.25
80	94.99
90	117.27

Table 4.8 shows that, the minimum value at level 4 gives the minimum total fuel consumption on this route at the same time and is equal to 54.38 ml. The recommended speed in this range for our vehicle is $v_f = 0$ and $v_i = 30$ km/h which means our vehicle should have the speed of 30 km/h while passing through point E and stopped at point F.

To sum up, optimum total fuel consumption is 54,58 ml for the given route. The suggested velocities for each segments are 0 km/h, 40 km/h, 50 km/h, 40 km/h, 30 km/h and 0 km/s respectively. These values (indicated in bold) are obtained from Tables 4.4-4.8 by backward recursion.

4.5 VALIDATION OF MODEL

Using the proposed model presented above, an online application is developed. Given a starting and destination addresses, the application finds the possible routes and estimates the trip costs for each route based on the DP technique which uses only three modes (acceleration, deceleration and cruise) of the four mode fuel consumption model. The vehicle is assumed to be in continuous motion, moreover, traffic jams, traffic lights and speed limits are not taken into account.

The four-mode model uses slope and distance as parameters. Geographical data in the online application website is obtained by using Google's Map API. Given two geographical points (A,B) the system then finds the distance between the two points and

automatically delaminates segments of A and B. Elevation value of each segment is also provided by online application. Figure 4.3 shows the elevation in meters of the segments on a sample route.

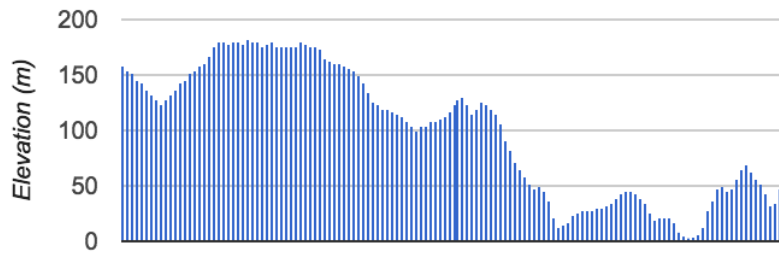


Figure 4.3 Elevation graph between the two geographical points.

Considering distance between consecutive segments and their respective elevation values, the slope values can be calculated by dividing the change in elevation by their distance. Figure 4.4 shows an example of the 256 resulting slope values for the elevation points shown in Figure 4.3.

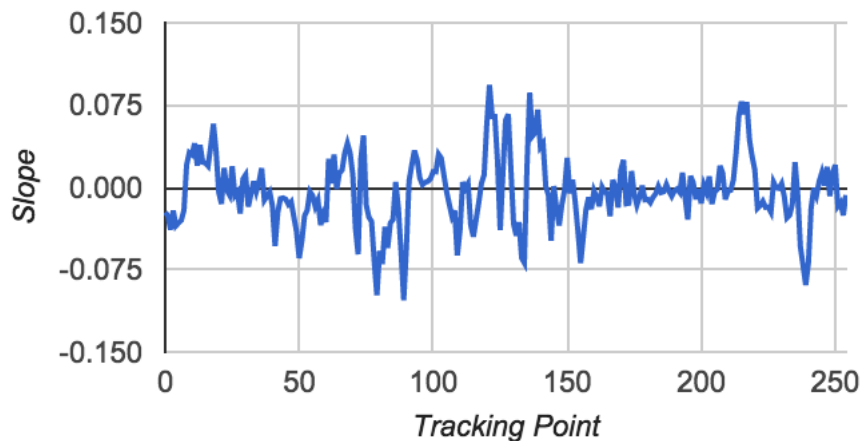
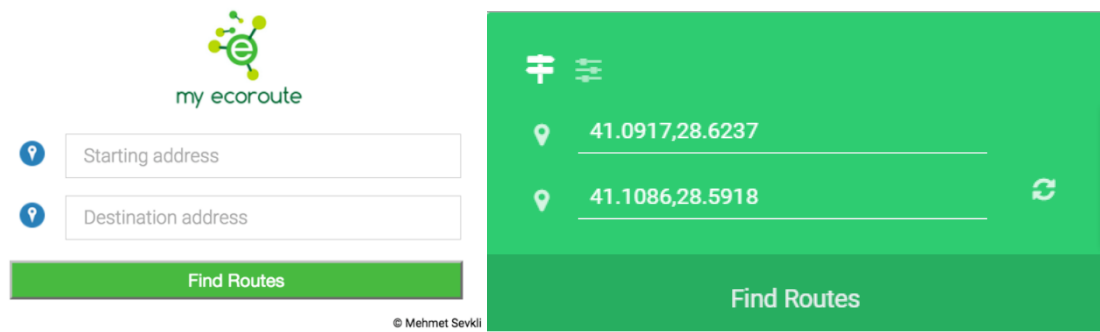


Figure 4.4 Tracking point-slope graph.

Figure 6 shows the online application website's interface. Starting and destination addresses can either be coordinates of latitude and longitude or written address.



my ecoroute

Starting address

Destination address

Find Routes

© Mehmet Sevkli

41.0917,28.6237

41.1086,28.5918

Find Routes

Figure 4.5 Starting and destination coordinates entries to the website.

The routes used for validation is located in Istanbul, Turkey, and are shown on the maps that appear in Figure 4.6, along with their elevation graphs. The maps show the beginning and ending of the routes with the letters A and B. Route 1 (A-B) is part of what is known as the Hadımköy Road between Fatih University -Karaağaç, and is of 3.4 km length. The latitude and longitude coordinates of the start and end points of the route are (41.0917, 28.6237) and (41.1086, 28.5918), respectively. Route 2 (B-A) is part of the Hadımköy Road between Karaağaç-Fatih University (reverse direction of the route 1), and is of 3.4 km length.

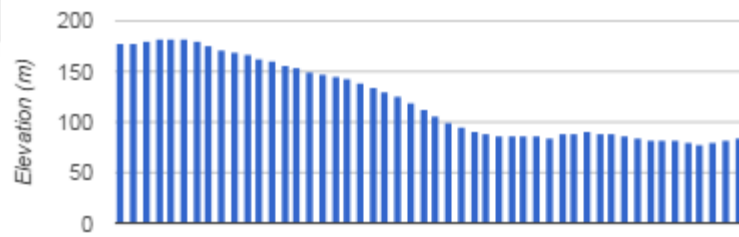


Figure 4.6 Route 1 (A-B) and its elevation graph.

Data from the vehicle has been collected in real-time using existing on-board diagnostics (OBD2), a Bluetooth interface and a smartphone.

4.6 RESULTS OF DYNAMING PROGRAMMING

In this section, a comparisons of the consumption values of proposed model and real fuel usage values. For the sake of consistency, five replications of data gathering are conducted for both directions indicated in Figure 4.6. Total fuel consumptions for each direction displayed in Table 4.9. The average and standard deviation of real-time fuel consumption values out of five replications are also given in Table 4.9.

Table 4.9 Comparison of the fuel consumption calculation with DP and real time values.

Route	Distance (km)	Calculated Consumption (ml)	Real-Time Data	
			Average Consumption(ml) μ	Standard Deviation (σ)
A-B	3.40	93.47	90.45	0.00768
B-A	3.40	259.82	251.65	0.00965

As shown in Table 4.9, the average real time consumption for the direction of A-B and B-A are 90.45 ml and 251.65 ml respectively. These values are obtained by the proposed speed that is recommended by application of DP technique. The deviation from the real-time and calculated fuel consumption for direction A-B and B-A are 3.23% and 3.14% respectively. These deviations can be considered as reasonable values. The DP technique is promising for the real case application via www.mycoroute.com website.

Another advantage of this technique is suggesting an economic route among the all alternative routes even if the total distance is bigger than others. In order to prove this a starting and destination addresses are marked to online web application which two cities in west of Turkey namely Demre and Izmir. Figure 4.7 is demonstrates all routes together with total distance and fuel consumption.

While second route has a 498 km total traveling distance among the others, it seems an economic route that consumes 16512.02 ml comparing the others. Suggested speeds for the second routes are depicted right hand side of the Figure 4.7.

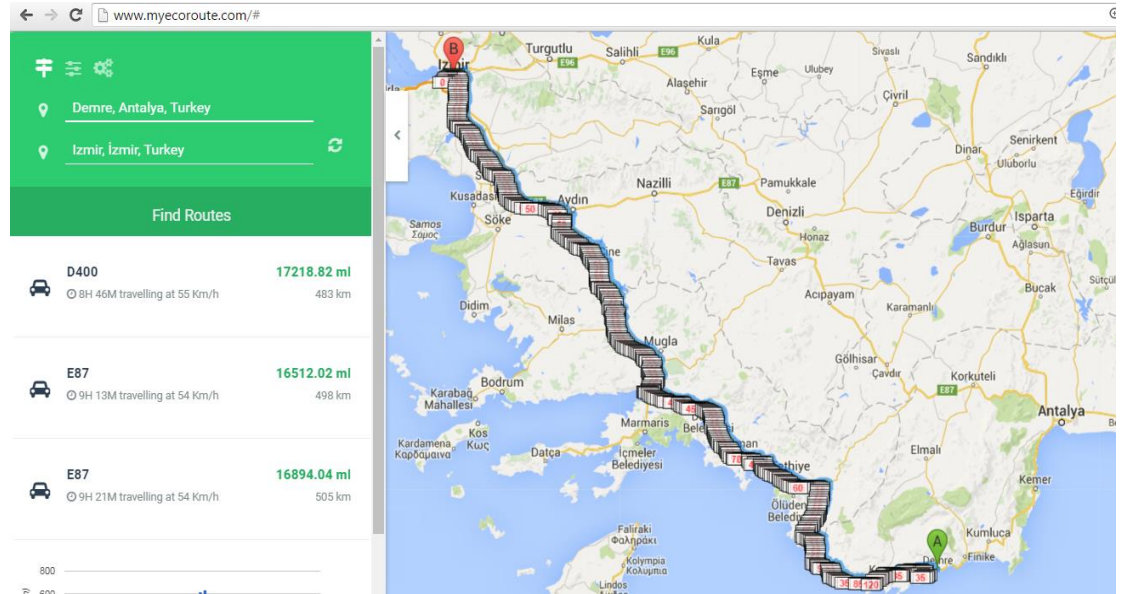


Figure 4.7 compare fuel consumption two route alternatives.

Elevation graph of the first two routes is given in Figure 11. The slope deviation in the second route is less than the first route. This could be the reason of the selecting second route as most economical route even if longer traveling distance.

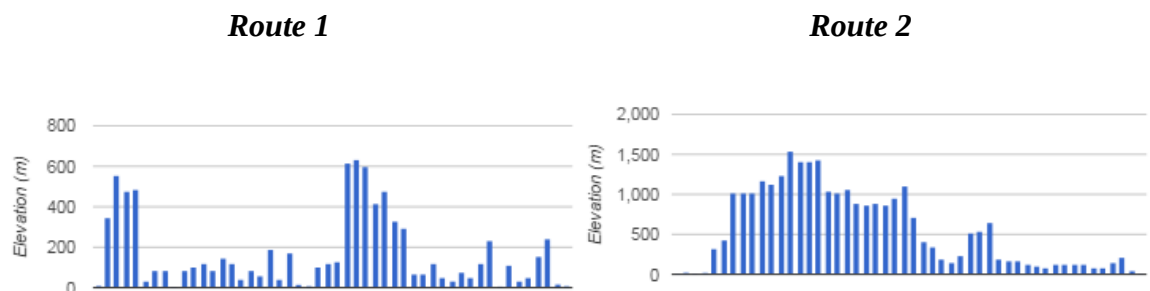


Figure 4.8 Route1 and Route2 elevation graphs with respectively.

5. CONCLUSION

In this thesis, A numerical comparison of six instantaneous fuel consumption models from the literature against actual fuel usage data collected from two passenger car from three different route. The routes primarily differ with respect to their road gradient, in particular Route 1 is almost flat, Route 2 has a negative gradient and Route 3 has a positive gradient. Route 1 that has flat indicate that PERE and VSPM yield estimations for Toyota corolla and VSPM yield estimations for Volkswagen Passat that have the least MAE when compared with real data on average. Route 2 that has a negative gradient suggest that VSPM once again performs the best with respect to the MAE both two vehicles. It is outperformed slightly by IFCM for the speed 90 km/h and by CMEM for the speed 120 km/h but the difference is not significant. The results concerning Route 3 suggest that whilst VSPM once again provides the lowest MAE for two passenger vehicle, the quality of the estimation deteriorates for speeds higher than 105 km/h. For such speeds, CMEM, FMEFCM or IFCM provide better results. As a result it is suggested that a vehicle power specific model yields the smallest mean error for three different routes with varying road gradients. In contrast, IFCM performs poorly on low speeds. Of the other formulations, a comprehensive modal emission model and a physical emission rate estimator also provide satisfactory results.

In this thesis, five fuel consumption models from the literature is compared using real-time data collected from three vehicles in three different routes. It is developed, tested and compared three regression models linear regression (LR), neural networks (NN) and support vector regression (SVR) against the five fuel consumption models and the real-time data. In order to predict the fuel consumptions with the regression models, speed, acceleration, engine RPM, volumetric efficiency, EGR commanded and slope of the road are used as input variables for the full regression model. When all the variables are used in analysis, the correlation between real data and predicted data is

quite high. However, although all variables are used in the analysis, not all of them are controllable. Given that speed and acceleration are controllable by driver and the slope is dependent on route selection, further analysis was conducted with these three parameters alone. In particular, a randomly selected 80% of the data is used for training and 20% for testing for each run. The procedure is repeated for 1000 times. SVR outperforms other models in terms of both accuracy and consistency, as indicated by the average and standard deviation of correlation coefficient (R) values. Even when only speed, acceleration and slope are used as input values, SVR delivers better results. In the next set of experiments, it is presented more general results instead of constructing a model for each kind of vehicle. These models are constructed by considering additional input variables such as frontal area, engine displacements, and mass of vehicle. The new model can be applied all kinds of vehicles. Similar to previous test model, it shows that SVR outperforms other methods in both cases, where in the first case all variables are used as input, and in the second in addition to. ANN also provides competitive results, however SVR yields more robust results especially for testing data which can be seen from standard deviations of the R values. The results suggest that the statistical models can be applied easily for predicting fuel consumption of vehicles, and the results indicate that they are superior to the existing fuel consumption models in terms of prediction accuracy.

The most significant factors that affect fuel consumption are speed and route of the slope. In this paper a dynamic programming approach is proposed for a vehicle travelling from origin to destination with a set of possible routes. The calculation is based on a mathematical model named four-mode elemental fuel consumption with respect to slope of the route and vehicle speed. The speed which is required for a vehicle, has been determined by taking into consideration the conditions such as the type, weight, geographical location on a certain route for the most economic fuel consumption. The approach estimates a continuous optimal travelling speeds for a selected route in terms of total fuel consumption.

An online web application is developed. Given a starting and destination addresses, the application finds the possible routes and estimates the trip costs for each route based on the DP technique which uses only three modes (acceleration, deceleration and cruise) of

the four mode fuel consumption model. The vehicle is assumed to be in continuous motion, moreover, traffic jams, traffic lights and speed limits are not taken into account.

A comparisons of the consumption values of proposed model and real fuel usage values are made. The deviation from the real-time and calculated fuel consumption can be considered as reasonable values. The DP technique are promising for the real case application via www.mycoroute.com website.

Another advantage of the DP is suggesting an economic route among the all alternative routes even if the total distance is bigger than others.

Further research, It is suggested that a mobile applications can be improved about greenhouse gas emission release for vehicle and optimum fuel consumption module can be added at the present navigation mobile applications.

REFERENCES

- Ahn, K., Rakha, H., 2008, The effects of route choice decisions on vehicle energy consumption and emissions, *Transport Res.*, 13, pp. 151-167.
- Akçelik, R., Besley, M., 2003, Operating cost, fuel consumption, and emission models in aaSIDRA and aaMOTION, *25 th Conference of Australian Institutes of Transport Research (CAITR 2003)*, University of South Australia, 3-5, Adelaide, Australia.
- Akçelik, R., Besley, M., 1990, *SIDRA 5 User Guide. Technical report*, ARRB Transport Research Ltd., Vermont South, Australia.
- Aksoy, A., Küçükoğlu, İ., Ene, S., Öztürk, N., 2014, Integrated emission and fuel consumption calculation model for green supply chain management, *Procedia Soc Behav Sci* , 109, pp. 1106-1109.
- Alonso, J.M., Alvarruiz, F., Desantes, J.M., Hernández, L., Moltó, G., 2007, Combining neural networks and genetic algorithms to predict and reduce diesel engine emissions, *IEEE T Evolut Comput*; 11(1), pp. 46-55.
- Alpar, R., 2003, *Uygulamalı Çok Değişkenli İstatistiksel Yöntemlere Giriş I* , Nobel Yayın Dağıtım, 408 s, Ankara.
- Alpaydın, E., 2004, *Introduction to Machine Learning*. MIT Press, Cambridge.
- Alpaydın, E., 2011, *Yapay Öğrenme*. Boğaziçi Üniversitesi Yayınları, İstanbul.
- Altun, H., Eminoğlu, U., Tezekici, B. S., 2002, MLP Yapay Sinir Ağlarında Öğrenme Sürecinin Aktivasyon Fonksiyonu ve İstatistiksel Değişim Gösteren Giriş Verilerine Bağımlılığı. *Eleco'2002, Elektrik-Elektronik-Bilgisayar Mühendisliği Sempozyumu*, Elektronik, 310-314, Bursa.
- Alwakiel, H.N., Leveraging, 2011, *Weigh-In-Motion (WIM) data to estimate link-based heavy-vehicle emissions*. PhD thesis, Portland State University, USA.
- Ardekani, S., Hauer, E., Jamei, B., 1996, Traffic impact models, *Traffic Flow Theory*, US Federal Highway Administration, Washington, DC, pp. 1–7.
- Barth, M., Boriboonsomsin, K., 2008, Real-world CO2 impacts of traffic congestion, *Transport Res Rec*; 2058(1): 163–171.

- Basak, D., Pal, S., Patranabis, D.C., 2007, Support vector regression, *Neural Information Processing-Letters*, 11.10, 203-224.
- Baş, N. , 2006, *Yapay Sinir Ağları Yaklaşımı Ve Bir Uygulama*, Ms Thesis, Mimar Sinan Güzel Sanatlar Üniversitesi, pp 31-32, İstanbul.
- Bellman, R.E., Dreyfus, S.E., 1962, *Applied Dynamic Programming*; Princeton University Press:Princeton, NJ, USA.
- Bera, P. , 2013, Fuel consumption analysis in dynamic states of the engine with use of artificial neural network, *Combust Engine*, 155 (4), pp. 16-25.
- Bertsekas DP., 2000, *Dynamic programming and optimal control*, Athena Scientific, Belmont.
- Biegler, L.T., 2007, An overview of simultaneous strategies for dynamic optimization, *Chem. Eng. Process*, 46, pp. 1043–1053.
- Bigazzi, A. and Bertini, R.L., 2009, Adding Green Performance Metrics to a Transportation Data Archive. *Transportation Research Record*, 2121, pp.30-40.
- Biggs, D., Akçelik. R., 1987, Estimating Effect of Vehicle Characteristics on Fuel Consumption, *J Transp Eng-ASCE*; 113(1), pp. 101–106.
- Binder, T., Blank, L., Bock, H.G., Bulirsch, R., Dahmen, W., Diehl, M., 2001, Introduction to model based optimization of chemical processes on moving horizons, Grötschel M, Krumke SO, Rambau J, editors. *Online optimization of large scale systems: state of the art*. Heidelberg, Springer, pp. 295–340.
- Boriboonsomsin, K., Barth, M., 2009, Impacts of road grade on fuel consumption and carbon dioxide emissions evidenced by use of advanced navigation systems, *Transport Res Rec*; 2139, pp. 21-30.
- Boroujeni, B.Y., Frey, H.C., 2014, Road grade quantification based on global positioning system data obtained from real-world vehicle fuel use and emissions measurements, *Atmos Environ*;85: 179-186.
- Boulter, P. G., and McCrae, I., 2009, *ARTEMIS: Assessment and reliability of transport emission models and inventory systems: Final report, Technical report*, Berkshire, UK., <<http://www.inrets.fr/ur/lte/publi-autresactions/fichesresultats/fichear%temis/artemis.html>> (01.12.13).
- Bowyer, D.P., Biggs, D.C., Akçelik, R., 1985, Guide to fuel consumption analysis for urban traffic management, *Australian Road Research Board Transport Research*, 32.
- Cappiello, A., Chabini, I., Nam, E. K., Lue, A., and Abou Zeid M., 2002, A statistical model of vehicle emissions and fuel consumption, *In Proceedings the IEEE 5th international conference intelligent transportation systems*, pp. 801–809, Singapore.

- CARB, 2011, *EMFAC2011 technical documentation. Technical report*, California, USA, 2011. <<http://www.arb.ca.gov/msei/emfac2011-documentation-final.pdf>> (01.12.13).
- Carrese, S., Gemma, A, La Spada, S., 2013, Impacts of driving behaviours, slope and vehicle load factor on bus fuel consumption and emissions: a real case study in the city of Rome, *Procedia Soc Behav Sci*; 87, pp. 211-221.
- Cay, Y., 2013, Prediction of a gasoline engine performance with artificial neural network, *Fuel*, vol. 111, pp. 324–331.
- Chaim, M.B., Smerling, E., 2013, A model for vehicle fuel consumption estimation at urban operating conditions, *Int J Mech*; 7:18-25.
- Chaim, M.B., Smerling E., Kuperman A., 2013, Analytic modeling of vehicle fuel consumption, *Energies*, 6, pp. 117-127.
- Chakraborty, A., Roy, S, Banerjee R. 2016, An experimental based ANN approach in mapping performance-emission characteristics of a diesel engine operating in dual-fuel mode with LPG, *J Nat Gas Sci Eng*, 28, pp. 15-30.
- Chang D., Morlok E., 2005, Vehicle speed profiles to minimize work and fuel consumption, *Journal of Transportation Engineering*, 131 (3), pp. 173–182.
- Coates, A. , Andrew Y., and Lee, H., 2011, An analysis of single-layer networks in unsupervised feature learning. *Journal of Machine Learning Research - Proceedings Track*, 15:215–223.
- Copeland, J., 2015, *Artificial Intelligence: A Philosophical Introduction*, John Wiley & Sons, Massachussets.
- Coşkun, E., Karaoğlu, E., 2011, Veri madenciliği yöntemleriyle mikro dizilim gen ifade analizi, *Hacettepe Tıp Dergisi*, Ankara.
- Cristianini, N. , Elisseeff, A. and Shawe-Taylor J., 2001, On optimizing kernel alignment. *Technical Report NC-TR-01-087*, Royal Holloway, University of London, UK.
- Cybenko, G. , 1989, Approximation by superpositions of a sigmoidal function, *Mathematics of control, Signals and systems*, 2.4, pp. 303-314.
- Çömlekçi N., 1998, *Temel İstatistik İlke ve Teknikleri*. Bilim Teknik Yayınevi, 493 s, Eskişehir.
- Da Rocha, T.V., Can, A., Parzani, C., Jeanneret, B., Trigui, R., Leclercq, L., 2013, Are vehicle trajectories simulated by dynamic traffic models relevant for estimating fuel consumption?, *Transport Res.*, 24, pp. 17-26.

- Della Ragione L, Meccariello G, Prati MV, Costagliola M A., 2014, Statistical evaluation of slope's effect on real emissions and fuel consumption performed with different cars in Naples urban area, *TRA Transport Research Arena Conference*, Paris, France.
- Delucchi, M., 2003, *A lifecycle emissions model (LEM): Lifecycle emissions from transportation fuels, motor vehicles, transportation modes, electricity use, heating and cooking fuels, and materials*, Technical report, California, USA.
<<http://www.escholarship.org/uc/item/9vr8s1bb>> (01.12.13).
- Demir, E., Bektaş, T., Laporte, G., 2011, A comparative analysis of several vehicle emission models for road freight transportation, *Transport Res.*, 16(5), pp. 347–357.
- Demir, E., Bektaş, T., Laporte, G., 2014, A review of recent research on green road freight transportation, *Eur J Oper Res*, 237(3), pp. 775–793.
- Drucker, H., Burges, C.J.C., Kaufman, L., Smola, A.J., Vapnik, V.N., 1997, Support Vector Regression Machines, in *Advances in Neural Information Processing Systems*, 155–161, MIT Press.
- Efe M. Ö., Kaynak O. 2004, *Yapay Sinir Ağları ve Uygulamaları*, pp 1, Boğaziçi Üniversitesi, İstanbul.
- EPA, 2003, *User's guide to MOBILE6.1 and MOBILE6.2: Mobile source emission factor model*, Technical report, United States Environmental Protection Agency, USA. <<http://www.epa.gov/oms/models/mobile6/420r03010.pdf>> (01.12.13).
- EPA, 2012, *Motor vehicle emission simulator (MOVES): User's guide for MOVES2010b* Technical report, United States Environmental Protection Agency, USA,. <<http://www.epa.gov/oms/models/moves/documents/420b12001b.pdf>> (01.12.14).
- EPA, 2015, *Carbon Dioxide Emissions-Climate Change*, USA.
<<http://www3.epa.gov/climatechange/ghgemissions/gases/co2.html>> [accessed 15.12.2015].
- Erdal, H. İ. , 2011, *Destek Vektör Makineleri ile Tahmine Dayalı Bir Modelleme ve Bir Uygulama*, PhD Thesis, İstanbul Üniversitesi, FBE, İstanbul.
- Ertekin, T., 2000, *Ekonometriye Giriş*. Beta Yayınları, No. 652, pp 334, Ankara.
- Freij K.B., Ericsson E., 2005, Influence of street characteristics, driver category and car performance on urban driving patterns, *Transport Res D-Tr E*, pp. 213-229.
- Froberg, A., and Nielsen,L., 2007, Optimal fuel and gear ratio control for heavy trucks with piece wise affine engine characteristics. In *5th IFAC symposium on advances in automotive control*, Monterey, CA, USA.

- Froberg, A., Hellstrom, E., and Nielsen, L., 2006, Explicit fuel optimal speed profiles for heavy trucks on a set of topographic road profiles, *Transportation Research*, 11(4), pp. 279–286.
- Gujarati, D. N., 2005, *Temel Ekonometri* (Çev. Ü. Şenesen ve G. Şenesen), Literatür Yayıncılık, 850 s, İstanbul.
- Günaşdı, N. , E. , 2014, *Examination of Multivariate Multiple Linear Regression Analysis*, Ms Thesis, Atatürk University,Erzurum.
- Hausberger, S., Rexeis, M., Zallinger, M., and Luz, R., 2009, *Emission factors from the Model PHEM for the HBEFA: Version 3, Technical report*, TU Graz, Austria.
- Haykin, S., 1994, *Neural networks: a comprehensive foundation*, New York: Macmillan.
- Hellstrom, E., Ivarsson, M., Aslund, J., and Nielsen, L., 2009, Look-ahead control for heavy trucks to minimize trip time and fuel consumption, *Control Engineering Practice*, 17, pp. 245–254.
- Hickman, J., Hassel, D., Joumard, R., Samaras, Z., and Sorenson, S., 1999, *Methodology for calculating transport emissions and energy consumption (MEET)*, European Commission, DG VII., Technical Report.
- Ho, S.H., Wong, Y.D., Chang, V.W.C., 2014, Developing Singapore Driving Cycle for passenger cars to estimate fuel consumption and vehicular emissions, *Atmos Environ*, 97, pp. 353-362.
- Hucho, W.H., 1998, *Aerodynamics of road vehicles, (4th ed.) SAE International*.
- iea.org, 2015, *International Energy Agency, Key World Energy Statistics*, <https://www.iea.org/publications/freepublications/publication/KeyWorld_Statistics_2015.pdf>
- INFRAS, 1995, *Workbook on Emission Factors for Road Transport: Explanatory Notes*, Technical Report, Bern.
- ISSRC, 2008, *IVE model user manual version 2.0., Technical report, International Sustainable Systems Research Center*. <<http://www.issrc.org/ive/downloads/manuals/UsersManual.pdf>> (01.12.13).
- Jain, A.K, Mao J., Mohiuddin, K.M., 1996, Artificial neural networks: a tutorial, *Computer IEEE Journals & Magazines*, 29, pp. 31 – 44.
- Jimenez, F., and Montiel, C.W., 2014, System for Road Vehicle Energy Optimization Using Real Time Road and Traffic Information, *Energies*, 7, pp. 3576-3598.

- Jimenez-Palacios J L., 1998, *Understanding and quantifying motor vehicle emissions with vehicle specific power and TILDAS remote sensing*, PhD thesis, USA, Massachusetts Institute of Technology.
- Kakaee, A.H., Rahnama, P., Paykani, A., Mashadi, B., 2015, Combining artificial neural network and multi-objective optimization to reduce a heavy duty diesel engine emissions and fuel consumption, *J Cent South Univ*; 22, pp. 4235-4245.
- Kalogirou, S.A., Bojic, M. , 2000, Artificial neural-networks for the prediction of the energy consumption of a passive solar-building, *Energy*, 25, pp. 479–91.
- Kartal, H. B. , 2012, *Envanter Sınıflandırmada Yapay Öğrenme Yöntemlerinin Kullanımı ve Destek Vektör Makineleri İle Bir Uygulama*, Ms Thesis, İstanbul Thecnical University, İstanbul.
- Kılıçbay, A.,. 1980, *Ekonometrinin Temelleri*, İstanbul Üniversitesi İktisat Fakültesi Yayını, 67 s, İstanbul,.
- Knörr, W., Seum, S., Schmied, M., Kutzner, F., & Anthes, R. ,2011, *Ecological transport information tool for worldwide transports. Technical report*.
<http://www.ecotransit.org/download/ecotransit_background_report.pdf> (01.12.13).
- Kouridis, C., Gkatzoflias, D., Kioutsioukis, I., Ntziachristos, L., Pastorello, C., and Dilara, P., 2010, *Uncertainty estimates and guidance for road transport emission calculations, Technical report*, European Commission Joint Research Centre Institute for Environment and Sustainability.
<<http://publications.jrc.ec.europa.eu/repository/handle/111111111/14202>> (01.12.13).
- Koutsoyiannis, A., 1992, *Ekonometri Kuramı*. (Çev. Ü.Senesen ve G. Senesen), İstanbul Teknik Üniversitesi Matbaası, 638 p, İstanbul.
- Larsson, H., and Ericsson, E., 2009, The effects of an acceleration advisory tool in vehicles for reduced fuel consumption and emissions, *Transport Res.*, 14, pp. 141-146 .
- Levenberg, K., 1944, A Method for the Solution of Certain Non-Linear Problems in Least Squares, *Quarterly of Applied Mathematics*, 2, pp. 164–168.
- Li, X., Sun, J.Q., 2014, Effect of interactions between vehicles and pedestrians on fuel consumption and emissions, *Physica A*, 416, pp. 661-675.
- Marquardt, D., 1963, An Algorithm for Least-Squares Estimation of Nonlinear Parameters, *SIAM Journal on Applied Mathematics*, 11. 2, pp. 431–441.
- Martínez-Morales, J.D., Palacios-Hernández, E.R., and Velázquez-Carrillo, G.A., 2015, Modelling engine fuel consumption and NOx with RBF neural network and mopso algorithm, *Int J Automot Tech*, 16(6), pp. 1041-1049.

- Monastyrsky, V., and Golownykh, I., 1993, Rapid computations of optimal control for vehicles. *Transportation Research*, 27B(3), pp. 219–227.
- NAEI, 2012, *Emission factors, Technical report*, National Atmospheric Emissions Inventory, United Kingdom,. <<http://naei.defra.gov.uk/data/emission-factors>> (01.12.13).
- Nagy, I., Suzdaleva, E. and Mlynarova, T., 2013, Optimization of Driving Based on Currently Measured Data, *Proceedings of the 16th International IEEE Annual Conference on Intelligent Transportation Systems*, The Hague, The Netherlands.
- Nam, E.K., Giannelli, R.A., 2005, *Fuel consumption modeling of conventional and advanced technology vehicles in the physical emission rate estimator (PERE), Technical report*, Washington, USA.
<<http://www3.epa.gov/otaq/models/ngm/420p05001.pdf>> [accessed 15.12.2015]
- NTM Road, 2010, *Environmental data for international cargo transport, Technical report*.
- Ntziachristos, L., and Samaras. Z., 2009, Exhaust emissions from road transport, *EMEP/EEA emission inventory guidebook*, updated May 2012.
- Oduro, S.D., Alhassan, T., Ansah, P.O., Andoh, P.Y., 2013, A mathematical model for predicting the effects of tyre pressure on fuel consumption, *Res J Appl Sci, Eng Tech*, 6(1), pp. 123-129.
- Oguchi, T., Katakura, M., & Taniguchi, M., 2002, Carbondioxide emission model in actual urban road vehicular traffic conditions, *Journal of the Japan Society of Civil Engineers*, 695, pp. 125–136.
- Oh, Y., Park, J., Lee, J., Eom, M., Park, S., 2014, Modeling effects of vehicle specifications on fuel economy based on engine fuel consumption map and vehicle dynamics, *Transport Res*, 32, pp. 287–302.
- Özbek, A. , 2007, *Bazik Oksijen Fırınlarında Yapay Sinir Ağlarının Kullanılması*, Ms Thesis, Sakarya University, Sakarya, 20-22.
- Parlak, A., Islamoglu, Y., Yasar, H., Egrisogut, A., 2006, Application of artificial neural network to predict specific fuel consumption and exhaust temperature for a Diesel engine, *Appl Therm Eng*, 26, pp. 824-828.
- Post, K., Kent, J.H., Tomlin, J. and Carruthers, N., 1982, Vehicle characterization and fuel consumption prediction using maps and power demand models. *International Journal of Vehicle Design*, Volume 6, Issue 1.
- Rahimi-Ajdadi, F., Abbaspour-Gilandeh, Y., 2014, Artificial neural network and stepwise multiple range regression methods for prediction of tractor fuel consumption, *Measurement*, 44, pp. 2104-2111.

- Rakha, H., Ahn, K., Moran, K., Saerens, B., and Bulck, E., 2011, Virginia tech comprehensive power-based fuel consumption model: Model development and testing, *Transport Res.*, 16(7), pp. 492–503.
- Rakha, H., Ahn, K., and Trani, A., 2003, Comparison of MOBILE5a, MOBILE6, VTMICRO, and CMEM models for estimating hot-stabilized light-duty gasoline vehicle emissions, *Canadian Journal of Civil Engineering*, 30(6), pp. 1010–1021.
- Reimpell, J., Stoll, H., Betzler, J., 2001, *The Automotive Chassis: Engineering Principles* 2nd edition, Butterworth-Heinemann.
- Rexeis, M., Hausberger, S., and Riemersma, I., 2005, *Emissions and fuel consumption from Heavy Duty Vehicles*, Technical report, COST 346, TU Graz, Austria.
<http://www.transport-research.info/Upload/Documents/200906/20090619_171%904_26922_II_COST346_WGA_FinalReport.pdf> (01.12.13).
- Roy, S., Banerjee, R., Bose, P.K., 2014, Performance and exhaust emissions prediction of a CRDI assisted single cylinder diesel engine coupled with EGR using artificial neural network, *Appl Energy*, 119, pp. 330–340.
- Saboochi Y, Farzaneh H., 2009, Model for developing an eco-driving strategy of a passenger vehicle based on the least fuel consumption, *Appl Energy*, 86, pp. 1925–1932.
- Saerens, B., Vandersteen, J., Persoons, T., Swevers, J., Diehl, M., Van den Bulck, E., 2009, Minimization of the fuel consumption of a gasoline engine using dynamic optimization, *Applied Energy*, 86, pp. 1582–1588.
- Sahlholm, P., Johansson, K.H., 2010, Road grade estimation for look-ahead vehicle control using multiple measurement runs, *Control Eng Pract*, 18, pp.1328–1341.
- Sayin, C., Ertunc, H.M., Hosoz, M., Kilicaslan, I., Canakci, M., 2007, Performance and exhaust emissions of a gasoline engine using artificial neural network, *Appl Therm Eng*, 27, pp. 46–54.
- Schubert, K., Drewitz, H., von Korff, P., 1988, Optimization of the drive train of city buses, *Int. J. Veh. Des.*, 9, pp. 67–84.
- Schwarzkopf, A., and Leipnik, R., 1977, Control of highway vehicles for minimum fuel consumption over varying terrain., *Transportation Research*, 11(4), pp. 279–286.
- Scora, G., Barth, M., 2006, *Comprehensive modal emission model (CMEM), version 3.01: User's guide*, Technical report, University of California, USA.
<http://www.cert.ucr.edu/cmем/docs/CMEM_User_Guide_v3.01d.pdf> [accessed 15.12.2015].

- Şevkli M, Çapraz A. G., Togun N., Özel P., Bektaş T., Şevkli A.Z., Analysis and Validation of Several Fuel Consumption Models for Automobiles Using Real-Time Data, *Energy*, (Under Review)
- Smit, R., Brown, A.L., Chan, Y.C., 2008, Do air pollution emissions and fuel consumption models for roadways include the effects of congestion in the roadway traffic flow?, *Environ Modell Softw*, 23, pp. 1262-1270.
- Smit, R., Smokers, R., and Rabe, E., 2007, A new modelling approach for road traffic emissions: VERSIT+, *Transportation Research Part D: Transport and Environment*, 12(6), pp. 414–422.
- Tamsanya, N., Chungpaibulpatana, S., 2009, Influence of driving cycles on exhaust emissions and fuel consumption of gasoline passenger car in Bangkok, *J Environ Sci*, 21, pp. 604-611.
- Tang, T.Q., Li, J.G., Yang, S.C., Shang, H.Y., 2015, Effects of on-ramp on the fuel consumption of the vehicles on the main road under car-following model, *Physica A*, 419, pp. 293-300.
- Togun, N, Baysec S., 2010, Genetic programming approach to predict torque and brake specific fuel consumption of a gasoline engine, *Appl Energy*, 87, pp. 3401-3408,.
- Togun, N.K., Baysec, S., 2010, Prediction of torque and specific fuel consumption of a gasoline engine by using artificial neural networks, *Appl Energy*, 87, pp. 349-355.
- Tolun, S., 2008, *Destek Vektör Makineleri : Banka Başarısızlığının Tahmini Üzerine Bir Uygulama*, PhD Thesis, Istanbul University.
- Torque Pro (OBD 2 & Car)*, 2015,
<<https://play.google.com/store/apps/details?id=org.prowl.torque&hl=en>> [accessed 15.12.2015].
- Tsang, K.S., Hung, W.T., Cheung, C.S., 2011, Emissions and fuel consumption of a Euro 4 car operating along different routes in Hong Kong, *Transport Res* , 16, pp. 415-422.
- Ünver, Ö. ve Gamgam, H., 2008, *Uygulamalı Temel İstatistik Yöntemler*, Seçkin Kitapevi, 424 s, Ankara.
- Van Mierlo, J., Maggetto, G., Van De Burgwal, E., Gense, R., 2004, Driving style and traffic measures-influence on vehicle emissions and fuel consumption, *P I Mech Eng D- J Aut*, 218, pp. 43-50.
- Velázquez-Martínez, J.C., Fransoo, J.C., Blanco, E.E., Valenzuela-Ocana, K.B., 2016, A new statistical method of assigning vehicles to delivery areas for CO2 emissions reduction, *Transport Res* , 43, pp. 133-144,.

- Walnum, H.J., Simonsen M., 2015, Does driving behavior matter? An analysis of fuel consumption data from heavy-duty trucks, *Transport Res* , 36, pp. 107-120.
- Wang, A., Ge, Y., Tan, J., Fu, M., Shah, A.N., Ding, Y., Zhao, H., Liang, B., 2011, On-road pollutant emission and fuel consumption characteristics of buses in Beijing, *J Environ Sci*;23 (3), pp. 419-426.
- Wang, H., Fu, L., Zhou, Y., Li, H., 2008, Modelling of the fuel consumption for passenger cars regarding driving characteristics, *Transport Res*,13(7), pp. 479–482.
- Wang, M. Q., 1999, *REET 1.5-transportation fuel-cycle model-Vol. 1: Methodology, development, use, and results*, Technical report, Argonne National Laboratory, Illinois, USA.
- Watson, N., 1981, *Transient Performance Simulation and Analysis of Turbocharged Diesel Engines*, SAE Technical Paper, 810338.
- Wollaeger, J, Kumar S.A., Onori, S., Filev, D., Ozguner, U., Rizonni, G., Cairano, S.D., 2012, Cloud-computing based Velocity Profile Generation for Minimum Fuel Consumption A Dynamic Programming based Solution, *American Control Conference*, Canada.
- Wong, P.K., Wong, H.C., Vong, C.M., 2016, “Online time-sequence incremental and decremental least squares support vector machines for engine air-ratio prediction”, *Int J Engine Res*, pp. 1-13.
- Wong, J. Y., 2001, *Theory of ground vehicles*, Wiley-Interscience, New York,.
- Wu, J.D., Liu, J.C., 2012, A forecasting system for car fuel consumption using a radial basis function neural network, *Expert Syst Appl*,10, pp. 1883-1888.
- Wu, J.D., Liu, J.C., 2011, Development of a predictive system for car fuel consumption using an artificial neural network, *Expert Syst Appl*, 38 , pp. 4967-4971,.
- Wyatt, D.W., Li, H., Tate, J.E., 2014, The impact of road grade on carbon dioxide (CO₂) emission of a passenger vehicle in real-world driving, *Transport Res D-Tr E*, 32, pp. 160-170.
- Yıldırım, U., 2014, *Ankara’da şehir içinde meydana gelen trafik kazalarının analizi, kritik noktaların belirlenmesi ve bir yapay sinir ağı ile modellenmesi*, PhD Thesis, Gazi Üniversitesi.
- Zervas, E., 2011, Impact of altitude on fuel consumption of a gasoline passenger car, *Fuel*; 90, pp. 2340-2342,.
- Zhang, K., Frey, H.C., 2006, Road grade estimation for on-road vehicle emissions modeling using light detection and ranging data, *J Air Waste Manage*, 56 (6), pp. 777-788.

Zhang, S., Wu, Y., Liu, H., Huang, R., Yang, L., Li, Z., Fu, L., Hao, J., 2014, Real-world fuel consumption and CO₂ emissions of urban public buses in Beijing, *Appl Energy*, 113, pp. 1645-1655. |



APPENDIX A**DECLARATION STATEMENT FOR THE ORIGINALITY OF THE
THESIS, FURTHER STUDIES AND PUBLICATIONS FROM
THESIS WORK****A.1 DECLARATION STATEMENT FOR THE ORIGINALITY OF THE
THESIS**

I hereby declare that this thesis comprises my original work. No material in this thesis has been previously published and written by another person, except where due reference is made in the text of the thesis. I further declare that this thesis contains no material which has been submitted for a degree or diploma or other qualifications at any other university.

Signature:

Date: May 18, 2016

A.2 FURTHER STUDIES

Further studies related to this thesis work can be done in the following areas:

- (a) Improve mobile applications about greenhouse gas emission release for vehicle.
- (b) Adding optimum fuel consumption module at the present navigation mobile applications. |

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Çapraz, A.G., Togun, N., Şevkli, M., Özel, P., Bektaş, T., Şevkli, A.Z., “Analysis and Validation of Several Fuel Consumption Models for Automobiles Using Real-Time Data”, Transportation Research Part D- Transport and Environment , Under review	

- Çapraz, A.G., Beyca, Ö.F., Şevkli, M., Özel, P., Bektaş, T., Şevkli, A.Z., “*Estimating the fuel consumption of passenger vehicles using regression models*”, International Journal of Energy Research, Under review.
- Çapraz, A.G., Malambane, H., N., Şevkli, M., Özel, P., Bektaş, T., Şevkli, A.Z., “*Optimizing Paths and Speeds for Passenger Cars to Reduce Fuel Consumption*” To be Submitted

Conference Proceedings

- Çapraz, A.G., Şevkli, M., Özel, P., Beyca, Ö.F., “*Fuel Consumption Models Applied to Automobiles Using Real-Time Data: A Comparison of Statistical Models*”, Procedia Computer Science (2016) pp. 774-781, May 2016
- Çapraz, A.G., Beyca, Ö.F., Şevkli, M., Özel, P., Bektaş, T., Şevkli, A.Z., “*Analysis and Validation of Several Emission Models for Automobiles Using Real-Time Data*” Proceedings of the Global Joint Conference on Industrial Engineering and Its Application Areas, Istanbul, Turkey, July 2016

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- Çapraz, A.G., Malambane, H., Togun, N., Şevkli, M., Özel, P., Bektaş, T., Şevkli, A.Z., “*Araçlarda Mevcut Rota Üzerinde Yolun Eğim Bilgisine Göre Ekonomik Yakıt Tüketimi İçin Hız Belirleme*”, YAEM 2015, ODTU, Ankara-Turkey, September 2015.